ABDIRAHIM SALAD HUSSEIN

Analyzing Urban Runoff with Climate Parameters and Soil Moisture Using Artificial Neural Network (ANN) and Ordinary Least Square (OLS) in GIS: A Case Study Mogadishu-Somalia.

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M.Sc. THESIS

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Approval

We certify that we have read the thesis submitted by **Abdirahim Salad Hussein** titled **"Analyzing Urban Runoff with Climate Parameters and Soil Moisture Using Artificial Neural Network (ANN) and Ordinary Least Square (OLS) in GIS: A Case Study Mogadishu-Somalia.)"** and that in our combined opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Educational Sciences.

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Declaration

I affirm that the compilation and presentation of all data, documents, analyses, and findings in this thesis adhere to the ethical principles and academic regulations of the Institute of Graduate Studies, Near East University. Furthermore, I certify that in adherence to these guidelines and principles, I have adequately referenced and cited all data and information that does not originate from this research.

Abdirahim Salad Hussein.

04 /09 /2024

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Abdirahim Salad Hussein

Abstract

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Flood risk management needs to anticipate urban runoff accurately; nonetheless, this continues to be challenging due to the unpredictable and ambiguous nature of urban runoff. The identification of the most significant affecting variables is an essential step in the process of making accurate predictions. Consequently, the primary objective of this research is to investigate the utilization of an artificial neural network (ANN) and ordinary least squares (OLS) to determine the most significant parameters for the prediction of monthly runoff. The maximum and lowest temperatures, rainfall, and soil moisture are the four input factors that are taken into consideration in this study. The location of the case study is Mogadishu, which is located in Somalia. For study, global meteorological data spanning the years 1985 to 2022 are gathered. The results of this research indicate that rainfall and soil moisture are the most significant input elements in the process of predicting runoff. This allows for better accuracy while also reducing the complexity of the process. As a result of the fact that these two components have a direct and significant influence on the quantity and behavior of water flow across the land surface, they are essential in determining the patterns of runoff.

Keywords: Mogadishu, Urban runoff, Geographical Information System, Artificial Neural Network, Ordinary Least Square.

ÖZET

CBS'de Yapay Sinir Ağı (YSA) ve Sıradan En Küçük Kare (OLS) Kullanılarak Kentsel Akışın İklim Parametreleri ve Toprak Nemi ile Analiz Edilmesi: Mogadişu-Somali Örneği.

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Yüksek Lisans, İnşaat Mühendisliği Bölümü

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Sel risk yönetiminin kentsel akışı doğru bir şekilde tahmin etmesi gerekir; yine de kentsel akışın öngörülemeyen ve belirsiz doğası nedeniyle bu durum zorlu olmaya devam ediyor. En önemli etkileyen değişkenlerin belirlenmesi, doğru tahminler yapma sürecinde önemli bir adımdır. Sonuç olarak, bu araştırmanın temel amacı, aylık akış tahmini için en önemli parametreleri belirlemek amacıyla yapay sinir ağının (YSA) ve sıradan en küçük karelerin (OLS) kullanımını araştırmaktır. Maksimum ve en düşük sıcaklıklar, yağış ve toprak nemi bu çalışmada dikkate alınan dört girdi faktörüdür. Vaka çalışmasının yeri Somali'de bulunan Mogadişu'dur. Çalışma için 1985-2022 yıllarına ait küresel meteorolojik veriler toplanıyor. Bu araştırmanın sonuçları, yağış ve toprak neminin yüzey akışının tahmin edilmesi sürecinde en önemli girdi unsurları olduğunu göstermektedir. Bu, daha iyi doğruluk sağlarken aynı zamanda sürecin karmaşıklığını da azaltır. Bu iki bileşenin arazi yüzeyindeki su akışının miktarı ve davranışı üzerinde doğrudan ve önemli bir etkiye sahip olması nedeniyle, akış modellerinin belirlenmesinde hayati öneme sahiptirler.

Anahtar Kelimeler: Mogadişu, Kentsel akış, Coğrafi Bilgi Sistemi, Yapay Sinir Ağı, Sıradan En Küçük Kare.

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List of Abbreviations

ANN: Artificial Neural Network

GIS: Geographical Information System

HL: Hidden Layer

MAE: Mean Absolute Error

NN: Associate Neurons

OK: Ordinary Kriging

OLS: Ordinary Least Square

R: Rainfall

RMSD: Root Mean Square Deviation

RMSE: Root Mean Square Error

RO: Runoff

RRMSE: Relative Root Mean Square Error

RSQ: R Squared (Coefficient of Determination)

SM: Soil Moisture

TF: Transfer Function

Tmax: Temperature Minimum

Tmin: Temperature Maximum

CHAPTER I

Introduction

This chapter comprises a general introduction, a statement of the problem, the study's objective, and the study's cope.

1.1. Background

Throughout the world, cities are now experiencing a growing challenge associated with managing urban runoff and the nexus of water quality and flood risk. The research is going to offer a critical appraisal of the in-depth investigation of urban runoff in Mogadishu, Somalia. This research presents a very good case study of urban development, climate change, and water management. Through a meticulous study covering several decades, this research not only sheds light on the local phenomena but contributes to the greater general discourse of sustainable urban planning. This makes Urban Runoff Management a very critical challenge in modern environmental science, especially in regions that are turning urban at a fast pace while at the same time suffering from the consequences of climate change. The elaborate study gives an in-depth examination of the multifaceted challenges and innovative solutions associated with urban runoff management in Mogadishu, Somalia. This research is a clear testimony that urban resilience in the face of environmental threats would be enhanced with scientific research in urban planning and policy. The literature clearly outlines the basic processes of urban runoff and what it portends for water resources. The study further investigates how urbanization intensifies runoff and pollutant loads into water bodies, hence the urgent need for management strategies that are robust enough to offset such increases. Literature has also noted that climate change poses such challenges at higher magnitudes, making prediction and management of urban runoff a very complex and critical task.

The methodology chapter presents the hybrid analytic framework that uses both traditional and advanced computational techniques: Ordinary Least Squares (OLS) regression and Artificial Neural Networks (ANN), respectively. This hybrid approach is designed to utilize the strengths of each method to boost the prediction accuracy and reliability of urban runoff. The study used a data set from 1985 to 2022, with all variables that determine soil moisture, temperature, and rainfall, to model the dynamics of urban runoff under different scenarios. The results brought out in the following chapters are important in a way that they show how good these models are. This comparative analysis between the OLS and ANN models has brought forth both the strengths and weaknesses of the models. Whereas OLS models are clear and easy to comprehend linear relationships, ANNs are superior in capturing complex, nonlinear interactions in the data. In this way, detailed forecasting could be done, which is very important in urban water management. General conclusions synthesize the results and set them in the context of applications for an urban planner and policymaker. The study gives strong recommendations for strengthening the resilience of urban systems under the dual stresses of flooding and pollution. This includes the improvement in meteorological data collection, increased use of predictive models in planning processes, and infrastructure investment that benefits from the insights learned from the study. It also further calls for interdisciplinary action of scientists, urban planners, and policymakers to make these recommendations operational strategies. In general, these documents will provide a full view of the various challenges and strategies in dealing with urban runoff management under a climate change scenario. The study focused on Mogadishu in addressing specific local needs and at the same time contributed to the global knowledge base by learning lessons that can be adapted and applied in other urban settings going through similar challenges. This research epitomizes the critical link that should exist between scientific inquiry and urban planning, stressing that such information helps decision-making that is fully informed and data-driven for the development of sustainable and resilient urban setups.

1.2. Statement of Problem

Rapid urbanization in Mogadishu, Somalia, has outpaced the establishment of proper water management systems, leading to an escalated risk of flooding due to increased urban runoff. This has been worsened by climate change, which alters precipitation patterns, increasing rainfall intensity and making events very erratic. The traditional urban runoff strategies in Mogadishu are thus inappropriate to predicate or handle the complex interaction between the changes in climate and urban infrastructures. Therefore, advanced predictive models are very essential in guiding urban planning to avert such risks. This study thus advances the above gap by integrating the performance of OLS regression and Artificial Neural Networks to improve the accuracy and reliability of urban runoff estimations in Mogadishu

1.3. Objectives of the study

The main objective studies are as follows:

- To develop predictive: Develop robust models using the regression technique, especially ordinary least squares (OLS), and Artificial Neural Networks (ANN) to correctly predict the patterns of urban runoff in Mogadishu.
- To compare modeling approaches: Evaluate how well the effectiveness of OLS regression and ANN compares in modeling urban runoff, and what their specific strengths and weaknesses are.
- To Provide Management Strategies: Propose operative management strategies for urban water management, based on model findings, that could contribute to flood risk reduction and increase urban infrastructure resilience in the face of increasing climate variability.

1.4. Scope of study

This study combines the use of climatological data, analysis of urban infrastructure, and advanced predictive modeling to address complex issues in urban water management in predicting urban runoff in Mogadishu, Somalia. This research is geographically focused on Mogadishu and delves into the impacts of urbanization and infrastructural dynamics that have contributed to increasing problems of runoffs. Within the considerable period between 1985 and 2022, it provides a long-term perspective on the characteristic patterns and trends of precipitation, temperature, soil moisture, and the resultant runoff events that seriously complicate the urban planning and sustainability agenda. The study hereafter further performs the modeling exercise applying both the OLS regression and ANN method. These models will also be further enriched with adaptation strategies in the mitigation of flooding and building the resilience of infrastructure with recommendations that will support urban planners, policymakers, and community stakeholders in fostering sustainable urban development in Mogadishu.

CHAPTER II

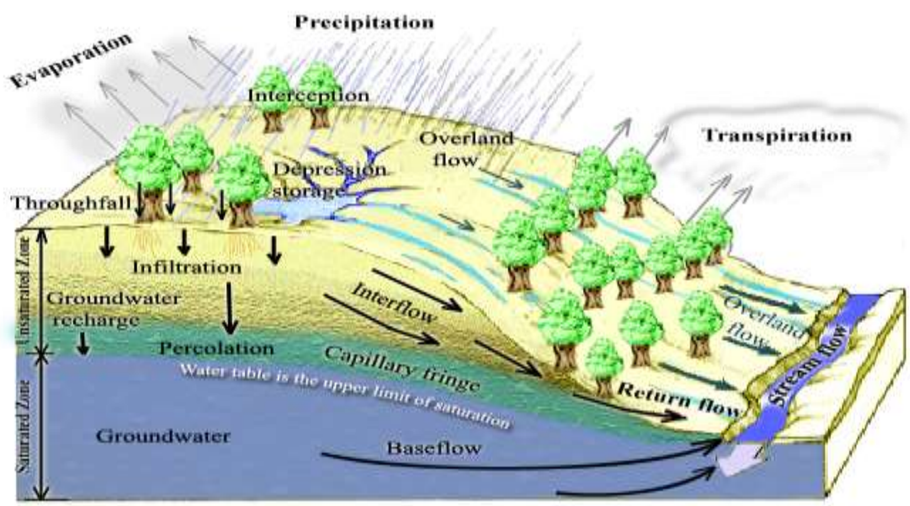
Literature Review

2.1. Introduction to Urban Runoff

Runoff is one of the interrelated components; it connects the chain of precipitation and streamflow in the hydrological cycle. Surface runoff results from the overflow of rainwater over land surfaces into surface rivers and does not infiltrate into the soil. Runoff helps in controlling the Hydrological cycle from the side of replenishing the surplus of precipitation and also manages the amount of water that goes to the stream channels. Surface runoff is an important area of monitoring interest to water supplies and also seeks to address quantity and quality issues, flood forecasting, and ecological and biological interactions in aquatic ecosystems. It is the principal agent of pollution transport as excess fertilizers and pesticides from agricultural lands are carried into streams by rainfall. This information can be used by water resource managers for considering runoff-related pollutants (Sitterson et al., 2018). A greater understanding of runoff mechanisms facilitates the assessment of surface and groundwater risk in terms of quality and quantity. Short-duration, high-intensity rainfall is considerably more likely than longer-duration, less intense rainfall to exceed the soil's capacity to digest water and cause overland flow. While a more humid environment with shallow water tables is less prone to experience stream infiltration losses, even light rainfall, when distributed and aggregated over extensive areas, can cause high stream flows. In arid settings with deep water tables, heavy rainfall over a limited area can cause local runoff that infiltrates downstream (Tarboton, 2003). The term "runoff" describes the flow of water over the surface of the ground and is a crucial phase in the water cycle that unites aquatic, terrestrial, and aerial systems. From Figure 2.0 generation of runoff begins with precipitation, any form of liquid and solid water that comes from the sky. This water can take some different pathways: it may be intercepted by vegetation, be added to the depression storage, or reach the surface of the soil. A fraction of the water that reaches the ground is used to return vapor to the atmosphere via evapotranspiration, but a further remainder will instead travel over the land's surface in what is known as overland flow.

***Figure* 1**

Physical Process of Runoff Generation, *Source (*overview and runoff processes, 2003).



Water in the soil may percolate deeper to recharge the groundwater, or move laterally as interflow to a near return via surface water bodies through return flow, or to maintain stream levels of base flow. The term "runoff" is used both for overland flow and that part of the return flow reaching rivers and streams, adding to streamflow. This water movement, both overland and through the subsurface, is critical for landscape development, ecological health, and water supply planning for both human and environmental needs (overview and runoff processes, 2003).

2.2. Climate Change and Urban Runoff Prediction

For over a decade now, our world has experienced the adverse impacts of climate change. In particular, it is made abundantly clear by the way that natural disasters physically affect the environment and socioeconomic components. Climate change is regarded to be the most important element in the causes of natural disasters such as severe drought and flooding, despite efforts to mitigate any loss, damage, or destruction across all relevant dimensions (Hormwichian et al., 2023). It is linked to an increase in extreme weather events, changes in rainfall patterns, more intense floods and droughts, significant forest fires, rising sea levels, flooding, melting polar ice, catastrophic storms, and a decline in biodiversity (Tsakiris & Loucks, 2023). Because of the catastrophic implications of climate change on individuals, society, and the environment, water resource research under climate change has received a lot of attention in the scientific community. The hydrological cycle and climatic factors like temperature and precipitation will be disrupted by future climate change, which poses serious risks to the operation of hydro-junctions. Therefore, it is imperative to create workable ways to deal with how climate change affects the management of water resources (Bai et al., 2023). Monthly runoff forecasting is the most important in the management, operation, and development of reservoirs. In the meantime, the non-stationarity, skew, and nonlinearity caused by climate change and human activities ruin the runoff, which sharply reduces the accuracy of the projection about monthly runoff. That leads the monthly runoff to be considered hard and demanding work in the prediction of accuracy. In general, the models used for runoff predictions are of two types: physical models and data-driven models. Physical models involve very complex calculating techniques and need substantial meteorological data. Recently, more attention has been paid to data-driven models because of their simpler structure and lower data demand. Among all these techniques, the ANN has attracted tremendous attention in data-driven runoff forecasting during the last 20 years. Consider the backpropagation model (BP neural network). As a result, accurate monthly runoff prediction is regarded as a challenging issue. Researchers have worked for decades creating algorithms for hydrologic forecasting. Runoff is impacted by vegetation cover, land use change, human activities, and climate change. Runoff series display nonstationary and multi-frequency characteristics due to the effect of these uncertain components, which poses considerable difficulty for relevant departments in conducting accurate runoff forecasts. (W. chuan Wang et al., 2024). To reduce the damage caused by urban floods, drainage district units need to have a flood prediction system in place when localized heavy rainfall increases as a result of accelerated changes in climate patterns. Major floods that occurred in Seoul on September 21, 2010, and July 27, 2011, in the past, significantly damaged property. In Seoul, the damage from heavy rains in 2010 and 2011 was $ 35 million and $25 million, respectively (Kim & Han, 2020). Rainfall patterns and intensity have changed due to global climate change, which has an impact on drainage. This has led to regular floods, which have resulted in fatalities and large financial damage. Due to road inundation, Beijing issued a flood emergency in July 2012. 79 people died as a result of the lack of a prompt flood forecast, which would have enabled the implementation of appropriate protocols and preventive measures. Large losses occur when floods are not responded to quickly, and swift response depends on timely and accurate forecasts. To provide decision-makers ample time to intervene and minimize disaster costs, flood disasters must be forecasted quickly (Yan et al., 2021).

Hydrology is a fundamental topic in geosciences, and rainfall-runoff modeling has historically been a prominent research area in hydrology. Since the eighteenth century, hydroscientists have widely used differential equations (DE) to explore a variety of hydrological phenomena and processes, including evapotranspiration and snowmelt, baseflow, and surface flow. Researchers have gradually developed these DE into a series of relatively complete and well-interpretable process-based models, which have been used to predict and explain various hydrological tasks, particularly flood forecasting (Li et al., n.d.). Runoff is critical in managing the hydrological cycle because it returns excess rainfall to surface water bodies, moderating flows. The rainfall-runoff interaction is quite complex due to its composite hydrological aspect. This is due to the significant spatiotemporal variability of watershed and rainfall patterns. Because the hydrological cycle comprises so many factors, it is difficult to articulate the runoff mechanism that ultimately affects the climate regionally. The mathematical description of rainfall-runoff fueled the rise from the 1980s to the late 1800s. It has been an invaluable resource for hydrologists and engineers in predicting and developing urban runoff. The short-range streamflow forecast with less than 24 hours of lead time is useful for flood warning systems and reservoir operation. Surface runoff estimations in the nineteenth century were based on empirical formulas. For smaller catchments, estimations were based on time of concentration, but for large-scale concerns, rational approaches had to be modified (Prasanna et al., 2023).

2.3. Variables Influencing Urban Runoff

Such variables affecting urban runoff are so important in the prediction of and proper management of urban water systems to overcome the risk associated with flooding events and to preserve good water quality. This study analyzes Mogadishu, Somalia, key variables such as maximum temperature, minimum temperature, soil moisture, and rainfall, using ordinary least square (OLS) and artificial neural network (ANN) methods. Other parameters need to be taken into account, as they affect the volume and quality of urban runoff. Rainfall and soil moisture are the two best parameters concerning determining runoff volume from specific areas, a fact which could determine their overall impacting importance in the hydrological cycle of urban centers.

2.3.1. Temperature

Climate change and urbanization have increased the likelihood of urban flooding (H. Il Kim and Kim, 2020). Climate change, induced by a variety of human activities, has emerged as a major focus of scientific inquiry (S. Zhang et al., 2011). The current climatic change is highly sensitive to runoff from glacierized basins. Elevated temperatures have the potential to accelerate the melting of glaciers and snowmelt in numerous river basins, leading to increased meltwater availability for rivers shortly (A. Wang et al., 2023). Between 0.8 and 1.2 degrees Celsius have increased global air temperatures from pre-industrial levels. The hydrological process and sources of major seasonal snow-fed river basins have been negatively impacted by variations in temperature and precipitation. These processes are crucial for the management of water resources, the production of hydropower, agricultural output, and environmental impact assessments. Results from general circulation models (GCMs) and other analyses show that by the middle of the next century, there will be significant global warming due to rising CO_2 concentrations in the atmosphere. Temperatures in the middle latitudes are expected to rise by 1 to 4 degrees. The first step in tackling this issue is to investigate the links between changing climate and surface water runoff (Zhao et al., 2021).

2.3.2. Rainfall

The impact of precipitation is one very pertinent aspect that has increasingly gained importance in the research of urban runoff in recent years, mainly due to the large alterations of natural urban hydrology derived from both natural climatic variations and human-induced changes. Somehow, the available research tends to suggest that precipitation concentration and human impacts change runoff patterns significantly in urban environments, particularly in the case of extremely urbanized areas. Findings in one study related to the city of Guangzhou from 1970 to 2020 showed an increase in rainfall-runoff by 132.9 mm during 2013-2020, with human activities contributing most Through the joint effects of precipitation attention and human activities. Human activities contributed to the rise in the runoff by 141.4 mm, and a decrease in the concentration of precipitation brought a reduction in the runoff by 8.5 mm. In this way, there emerges a 94% significant contribution rate from human activity towards the changes in runoff compared to precipitation concentration changes of -6%. Such findings point towards the need to integrate both hydrologic and urban development considerations for effective management of urban runoff, which is crucial in reducing flood risks (Lv et al., 2023).

2.3.3. Soil Moisture

The hydrological condition of a watershed is the primary element influencing runoff (Hassan & Al-Shamma, n.d.). Soil moisture levels before rainfall have a crucial role in influencing the hydrological response, as they impact infiltration and runoff generation. In hydrologic modeling, the forecast of runoff is thus heavily dependent on the description of antecedent soil moisture levels (Minet et al., 2011). Soil moisture has stretched and been assigned a key position in the hydrologic cycle, and studies have been conducted to better understand its link to watershed runoff or streamflow. Texture, % organic matter, coarse fragments, bulk density, and structure all have an impact on how much moisture a soil retains. These and other soil qualities are used to classify soils, and soil scientists have created categorization systems based on soil physical and chemical properties, parent material, and climate. Because soils vary, so do their interrelationships (Henninger et al., n.d.).

2.4. Global Studies on Urban Flood Prediction Methods

(H. Wang et al., 2021) used the theory of the Naïve Bayes (NB) in multi-factor analysis to estimate the depth of floods and the raised risks worldwide, seriously ruling out the temperature rise. By combining multi-factor analysis with the Naïve Bayes theory to predict the increasing urban flood depths of Zhengzhou, better disaster-predicting results in this paper are put forward by establishing an NB model of 11 key relevant factors in flood disasters, including features of rainfall and surface condition. The model was trained and tested with a series of historical data for rainfall and flood depth, demonstrating results on the performance of the model for the estimates of flood depth across different rainfall conditions. It is a research fact that flooding in the urban area of Zhengzhou has intensified after the reappearance period of two years, mainly in the older urban area. Accordingly, the effectiveness of the NB model in predicting the flood depth gave rise to an average root mean square error value of 0.062, which is essentially valid to yield altogether good insights under early warning systems in an attempt to reduce the adverse impact of a flood event on the concerned areas. This research review is based on the case study of "Urban Flood Risk Assessment" by (Li et al., 2023) is published in the journal "Sustainability". It is a novel issue of concern concerning urban flood disasters occurring in tandem with rapid urbanization and changes in climatic conditions. The conducted research highlights the importance of access to flood disaster risk assessment, a non-engineering measure, in the anticipation and reduction of disasters in cities. It stipulates it as an important principle in management. Authors engage in the study to systematically review mechanisms of flood disasters including impacts from global climate change to urbanization and adaptation lag of municipal facilities collectively intensify the frequency and impact of the floods. The methodology of the study consists of an overall summary of the derived methods of flood risk assessment based on an analysis of the international literature for the past two decades. Notable in this regard is the fact that the analytic tools bring several methods on board in analyzing urban flood risk, including historical disaster statistics, multi-criteria index systems, remote sensing (coupled with GIS), scenario simulation evaluations, and machine learning in-depth discussions of this paper on the current standing of each method, to what the case helps for in foreseen urban flood risks.

In a comparative study, machine learning techniques have been applied to reduce urban damage caused by flooding and to produce a map representing flood hazards from minimal data in dealing with hydrological and hydraulic. The procedure was applied to two models of machine learning: the Genetic Algorithm Rule-Set Production (GARP) Model and the Quick Unbiased Ethical Statistical Tree (QUEST) Model. These models seek to integrate many flood-conditioning factors such as precipitation, slope, curve number, distance to river and channel, depth to groundwater, land use, land cover, and elevation in modeling flooding. The adopted salient influencing factors in the prediction from the experts on the interdisciplinary field through the Fuzzy Analytical Network Process (FANP) are assigned the weights to produce the maps of flood hazard and vulnerability. The model's performance was tested by incorporating a receiver-operator characteristic (ROC) curve and calculating the area under the ROC curve (AUC-ROC). The results of the model's accuracy based on the validation subset are given in Table 4. From the table, it can be seen that GARP performs comparatively with a better accuracy level than QUEST. This is crucial for this research as it will portray the real effectiveness of the machine learning models in flood risk mapping in places with no detailed hydrological and hydrodynamic data. (Darabi et al., 2007). In the study by (S. Kim et al., 2021) titled "High-Resolution Modeling and Prediction of Urban Floods Using WRF-Hydro and Data Assimilation," it was stated that increased high resolution of the hydrological model in this framework allows influence to be made from an increment in the parameter. In this study, data assimilation impact on high-resolution hydrologic modeling and calibration of model parameters in the WRF-Hydro framework is carried out, refining urban flood modeling and prediction in the Dallas-Fort Worth area. It uses high spatiotemporal quantitative precipitation estimates (500 m and 1 min) summed up by the radar network, called the Collaborative Adaptive Sensing of the Atmosphere (CASA), a calibration approach by the name of Stepwise Line Search, and data assimilation provided by the fixed-lag smoothing approach. It covers three urban catchments in Arlington and Grand Prairie, with a total area coverage of interest totaling 144.6 km^2. The result of the study described indicates that the six-pointed parameters of the WRF-Hydro model considerably increase the accuracy of hydrographs' predictions, applied primarily at the increasing branches of flood events, while less accurate during the attenuated peaks or at the over-fast falling limbs. There is also the 250 m requirement of land surface model spatial resolution needed. Another study gives empirical results that high-resolution precipitation data and associated land cover data highly contribute to accuracy in flood prediction. Thus, quality initialization is put as one of the contributors to improvements in event-based urban flood forecasting. Through data assimilation, the forecast accuracy is substantially ameliorated since the initialization is with the realistic conditions in conducting high-resolution urban floods. This study developed an integrated system of flood forecasting and warning, intended to be urban-based and to fit an urban area that is flood-prone due to flash rainfall along a focused small-scale urban stream. It constitutes a mixture of short-term and very short-term forecasts of inundation using high technology to quantify the risks of flooding, hence accurate warning. In the short term, through LSTM, the data in terms of upstream depth time series feeding is done by a lead time of inundations at 30-90 minutes. The ultra-short-term forecast uses radar-based rainfall. It has a rainfall-runoff model in the integration of both inland and river dynamics through SWMM and HEC-RAS software. In addition, these are often implemented along with the models for drainage network automatic simplification, and with the calibration of SWMM parameters by Dynamically Dimensioned Search (DDS) algorithm and a 2D inundation database for betterment in the prediction accuracy. Altogether, all these work on water level prediction and areas with the inundation risk with lead times of 10 to 60 minutes. PREDICT has shown better performance in the results for the forecast. The offering shows a remarkable difference from the existing Seoul Integrated Disaster Prevention System when handling critically important support to the urban flooding forecasting system and the warning system (Lee et al., 2020).

2.5. Flood Modelling Studies in Somalia

As a result, in response to this need, this study (Osman & Das, 2023) assessed flood risk in the Shebelle River Basin, Southern Somalia, with a focus on GIS-based flood risk assessments using Multi-Criteria Decision Analysis (MCDA), focusing on flood hazard analysis, vulnerability, and risk level computation. The approach was distinguished by the use of seven major causative elements for elevation, slope, drainage density, distance to river, rainfall, soil, and geology in the creation of a flood hazard map. The spatial layers considered are as follows: land use/land cover, population density, distance to roadways, Global Man-made Impervious Surface (GMIS), Human Built-up Area, and Settlement Extent (HBASE). We used the Analytical Hierarchy Process (AHP) to assign weights to the data based on their respective contributions to flood risk. The study demonstrated that there are varying levels of flood danger and susceptibility, which led to the creation of a flood risk map for the basin. The graphic grouped the research region into five flood risk zones: very low, low, moderate, high, and very high. The flood hazard model for the Receiver Operating Characteristics-Area Under the Curve (ROC-AUC) was validated and found to have a good prediction accuracy of 0.781. As a result, the study will be critical not only for providing authorities with hazard, vulnerability, and risk maps but also for other uses and the general public to assist them in improving their flood protection awareness and efforts in those locations.

(Thiemig et al., 2010) has conducted an even more detailed study on using the European Flood Alert System (EFAS) for such an environment in a particular hydro-meteorological setting: equatorial river catchments of Africa. "Being the avant-garde warning software, it provides a 2–10-day implicit flood forecast over the whole of Europe using probabilistic intensive weather conditions, along with a set of predefined criteria that includes the threshold exceedance and persistence. It was, however, applied in this study to the new frontier, the Juba–Shabelle basin shared transboundary by Somalia, Ethiopia, and Kenya. In principle, the continental-scale climate evolves around changing and somewhat progressively challenging to forecast seasonally and inter-annually. In addition, the current and future climate conditions have been assessed for changing and sometimes contradictory, hence, identifying the meteorological input needed for understanding the nature of the changing climatology of the study area. Endowed with diverse meteorological datasets, notably that of ERA-40 and CHARM for Climatological analysis and information; yield flood-oriented simulations information alongside the operational predictions from the European Centre for Medium-Range Weather Forecasts model for historical flood event hindcast of the LISFLOOD model. A comprehensive review of the performance of the system concludes that a very promising outcome is above

85% of flood events for both timing and magnitude. This is quite an evident result, emphasizing the potential related to the applicability of EFAS methodologies, accurate Metrologic data, and powerful hydrological modeling in African realities. This would go a long way in providing a reliable guideline on what to do and in the improvement of flood prediction capabilities for critical lead time on such disasters across the continent, for better preparedness and mitigation efforts. On these premises, the study is not only evidence but opens further research to be used in wider, non-European environments with the aim of adaptability on Earth.

this paper titled "Real Time Flood Detection System Based on Machine Learning Algorithms" by (Saeed et al., 2021), appreciates the development of efficient and real-time detection of floods made for regions like Somalia where the setting up of infrastructure for the prevention of flood disasters is technically and economically untenable, courtesy of machine learning algorithms. The principal objective is to introduce an efficient model that can detect potential floods before they occur, deploying a mixture of Machine Learning algorithms such as Random Forest, Naive Bayes, and J48. These algorithms will be used as part of the analysis of the data for water levels and predictions of floods with their intent toward the early warning population at ecosystem service. The solution proposed entails installing sensors in the rivers so that current information about the water levels is captured as it happens. The information thus captured is relayed for further processing and analysis through the required machine-learning algorithms and developed hardware architecture designed to use the Arduino boards for data-capturing systems while GSM modems are used for SMS alerting. The experimental results showed that the achieved accuracy in the detection of flood by the Random Forest algorithm is 98.7%, therefore, compared with the Naïve Bayes and J48 algorithms, it shows competent performance. This is intended to provide a necessary cushion period for important times associated with the evacuation and the taking of measures for prevention. The paper comes up with a unique take on a low-to-no-cost solution that comes in the form of a very different machine learning Methodology for Flood Detection and Forecasting without high-class infrastructure, which may even be exemplary of the scope of Machine Learning Algorithms in forecasting natural disasters.

2.6. Predictive Modelling of Urban Runoff

In this section previous studies related to the predictive modeling of urban runoff using the respective approaches to artificial neural network (ANN) and ordinary least square (OLS) regression are discussed, allowing for predictive considerations to be summarized through a holistic viewpoint on the understanding and forecasting of urban area runoff dynamics. Models are based on different methodologies of interpretation of the computational runoff patterns analyzed to give helpful information for urban planning and water management.

2.6.1. Artificial Neural Network

Hydrological simulations commonly use three modeling systems: distributed physically based models, lumped conceptual models, and empirical black box models. The latter two groups encompass a wide range of physical phenomena with a focus on understanding hydrological processes. Because the rainfall-runoff process is so complex, these physical process simulations and model calibrations necessitate a large amount of hydrological data. Numerous black-box models, including support vector machines, fuzzy theory, artificial neural networks, chaos, genetic programming, and others, have been developed and applied to hydrological forecasting. An artificial neural network is a flexible structure with self-learning and self-adaptive properties that was inspired by research into biological brain networks. In 2000, the American Society of Civil Engineering (ASCE) Task Committee investigated the use of artificial neural networks in hydrology. According to Hsu et al., even though the model's parameters and structure do not correlate to the physical processes that occur in catchments, the artificial neural network (ANN) model may recognize the complex nonlinear relationship between runoff and rainfall time series (Y. Wang et al., 2015). Over the last two decades, Artificial Neural Networks (ANNs) have evolved into powerful computer systems capable of handling exceedingly complex and nonlinear systems. Artificial neural networks (ANN) are a rapid and versatile solution to time series modeling. Because of their parallel structure, these models can deal with system nonlinearity to some extent. For instance, several such researches have found the ANN models underperform compared to the traditional models. Feed-forward ANNs versus a conceptual and linear model by Gaume and Gosset. They found both the linear and ANN models perform poorly compared to their conceptual model. Other research shows just how well ANN models can be used to predict future run-offs accurately. After comparing ANN with Box & Jenkins techniques, it has been found by (48_233, n.d.) that ANN gave good results for prediction compared to Box & Jenkins model. In a tiny watershed in Tono, Japan, (Sohail et al., 2008) compared ANN to MARMA (multivariate autoregressive moving average models) models during the wet and dry seasons. They concluded that when the R-R process's nonlinearity is higher during wet seasons, ANN models function better. It is evident from the discussion that before ANN models performed better than traditional models (Ghumman et al., 2011).

Artificial Neural Networks (ANNs) are widely accepted due to their capacity to solve complicated issues. They are composed of interconnected neurons that work together to solve problems in disciplines like as control, pattern recognition, forecasting, and optimization. One type is the feedforward neural network, which uses backpropagation for training. This design consists of interconnected layers of neurons, with data flowing unidirectionally from input to hidden to output. The backpropagation algorithm reduces errors by changing the weights of neurons during training. As data goes through the hidden layers, each neuron uses an activation function to generate output for the following layer, culminating in the output layer. During the training process, network weights are updated based on the error gradient associated with them. Backpropagation propagates errors backward across the network by computing gradients for each connection and changing weights in the opposite direction of the gradient. This repetitive method gradually reduces the mistake. Feedforward neural networks using backpropagation have proven effective in a variety of applications (Kassem & Hussein, n.d.).

2.6.2 Ordinary Least Square

Regression analysis allows you to model, examine, and research spatial relationships to better understand the factors that drive visible spatial patterns and predict outcomes based on that understanding. Ordinary Least Squares (OLS) is a global regression method. The Spatial Statistics Tool includes a method called spatial regression, which allows the relationships you're modeling to vary across the research area. Ordinary least squares (OLS) have been used as effective modeling approaches for understanding how runoff affects metropolitan situations. Several studies have utilized OLS to estimate runoff at various time scales around the world. "Surface Runoff Responses to Suburban Growth: An Integration of Remote Sensing, GIS, and Curve Number" (Jahan et al., 2021a) as well as "A GIS-Based Approach for Determining Potential Runoff Coefficient and Runoff Depth for the Indian River Lagoon, Florida, USA" (Bellamy and Cho, no date). "The use of geographically weighted regression models to predict spatial characteristics of nitrate contamination: Implications for an effective groundwater management strategy" (Koh et al., 2020), while surface runoff response to sprawling can be evaluated using remote sensing, GIS, and curve numbers (Jahan et al., 2021b). Remote sensing gives rich data for hydrological investigations. OLS regression was used to investigate the correlation between precipitation, land use, geology, and potential site locations (Fu et al., 2022). The link between yield and precipitation was investigated with OLS regression and GWR. The OLS regression model was thought to apply to the entire research region because of the geographical stability of the variables (Sharma et al., 2011). Different relationships would be useful in achieving a first step towards a useful assessment of yield variation on a regional scale. This starts with how different variables such as soil moisture, the pattern in precipitation, and temperature changes, From a systematic perspective, mineral researchers such as the Desert Regional Global Risk Assessment Model of urban flood. Examining historical occurrences and their correlation with explanatory variables might help better understand the incidence of pluvial floods in a specific city. While disaster databases exist on global, national, and regional sizes, few provide high spatial resolution for urban pluvial floods (C. Wang et al., 2017).

Ordinary Least Squares (OLS) regression applies a statistical methodology in ArcGIS, where geographical relationships between variables in a dataset are analyzed. The tool within the Spatial Statistics toolbox is particularly useful for exploring how one or more independent variables vary according to a dependent variable across space. The results for the values of R squared and root mean square errors in general for OLS analysis and geostatistical analysis are derived from ArcGIS. That is, these findings contribute to the means of evaluating the strength and relevance of connections so that researchers and analysts have a better understanding of the spatial distribution of phenomena. Utilizing ArcGIS in this context in spatial analysis is considered an effective tool since it helps to explore and communicate spatial patterns and relationships that OLS regression produces maps of, consequently enabling visualization of the results.

2.7. Relationship between urban flooding and runoff

Urban development significantly increases surface runoff, both in terms of impervious surfaces and total runoff volume flowing to the receiving watershed. Furthermore, the development of storm sewer systems and river culverts throughout the urbanization process contributes to increased runoff. The peak velocity of runoff unavoidably rises when more runoff is released at shorter intervals, increasing the risk of overflow. Urbanization, combined with the concentration of population and property in the watershed, often increases flood potential (Kawamura et al., 2023).

Floods are one of the most devastating natural calamities, with the potential to destroy everything, including buildings, residences, cars, bridges, animals, flora, and even people. Floods are the most common sort of disaster, and their frequency is growing as urban runoff increases. Floods are split into two types: rainy season and flash floods. These categories are determined by the location of geography and topography. As a result, flood episodes vary in duration and month between countries. For example, the Malaysia Meteorological Service (MMS) reports that the largest risk of flooding occurs between November and February, coinciding with the Northeast monsoon season. The rainy season in Thailand typically lasts from May to October, followed by the dry season from November to April. This is also known as the tropical savannah climate (Jaafar et al., 2016). More than half of the world's population now lives in cities, and over 500 cities have more than one million residents. This increase causes urban sprawl, with the surface of metropolitan areas expanding fast. Urbanization has a significant impact on watershed hydrology, resulting in higher runoff rates and volumes, as well as loss of infiltration and baseflow. The construction of impervious surfaces, as well as the simplification of the drainage network, result in a considerably faster runoff response to rainfall, resulting in shorter concentration and recession times (Fletcher et al., 2013). Current and future flood risks are rising due to climate and land use change, with peak runoff flows estimated to increase at a rate of over 5% per decade and 10% of new homes being built in areas of significant flood risk (Quinn et al., 2022).

***Figure* 2**

Schematic Representation of the Flooding Process in an Urban Area, Source: (Tom et al., 2022).

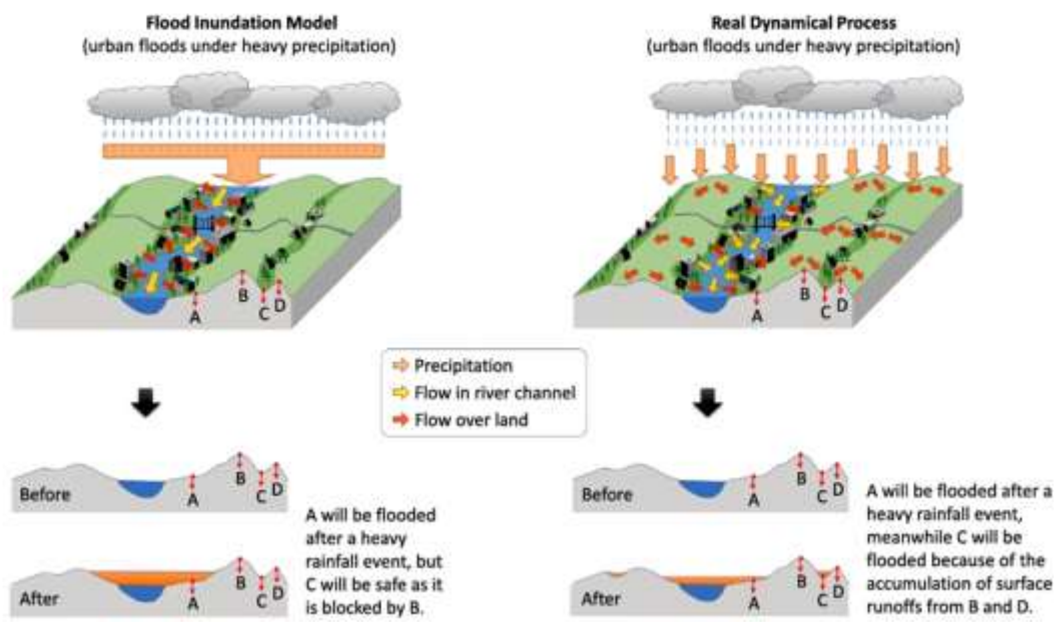


Figure 2.6: Highlights comparison of two different conflict cases with two different scenarios of the flood inundation models during heavy precipitation situations, runoff, and urban flooding. In a "Flood Inundation Model," an area receives an excess overland flow as a result of the heavy rainfall, thus flooding part of the area. This diagram

presents activities after the occurrence of heavy rainfall in Area A. According to the diagram, one thing depicted is that Area A gets flooded after a heavy rainfall event occurs. On the other hand, Area C remains safe as a result of a blocking effect towards C that is caused by Area B. On the right, there is a "Real Dynamical Process" showing the complex massive situation: heavy rainfall leads to flooding in Area A, but it also affects Area C. In such cases, domination in the accumulation of surface runoffs coming from Areas B and D also contributes to the volumes responsible for the flooding in Area C. This implied that the water from floods overland moved and was collected from various areas in the real dynamics of the world as opposed to bursting from a river channel emptying banks.

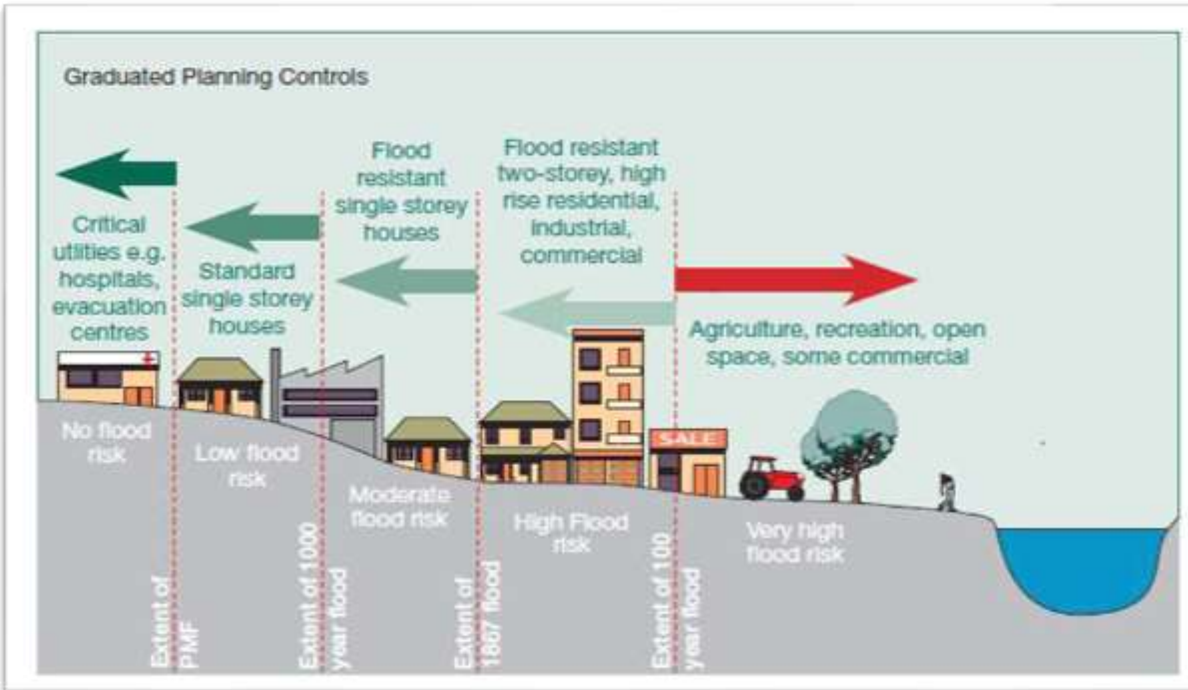
One of the prominent effects of climate change is the disruption of rainfall patterns. The changing rainfall patterns directly affect urban runoff and flooding. In areas with frequent and heavy rainfall, urban drainage systems can become flooded due to the increased volume of runoff. Generally, urban areas with impervious surfaces obstruct natural water infiltration. Rainwater flows over surfaces, collecting pollutants and entering stormwater drains, causing urban runoff. Furthermore, the combination of intensified rainfall and urban runoff increases the risk of flooding in urban areas. Hence, predicting and modeling urban runoff is essential for informed decision-making, flood preparedness, pollution control, and sustainable urban development (Kassem & Hussein, n.d.).

2.8. Relationship between Urban Flooding and Land Use

According to the study by (Alexakis et al., 2014), any telling relation of change in land use, particularly towards urbanization, is associated with urban flooding in the Yialias basin in Cyprus. That is to note that changes in terms of urban sprawl and land use alteration have to bear the blame for the cited phenomenon. In this study, GIS and remote sensing techniques are used to evaluate the hydrologic impacts of land use change at a multi-temporal scale and build a calibrated hydrological model to understand the internal dynamics in the basin and the consequences that such dynamics pose on hazardous flood risk. The results showed a striking rise in the runoff from urban sprawl that has been so evident for the last ten years, showing an evident close link between the rise in built-up size, the decrease in surfaces that can allow infiltration, and the consequential rise in flood risks. Moreover, the analysis appropriate Cellular Automata (CA)-Markov Chain analysis for the prediction of future change in land use and land cover and their likely hydro-ecological impacts status based on the critical sustainable need for land usage management and integrated urban planning in reducing the adverse hydro-ecological impacts and vulnerability of urban areas against flooding. The relationship between land use and urban flood was understood with geographic information systems (GIS) tools and analysis of the Zăbala catchment in Romania on a temporal scale between 1989 and 2019. Summing up so much exciting complexity in land use/land cover change dynamics and its significant effects on potential flash floods was done. This relation is crucial in the setting of human alterations to a natural landscape, such as vegetative covers, flash floods, and examples of urban flooding. The study used Landsat imagery to derive land covers of 1989 and 2019, where seven land-use/land-cover classes were identified using supervised classification. Land use/land cover change potentials in 2019 were seen to have raised surface runoff classes and the potential for flash floods, covering close to 46% of the study area, compared to their classification of about 34% in 1989. Flash flood potential had also increased remarkably because of land use/land cover changes. Geographical Weighted Regression (GWR) was applied to land use/land cover change indicators with the relative evolution of the flash flood potential index. The high values of the Pearson coefficient were close to 17.4% out of the study area, hence giving high correlations on the land use/land cover changes over the flash flood potential changes in those areas. This would make this study, therefore, feasible in the application of GIS, Remote Sensing, and Machine Learning in determining the strong correlation between change in land use/land cover and flash flood potential. It is the enhanced flash flood potential from 1989 to 2019, when further establishing a human footprint on the natural topography, that insists on the importance of land use and management strategies in mitigating flash flood risk (Costache et al., 2020).

***Figure* 3**

Distribution of Land Use on the Flood plain, Source: (Santato & Bender, n.d.)



A design for graded planning restrictions based on flood risk is shown in Figure 2.7, suggesting different land uses by the level of flood hazard. Hospitals and evacuation facilities should be located in areas free of flood danger. The figure indicates that standard single-story homes for low risk, flood-resistant single-story homes for moderate risk, and flood-resistant two-story, high-rise residential buildings, industrial, and commercial structures for high risk are the recommended uses as the flood risk increases to low, moderate, and high.

2.9. Impervious Surfaces of Urban Runoff

The term "impervious surface" refers to a surface that keeps water from seeping through to the soil beneath it. The most crucial indicator of how urbanization is affecting the aquatic environment is imperviousness. Because of the way urban expansion has affected habitat health, impermeable surfaces have emerged as a major issue for growth management and watershed planning. Water quality is decreased by impervious surfaces because they increase the frequency and intensity of downstream discharge. The number of highways, parking lots, rooftops, and other impermeable surfaces has increased along with urbanization, while the quantity of wetlands, forests, and other open spaces that naturally absorb and cleanse stormwater has decreased. The impervious-pervious surface balance has changed, leading to significant alterations in the quantity and quality of stormwater runoff, which has negatively impacted stream and watershed systems. When more than 10% of the watershed is impermeable, stream quality starts to decline (Harindranathan Nair, n.d.). Impermeable surfaces are a major environmental concern since urban runoff from parking lots, rooftops, and roads is mostly responsible for polluting metropolitan rivers (Ebrahimian et al., 2016). Only a small amount of stormwater can be infiltrated, evaporated, detained, or retained by vegetation on impervious surfaces like roofs, asphalt roads, and concrete. This results in high-volume runoff episodes, problems with the hydraulic efficiency of older sewer systems, and direct discharge to a downstream recipient. The characteristics of urban surfaces, human activity, and natural processes within each watershed all have an impact on the chemical properties of stormwater. In a typical metropolitan setting, the impermeable areas usually make up 60–100% of the total area (Jartun et al., 2008). In urban environments, impermeable surfaces have a major influence on the relationship between rainfall and runoff. During storms, urban imperviousness raises peak discharges, runoff volumes, and runoff episode frequency. Negative effects on stream health and water quality have been repeatedly demonstrated by research. There are two categories for impermeable surfaces: linked and unconnected. Any surface that has a direct connection to the drainage system is considered a directly connected impervious area (DCIA). Rooftop areas that drain into landscaping are examples of unconnected impervious areas (UIAs), which are regions that drain into pervious surfaces. Because UIA runoff may spread over pervious surfaces and penetrate before reaching the drainage system, this distinction is critical during small storms (Schoener, 2018).

2.10. Challenges for Predicting Urban Runoff

Rapid urbanization in many nations has increased impermeable surfaces, increasing the risk of flooding and stormwater runoff accumulation. Stormwater runoff contains pollutants and contributes to low water quality in many natural bodies. Reducing urban stormwater runoff contamination is thus a major concern. The government, particularly in China, has implemented a series of initiatives to reduce stormwater runoff and related pollutants, such as the introduction of natural reservoirs and sponge cities based on the nation's low-impact development (LID) policies (Zhang et al., 2018). Urban hydrology will become more crucial to maintaining the sustainability of human society. Urban population growth is outpacing the decline in water sources, or at best, the decline in quantity but a decline in quality of the sources of water supply. The physical characteristics of land undergo significant changes due to the expansion of urban centers. Soil permeability and infiltration decrease when the amount of paved surfaces grows, yet surface runoff rises. Strong peak flows and quick runoff are produced by natural stream channeling. For the entire river basin downstream of the city, such modifications to the natural regime of a relatively small area of the city have significant and usually disastrous effects (Niemczynowicz, n.d.). Identifying explanatory variables (predictors) that affect the flood (predictand) and getting previous data on both the predictand and predictors are necessary steps in developing an effective flood prediction model (current science Challenges in Predicting Floods, n.d.). The world's scientific community and the public are becoming increasingly concerned about the growing risks of urban rainstorms and floods brought on by rapid urbanization and climate change, as well as the resulting socioeconomic losses. In addition to being a major issue for sustainable urban growth, assessing and controlling the risks associated with urban flood disasters is an essential part of urban stormwater management. Many solutions have been proposed to solve the different issues of urban water management, including best management practices (BMPs), low-impact development (LID), green infrastructures (GIs), water-sensitive urban design (WSUD), and resilient cities (Yang et al., n.d.).

CHAPTER III

Methodology

3.1. Introduction

In this chapter, the methodological framework is marked to promote the study of urban runoff and its intricate relationships with meteorological parameters that encompass soil moisture, temperature, and rainfall within the periphery of Mogadishu, Somalia. Since one of the objectives of the study is to establish the impacts of selected factors on urban runoff discharges accurately in an environment where the estimation of such parameters is very uncertain, it emphasizes the importance of identifying and examining significant influencing variables using both Ordinary Least Squares (OLS) regression and Artificial Neural Networks (ANN). The approach of the methodology is based on a duel approach based on Ordinary Least Squares (OLS)) and Artificial Neural Networks (ANN)). The methodology applied in this study develops a hybrid framework rooted in both approaches to minimize their weaknesses while leveraging their inherent strength for improved accuracy and reliability of urban runoff predictions. The study area, Mogadishu, Somalia, is presented as a challenge and opportunity due to the global changing climate patterns leading to urbanization.

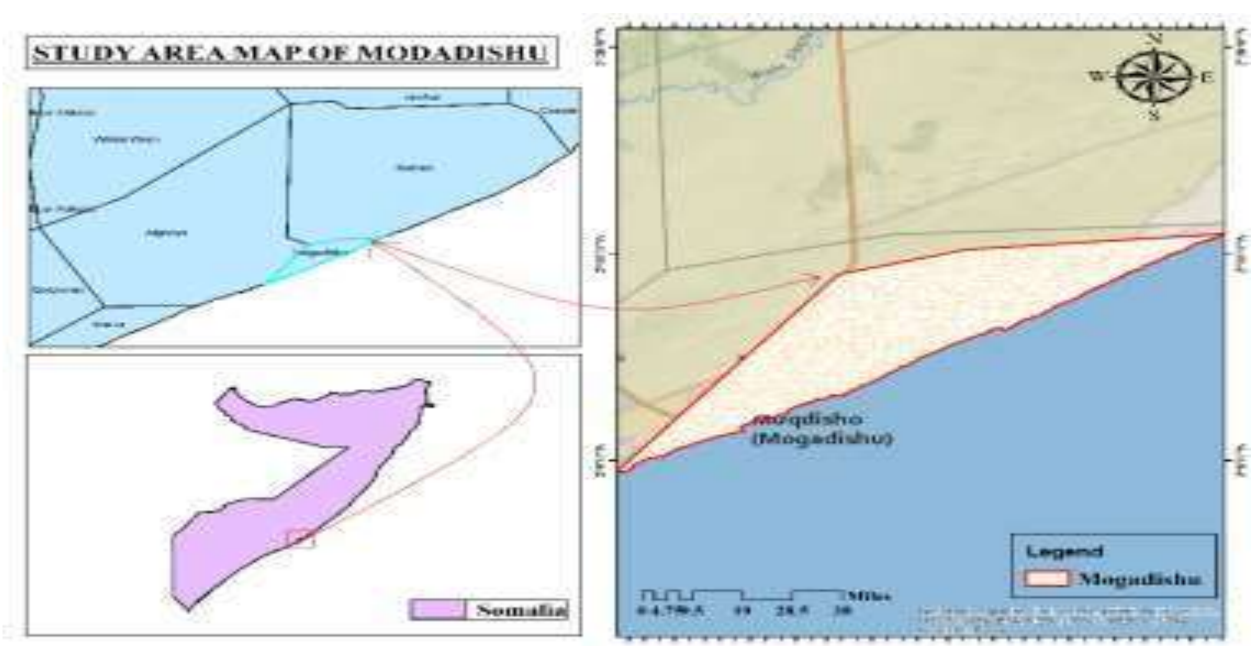
The analysis is based on the most complete data set available, covering the period between 1985 and 2022; it comes from global meteorological reanalysis. This study contains a lot of essential variables: maximum and minimum temperatures, precipitation, and soil moisture. This chapter includes data preparation, their standardization, and methods used for its analysis. It sets the framework in which OLS and ANN models are applied. The OLS regression part of the study puts measurements to the relationships between urban runoff and a selection of meteorological parameters. This chapter outlines variable selection, methodologies used in model construction, and the interpretation of the coefficients, p-values, and R-squared of the model. The potential of OLS to capture linear relationships is like a foundation capable of precipitating further insight into urban runoff dynamics. ANN has more focus on developing computational architectures that capture nonlinear patterns and relationships between the derived random variables. This part outlines the architecture that would be used in this neural network, i.e., the number of hidden layers, neurons and others like the type of activation functions to be used. Further discussed here are the training, validation, and testing phases regarding the model prediction performance and related implications in urban runoff management. The OLS and ANN models are compared against each other by their respective performance-evaluating statistical indices, such as R^2, RMSE, and MAE, among others. The validation presented not only the predicting capabilities of each model but, on top of that, elucidated certain attributes and limitations of each model regarding urban runoff anticipation. Accordingly, the methodology chapter of this dissertation has been concluded with a reflective commentary on the methodological contribution of this study toward urban hydrology and environmental management. It further underscores these efforts of integrating conventional statistical methodologies with advanced computational models as very crucial for better understanding and prediction of urban runoff given valuable urban planning and sustainable development pursuits.

3.2. Study Area

The capital town of Somalia, Mogadishu, with coordinates of Latitude 2.0469° N and Longitude 45.3182° E, is a throbbing urban town along the Indian Ocean. Mogadishu happens to be Somalia's largest city based on population and is viewed as an economic, cultural, and political hub for the country. This city experiences a hot semi-arid climatic condition marked by two seasons, known as the dry seasons and wet seasons. That season variability, coupled with the geographic positioning of the city, becomes one of the players in the urban water management challenges—in recognition of urban hydrological changes from different drivers, especially in components on the most critical runoff and flood risks. Over the last few decades, Mogadishu city has been experiencing rapid urbanization that has come with great changes in land use and the construction of greater proportions of impervious surfaces such as roads and buildings. In enhancing economic growth, this kind of urban expansion has stressed existing infrastructural systems, in particular those handling drainage systems. The rapid population increase and migration have outpaced the proper development or implementation of water management systems and flood mitigation, hence increasing the risk of flooding within the cities. Mogadishu faces a variety of environmental problems and is rampant with urbanization patterns, climatic conditions, and inadequacies in infrastructures. The city often becomes inundated with floodwater problems, particularly during the rainy seasons where the incidence of the drainage systems get overwhelmed and the infiltration capacity of the ground becomes inefficient. Thus, the respective condition gets further aggravated by its coastal location which is susceptible not only to sea-level rise but also storm surges, thereby complicating further urban runoff management for the city. Besides the quantity aspect, the urban runoff in Mogadishu further touches on the quality aspect. During stormwater events, urban runoff is known to transport pollutants from the streets, residential areas, and industrial sites into receiving water bodies. Such pollution leads not only to the deteriorated integrity of the ecosystem but also to the general health of the public population residing around such localities. Such environmental issues are only possible through complex reasoning that incorporates the sophisticated relation between climate change dynamics, urbanization factors, and indeed general water management paradigms.

***Figure* 4**

Study Area, Source: ArcGIS Desktop 10.7.1



Urban runoff study in Mogadishu is crucial for several reasons. First, through it, an understanding of how urbanization coupled with climate variability affects the water management systems. Mogadishu presents a strong case for understanding some of the multi-dimensional problems related to urban runoff, their effects, and causes against the backdrop of an increasingly changing climate and rapid urbanization. The work in this area is therefore highly informative and provides a basis for building sustainable solutions to water management challenges facing Mogadishu and other urban centers within the region and beyond.

3.3. Dataset

The dataset applied in the investigation of urban runoff in Mogadishu, Somalia, is very crucial to understanding the complex interrelationship that exists between urban runoff and meteorological variables, such as soil moisture, temperature, and rainfall. In particular, this section is aimed at emphasizing the composition, source, and importance of the used dataset against the background of applying Ordinary Least Squares (OLS) regression and Artificial Neural Networks (ANN) techniques in predictive analytics. This data is a wide scope of meteorological data from around the globe, starting from 1985 up to 2022. This set was collected over several years with the objective of this entire thing being to study several environmental factors which are capable of influencing urban runoff, giving a comprehensive set of metrics for analysis. Taken from the Terra Climate database and characterized by high spatial resolution (approximately 1/24 or ~4 km), the dataset delivers one of the most detailed and accurate representations of climatic conditions in Mogadishu. For an OLS regression, the dataset formed the basis to explore linear associations among meteorological parameters with urban runoff. From this data, the study adopted quantitative analysis of these variables to identify the significant predictors for runoff, thereby enabling the formulation of models that predict runoff volumes based on changes in climatic conditions. The detailed statistical analysis, supported with coefficients, p-values, and R-squared values derived from the data, further underlines the significance of certain meteorological parameters to have essential characteristics in the shaping of urban runoff characteristics in Mogadishu. Descriptive statistics for the collected data are summarized in Table 3.3.1

Table 1

Specific Details of each Variable in the Study

Variable	Units	Mean	Standard deviation	Minimum	Maximum
Tmax	°C	30.72	0.145	30.46	30.97
Tmin	°C	23.33	0.093	22.99	23.46
R	mm	33425.9	1421.6	31190.2	37423.7
SM	mm	11.99	0.993	10.22	14.66
RO	mm	2420.2	282.65	1984.1	3274.9

in the case of ANN modeling, the same dataset is put through a different type of analysis—interested in the actual interactions of the variables. Paradoxically, nowadays, urban runoff can be best forecasted with greater precision and nuance in ANNs developed with deeper datasets and allowing for the training of computational models. The ability of an ANN to handle complex multidimensional data facilitates a more comprehensive analysis, explanation of the intricate dynamics associated with urban runoff situations, and presentation of an insight into how many factors jointly influence runoff behavior. Descriptive statistics of all the gathered data are provided in Table 3.3.2.

Table 2

Descriptive statistics of all variables

Variable	Units	Mean	Standard deviation	Minimum	Maximum
Tmax	°C	30.51	1.36	27.00	34.40
Tmin	°C	23.45	0.95	20.00	27.20
R	mm	40.37	50.90	0.00	327.00
SM	mm	10.22	13.70	1.30	78.40
RO	mm	2.66	8.76	0.00	163.00

The importance of this dataset lies in its detailed representation of a large number of climatic variables over long durations, which provides a solid foundation to carry out studies on both statistical and computational analyses. Of these detailed metrics of the variables present in this dataset for the OLS regression, it gives strong ground on linear correlations and ANN modeling, it is made comprehensive enough to allow one to attempt investigating intricate patterns beyond the realms of conventional statistical methods. the dataset utilization in employing both OLS and ANN methodologies brings a holistic approach to understanding and prediction of urban runoff. This dual-method approach further strengthens the study's ability to develop effective prediction models that will contribute to making informed choices during urban planning and actual water management practices in Mogadishu.

Mainly, Tmax (maximum temperature), Tmin (minimum temperature), and moisture in the soil were considered the main inputs that would be included in the study. The choice of these parameters is owing to the direct effect on the hydrological features which changes the flow of water over the land surface and at the point of its distribution. In elements of urban runoff phenomena understanding and forecasting, they are very critical. This will affect the rate of evaporation through the minimum and maximum temperatures, and, in total, the potential of the soil to absorb submitted water. This relationship between the temperature of the day and evaporation rates may lead the soil moisture levels that are vital to the capacity of a certain soil to absorb water to change and create a runoff. More appropriately, soil moisture is a vital factor since it points out the area at which further rainfall will create runoff and flooding in terms of its urbanization. Through the analysis of global meteorological data spanning from 1985 to 2022. While the wind speeds and average temperatures were not considered as primary input parameters of the modeling, because the study aimed to focus on factors that had more proximate and significant impacts on urban runoff. Most notably, the exclusion of parameters such as mean temperature and wind speed from the input in modeling urban floods for Mogadishu, Somalia, can be attributed to the specific relevance and direct impact experienced from the chosen variables on runoff dynamics. Indeed, this study has considered Tmax and Tmin peculiar in nature towards influencing the increased rate of evaporation and low soil moisture, among other reasons for understanding runoff. Maximum and minimum temperatures directly influence the soil's capacity to absorb and retain water, thus affecting potential runoff in rainfall. Soil moisture was selected as the saturation can be determined directly for the volume of the runoff. Wind speed, of course, has to do with evaporation, but this aspect is unlikely to have been considered as having such a high impact on the immediate processes that result in urban runoff and flooding as the chosen variables. This, therefore, would be a consideration of parameters that have a direct and substantial influence on the hydrological processes that define urban flooding, to ensure an increased prediction performance of the model in managing such a source of flood risk.

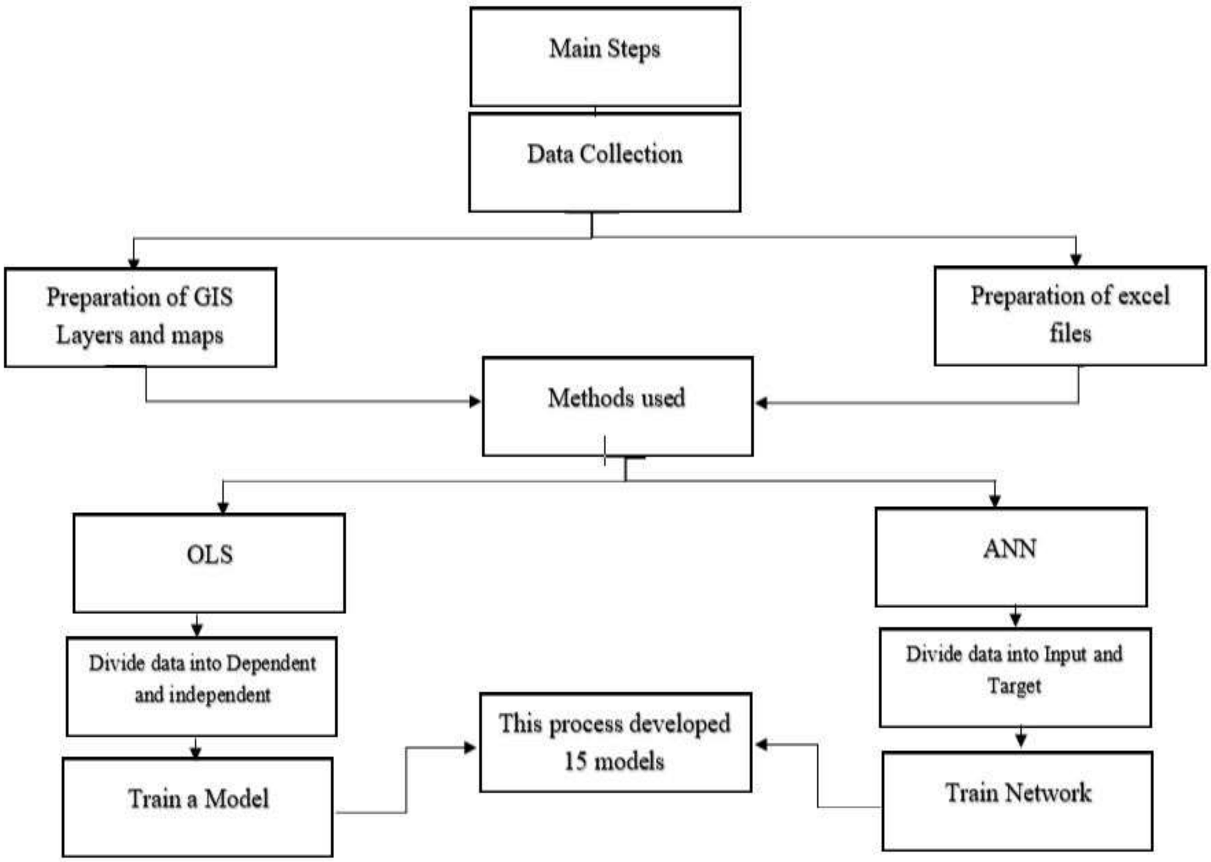
3.4. Methodological framework

The methodological framework of this research is such that a combination of statistical and computational modeling techniques gives a holistic insight into understanding and estimating the dynamics of urban runoff. These statistical and computational techniques are applied in this framework to understand or estimate this complex interplay of processes as it bears relation to human activities, urbanization, climate change, and other hydrologic occurrence. This is done in this study through the use of Ordinary Least

Squares (OLS) regression and Artificial Neural Networks (ANN) as the main analytical tools.

***Figure* 5**

The Study Outline

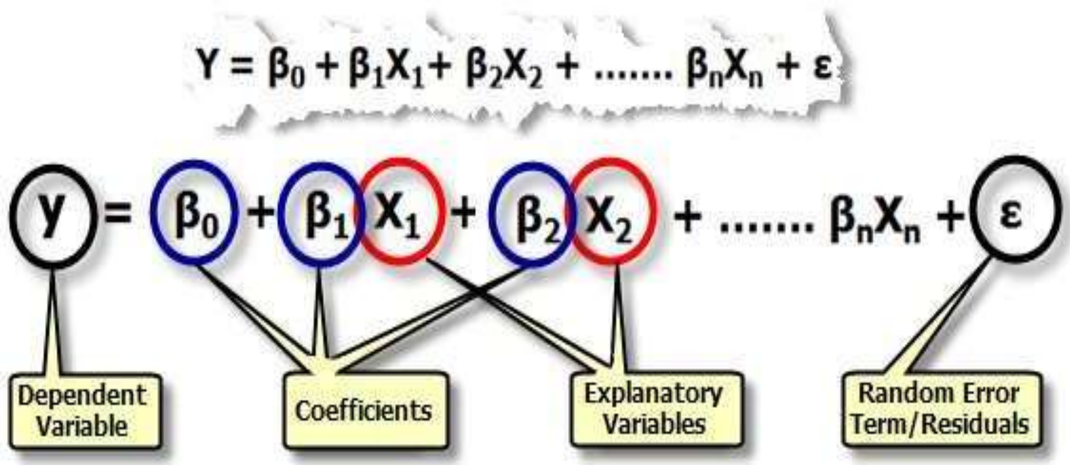


3.4.1. Ordinary least square (OLS)

The OLS regression is used to discover and quantify dependencies in a linear relation between meteorological variables and urban runoff. The statistical technique offers a clear understanding of the degree of impact that single factors have on volumes of runoff, such as rainfall and soil moisture, leading to the discovery of major predictors. Coefficients produced by the OLS model, root mean square error, and R-squared values are summarized here, giving an impression of the strength and significance of these relationships, and helping in the deriving of models that will predict urban runoff.

***Figure* 6**

Parts of Regression Analysis (OLS), Source (48_233. (n.d.)).



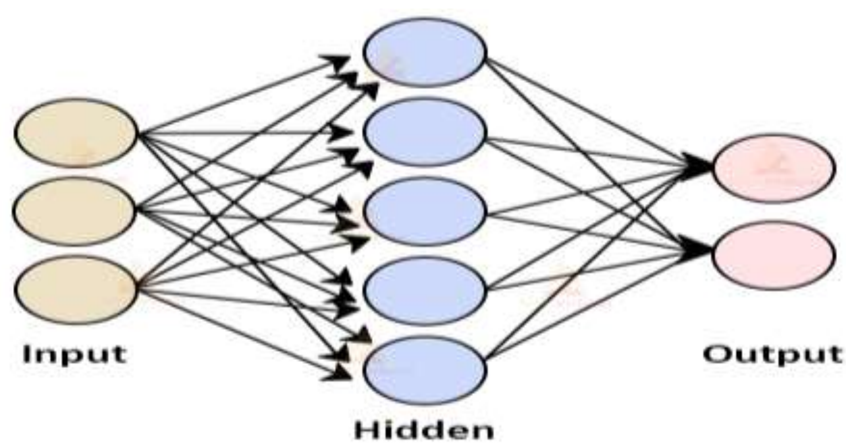
This is the multiple linear regression model, a statistical technique that predicts the value of a dependent variable (Y) based on the values of one or more independent or explanatory variables (X1, X2,... Xn). In the equation above, Y is the predicted value or outcome, β0 is the intercept (i.e., if all X variables take the value of zero, this will be the predicted value of Y), β1 to βn are coefficients representing the contribution delivered by corresponding explanatory variables to the dependent variable, and ε stands for random error term or residuals that capture variation in Y that cannot be explained by the independent variables. The model assumes a linear relationship between the dependent variable and the independent variables, which means that each coefficient of the independent variable reflects the change in the dependent variable caused by a one-unit change in the respective independent variable, assuming all other independent variables remain constant.

3.4.2. Artificial Neural Network(ANN)

Artificial neural networks are made up of artificial neurons known as units. These units are grouped into layers, which together make up the full Artificial Neural Network in a system. A layer can contain a dozen or millions of units, depending on how complex neural networks are required to comprehend the dataset's underlying patterns. An Artificial Neural Network normally consists of an input layer, an output layer, and the so-called hidden layers that lie in between. The input layer receives the inputs from the environment, which the neural network is supposed to interpret or learn. These are then passed through one or more hidden layers to be converted into useful data for the output layer. Finally, the output layer generates a response from an Artificial Neural Network to the input data. The overwhelming majority of neural networks interconnect units from one layer to the next. Each of these links has a weight, which relates to how much one unit influences another. The data is passed through these series of units where the neural network learns more about the data until it presents an output from the output layer. The process through which this computation is done is the training of the neural network in the recognition and modeling of the complex dynamics of urban runoff about the input variables. ANN is pretty adept in capturing the multifaceted character of urban runoff, so it exhibits such qualities as flexibility and learning capability and hence makes it possible to predict the volume of runoff for different climatic scenarios.

***Figure* 7**

Architecture of Artificial Neural Network, Source (Tech Vidvan).



The above figure provides a simplified diagram of the architecture for an Artificial Neural Network (ANN). It mainly constitutes the input layer, hidden layer(s), and output layer. Every layer comprises nodes represented in a circular form, each of which is similar to some real biological brain neuron. The input layer receives the data to be subjected to processing via the hidden layers, through which real computation on weighted connections (drawn as lines between nodes) is performed. These weights are then fine-tuned over epochs of training to minimize the errors in generalization. The output layer at the end activates and shows the result or prediction of the neural network. This type of network forms the backbone of deep learning and can be applied to all sorts of tasks, from the simplest to more complicated functions, depending on the complexity and depth of a given network.

3.5. Model Development and Evaluation

Generally, in model development, the process starts by picking up important meteorological variables that influence urban runoff, such as maximum and minimum temperatures (Tmax and Tmin), rainfall (R), soil moisture (SM), etc. The above dataset helps to relate these factors with runoff (RO) in linear functions so influential predictors are established through statistical analysis. The model is simple and clear in revealing the contribution of each factor to runoff; hence, it is valuable in analysis and prediction.

3.5.1. Ordinary least square (OLS)

A full range of fifteen Ordinary Least Squares (OLS) regression models was developed for this study, using a distinct set of input parameters as specified in Table 3.4.1. The models were then logically grouped concerning the number of input covariates each contained. In particular, Models 1- 4 contained only a single predictor each and could thus be used to consider in isolation the effect of individual variables. Models 5-10 developed this structure further by the inclusion of pairs of predictors, through which it is possible to scrutinize the interaction between the two variables. Models 11-14 developed this further to include three covariates and hence give a view of the dynamics of more than the interaction of two variables and the joint effect on the response variable. Finally, Model 15 aimed to bring out the most complex scenario in the sense of accommodating four different predictors while synthesizing a holistic view of the interplay among the maximum number of studied variables. The predictors selected across all models were maximum temperature (Tmax), minimum temperature (Tmin), rainfall (R), and soil moisture (SM), to predict the target variable of monthly runoff (RO). This organized approach facilitated a clear understanding of the influence of each variable acting alone and also provided good information on how variables interact with one another to affect the runoff in diverse climatic and environmental conditions.

Table 3

OLS Models of Different Input Variables.

Modal	**Input**	**Modal**	**Input**	**Modal**	**Input**
OLS#1	Tmax	OLS#6	Tmax R	OLS#11	Tmax Tmin R
OLS#2	Tmin	OLS#7	Tmax SM	OLS#12	Tmax Tmin SM
OLS#3	R	OLS#8	Tmin R	OLS#13	Tmax R SM
OLS#4	SM	OLS#9	Tmin SM	OLS#14	Tmin R SM
OLS#5	Tmax Tmin	OLS#10	R SM	OLS#15	Tmax Tmin R SM

The general regression methodology, based on the ordinary least squares (OLS) approach, makes it possible to obtain a quantification of the relation between the factors to be explained (Tmax, Tmin, R, and SM) with the independent variables (RO). In fact, according to the definition provided by ArcGIS Desktop 10.7.1 Help, the ordinary least squares (OLS) is regarded as a prediction or modeling process considering the correlation between one dependent variable and several explanatory variables.

3.5.2. Artificial Neural Network

In the current study, fifteen distinct ANN models were created for diverse combinations of input variables. The details of these ANN models are shown in Table 4. Model #1 only used one input, whereas Model #15 trained the ANN with four inputs. The independent variables that represented the input data were maximum temperature (Tmax), minimum temperature (Tmin), rainfall (R), and soil moisture (SM). These sets of inputs have been designed to work together to teach ANN, with the predicted variable being monthly runoff (RO) data.

Table 4

ANN Models of Different Input Variables

Modal	Input	Modal	Input	Modal	Input
ANN#1	Tmax	ANN#6	Tmax R	ANN#11	Tmax Tmin R
ANN#2	Tmin	ANN#7	Tmax SM	ANN#12	Tmax Tmin SM
ANN#3	R	ANN#8	Tmin R	ANN#13	Tmax R SM
ANN#4	SM	ANN#9	Tmin SM	ANN#14	Tmin R SM
ANN#5	Tmax Tmin	ANN#10	R SM	ANN#15	Tmax Tmin R SM

In the model performance analysis, 70% of the dataset was used for training, and the remaining 30% was used for testing the trained networks. Out of the fifteen ANN models developed one that yielded a good performance was selected using statistical techniques. The purpose was to find out which ANNs of the created models result in more precise monthly runoff estimates based on the input variables chosen.

3.6. Statistical Analysis

This comprehensive work of urban runoff in the geographic location of Mogadishu, Somalia, has deep connotations for showing how the flow of urban water is tightly linked to several meteorological variables: temperature, precipitation, and soil moisture content. The behavior of urban runoff was also looked at through statistical analysis, which is central for the complete understanding of the numerous relationships given one behavior of urban runoff. Through the application of advanced analytics, this research aims to unravel the underlying meteorological influences related to urban runoff. This therefore gives a thrust toward the accuracy of prediction models in urban water management.

3.6.1. Ordinary Least Square

Ordinary Least Squares (OLS) regression applies a statistical methodology in ArcGIS, where geographical relationships between variables in a dataset are analyzed. The tool within the Spatial Statistics toolbox is particularly useful for exploring how one or more independent variables vary according to a dependent variable across space. The results for the values of R squared and root mean square errors in general for OLS analysis and geostatistical analysis are derived from ArcGIS. That is, these findings contribute to the means of evaluating the strength and relevance of connections so that researchers and analysts have a better understanding of the spatial distribution of phenomena. Utilizing ArcGIS in this context in spatial analysis is considered an effective tool since it helps to explore and communicate spatial patterns and relationships that OLS regression produces maps of, consequently enabling visualization of the results. In this regard, an evaluation of such models will involve a keen check on their performance with the use of various indicators in statistics such as Coefficient of Determination (R2) (as per Table 5), and root mean square error. Our work uses mathematical representations, so it will support assessing the help of these criteria in finding a quantitative basis for accuracy and reliability in the models.

Table 5

R2-Based Model Performance Rating

Performance Rating	**Range of R^2**
Excellent	>70%
Good	$50\% < R^2 < 70\%$
Poor	$0\% < R^2 < 50\%$

In geostatistical analysis, "interpolating" and "non-interpolating" techniques or "interpolators" and "non-interpolators" are two terms used to differentiate between the multiple spatial interpolation techniques established in different disciplines. This work covers a single spatial interpolation technique, which is kriging, more especially ordinary kriging. The spatial patterns and the values of the main variable at unsampled sites are described and the uncertainty or error of the estimated surface is modeled using geostatistical methods. Kriging, also known as Gaussian process regression, is an interpolation technique first used in geostatistics. To maximize the smoothness of the fitted values, the interpolated values are represented by a Gaussian process that is driven by prior covariances. Kriging is a linear interpolation technique that provides the most precise linearly unbiased estimation of the values taken to be intermediate if the priors are correctly taken. The ordinary kriging (OK) method is a linear interpolator that estimates a value at a location in a region with a known variogram, without information about the mean of the distribution. It computes the error variance and then weights the samples around it in such a way that the average error of the model is zero and the modeled variance is the smallest. This section will give a brief description of all the statistical metrics we used in our analysis: (i) Root Mean Square Error, RMSE; (ii) Mean Absolute Error, MAE. RMSE is an error metric for accuracy in spatial analysis and remote sensing products. Root mean square deviation (RMSD) is a common measure of the differences between the expected values for the sample and population and their observed values. The RMSE is the sample standard deviation of the difference between expected and observed values. These individual differences are known as residuals when computed across the data sample used for estimation, and prediction errors when computed out-of-sample. RMSE combines the magnitudes of prediction errors over time to get a single measure of predictive capacity. RMSE is an accurate measure, however, it can only be used to compare predicting errors of various models for a single variable, not between variables, due to scale dependence. The model's performance improves as the RMSE value falls. MAE examines the average amount of errors in a group of forecasts without regard to direction, as well as accuracy for continuous variables. It is a metric used to assess how close forecasts or predictions are to actual events, as well as a popular measure of a model's forecast error. It is a linear score, which means that all the differences that people show are taken to have equal importance in the mean. The adjusted R squared, on the other hand, varies from 0 to 1.0, meaning how much the model explains the variance in the dependent variable.

3.6.2. Artificial Neural Network

The created models are evaluated using a plethora of statistical indicators. This study uses four metrics: the coefficient of determination (R2), root mean squared error (RMSE), mean absolute error (MAE), and relative root mean square error (RRMSE). These indices for measuring the forecast accuracy show how well the model matches the actual data. The models were developed to forecast urban runoff for Mogadishu, and they were checked with the root mean square error, mean absolute error, relative root mean square error, and coefficient of determination. The statistical indices thus evaluated the value of the model being tested. These methods are used only for comparison purposes of the observed and the expected values. Equations (1),(2),(3), and (4) will be used to explore the potential of mathematical and empirical models to predict urban runoff in Mogadishu. One of the common statistical measures that apply to testing the effectiveness and accuracy of the resulting empirical models is termed R-squared or the coefficient of determination. It is simply denoted as R2. R-squared is a measure describing the extent of variance from the empirical data, and a higher value will show a better performance of the model. The best model performance strategies are normally those whose R-squared is close to one and whose root mean squared error is close to zero. The R-squared statistic can be used to assess how close an observed collection of data points is to an underlying hypothetical model of what is expected. This statistical index could be used for the approximation of how close the urban projected runoff is to Mogadishu. The values of R-squared lie between 0 and 1, with 1 being very close to a model of the data being described. A score of close to zero for a number conveys the lack of power in the model to describe, but a close-to-one score shows that correspondence between the model and data points is performed. The MAE indicates an average absolute difference in model-predicted values and actual data points. It is measured as the average of the difference between observed and predicted values in absolute terms, making it a very effective procedure for model evaluations. Being a linear score, MAE implies that each of the individual differences is going to contribute directly towards the average value. It measures how far the model is off, but not in which direction—either over- or under-predicting. RMSE is an acronym for Root Mean Square Error, one of the pivotal statistical indicators that help to measure the performance of a regression model. It is a metric that measures the average difference between the expected and observed values of the dependent variable. This can be used to study and evaluate both the adequacy of the model and the degree to which data fit the model. In diverse empirical models, the root mean square error (RMSE) is used to scrutinize the actual and predicted value discrepancies. The RMSE value varies from 0 to infinity, where the smallest values are considered the best and a more accurate model gives values that are close to zero. Despite benefits related to the sensitivity of the outer layers, RMSE would be sensitized by the measure of the dependent variable. Normalization techniques can be applied to describe this to avoid indecisive errors. See Table 6.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(a_{a,i} - a_{p,i}\right)^2}{\sum_{i=1}^{n} \left(a_{p,i} - a_{a,ave}\right)^2} \qquad eq(1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(a_{a,i} - a_{p,i}\right)^2} \qquad eq(2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|a_{a,i} - a_{p,i}\right| \qquad eq(3)$$

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(a_{a,i} - a_{p,i}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n} \left(a_{p,i}\right)^2} \qquad eq(4)$$

where i is the number of input variables; ap, i is the projected value; aa,i is the average actual value; and n is the number of data points. Notably, in model evaluation, one should put more emphasis on prediction accuracy about benchmarks.

RMSE is used primarily for checking how good predictive models are at prediction. This measures how far the predictions are from the true outcomes. In a scenario where you need an exact prediction, like in weather forecasting or stock markets, RMSE will provide a simple measure of the model's effectiveness. Further, RMSD and RRMSE describe how good the predictions of the model fit with the actual data, and hence provide an easy, intuitive sense of the potential performance of the model. Such statistics are used for model comparison—quantitatively, one can observe which of the models available yields the best work concerning a dataset since it has both RMSD and RRMSE values. When multiple models are built to address the same prediction task, RMSE is used as a baseline metric to compare models.

Table 6

RRMSE-based Model Performance Rating

Performance rating	**Range of RRMSE**
Excellent	< 10%
Good	10% < $RRMSE$ < 20%
Fair	20% < $RRMSE$ < 30%
Poor	> 30%

CHAPTER IV

RESULTS AND DISCUSSION

This chapter will discuss results, an overview of methods, preparation of input variables, preparation and Utilization of methods

4.1. Introduction to Data Analysis Methods

In handling urban runoff, two key techniques have their applicability and precision, i.e., Ordinary Least Squared (OLS), and Artificial Neural Network (ANN). This presents the strong boundary of analysis over the multidimensional data of the environment and gives the prediction for the urban runoff. This chapter delves deep into the result of the operating characteristics of both models, that is, OLS in GIS and ANN, besides the comparative strengths of ANN in predicting urban runoff; it underlines how indispensable and proven to be in environmental engineering and management works.

4.1.1. Brief Overview Of OLS Methodologies.

Ordinary least squares (OLS) is an elementary and standard method of statistical estimation that tries to dynamically explain the changes in a dependent or target variable such that they are linearly related to one or several independent or explanatory variables by minimizing the sum of the squares of the differences between the observed and predicted values. The basic method of analysis lies at the core within routes of the regression methodology and forms, in essence, a cornerstone approach towards predictive modeling within multiple disciplines, including hydrology, geoinformatics, and urban planning. The trick behind OLS lies in reducing or minimizing these differences between the known values and the measured values of the dependent variable here, urban runoff volume. OLS adjusts the coefficients of the linear equation modeling this relationship in such a manner that it endeavors to locate a line of best fit amidst the data points. This is done by working out the least squares estimator, being the criteria that minimize the sum of the squares of the residuals–differences between observed and estimated values. One of the most powerful selling factors and justifiable reasons why reliance should be put on OLS as a regression technique is because it is simple and interpretable. This method clearly states the direct impact of a relationship between variables, thus being very valuable for preliminary data analysis and model building.

4.1.2. Brief Overview Of ANN Methodologies.

Artificial Neural Networks (ANNs) are one of the most popular machine learning algorithms that have modeled the biological neural networks of animal brains. ANNs present the ability to model complex nonlinear relationships between inputs and outputs, providing there is observational data. This therefore makes them more appropriate for the task of predictions, classifications, and pattern recognition across disciplines as the discipline of urban hydrology. An Artificial Neural Network consists of primitively connected nodes in layers: an input layer, one or more hidden layers, and an output layer. Each of these connections has a weight associated with the neurons adjusting as the rest of the network learns from the data. The task is applied by pushing the given input data (independent factors) through the network and then across the hidden layers, inside which the data is adjusted according to the weights and the activation functions. The output of an ANN predicts the value of the dependent variable. Such training is done by adjusting how connections' weights are distributed to minimize the difference between the predicted and actual output. In other words, this would be implemented by utilizing techniques based on backpropagation of errors, where one gets a gradient for a loss function (a spread measure of prediction error) and then subsequently updates weights so that the error is reduced. Some of the advantages of ANNs include the capability of modeling all kinds of functions, hence making it a flexible and very strong modeling tool in a complex situation like urban runoff. The other is a potential device for processing huge datasets and identifying patterns or relations that may go unapparent. On the other hand, OLS and ANN methodologies are equated. On average, the estimation using the OLS method has tended to be more comprehensive as it uses many variables affecting urban runoff. The empirical analysis seems to provide some strong and impressive insights and tools for predicting urban runoff with the inclusion of many variables. The choice of the OLS model and ANN will only depend on the main criteria behind the research such as the nature of the data at hand and the level of complexity of the modeled interrelationships. The explicit nature of how these methodologies work and their application is, therefore, very essential for urban planners and environmental scientists in putting up good strategies for managing the risk of floods and sustainability in urban development.

4.2. Description Of Global Meteorological data (1985-2022)

The global meteorological dataset employed for the analysis, ranging from 1985 to 2022, provides aggregated details of the climatic variables, used in the analysis of precipitation forecast of the urban runoff heterogeneities, but more so in the aspect of Mogadishu, Somalia. It can be assumed that the output of this effort is a composite dataset, with a greater magnitude of sources including TerraClimate comprising most of it. This dataset has a tremendous spatial resolution and corresponds to observations made at a global monthly scale, providing the unprecedented granularity and precision required. Spanning nearly four decades, the dataset encapsulates the most important point within the history of modern climate that, in terms of stylistic features and fundamental shifts in international weather patterns, heavily puts focus on the aggravation of extreme weather, changes in precipitation regimes, and warming the feature of the larger phenomenon of global climatic change. Such a temporal spread is very important so as not to overlook the inherent variability in climatic systems, but equally to understand long-term trends necessary inputs to carry out accurate urban runoff modeling. The period chosen of 1985-2022 is especially relevant in the light that it captured most climatic cycles with huge effects on weather, mainly focusing on the Horn of Africa, especially Somalia. These phenomena are characterized by changing temperatures in the ocean in the equatorial Pacific which has been proven to affect the pattern of precipitation and temperature affecting the world therefore affecting the volumes of the urban runoff. In this regard, by integrating data streams over such cycles, the analysis developed a much more sophisticated appreciation of how such global climatic phenomena relate to local weather events and their subsequent implications for urban runoff. All of these factors associated with the maximum and minimum temperatures (Tmax and Tmin), the maximum soil moisture (SM), and precipitation input (R) in urban runoff studies have been the core conditions of concern. All these factors were recorded and validated in measures to ensure that the analysis is carried out on the data having a solid and reliable background. The minimum and maximum temperatures are essential for characterizing the thermal dynamics bearing on evaporation rates, and hence, the moisture available for initiation of runoff from the soil. Soil water levels offer a direct measure of the land's ability to take in rainfall, an important element in runoff generation, in which wet soils produce greater runoff in rain events than dry soils. Rainfall is the main factor in generating an amount of surface runoff and is correlated with the intensity, duration, and frequency of the rainfall that directly correlates with the amount generated in generating runoffs in the urban fraction. Data in the dataset are collected appropriately in the study. Data preparation and cleaning go through in-depth analytical data-driven steps, which include cleansing from anomalies and inaccuracies, normalization for making the different units of measurements comparable and splitting according to some specifications, for example, seasonal variations, to make the extraction of the detailed trend analysis. The basis of such painstaking preparation is the assurance that the data is arid: it reflects the climatic conditions through the historical data, correctly prepared yet primed for inputs into predictive models toward forecasting urban runoff. These are years with global empirical meteorological data, from 1985 to 2022, which form the backdrop for a foundational empirical study of urban runoff; in other words, from which to anchor the development of predictive models. These data would shed some light not only on artists of climate conditions in the past but also on contemporary artists by assisting in the quest for thorough analysis, quantification, and mitigative measures of such problems on an anticipatory basis.

4.3. Preparation Of Input variables: Tmax, Tmin, SM, and R.

In general, the input variables (Tmax, Tmin, SM, R) used in this study to forecast the urban runoff using an Artificial Neural Network (ANN) and OLS in the study area covering Mogadishu, Somalia, were prepared through the collection and screening of a global meteorological dataset ranging from the 1985-2022 time period. The preparation and use of each of these variables in this chapter are described in this section.

4.3.1. Maximum and Minimum Temperature

The temperatures were the reanalysis especially maximum and minimum temperatures from TerraClimate. The dataset presented a high spatial resolution of monthly data, giving the Tmax and Tmin values for the whole period of the study. Temperature variables are very important in understanding the earth's surface energy balance, which will give rise to the evaporation rates, levels of soil moisture, and in turn events in the process of the production of runoff. The temperatures were processed to obtain monthly mean values, which served as input variables for the ANN models.

4.3.2. Soil Moisture

The TerraClimate data was also used to generate soil moisture, which gives information on the volume of water available within the soil. Soil moisture is an important measure for runoff prediction; hence, this is because of its direct implication on the compactness of the soil for water absorption. High soil moisture values correspond to the level of saturating the soil with water and, therefore, holds little water during an event; it is also translated into higher runoff. however, the soil water capacity suggests more capacity for infiltration, which thereby probably reduces runoff. The monthly soil moisture values were used as input to the ANN to model their impact on runoff generation.

4.3.3. Rainfall

Rainfall is the main driver of runoff since it provides water that enters the soil, hence either infiltrating for recharge into groundwaters or forming an overland flow. In this regard, the monthly time-series data of rainfall by TerraClimate have been applied to bring out its direct relationship with the quantities of runoff. This is among the most basic variables to any hydrological model, be it ANN or OLS, since, as aforementioned, the intensity, time duration, and amount of rainfall essentially define the rate and volume of generated runoff.

4.3.4. Preparation and Utilization in ANN Models

The ANN models were developed to predict monthly runoff (RO) for the corresponding period with the best-suited input variables (Tmax, Tmin, R, SM) combinations. Developing or testing ANN models involved partitioning the dataset into 70% and 30% as specific training and testing portions used to predict monthly runoff.

However, the complexity of the model changes with the input variables, such that the least complex Model #1 used the single input variable, while the whole of Model #15 used all four variables (Tmax, Tmin, R, SM). Hence, the objective of this study was to try and get the most influenced parameters, with a significant influence on urban runoff prediction. This checks the performance of each model with the aid of statistical tools such as R-squared, Root Mean Squared Error, and Mean Absolute Error. This section elaborates on training an Artificial Neural Network (ANN) for urban runoff prediction, trying to capture the methodological approach that provides for the analysis of global meteorological data in the search for important parameters that affect urban runoff. That is, in so doing, the study critically takes a look at some combination of input variables such as maximum and minimum temperatures, rainfall, and soil moisture against the observed values over the period from which data is collected, 1985-2022, and carries out the training of a feed-forward neural network trained using backpropagation. The ANN models were developed and assessed over a dataset split into 70% as the training set and 30% as the testing set, where the statistical indices, coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE), are used for tuning the model to performance. ANN provided a stringent deployment process, and among the crucial features of the results, empirical findings were rainfall and soil moisture as key drivers, thus associating the success of ANNs in discharge predictions and justifying in principle the effectiveness of flood risk management and urban planning activities.

4.3.5. Preparation and Utilization in OLS Models

The input variables to be considered shall entail Tmax, Tmin, SM, and R in the prediction of urban runoff within Mogadishu, Somalia, as analyzed using Ordinary Least Squares (OLS). The study was designed to find the major influencing factors that are essential for the forecasted urban runoff using monthly global meteorological data available in the TerraClimate dataset. This was done through an Ordinary Least Squares in ArcGIS, notably beginning from the collection of spatially referenced data on abiotic factor variables such as temperature, and precipitation, among others. ArcGIS uses an ordinary least squares model to model the relationship between the variables and the predictors and it is run under the Spatial Statistics toolbox and then applied to geostatistical analysis to find the coefficient of determination (R^2), root mean squared error (RMSE).

***Figure* 8**

Maximum and Minimum Temperature map, Source (GIS).

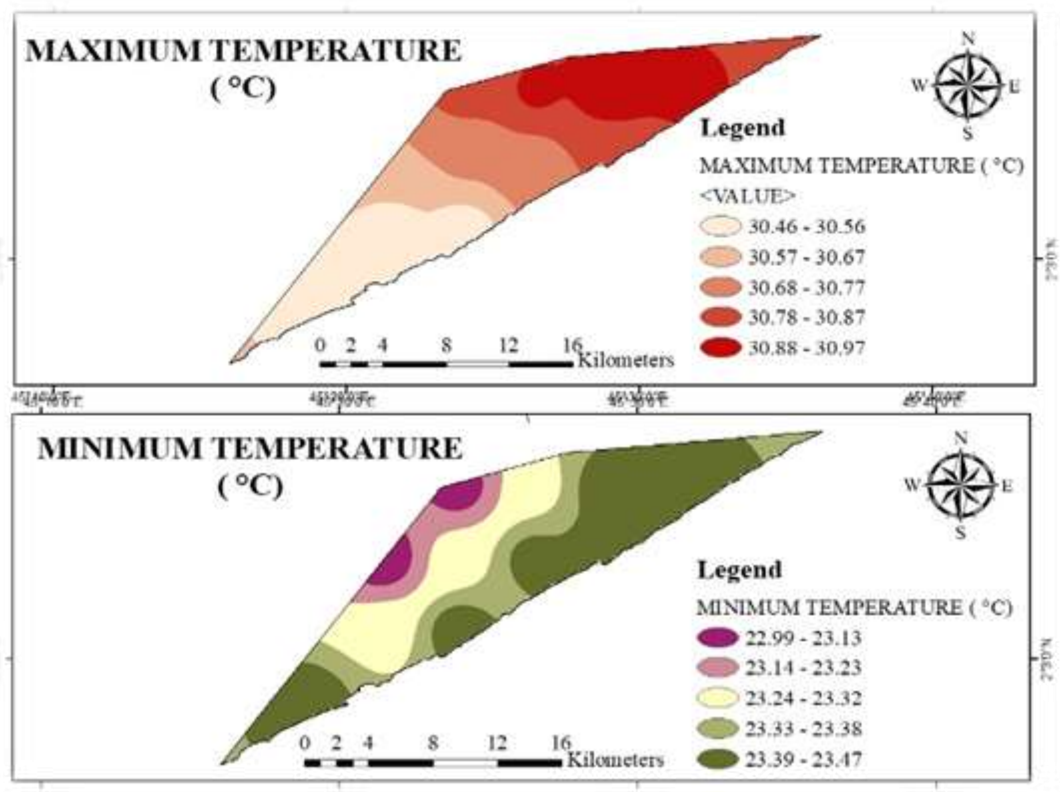
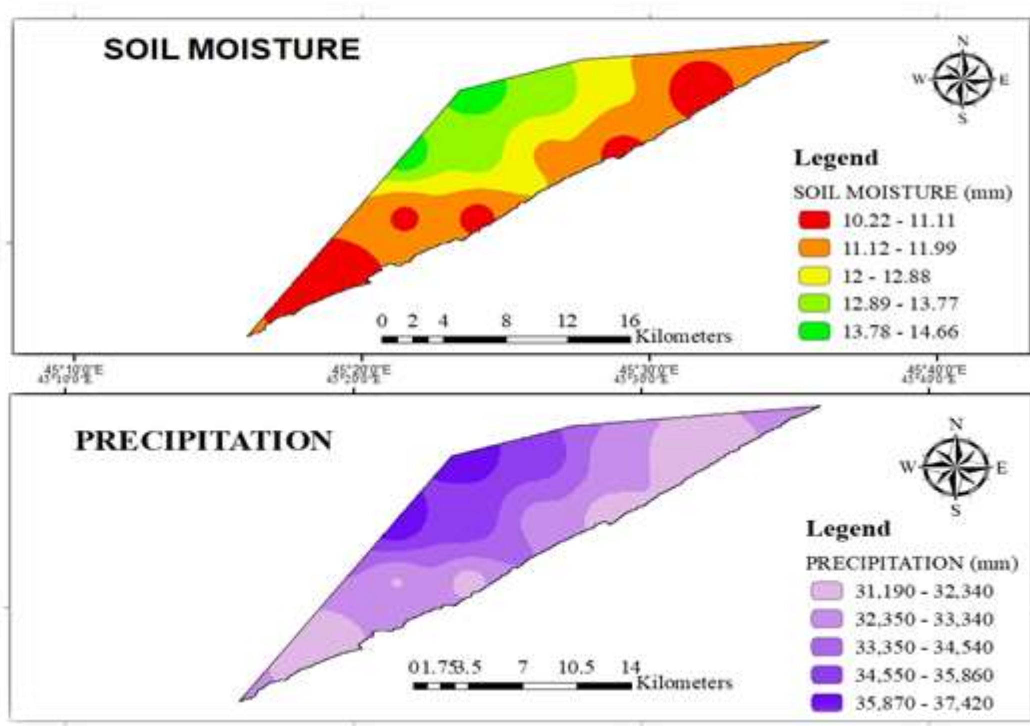


Figure 4.3.5 portrays two maps: one that determines the maximum and another that displays minimum temperatures in degrees Celsius. They represent the area of ranges of temperatures observed throughout, with the maximum one ranging from beige to dark red, which is indicative of hot temperatures, and the minimum temperature map ranging from light yellow to dark green, which indicates cooler areas. Each of these sets of maps is sided with a legend that shows the range of temperatures that range for each color; it acts as a translation of colors for the area on the map and temperature.

***Figure* 9**

Rainfall and Soil Moisture Map, Source (GIS).



The second image contains two more thematic maps: one for soil moisture and another for precipitation, and at their lateral side are its color-coded legends. The soil moisture gradient used in coding ranges from red to dark green, in increasing order of soil moisture levels in millimeters, and the precipitation gradient similarly ranges from shades of purples in an indicative amount in millimeters. Again, these are also fitted with legends that define the particular ranges of moisture and precipitation values, regarding each color. In addition, the two have units of a scale bar as well as a compass rose to indicate distance and orientation, with the two maps showing latitude and longitude coordinates which aid in the exact location of the various climatic zones. These maps are designed meticulously, keeping in mind even the minute details; these help a lot in understanding the environmental and climatic conditions due to accurate depictions of land cover needed to carry out agricultural planning, resource planning, and scientific research.

4.4. Ordinary Least Square (OLS) Method

The simple Ordinary Least Squares (OLS) approach to predicting urban runoff with datasets in Mogadishu, Somalia, will lay down the complete approach toward the below challenges in urban flooding and its management. The study aimed to get an estimation of urban runoff by OLS in 15 different global meteorological characteristics models to identify which would be the most significant for urban runoff forecasting. The maximum and minimum temperatures, monthly amount of rainfall, and moisture content obtained from 1958 to 2022 are among the input variables that will be taken into account. Flooding and urban runoff have been a problem greatly heightened by continual rapid urban growth, poor infrastructure, and undeveloped drainage in Mogadishu, Somalia. The potential reach of such impacts can be magnified, with the range of factors that will include runoff speed associated with rain, impermeable surfaces, drainage condition, and rate. During this rainy season, the intensity of the rainfall noticed is overwhelming the drainage and causing flooding issues with water quality. The analysis evaluates the relationship among all explanatory factors, like maximum temperature, minimum temperature, rainfall, and soil moisture, with the dependent variable (runoff) in OLS regression analysis.

This method helps very strictly in an urban setting to interpret the likely pattern for runoff and make predictions of the pattern; statistical indices like the coefficient of determination (R^2) and root mean squared error (RMSE) are used to show the performance of the models within the study. It was presented that soil moisture and rainfall rank very important and high in having the best formulation to predict runoff. The present finding is in agreement with the earlier studies which indicated that these variables offered very important variables in estimating the runoff. It has been established that all imperviousness is highly influential in the urban rainfall-runoff process. The OLS models indicated that clear concepts of mechanisms of runoff and effects of urbanization on storm runoff may be key for the effective management of urban rainwater. It further underlines that there have to be well-modeled hydrological inputs in the estimation of surface water flow, assess infiltration, and estimate runoff formation. In some models, the high R-squared is an indication of a strong explaining power such that the models will statistically explain the variations of the dependent variable strongly and hence increase the conclusion in the study.

4.5. Artificial Neural Network (ANN) Method

This section examines the use of Artificial Neural Networks (ANN) for predictions in one of the most important flood risk management elements (urban runoff). Urban runoff is described as flow resulting from precipitation in urbanized areas. The study was based on the previously indicated sense, which emphasizes the requirement to get accurate prediction results: urban runoff, on the ground of which effective prevention from the risk of flooding and consequently growth in the tendency of safety, should be. Widespread urbanization, with impervious surfaces, acts as natural infiltration barriers to the percolation of water, in a manner to collect pollutants and to entail flooding risk. In this work, the ANN will be relied on in the estimation of urban runoff based on four key meteorological parameters of maximum and minimum temperature, rainfall, and soil moisture from Mogadishu, Somalia, over a significant period (1985-2022). This approach tends to pick out the most regulating variables affecting urban runoff, improving model accuracy and in a way making the process of model development less complex by considering and incorporating important variables.

Artificial Neural Networks (ANNs) are computational models developed as an imitation of the human brain, whereby they acquire a capacity for learning skills by being exposed to trained data and later making predictions with new information. Against this background, the model of a network was built with back-propagation of a traditional kind of ANN architecture in the stage of training, i.e., feedforward neural network. Each neuron processes one input from the previous processing level in these layers and forwards it so that in aggregate, the network learns meaningful and complex patterns and relationships between input variables and urban runoff. The training process relates to the modification of connection weights between neurons in an ANN so that the errors of prediction are minimized. This nature makes ANNs highly suitable for the development of a model that has nonlinear and complex relationships, such as between different meteorological variables with urban runoff. Based on this four-variable input model, the study included a combination of these input variables in fifteen different possible ways to train the ANN model to predict the monthly urban runoff. After training the ANN models and reassessing these models statistically, statistically bounding the best possible model in the context of the chosen input variables is the research outcome. Such an approach can make a probabilistic assessment of the prediction count accurate, in a solicited way, in keeping with how variable these variables and their combination can be in predicting urban runoff. The study results found that the rainfall and soil moisture variables are necessary for predicting urban runoff. This result conforms to logic, in that the quantity and character of water flowing over land surfaces must be directly influenced by the character and quantity of precipitation, and soils' capacity to absorb water. These two parameters gave better performances than models that did not use them in predicting monthly runoff in all applied models and hence indicated that they were predictive in the runoff generation process.

4.6. Result Of Artificial Neural Network (ANN)

The present study systematically used all data from 1985 to 2022 to elaborate on knowledge in the forecasting of urban runoff with an Artificial Neural Network (ANN). About 70% of the datasets were put away for the training exercise, which is the most important in the model, leaving the balance of 30% to play an essential role in testing the model by predicting the performance. Setting up the good settings for the neural network was the approach with the step-by-step trial and error method, through which a methodological plan was worked out up to the finest receipts in the optimal definition of the configuration of the network. This has many sub-steps to optimize, which are determining the right number of hidden layers (HL), associated neurons (NN), and transfer function (TF) to be used. These are some of the key aspects that can aid in the modulation of model prediction to fit input data.

4.6.1. Result of Case 1: One Input

In this study, for every variable, one Artificial Neural Network (ANN) was fed. That is, four different models existed, denoted from ANN#1 through ANN #4, which made the impact of each variable on the network's predictability of urban runoff independent. The performance of the models is tested based on key statistical parameters as follows: R-squared (an indicator of how good a predictor variable is in explaining the variance in the response variable), Root Mean Squared Error (RMSE; to calculate the average prediction error in a model), and Mean Absolute Error (MAE; to obtain the sum of absolute errors divided by the number of data points). The ANN#3 emerged at the top of all; this is an indicator that the qualities used to implement such a network are better than the rest as it has higher accuracy in predicting urban runoff. Quantitatively, this was identified since associated statistical scores were also higher compared to other models available in making such an estimation. On the other hand, the remaining models in the study would have shown less precision in Table 4. This selective checking of input variables depicts how some of the researchers view the importance of proper input variables to enhance prediction models of ANN in various environmental studies.

4.6.2. Result of Case 2: Two Input

ANNs are put to practical examination in the sense of predicting urban runoff (RO) through six models (ANN#5-ANN#10), forming various pairs of inputs with a similar pattern. This approach targeted understanding the effect of different pairs of input variables on their prediction of runoff to the best estimations. The model that combined (R and SM) into the pair of input variables was the model ANN#10. The highest r-squared was given that portrays a relationship that prevails between predicted and observed RO values, shown by an R-squared of 0.8945. Such a high r-squared signaled high predictivity accuracy; therefore, a high signal existed showing that the interfacing of rainfall and soil moisture is a very critical aspect in runoff prediction. Further to that, among the ten, ANN#10 gave the lowest predicting errors with RMSE and MAE of 1.3512 mm and 0.3659 mm. End-User Outputs, User Acceptance, and Interpretability Evaluation These values underline the accuracy of the model in the prediction of runoff in the urban environment and show the efficiency that will be achieved in making use of soil moisture and rainfall data in such predictions. Thus, this seems to suggest potential benefits in the aspect of consideration of the enhancements of this model related to exact combinations of variables, an important segment of managing flood risks and urban planning.

4.6.3. Result of Case 3: Three Input

In more advanced stages of the research, effectiveness in Artificial Neural Networks (ANNs) was adopted by using three input variable combinations to anticipate urban runoff, and as such, four different models (ANN#11-ANN#14) were developed. In addition to several improvements in the parameterizations of these models, efforts were extended during this process to explore synergies between diverse environmental factors and their collective influence on the accuracy of runoff prediction. Among all these models, ANN#13 performed best, using a combination of (Tmax, R, and SM) as input. These gave an R-squared at 0.8811, meaning a very strong relationship existed between the predicted and obtained values of the rate. That is a very stunning performance to have Tmax, R, and SM together in their performance in capturing the dynamics of urban runoff. ANN #13 illustrated consistency for excellent accuracy, lowest among Root Means Squared Error (RMSE) at 1.3407 mm, and Mean Absolute Error (MAE) at 0.4701 mm of the tested models. These measurement metrics will emphasize the accuracy in predicting, driving the essentiality that multiple variables have to be integrated into developing methods for better predictions of urban runoff. This was relevant to town planning and flood risk management in so far as handling the same was concerned, whereby a proper prediction of runoff is extremely critical in the sense that it contributes very highly toward coming up with effective approaches as concerns flood risk mitigation and infrastructure.

4.6.4. Result of Case 4: Four Input

The inclusion of all the four inputs., (Tmax, Tmin, R, and SM), the Model ANN#15 developed in the present study, was done in respect of the performance of the Artificial Neural Network. This modeling approach was considered to have previously been carried out in other models, through inputs already used in models made to indicate research to create estimates of urban runoff. Key statistical indicators under which ANN#15 performed are included below: it has reached an R-squared of 0.8053, stating a strong relationship between the predicted and observed values of runoff; i.e., the inclusion of a larger set of somehow related water was able to track the runoff dynamics effectively. In the meantime, the model also records an RMSE of 1.7368mm and a low MAE of 1.0083mm, again indicating that follow-up prediction errors remain within a reasonable scope for the prediction of a complicated environmental process. All these results, on the robustness of the model integrating several environmental factors to predict urban runoff, show at the same time the problems in reaching precision in modeling complex systems. This will bring wholly comprehensive modeling further enhance our understanding of urban hydrology and further aid the development of predictive models in areas of flooding and urban planning.

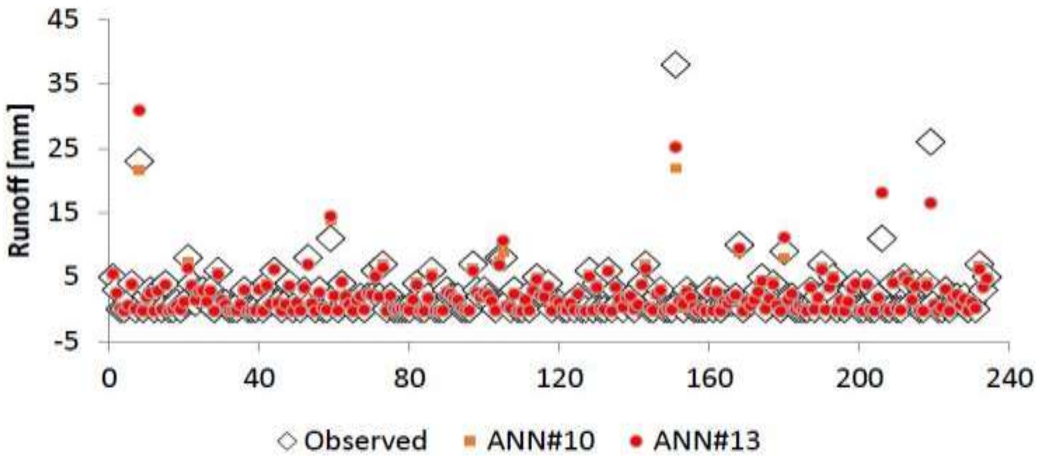
Table 7

Developed OLS Models to Forecast RO and Statistical Measures.

Model	**HL**	**NN**	**TF**	R^2	**RMSE [mm]**	**MAE[mm]**	**RRMSE**
OLS #1	1	5	*logsig*	0.0065	3.8968	2.3776	145.517
OLS #2	1	8	*logsig*	0.0001	3.9207	2.3850	152.764
OLS #3	1	10	*logsig*	0.7314	2.0428	0.5298	48.693
OLS #4	1	5	*logsig*	0.6257	3.4621	1.9569	56.797
OLS #5	1	8	*logsig*	0.0037	3.9154	2.4095	148.340
OLS #6	1	12	*logsig*	0.8141	1.6951	0.6315	44.311
OLS #7	1	5	*logsig*	0.6798	3.0188	1.8210	53.034
OLS #8	1	3	*logsig*	0.7672	1.8875	0.9318	50.052
OLS #9	1	3	*logsig*	0.5292	2.6703	1.8547	80.817
OLS #10	1	2	*logsig*	0.8945	1.3512	0.3659	35.610
OLS #11	1	5	*logsig*	0.7955	1.7845	0.7930	42.868
OLS #12	1	8	*logsig*	0.5817	4.1164	2.0456	61.396
OLS #13	1	15	*logsig*	0.8811	1.3407	0.4701	32.336
OLS #14	1	2	*logsig*	0.8329	1.7669	0.7511	36.457
OLS #15	1	16	*logsig*	0.8053	1.7368	1.0083	45.506

***Figure* 10**

Time Series of Observed and Predicted Value of Rainfall.



4.7. Result Of Ordinary Least Square (OLS)

This is a comprehensive statistical framework developed to study the performance of the developed models. Several statistical metrics are enumerated to measure this performance: Coefficient of Determination (R^2) and root mean square error(RMSE), These came to give a rich dimension to the performance of the models, indeed proving accurate, reliable, and possible multi-collinearity existence among variables. In similar processes of ANN models, the regression models were also subjected to even stricter trial and error. Thus, the iterative processes kept on refining the models, and in this sense, the ability of models to give more accurate and reliable regression results was constantly increased as the process of fitting models with data continued till the moment of precision. The application of the highly developed analytical technique to deal with such a hard challenge, the prediction of urban runoff, leaves the application of this or that methodology deeply committed. The application of such improved and new methods, corresponding to added insight, can revert to some fields of flood risk management and urban planning. Statistical metrics, including Coefficient of Determination (R2) and root mean square error (RMSEs), are used to evaluate the performance. Various models were analyzed through trial and error to obtain more accurate regression results.

4.7.1. Result of Case 1: One Input

In this instance, each input was fed individually into the OLS and designated as OLS 1-OLS 4. Each model's performance was evaluated using statistical tools such as Coefficient of Determination (R2) and root mean square error(RMSE). Among these models, OLS 3 showed high estimating capabilities, whereas the remainder of the models performed less accurately, as shown in Table 4.

4.7.2. Result of Case 2: Two Input

Six combinations were generated using two inputs (OLS 5-OLS-10), and their impact on RO prediction was evaluated, as shown in Table 4. OLS-10 with the input combination [SM, R] had the highest R-squared value of 0.996229 among these models. This shows a good correlation between projected (Tmax, Tmin, R SM) and observed (RO) values. According to the summary of OLS results, OLS-10 with the input combination of [SM, R].

4.7.3. Result of Case 3: Three Input

To assess the relationship, a total of four combinations were made with the three input variables. Table 4 displays the results of these models. Of these, OLS-13 with the input combination of [Tmax R SM] produced the lowest Root mean square error (RMSE) of 1.0346mm and the highest R-squared value of 0.998189mm.

4.7.4. Result of Case 4: Four Input

The relationship between the variables was analyzed utilizing the Ordinary Least Squares (OLS) approach, which considered all four input variables. The results, as shown in Table 4, illustrate that the OLS-15 model achieved a significant R-squared value of 0.998980. This R-squared value suggests that the model adequately explains approximately 99.9% of the variability found in the dependent variable, highlighting its robust explanatory capability. Employing the OLS approach enhances the reliability of the study's conclusions by affirming a substantial connection between the variables being investigated.

Table 8

Developed OLS models to forecast RO and statistical measures.

Model	**parameters**	R^2	**RMSE [mm]**
OLS #1	1	0.043305	0.4026
OLS #2	1	0.863232	0.9692
OLS #3	1	0.992993	0.9946
OLS #4	1	0.956593	0.6478
OLS #5	2	0.884389	0.9588
OLS #6	2	0.993007	0.9328
OLS #7	2	0.977147	0.9192
OLS #8	2	0.994910	1.1509
OLS #9	2	0.986590	1.1367
OLS #10	2	0.996229	0.9005
OLS #11	3	0.993158	1.0937
OLS #12	3	0.991163	1.1373
OLS #13	3	0.998189	1.0346
OLS #14	3	0.995923	1.0598
OLS #15	4	0.994580	0.8771

***Figure* 11**

OLS 10 Observed and Predicted Runoff Value.

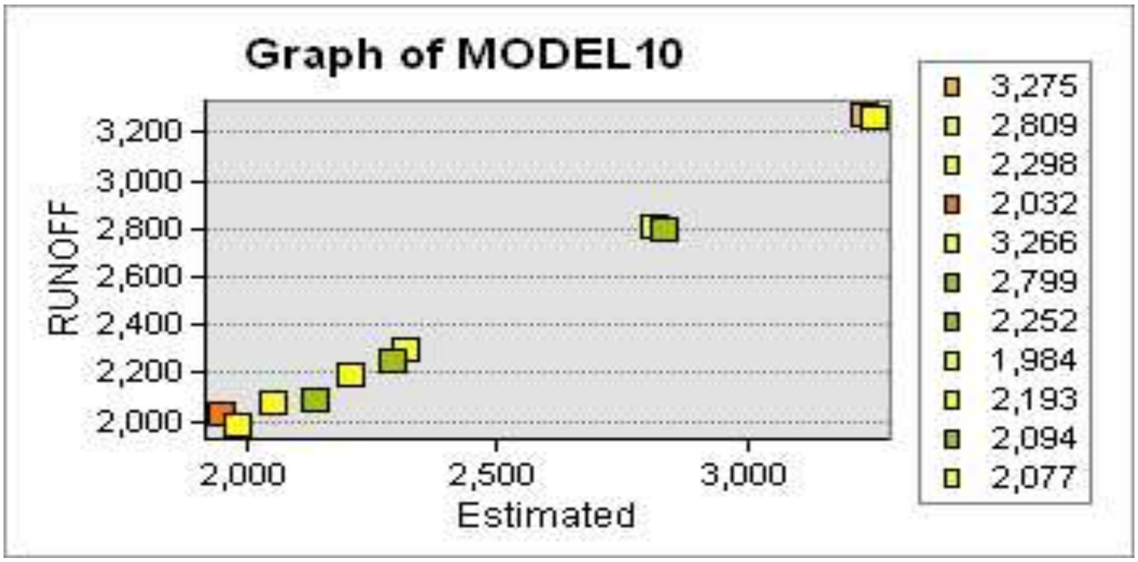


***Figure* 12**

OLS 13 Observed and Predicted Runoff Value.

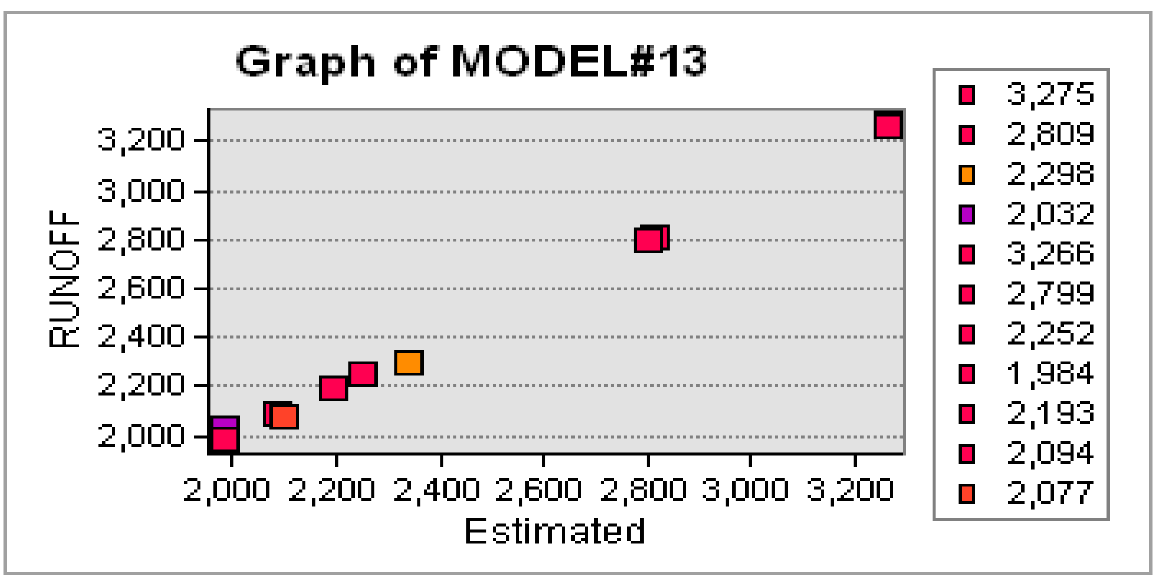


***Figure* 13**

Map of Model #1

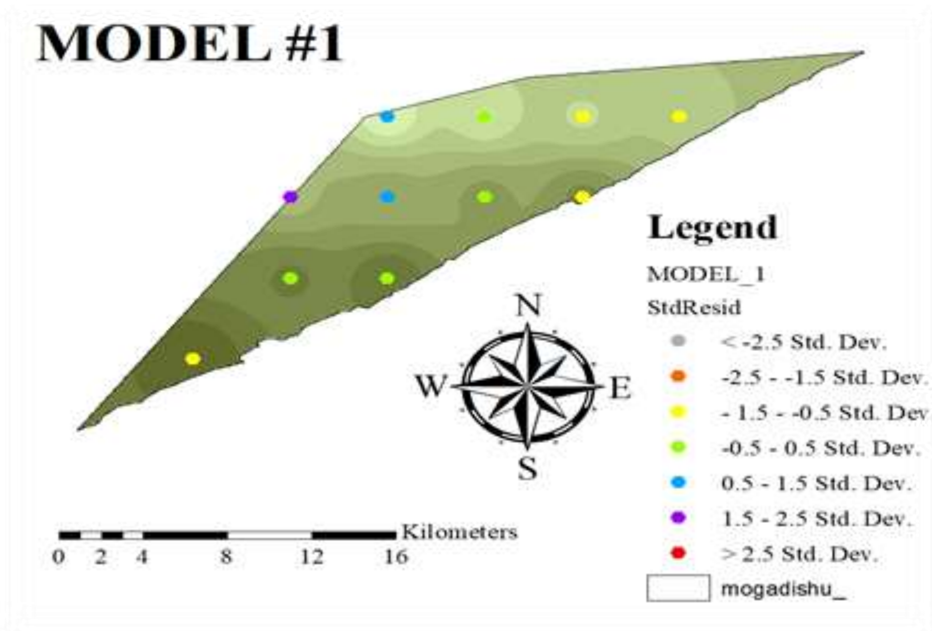


***Figure* 14**

Map of Model #2

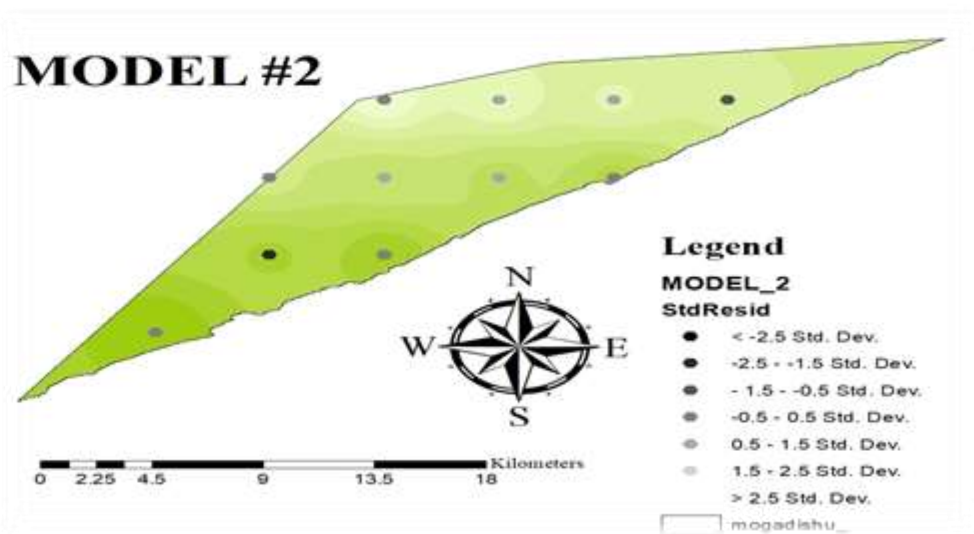


***Figure* 15**

Map of Model #3

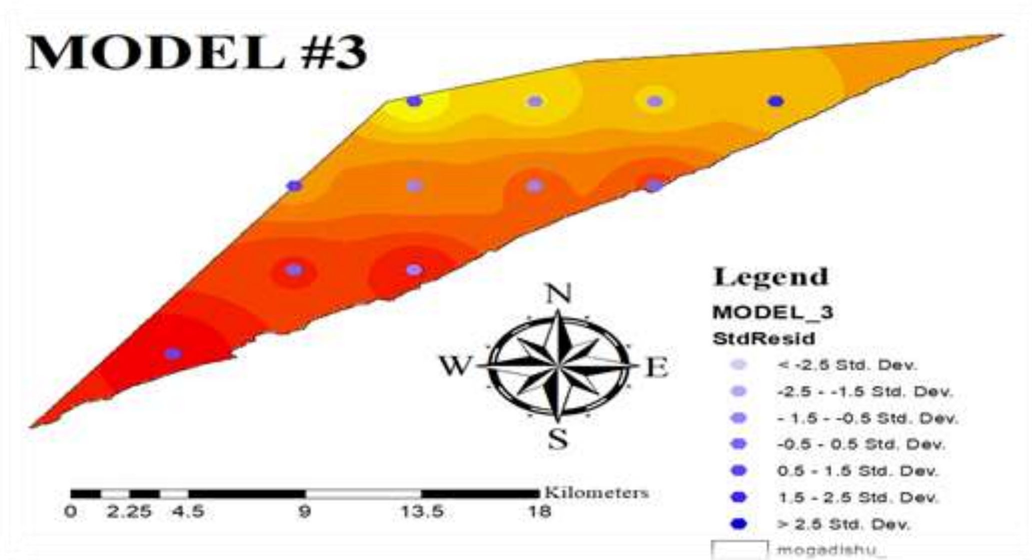


***Figure* 16**

Map of Model #4

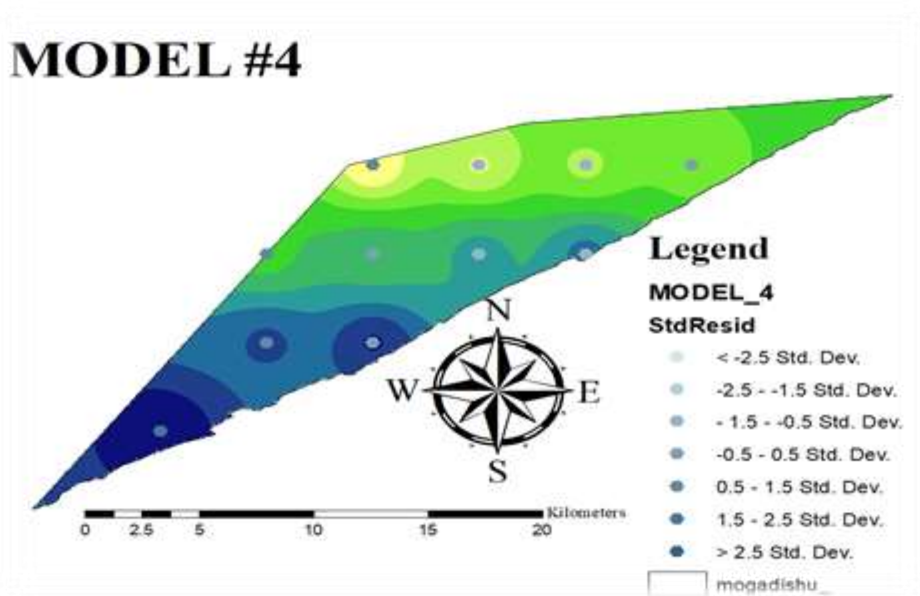


***Figure* 17**

Map of Model #5

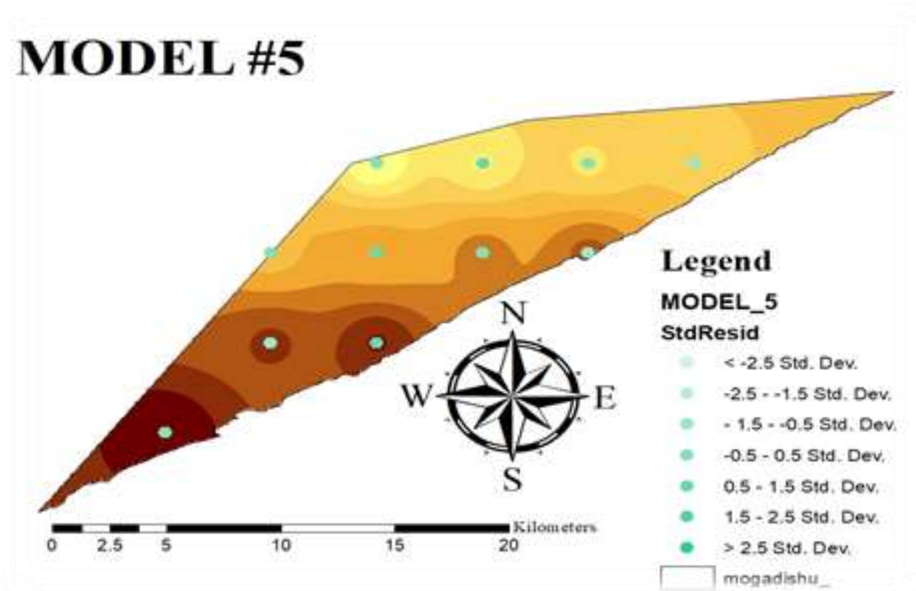


***Figure* 18**

Map of Model #6

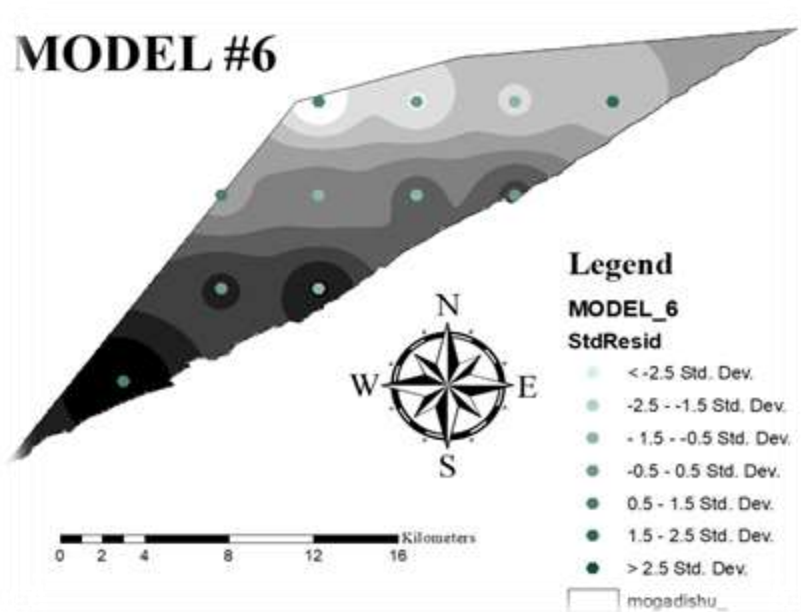


***Figure* 19**

Map of Model #7

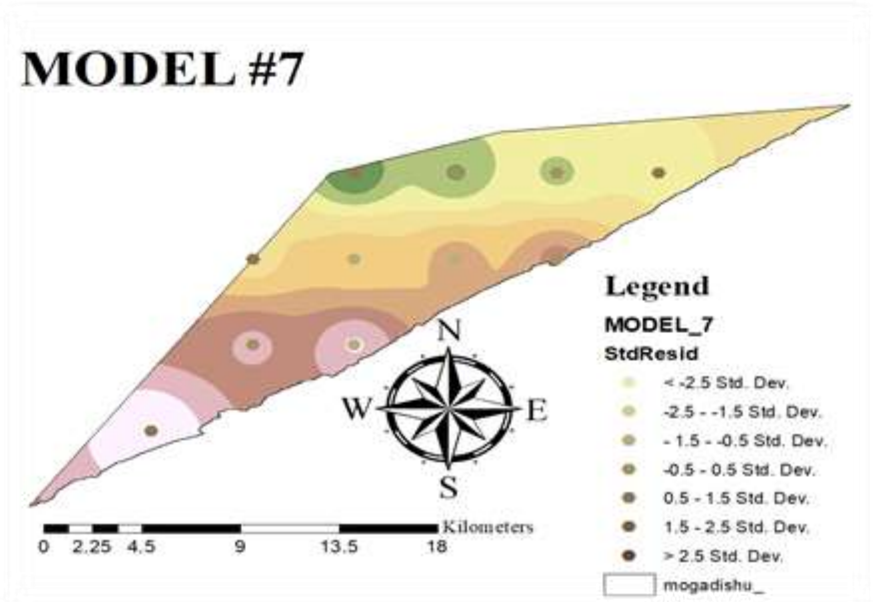


***Figure* 20**

Map of Model #8

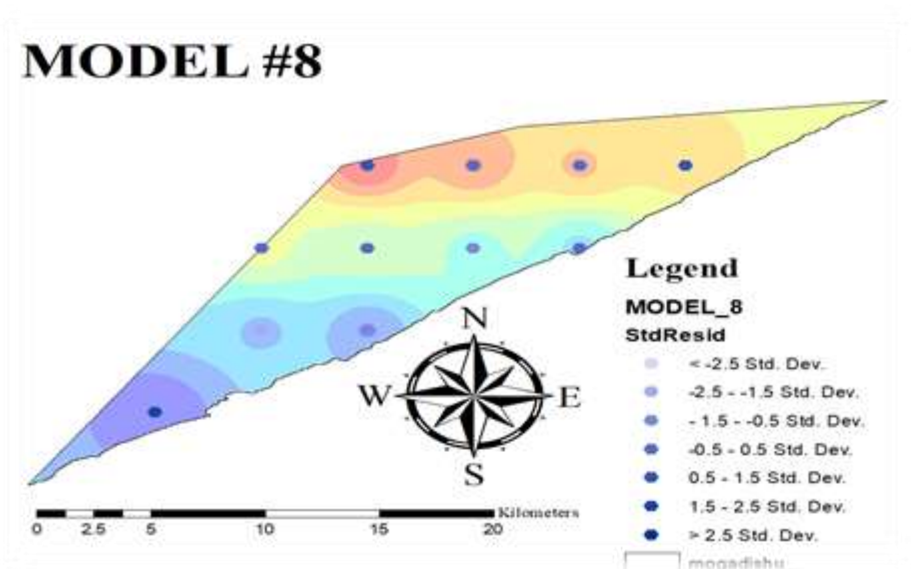


***Figure* 21**

Map of Model #9

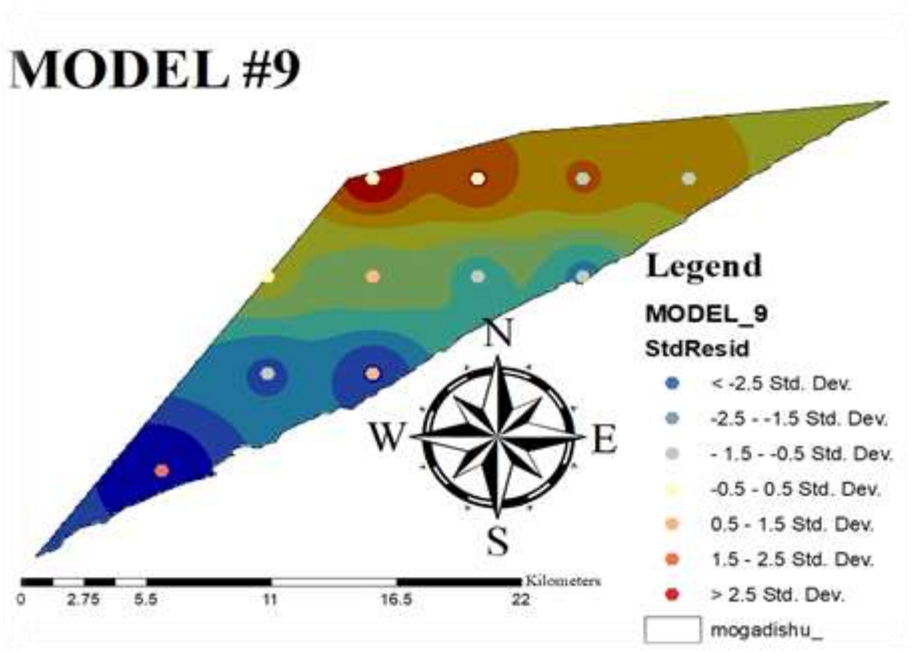


***Figure* 22**

Map of Model #10

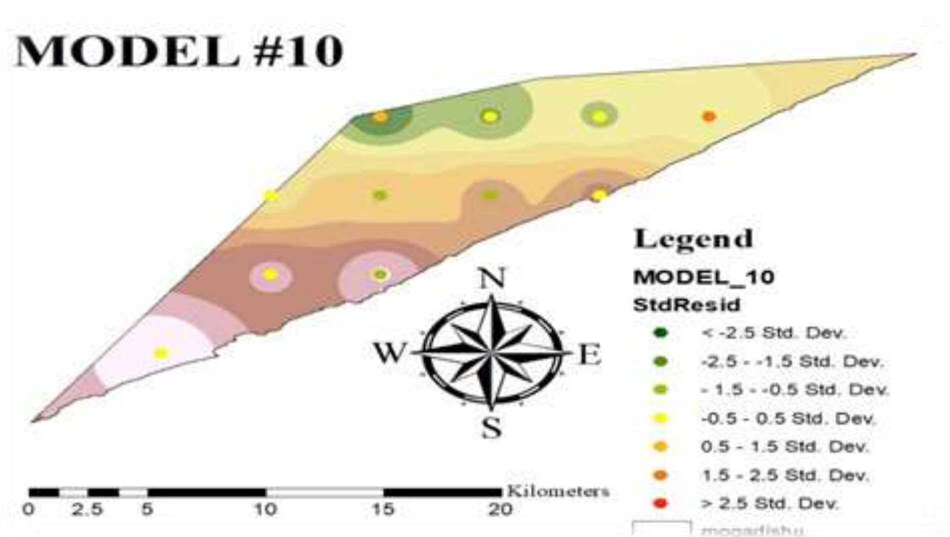


***Figure* 23**

Map of Model #11

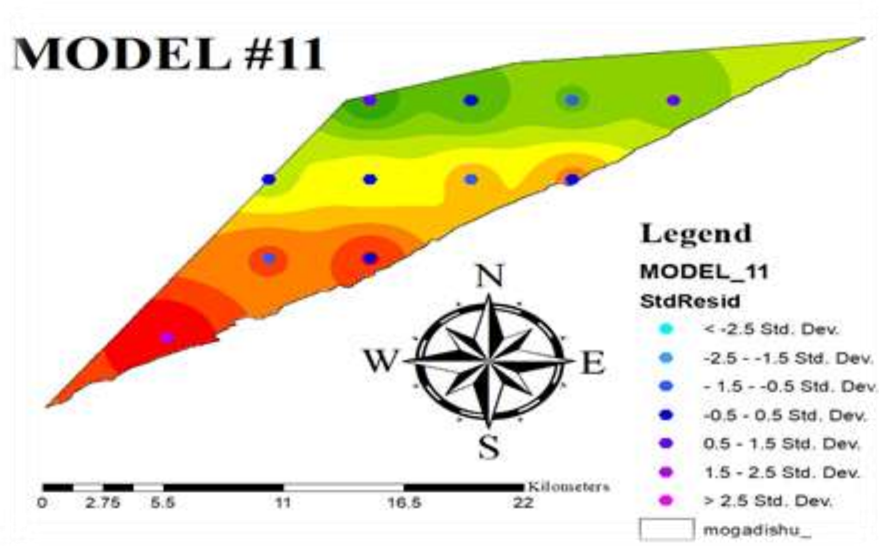


Figure 24

Map of Model #12

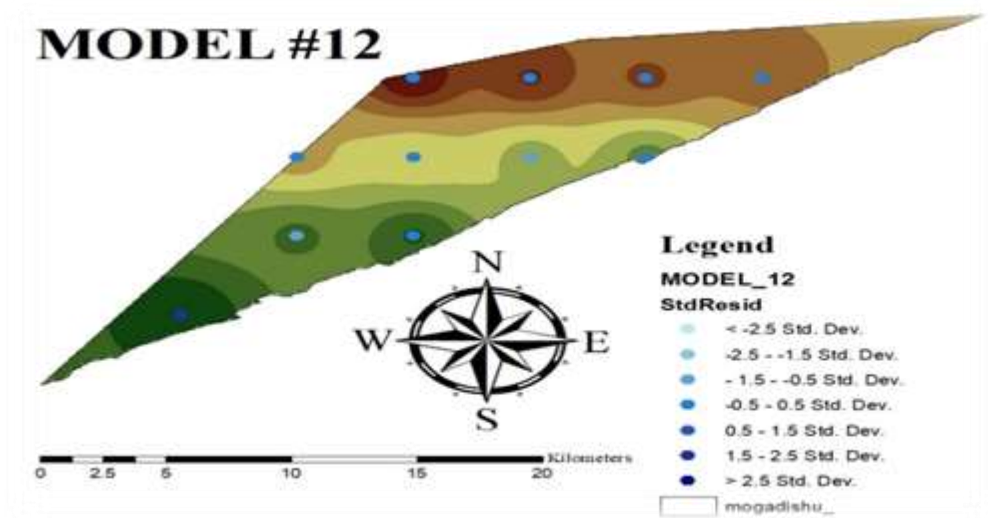


***Figure* 25**

Map of Model #13

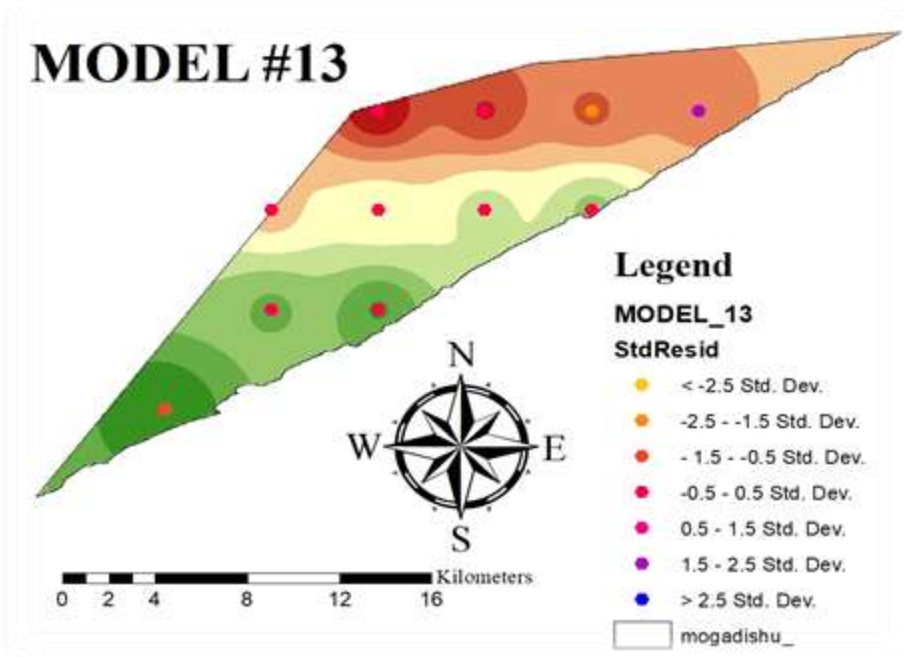


***Figure* 26**

Map of Model #14

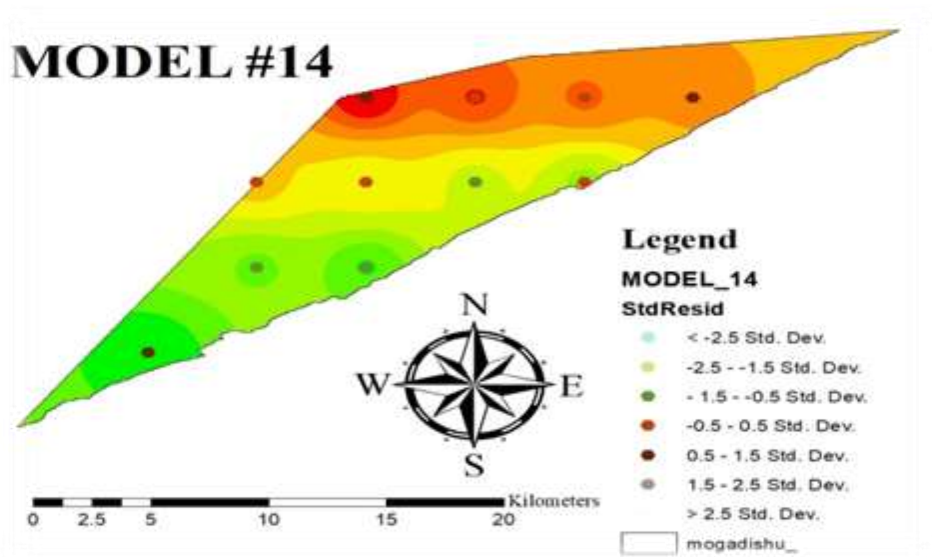
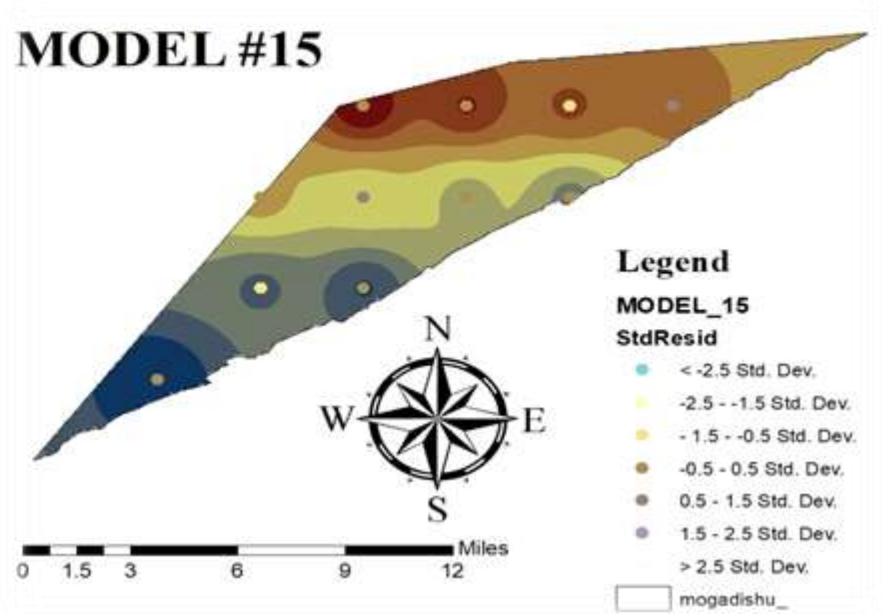


***Figure* 27**

Map of Model #15



4.8. Comparison of OLS and ANN Models

In contrast, the comparison of results between Ordinary Least Squares (OLS) and Artificial Neural Networks (ANN) models on urban runoff predictive models best depicts the congruent strength and impact of the two methodologies in equal measure. OLS models, OLS#10, depicted high values of R-squared at 0.996229 and root mean square error of 0.9005, while OLS#13 achieved R-squared of 0.998189 and RMSE of 1.0346. OLS #13 best predicts urban runoff volumes based on the input combinations provided.

This is in sharp contrast with ANN models such as ANN#10 and ANN#13, trained with the method of backpropagation and regarding the variables, which strongly estimated the importance, for instance, of rainfall and soil moisture to make good precision in prediction. Thus, ANN#10 realized both high R-squared results of 0.8945 with low prediction errors at RMSE 1.3512 mm and MAE 0.3659, whereas ANN#13 realized a result at 0.8811 with prediction errors at RMSE 1.3407 and MAE 0.4701 indicating good potential lies in the multiple variable integration power of enhancing prediction accuracy.

therefore, The difference between the estimation evaluation of OLS models with statistical metrics like R-squared and RMSE, and the estimation of ANN models with the use of RMSE and MAE indices, where each approach gives the diversity of the model's evaluation, will have to be incorporated after incorporating both methods to bring a critical analysis that will improve good reliability and accuracy for the predictions of urban runoff to ensure effective flood-risk management and strategies in urban planning.

4.9. Discussion

As simple and directly interpretable as they were, the OLS models tended to perform very well in prediction. This was particularly brought out in models like OLS#10 and OLS#13, which had very high R-squared values of 0.996229 and 0.998189, respectively, with the least RMSE values of 0.9005 and 1.0346. This is typical of high explanatory power or ability to account for a large proportion of variance about urban runoff based on the set of variables under consideration. This would then mean that the OLS is very effective when the relationship between the variables is known in good detail and can be assumed to be linear.

The ANN models, in contrast, displayed strength in handling complex, non-linear relationships among several variables. For example, both ANN#10 and ANN#13 gave R-squared values of 0.8945 and 0.8811, respectively, besides low prediction error values for RMSE and MAE, indicating the potential for flexibility in capturing urban runoff dynamics compared to OLS models. The ANN models are especially advantageous when the interactions among variables are complex and not purely linear; thus, such models are suitable for a detailed and nuanced analysis of the environment.

The choice between the OLS and ANN models depends on the data's nature and specific analytical needs. OLS models are preferable for their ease of use, while ANNs show high modeling potential to capture complex patterns, mostly for massive datasets with many variables. A more comprehensive picture of urban runoff prediction can be obtained by integrating both models, through the clear interpretability of the OLS and the advanced pattern recognition of ANNs for exploiting enhanced decision-making in urban planning and environmental management.

CHAPTER V

Conclusion and Recommendation

This chapter presents conclusions, recommendations, and limitations of the research based on the research findings and objectives.

5.1. Conclusion

This chapter will be a comprehensive summary based on what has been presented in the previous section on the analysis and examination of urban runoff or flooding in Mogadishu. This research has evaluated the influence of climatic parameters and soil moisture on urban runoff and further identified the variables having the greatest impacts on urban floods. The established dependence between the dependent and independent factors in Mogadishu has been achieved using machine learning techniques together with mathematical and statistical models.

The results of the study carried out for this research work revealed that maximum and minimum temperatures, soil moisture, and precipitation, among other variables, influence the outcome of the forecast of urban runoff in Mogadishu. Therefore, the identified attributes affect the availability of supplies and are considered to affect urban runoff. The outcome of this study will also help to comprehend how floods could be managed more effectively in the area of study.

The machine learning models Artificial Neural Network and Ordinary Least Squares have produced outstanding results in detecting complex patterns and linkages between climate factors, soil moisture, and urban runoff. After testing, the models produced exceptionally accurate forecast results for urban runoff based on input parameters.

Comparing machine learning models such as Artificial Neural Networks to OLS models, as well as statistical analysis, confirmed the connection models' effectiveness. The machine learning and OLS models produced significantly better outcomes than traditional mathematical methods. They were especially effective when dealing with complex data relationships and nonlinear interactions.

The integration of both the OLS and ANN models would be a more integrated approach to the prediction and management of urban runoff. Such modeling will enable scientists in urban planning and environmental science to improve the decision-making process using the clear interpretability of the OLS model and the high capability of pattern recognition by ANNs. This dual approach will allow a deeper perception of urban runoff dynamics and the formation of effective strategies in the field of flood risk mitigation and sustainable urban development.

In conclusion, the study indicates an emphasis that should be put on selecting the right modeling technique for the particular data characteristic and nature of the environmental question that one is concerned with. Both OLS and ANN are powerful tools, but they have their respective areas of strength and limitations. Likely, the combined use of both could cover a broader range of scenarios for effective urban water management.

5.2. Recommendation

To control urban runoff The following recommendations are focused on urban planning and environmental management, with much more insight into the study using both Ordinary Least Squares (OLS) and Artificial Neural Networks (ANN).

Model Integration: Urban Planners and Environmental Scientists shall integrate both OLS and ANN models to harness the strong points of both. While OLS provides a robust platform to perform initial analysis for simple scenarios, on the other hand, ANNs provide deep insights and predictions under complex scenarios. Both models could be used together to provide a more comprehensive understanding of urban runoff patterns.

Policy Formulation: In this regard, the policymakers, as well as the local authorities, should make policies that consider the insight offered by these predictive models so that the management of urban runoff and the mitigation of risks of flooding are ensured. These include infrastructural developments—like the building of enough and appropriate drainage—based on predictions by models for runoff patterns and volumes.

Investment in Data Collection: This will drastically improve the quality and quantity of meteorological and environmental data collection, enhancing the predictive models. Advanced data collection technologies, including remote sensing and the Internet of Things sensors in urban areas, should therefore be invested in.

Public Awareness and Education: Sensitization of the public and local business community to the impacts of urban runoff and the need for sustainable practices should be carried out. This would involve promoting green infrastructure through public advertisements to permeable pavements and rain gardens to reduce runoff and improve water quality.

Future Research: There is a need for more research to improve the developed models. It should include sensitivity analysis of more variables, further calibration or optimization of the model parameters, and application at different urban contexts and scales. The research is also recommended to focus on the effect of climate change on urban runoff to adapt the models to future scenarios.

Interdisciplinary Cooperation: The problem of urban runoff management is highly complex and, hence, warrants interdisciplinarity. Hydrologists, urban planners, climatic scientists, and policy-makers need to work in tandem for the realization of inferences drawn through predictive models in real-life strategies and solutions. These recommendations enhance preparedness in cities and allow them to handle the challenges of urban runoff and the associated environmental impacts. It helps in bringing advanced modeling into urban planning and policymaking, transforming urban environments into much more resilient and sustainable ones.

5.3. Limitations and Future Research

The analysis of urban runoff in the Mogadishu, Somalia area is limited by data quality, model complexity, interpretability, overfitting, computational resources, and generalization of the model by the Ordinary Least Squared (OLS) and Artificial Neural Network (ANN) methods. The quality of predictions is equal to the quality of the input data of meteorological variables and the specific Mogadishu urban environment. Other challenges with ANN models relate to the results' interpretability and the high possibility of overfitting, either to OLS or ANN models with such complex data while training. Future research in this study area should be guided toward data collection improvement, the development of localized models according to Mogadishu characteristics, and the integration of remote sensing. There is engagement with the local community and climate change resilience with an urban runoff analysis. The study will, therefore assist in making more accurate predictions and informed decisions regarding sustainable urban planning and flood risk management in Mogadishu by overcoming these limitations and pursuing these research directions**.**

Future research directions about the prediction of urban runoff will be towards the development of hybrid models that combine OLS and ANN or other machine learning techniques to achieve even higher forecast accuracies and interpretability. More feature engineering may be done on additional meteorological features or derived features to understand their performance concerning the developed models. Interesting research directions involve uncertainty analysis in the assessment of reliability, coupled with spatial and temporal analysis to capture variations in runoff patterns and trends over time. For this, more rigid validation studies with independent datasets and benchmarking of OLS and ANN models with other advanced methods in urban hydrology might be performed, helpful for sustainable urban planning and environmental management. By addressing these concerns, the future research direction, and researchers may improve the analysis of urban runoff in the present area, contributing to accurate and reliable predictions to make related decisions.

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Appendix A

Ethical Approval Letter

Date: July 8, 2024

To the Graduate School of Applied Sciences

REFERENCE: ABDIRAHIM SALAD HUSSEIN (20226277)

The research project titled **"Analyzing Urban Runoff with Climate Parameters and Soil Moisture Using Artificial Neural Network (ANN) and Ordinary Least Square (OLS) in GIS: A Case Study Mogadishu-Somalia."** has been evaluated since the researcher(s) will not collect primary data from humans, animals, plants or earth, this project does not need to go through the ethics committee.

Title: Dean, Faculty of Civil and Environmental Engineering
Name: Prof. Dr. Huseyin Gokcekus
Role in the Research Project: Supervisor

Appendix B

Turnitin Similarity report

Prof. Dr. Hüseyin Gökçekus

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