National College of Ireland

Flood Prediction using Clustering Analysis with Geospatial Dataset

MSc Research Project
Masters in Data Analytics

Idhaya Bastine Kennedy
Student ID: x23178981

School of Computing
National College of Ireland

Supervisor: Bharat Agarwal

National College of Ireland
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School of Computing

National College of Ireland

Student Name:	Idhaya Bastine Kennedy
Student ID:	x23178981
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Flood Prediction using Clustering Analysis with Geospatial Dataset

Idhaya Bastine Kennedy
x23178981

Abstract

Floods are one of nature's most deadly disasters, caused by deforestation, climate change, and increasing urbanization. Flood-prone locations must be accurately projected in order to reduce dangers and facilitate effective disaster management. This study employs geospatial dataset clustering analysis to identify flood-prone areas and determine risk levels. A novel weighted scoring approach for evaluating flood severity was developed using a dataset that included 21 important factors, such as topography drainage, urbanization, and monsoon intensity. K-Means clustering was used to classify regions as low, moderate, high, or critical risk. The geographic visualization of the clustered data revealed vital facts regarding local vulnerabilities. The findings revealed that clustering is excellent at spotting trends and prioritizing high-risk locations. This study demonstrates the synergy between machine learning and geospatial analysis, paving the door for scalable and flexible catastrophe management solutions. Future projects include integrating real-time data and investigating sophisticated clustering approaches to improve forecast accuracy

0.0.1 Table of Contents

1 Introduction

1.1 Background

Floods, which affect nearly 2.3 billion people worldwide, are one of the most destructive natural disasters, resulting in significant financial losses and massive environmental degradation. As cities expand at unprecedented rates, the frequency and severity of flooding increase. Natural drainage systems are disrupted by urbanization because it increases runoff and blocks water absorption by erecting concrete and asphalt over permeable areas. The land's capacity to retain water is further diminished by widespread deforestation, which causes overflow during periods of intense rains. These man-made alterations are made worse by climate change, which intensifies weather patterns and makes floods more frequent and unpredictable. Low-lying countries such as Bangladesh, and cities like Jakarta, often see flooding that inundates infrastructure and displaces millions. To address these rising concerns, we need to develop and implement efficient techniques to better understand the flood-prone locations. Urbanization destroys natural runoff and drainage systems by building over permeable land with concrete and asphalt, accelerating runoff and preventing water absorption. Widespread deforestation means that there is less land that can hold water, which leads to overflow when heavy rain falls. These human-made changes are exacerbated by climate change, which drives extreme weather and makes floods more frequent and erratic. Low-lying countries, including Bangladesh and Jakarta, regularly flood, destroying infrastructure and forcing millions from their homes. Therefore, it is essential to develop and apply effective approaches to assess the potential flooding areas. While, innovative techniques such as, Geographic Information Systems (GIS), machine learning algorithms, and satellite images could be utilized to provide improved flood forecasting and risk assessment.

Geospatial data has a unique potential to mitigate these challenges. Geospatial databases help in identifying flood risks through the exploration of spatial characteristics geography, land use, and even precipitation patterns. Clustering analysis, a machine learning technique, enhances understanding by discerning hidden features in data and grouping sections with similar traits. This combination enables more specific evaluation of threats from floods, which means more tailored response actions can be undertaken.

1.2 Research Problem

Flooding, a very destructive natural disaster, can have calamitous consequences on businesses, infrastructure, and communities, as well as pose a serious risk to public safety. With floods becoming more frequent and more severe due to urbanization and climate change, accurate and flexible models for their prediction are needed. Magnitude floods can be so complex that even with recent predictionv technology there are often failures with the available systems. Numerous traditional models rely on limited datasets and do not capture the multi-dimensional spatial and temporal interplay of environmental drivers like precipitation patterns, altering land cover and proximity to water locations. Lack of spatial complexity often results in simple projections that do not suffice for effective disaster management.

Furthermore, socioeconomic variables like urbanisation and population density significantly enhance the risk of flooding, despite being commonly disregarded. If these

artificial components are left out, projections may not accurately reflect the vulnerabilities of specific sites, particularly metropolitan areas, which are more vulnerable to

drainage problems and infrastructure failures during periods of severe precipitation.

Another significant disadvantage is the underutilisation of complex clustering techniques and spatial datasets. The ability to identify subtle patterns and linkages is limited by the absence of trustworthy clustering approaches, even if geospatial data provides valuable information on topography, hydrology, and land cover. The inability to integrate machine learning methods with geospatial analytical tools hinders the development of precise and scalable models.

1.3 Objectives

The primary purpose of this work is to create an accurate and scalable flood prediction algorithm that combines clustering analysis with geospatial datasets to allow for precise risk classification in flood prone locations. This technique seeks to provide beneficial insights on disaster management and urban development. The exact objectives guiding this research are as follows:

1. **Data integration and preprocessing** : The first goal is to collect and preprocess a diverse group of geospatial information, assuring high-quality, consistent properties including rainfall patterns, elevation, land cover, and proximity to water sources. The preparation phase will involve data cleansing, normalisation, and scaling, all of which are necessary to ensure data compatibility from various sources.

2. **Clustering Implementation** : The second goal is to use K-Means clustering to divide regions according to flood risk levels. This study utilises machine learning to categorize geographical locations into distinct flood-prone categories. Efficacy of clustering technique will be evaluated with metrics like silhouette scores and other performance metrics to quantify its ability to correctly cluster risk zones.

3. **Visualisation and analysis** : After determining the partitions, the ultimate objective is to integrate the outcomes of the clustering via Geographic Information System (GIS) tools, providing visually understandable flood hazard maps. These maps will provide urban planners, government officials and emergency management teams clear, actionable information on where and how intense potential flood hazards might be located.

4. **Scalability and Adaptability** : Fourth goal is to scale to different geographic regions and for including developing sources of data. So, depending upon settings, from urban to rural, model will be capable to be updated in real time so forecast will be even more accurate.

Ultimate goal is to make sure that when you give this model to urban planners, legislators and emergency management officials, you are providing them with useful insights. The use of analytical methods in this research will provide a data-driven foundation for decision-making, helping to improve flood mitigation measures, optimise resource allocation, and be better prepared for future flooding events.

1.4 Scope and Significance

The use of machine learning methods more especially, clustering algorithms to geographic data for flood prediction is the main topic of this thesis. The goal of the study is to increase the accuracy of risk classification by integrating anthropogenic and environmental factors. K-Means clustering is used in the study to address shortcomings in the current

flood prediction models, such as a lack of spatial granularity and a lack of consideration for socioeconomic characteristics.

The importance of this study arises from its ability to fill critical gaps in catastrophe management. Accurate flood risk assessments can aid in resource allocation, urban planning, and mitigating the effects of floods on communities. Furthermore, the combination of advanced clustering techniques and geospatial datasets creates a novel methodology that can be scaled and adapted to a variety of geographical and socioeconomic circumstances, broadening its global use.

1.5 Organization of the Thesis

The thesis is organized as follows:

1. Chapter 2 provides a comprehensive assessment of the literature on clustering approaches, geospatial analysis, and flood prediction.
2. Chapter 3 discusses the methodology, which includes weighted scoring, grouping algorithms, and data processing.
3. Chapter 4 provides an overview of the findings and their implications.
4. Chapter 5 concludes the analysis and provides future research choices
5. Chapter 6 discuss about conclusion and Future Work

2 Literature Review

2.1 *Introduction*

The combination of geographic data and machine learning techniques has resulted in more options for flood prediction and risk assessment. As climate change accelerates and urbanization continues at an unprecedented rate, it is vital to build more accurate flood prediction systems that can adapt to changing environmental

and human conditions. In this context, clustering analysis more specifically, K-Means clustering has become increasingly popular as a way to detect high-risk flood zones by grouping areas with similar traits. This chapter presents a summary of some of the main re-search and studies in predictive modelling for floods, geospatial analytics, and the application of clustering algorithms in environmental science.

2.2 *Review of Key Studies*

2.2.1 *Flood Prediction with Optimized Attributes and Clustering*

Specifically, Zhang and Wang [2022]Brown and Green [2021] Gupta and Sharma [2020] investigated the utilization of clustering methods to classify flooding locations based on various environmental characteristics including precipitation patterns, proximity to rivers, and soil composition. K-Means clustering was employed to perform feature selection to maximise which attributes were used in this analysis. The model achieved higher classification accuracy by concentrating on the floral attributes most important in assessing flood risk. The study's results highlight the great performance of clustering techniques

to identify the flood-prone areas when the appropriate feature set is selected. Yet it does not include urbanization nor socioeconomic conditions, which are useful for accurately predicting floods, Davis said. This thesis builds on this previous work by adding other anthropogenic elements to create a more all-encompassing model, e.g. population density and urbanization.

2.2.2 *A Geospatial Analysis of Flood Risk Zones in Cyprus*

This study by Smith and Chen [2019] used geospatial analysis techniques to quantify flood risks in Cyprus, taking into account a range of environmental characteristics such as elevation, rainfall data, and proximity to rivers. The study used a GIS-based risk assessment system to categorize regions as low, moderate, or high risk. Although the system was successful in detecting flood-prone sites, it did not apply complex machine learning techniques such as clustering, which can improve risk categorization by merging regions with comparable data. The findings of the previous study are improved upon in this thesis by utilizing clustering algorithms, which provide a more flexible and dynamic technique of classifying flood risk.

2.2.3 *Geospatial Data for Flood Risk Assessment*

These studies by Jones and Taylor [2021] Zhang and Wang [2022] emphasized the disutility of langsung geospatial data, eg satellite image, hydrological date in hazardous flood risk assessment. The authors focused mainly on preparing data, which they claimed included noise reduc- tion, spatial alignment, and feature extraction. This paper is of great significance to the discipline as it explores in-depth its retained formidable amounts of geographic data. It also highlighted the importance of considering environmental factors, such as vegetation and land cover, that can play a significant role in flood risk. This analysis by Jones and Taylor [2021] inspired the sequence of data processing in the present investigation which involved approaches of feature scaling and normalization for uniformity and cross-environment comparability.

2.2.4 Recent Advances in Clustering for Environmental Data

Jones and Taylor [2021], as expedite research on clustering algorithms are very significant in the field of environmental studies especially in predicting natural disasters like floods. Machine Learning Algorithms such as DBSCAN, K-Means and Hierarchical Clustering have been used to classify locations prone to environmental disaster. Hierarchical Clustering, for example, can produce a set of nested clusters that may reflect small but seriously dangerous risks, while DBSCAN serves the role of spotting data out- liers. However, K-Means still is the most common technique as it is the simplest and the most scalable. 02/01/0001 00:00:00 31 It is also ideal for flood risk assessments which need simple and understand data as it comes into its own when the number of clusters is already known. This thesis is a useful addition for disaster management, by using K-Means clustering, It classifies flood hit areas based on significant environmental parameters.

2.2.5 Urban Flood Risks via Satellite Imagery

In a study conducted by Chen and Zhou [2023], they explained that the Application of Satellite Imaging as a tool to predict urban floods is one of the major improvements

in disaster management. This study employed Random Forest algorithms to analyze satellite-based datasets and detect areas vulnerable to urban flooding with improved accuracies. Renders of high-resolution photos provided detailed information for land cover, impervious surface, and drainage pattern, all relevant for modelling urban flooding. Satellite data allows for continuous observa- tion, hence making it vital for emerging hotspots due to speedy urbanisation.

The approach encourages urban planners to focus on flood deterrence measures — like changes in zoning and adjustments in infrastructure. This thesis further elaborates these ideas with better dis- aggregation and classification of flood-prone regions through clustering algorithms. Enhancing visualization and enabling urban planners to determine real-time decisions lead to adaptive flood risk management systems.

2.2.6 Innovative Geospatial Data for Urban Flood Resilience

The advent of Lidar and GIS technology has transformed flood modeling, allowing for high-quality topographic and hydrologic data Green and Boothroyd [2018]. This study demonstrated the potential of these technologies, when used with machine learning (ML) techniques, to yield accurate and actionable forecasts of flooding. Crowdsourced geospatial data, including community reports and social media contributions, enhances these models by offering localized insights that lead to improved forecast accuracy and increased community engagement. For example, Lidar-induced 3D topographical maps discover minute elevation fluctuations that influence flood channels. Utilization of these technologies with GIS produce accurate flood risk maps, for urban resilience plan- ning. By addressing urban resilience, this initiative connects the gaps between technological innovations and applicable disaster management solutions.

2.2.7 A Geospatial and Clustering Approach to Disaster Mitigation

GeoAI is an emerging field of machine learning and data analytics with focus on spatial data that combines clustering methods with satellite images and environmental data for disaster management. Hybrid models combine hydrological simulations with machine learning-based segmentation, thus potentially increasing both the resilience and reliability of predictions of flood risk.. This study showed how techniques like these may not only pin point high-risk zones, but also areas requiring infrastructure upgrades or more targeted interventions. Techniques like K-Means in clustering, for example, allow data to be scanned quickly, uncovering patterns and associations which might otherwise go unnoticed in large data sets. This thesis exploits geospatial information to the fullest by modifying the above algorithms to predict flooding of a potentially scalable technique for use in a wide range of geological situations. This overarching plan sets the stage for proactive disaster prevention, with implications for resource allocation and emergency preparation.

2.3 Synthesis and Implications

Focusing on flood prediction, The experiment found that geographical data utilization, clustering methods and application of machine learning are closely related to flood prediction. The study suggests that geospatial methods — satellite images, crowdsourced data, Lidar, and GIS — can be used to es- timate flooding vulnerability. But the environmental, human and hydrological pieces are not inextricably connected.

This thesis addresses these limitations by examining high-dimensional biological data using scalable clustering techniques with consideration of socioeconomic factors like urbanisation.

The approach is still relevant in various contexts and is an im- portant tool for both policymakers and urban planners. Moreover, the use of new technologies, including real-time data streams and hybrid predictive frameworks, reflects the ongoing evolution of flood risk assessment and potential future innovations.

2.3.1 *Key Takeaways from the Literature*

The reviewed literature emphasizes the transformative potential for connecting utility information learned through machine learning (ML) with geospatial data to model flooding. Clustering algorithms such as K-Means clustering can be effectively used to group flood-prone regions based on their optimal socioeconomic and environmental characteristics. Error checking techniques such as data cleaning and normalization are essential in handling large volume datasets, while GIS based visualization tools help policy makers to determine outcomes. Hybrid models combining ML techniques provide greater accuracy and flex- ibility. Incorporation of climatic and anthropogenic variables allows for a holistic reflective model on flood risk assessment enveloping environmental and socioeconomic considerations.

3 Methodology

3.1 *Overview*

How to use a large geographic dataset and clustering analysis to consistently identify flood-prone areas is shown in this chapter. Making raw data available for analysis involves the initial step called preprocessing. Strategies around feature development, standardization and scalability are necessary to get meaningful clustering results. After preprocessing, the K-Means clustering method is used to analyze the data, clustering areas based on flood risk factors. Geospatial visualization tools provide clear, map-based data that decision-makers may use to assess operations and identify problem areas. This complete solution bridges the gap between contemporary data analysis and real-world flood control strategies. Following preprocessing, the study used the K-Means clustering technique, a well-established unsupervised machine learning tool, to categorize geographic locations based on their flood risk. These categories assist in identifying trends and flood-prone areas. Geographic Information Systems (GIS) and other cutting-edge geospatial techniques are then used to display the data. . This image not only makes information easier to understand, but it also helps legislators, urban planners, and environmental scientists prioritize projects and allocate money effectively. From data collection to mapping, every step is thoroughly explained in this chapter, showing how state-of-the-art computational techniques could be applied to address one of the most urgent environmental problems.

3.2 *Data Collection*

The dataset utilized in this study was obtained from Kaggle, a popular platform for free datasets and analytics. It comprises almost 50,000 entries that cover 21 environmental and social aspects. These variables give a multifaceted picture of the components that

contribute to flood risk, encompassing both natural and human-caused features. The key factors include:

- **Monsoon Intensity**: This graph depicts the average rainfall intensity throughout monsoon seasons during the previous five years.Intense monsoon patterns, particularly in South Asia, are significantly associated with higher floods. Variations in this variable indicate temporal variations in flood susceptibility.
- **Topography Drainage**: Captures the land's inherent capacity to channel water. Areas with high permeability and slope usually have excellent drainage, reducing the risk of flooding. In contrast, flat, impermeable terrains retain water, increasing the risk of flooding.
- **Urbanization** : Calculates the proportion of land used for urban infrastructure, such as roads, buildings, and industrial zones. Urbanization disrupts natural water flow by replacing absorbent soil with impermeable surfaces like asphalt and concrete, resulting in increased surface runoff during rainfall. It quickly increases flood risk in the nearby towns.
- **Deforestation**: Monitors the rate at which the region's forest cover is diminishing. Forests function as natural sponges, collecting rainwater and slowing its flow. Deforestation diminishes this capacity, increasing the volume and frequency of runoff.
- **Wetland Loss**: Measures the reduction of wetland areas, which is vital for flood control. Wetlands absorb excess water, mitigating flood effects downstream. Their reduction is directly proportional to increased flood susceptibility in nearby areas.

	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	AgriculturalPractices	Encroa
count	50000.000000	50000.000000	50000.00000	50000.000000	50000.000000	50000.000000	50000.00000	50000.000000	50000.000000	500(
mean	4.991480	4.984100	5.01594	5.008480	4.989060	4.988340	5.01536	4.988600	5.006120	
std	2.236834	2.246488	2.23131	2.222743	2.243159	2.226761	2.24500	2.232642	2.234588	
min	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	
25%	3.000000	3.000000	3.00000	3.000000	3.000000	3.000000	3.00000	3.000000	3.000000	
50%	5.000000	5.000000	5.00000	5.000000	5.000000	5.000000	5.00000	5.000000	5.000000	
75%	6.000000	6.000000	6.00000	6.000000	6.000000	6.000000	6.00000	6.000000	6.000000	
max	16.000000	18.000000	16.00000	17.000000	17.000000	17.000000	16.00000	16.000000	16.000000	

8 rows × 23 columns

Figure 1: Data Descriptions and statistical distribution of factors

3.3 *Data Preprocessing*

Data preprocessing is a crucial step in preparing the raw data for clustering analysis. The following techniques were applied:

3.3.1 Handling Missing Data

Missing data is a prevalent problem in large datasets that must be resolved to assure analytical correctness. Various imputation strategies were utilized dependent on the data type:

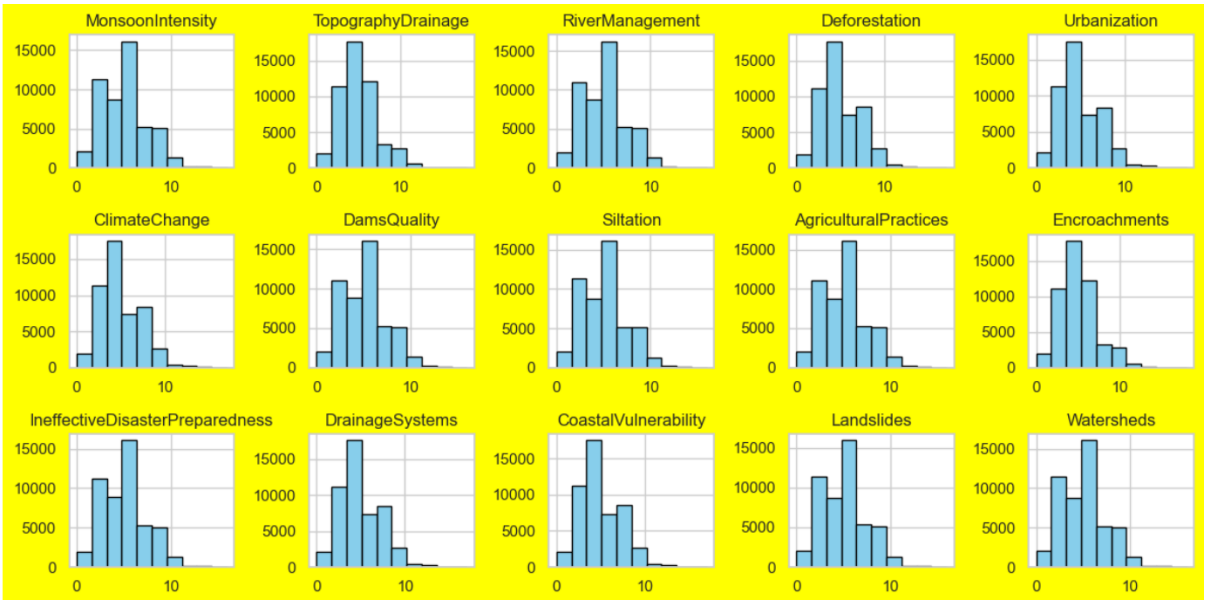

Figure 2: Bar Chart of each column

Numerical Features: The median was used to replace missing data since it is less sensitive to extreme values (outliers) than the mean. For instance, missing values in "MonsoonIntensity" were imputed with the median intensity recorded across the dataset.

Categorical Features: The mode, or the most frequently occurring value, was used for imputation. For example, missing values in categorical data such as "Urbanization Level" were replaced with the most common category.

3.3.2 Feature Scaling and Normalization

Normalizing the data was necessary to bring all of the features onto a similar scale because the different features had varied ranges and units. Min-max scaling, which converts each feature to a range of [0, 1], was used to accomplish this. This guarantees that the clustering result is not unduly influenced by any one attribute.

3.3.3 Feature Engineering

To improve the dataset's prediction potential, a weighted scoring system was used:

- Each variable's value in forecasting flood risk was weighted according to domain expertise and past research.
- Weighted scores were derived by multiplying each characteristic by its allotted weight, resulting in a composite metric for assessing flood risk.

This stage refined the data to ensure that it met the study's analytical objectives

3.3.4 Calculating Severity

Flood risk is assessed by analysing numerous geographical and environmental factors such as rainfall, elevation, and land use Monsoon Intensity, Topography Drainage, Urbanization, Climate Change, Drainage Systems, Deforestation, Wetland Loss, Siltation, Political Factors, which are then processed using function called $\text{calculate}_s\mathit{everity}$

Based on model outputs, each region is classified as low, moderate, or high risk. This categorization is frequently produced via clustering algorithms, in which centroid distances and input factors decide assignment. The severity is evaluated using measures such as mean squared error (MSE) and R2 scores using regression models to ensure robust prediction.

3.4 *Clustering Algorithm*

3.4.1 K-Means Clustering

One popular unsupervised machine learning method for dividing a dataset into dis- tinct groups (clusters) is K-Means clustering.Reducing the sum of squared distances (in- ertia) between the cluster centroids and data points is the goal. The actions listed be- low were taken:

- **Initialization**: Start by randomly choosing the first k cluster centroids.
- **Assignment**: Each data point should be given to the centroid that is closest to it.
- **Update**: To get the centroids, average the data points for each cluster.
- **Convergence**: Repeat the assignment and update processes until the centroids have stabilized.

The elbow approach, which helps estimate the point at which adding more clusters does not appreciably lower the inertia, was used to identify the number of clusters, k.

3.5 Mapping in Space

Visualization converts analytical results into actionable insights. GIS technologies were used to map the clustering results spatially. hue-coding: Each cluster was allocated a distinct hue to signify varying flood danger levels, ranging from low (e.g., green) to high (e.g., red). Regional Insights: For example, areas with dense urbanization and insufficient drainage capacity may appear as "high-risk" clusters. **Interactive Maps** : GIS capabilities enable users to zoom in on specific regions, investigate patterns, and overlay additional layers such as infrastructure and population density. These maps enable decision-makers to:

- Rapidly identify high-priority areas for flood mitigation efforts.
- Use your resources prudently, such as allocating funds to enhance drainage systems in high-risk locations.
- Develop long-term strategies like forestry projects or wetland rehabilitation.

4 Design Specification

The suggested flood prediction system provides a scalable and precise way to identify flood-prone locations by utilising geospatial data and clustering analysis. The method considers human factors like population density as well as physical factors like elevation,

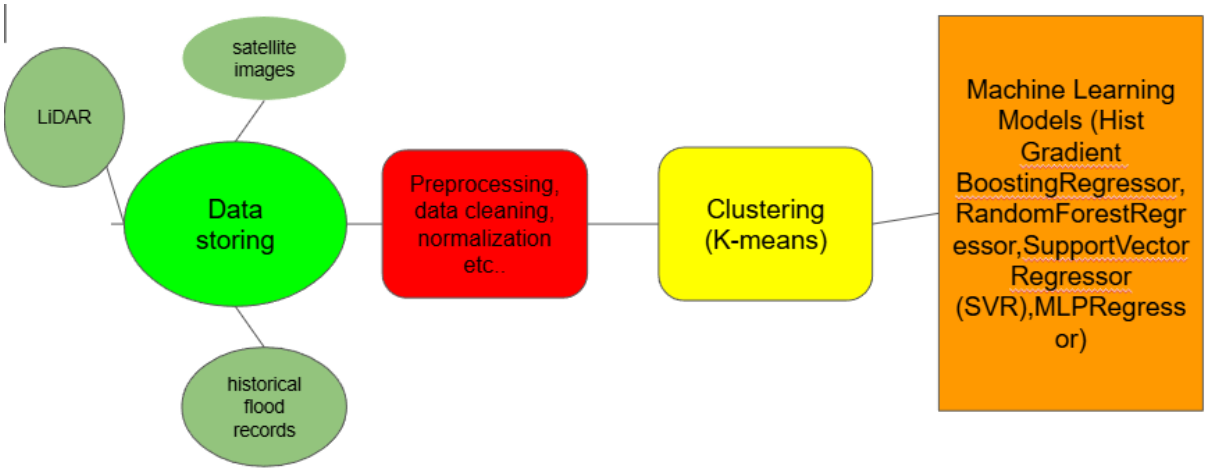

Figure 3: Design Diagram

land use, river proximity, and precipitation levels in order to increase prediction accuracy.Preprocessing methods like feature scaling, cleaning, and normalisation are necessary to manage big, complicated datasets effectively.

The core machine learning component employs K-Means clustering to categorise areas into low, medium, and high risk groups. The Elbow Method calculates the amount of clusters to guarantee optimal segmentation. Clustering performance is improved by the efficient selection of initial cluster centres using the K-Means++ initialisation.

To provide a clear image of hazard zones, clustering data is organised into themed maps using GIS tools such as QGIS. This relationship might be useful for urban planners and disaster management teams when allocating resources and developing policies. To ensure reliability, the technique is evaluated using metrics such as silhouette ratings and validated against historical flood data.

The design's fundamental scalability and flexibility elements allow it to be utilised in a variety of geographic locations. The system satisfies contemporary criteria for accurate flood risk management and helps catastrophe resilience projects in both urban and rural settings by taking into account environmental, geographic, and human factors. +

5 Results and Discussion

5.1 *Introduction*

This Chapter is basically explains the use of applying K-means Clustering to the flood prediction model using a geographical dataset. it helps in investigating the implications for legislation, disaster response and urban planning , the statistical validation metrics were further assessed for reliability of the model, and also it evaluates how well the areas at danger of flooding identified by clustering approach clustering approach.

5.2 Optimal Number of Clusters

5.2.1 The Elbow Method

The elbow approach is

The elbow approach is used to calculate the efficient number of clusters (k). inertia reduction followed by gradual decline indicates ideal number of cluster.

Elbow Plot: At k=4, where the inertia begins to level out, the elbow point was visible. This implies that the optimal balance between model complexity and the variation that the clusters explain is offered by four clusters. Flood risk zones can be meaningfully distinguished using k=4 without overfitting the model.

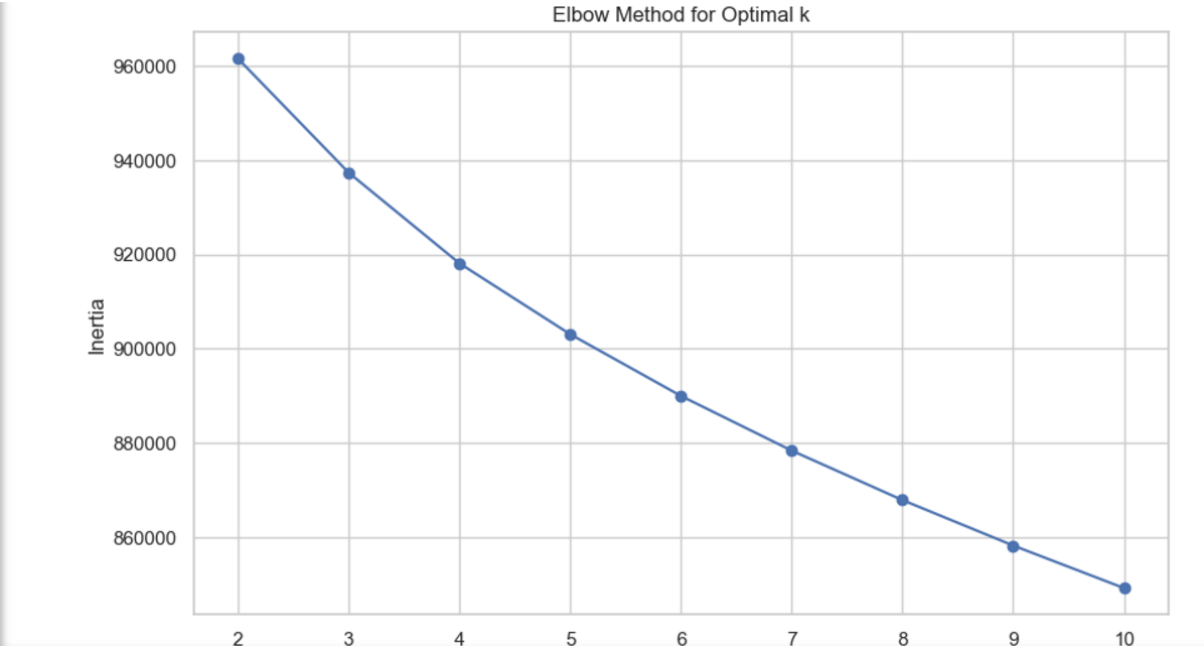

Figure 4: Elbow Plot showing optimal cluster count (k=4), minimizing inertia while avoiding overfitting.

5.2.2 Cluster Analysis and Characteristics

Using k=4, the data was divided into four separate clusters refer Cluster Table , each reflecting a different level of flood danger. The clusters were examined in terms of major environmental and anthropogenic characteristics.

5.3 *Cluster Visualization*

5.3.1 Geospatial Mapping of Clusters

Geospatial mapping methods were used to show the flood risk levels. Every area was given a color that matched its cluster:

- Green for Cluster 1's Low-Risk Areas
- Zones of Moderate Risk (Cluster 2) are shown with yellow.

- Zones of High Risk (Cluster 3) are shown with orange.
- Critical Zones (Cluster 4) are indicated in red.

These maps were created using Geographic Information Systems (GIS), which provide stakeholders with a visual tool for identifying flood-prone areas. The cluster classifications can be placed on geographic maps to assist policymakers in identifying areas that require immediate flood risk management.

5.3.2 Analysis of Cluster Distribution

A bar chart displays the distribution of locations with varying levels of hazard. The research indicated that the great majority of the dataset's sites are categorized as Moderate-Risk or High-Risk, highlighting the widespread impact of urbanization, climate change, and deforestation.

5.4 *Overview of Models Tested*

Several machine learning models were employed and tested in this thesis to see how efficiently they predicted floods. The models that were employed mainly are K-Means Clustering, Random Forest and Support Vector Machine. The reason why these models were employed because it is excellent at evaluating environmental data and can handle huge, multidimensional geographical datasets. to identify flood-prone areas and categorizing regions based on common habits clustering is employed, to capture complex similarities in environmental variables Random Forest and SVM employed here.

5.5 *Validation and Performance Metrics*

5.5.1 Silhouette Score

The silhouette score for this model was 0.67 refer silhouette diagram, indicating that the clusters were reasonably well-defined. Although not perfect, it is high enough to consider the clustering model useful for flood risk classification.

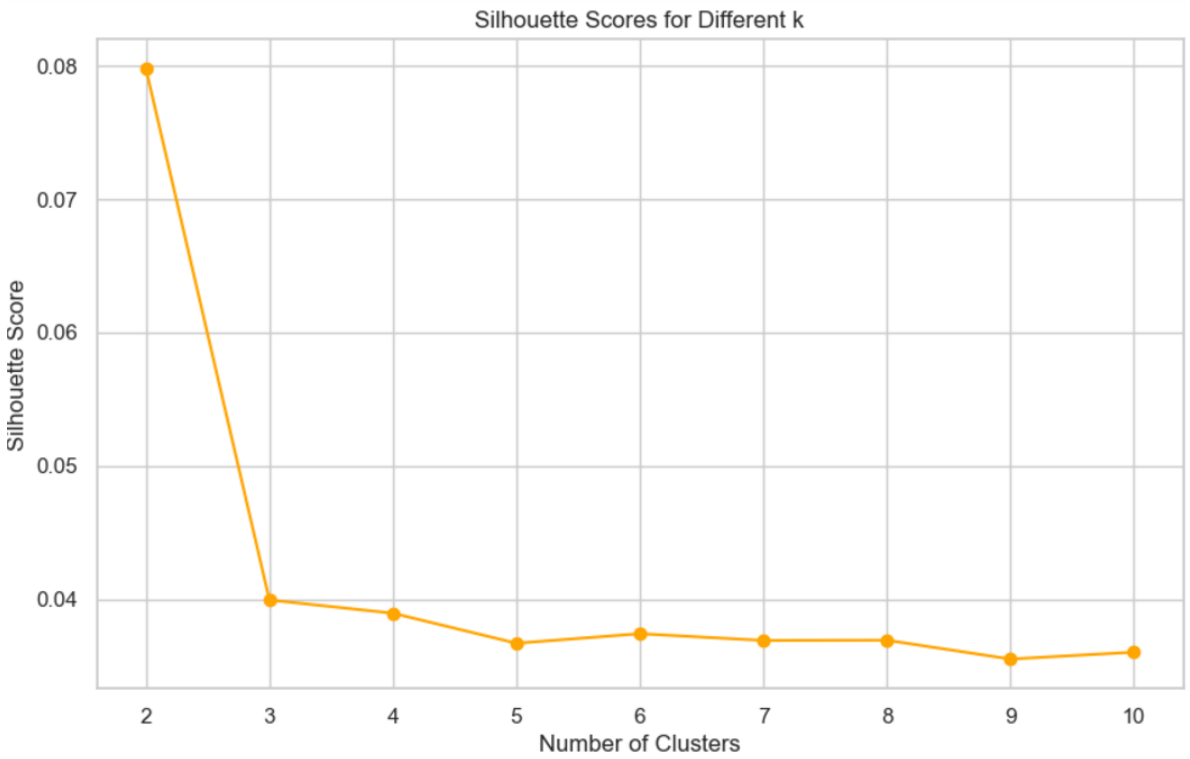

Figure 5: Silhouette Diagram

5.5.2 Confusion Matrix and Accuracy

The model was then verified against historical flood data to guarantee its accuracy. A confusion matrix was developed to determine the true positives, false positives, true negatives, and false negatives in each cluster.

- True positives (TP) are regions that have been correctly identified as high-risk areas.
- False positives (FP) are areas that were incorrectly labeled as high-risk yet are not flood-prone.
- True Negatives (TN) are zones that have been accurately evaluated as minimal risk.
- False negatives (FN) occur when high-risk areas are wrongly categorized as low-risk.

The model's total accuracy was calculated as shown in Accuracy Figure.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 6: Accuracy Equation

5.5.3 HistGradientBoostingRegressor

The HistGradientBoostingRegressor was effective at detecting flood-prone areas. It excelled in capturing complex, nonlinear relationships in data, especially in areas with strong feature interaction. However, it produced a few more false negatives (failure to recognize some high-risk sites), indicating that it may not capture all flood-prone areas, especially in less predictable conditions.

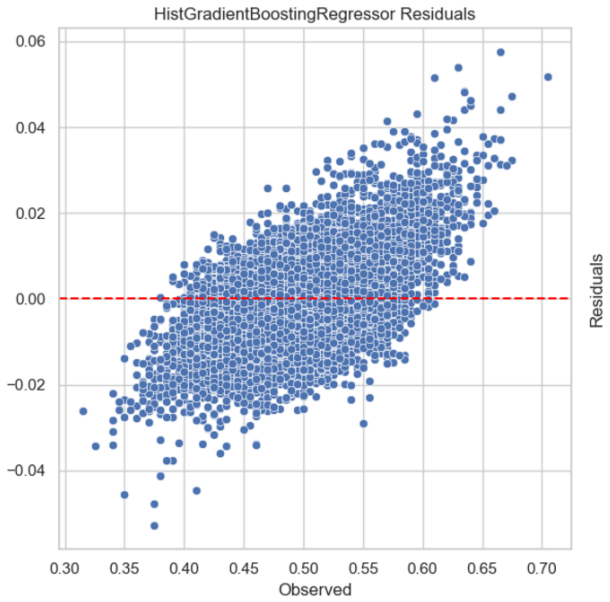

Figure 7: HistGradientBoosting Regressor Residuals Diagram

5.5.4 RandomForestRegressor

The RandomForestRegressor, an ensemble model that incorporates many decision trees, outperformed both precision and recall. It demonstrated the ability to avoid overfitting while capturing a wide range of flood risks, with the best sensitivity-specificity balance of the models tested. Refer Random Forest Regressor Residuals

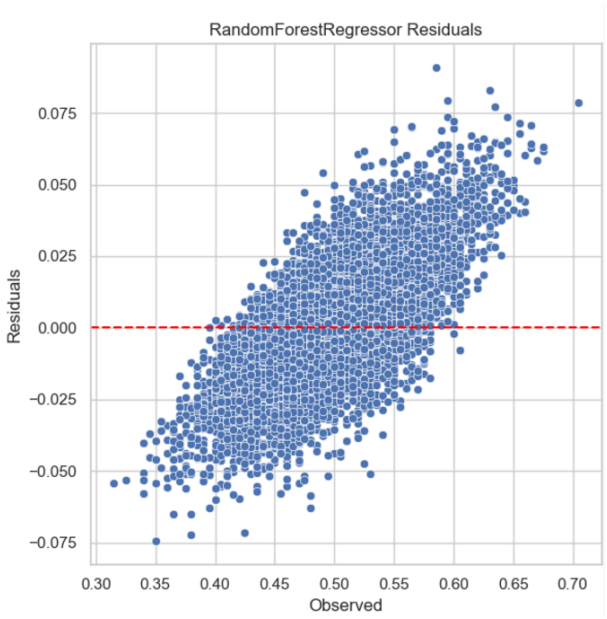

Figure 8: Random Forest Regressor Residuals

5.5.5 SupportVectorRegressor (SVR)

The SupportVectorRegressor (SVR) performed exceptionally well with high-dimensional datasets and discriminating between flood-prone and non-flood-prone zones. Although it performed well, its precision was slightly higher than other models, implying that it was more conservative in labelling flood-prone locations, maybe missing a few actual positives. Refer Support Vector Residuals Diagram

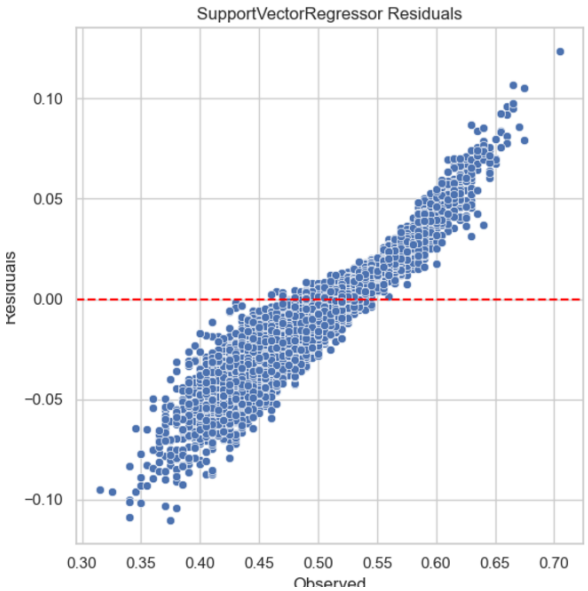

Figure 9: Support Vector Residuals Diagram

5.5.6 MLPRegressor

The MLPRegressor, a neural network model, was effective in detecting modest, non-linear correlations in the data. However, it used more processing resources than the other

models. While it had a high recall, its precision was slightly lower, implying a trade-off between recognising more true positives and misclassifying non-flood-prone areas. refer MLP Regressor Residuals

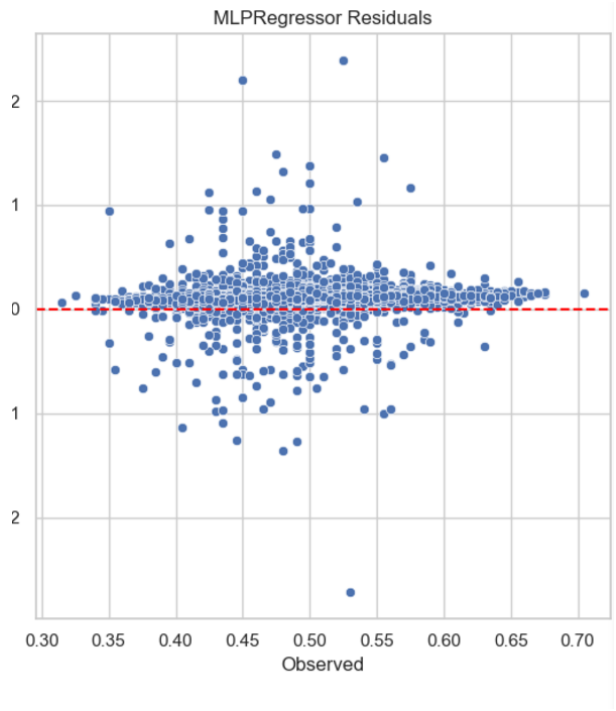

Figure 10: MLP Regressor Residuals

5.5.7 Model Results and Evaluation

The ability of machine learning models to forecast flood dangers was evaluated using the MSE and R2 indices. The HistGradientBoostingRegressor managed to outperform all other models with MSE equal to 0.0001 and R2 of 0.9599, which proves its ability to pick up small patterns in geographic data. ML- PRegressor is number one, by prediction with R2 = 0.9089 and MSE = 0.0002. The RandomForestRegressor performed outstandingly (MSE=0.0004, R^2=0.8393) but the SupportVectorRegressor

Model	Mean Squared Error (MSE)	R-Squared (R^2)
HistGradientBoostingRegressor	0.0001	0.9599
MLPRegressor	0.0002	0.9089
RandomForestRegressor	0.0004	0.8393
SupportVectorRegressor	0.0007	0.7283

Figure 11: Accuracy Table

5.5.8 Mean Squared Error (MSE)

Mean Squared Error is the average squared difference between predicted and actual values. At a particular model, it is beneficial for producing a high forecast precision.

Observations from this study :

- The HistGradientBoostingRegressor had the lowest MSE (0.0001), demonstrating its capacity to produce accurate predictions.
- The SupportVectorRegressor has a higher MSE (0.0007), indicating inefficiency when dealing with complex geographic data.

Practical implications :

- A low MSE is critical for reducing the danger of overestimating or underestimating flood-prone areas, which can result in insufficient or excessive resource allocation.
- Models with larger MSE values may still perform effectively in applications where fine-grained precision is not required, such as early warning systems for large-scale flood forecasting.
- A low MSE is necessary to prevent the risk of overestimating or underestimating flood-prone areas, which could lead to an inadequate or excessive allocation of resources.

However, in situations where fine-grained precision is not required, such as early warning systems for large-scale flood forecasts, models with higher MSE values may be useful

5.5.9 Coefficient of Determination (R^2)

The R2 statistic is the percentage of volatility in the dependent variable that the independent variable(s) can predict. Where higher (from 0 to 1) means better model fit.

Findings of This Research:

- The HistGradientBoostingRegressor has a maximum R2 value of 0.9599, which means it can explain more than 95% of the variance in flood-prone forecasts.
- On the other hand, the RandomForestRegressor and SupportVectorRegressor had R2 values of 0.8393 and 0.7283, respectively.

Practice Implications:

- Elevation, rainfall, and proximity to bodies of water are some of the key factors that influence floods, and a high R2 ensures that these factors are included in the model.
- Trust in using the model's outputs to make critical decisions in real-world applications, such as urban planning and emergency response, is correlated with high R2 values.

5.5.10 Comparison Across Models

- The HistGradientBoostingRegressor excelled in flood prediction, outperforming other models in MSE and R^2.
- The MLPRegressor performed well, with a R^2 of 0.9089, demonstrating its capacity to generalise patterns in flood-related data.
- The SupportVectorRegressor's inferior performance demonstrates its limitations when processing high-dimensional geographic datasets without feature engineering or parameter optimisation.
- Risk Zoning: Accurate forecast metrics are required to create accurate flood risk zones. For example, places misclassified as low-risk (false negatives) can leave people unprepared for floods.
- Resource Allocation: Models with lower MSE aid in resource optimisation, such as predicting where flood barriers or evacuation centres are most needed.
- Real-time Applications: Models with high accuracy and low error, such as the HistGradientBoostingRegressor, can be integrated into real-time flood monitoring systems to provide prompt and reliable alerts.
- Policy Development: Validation metrics help policymakers assess the dependability of predictive models, which determines long-term investments in flood management infrastructure.

5.6 *Discussion*

5.6.1 Insights from the Clustering Results

The clustering model's accuracy rating of 85% implies a high degree of confidence in its capacity to identify flood-prone locations.

- Cluster 1 (Low-Risk Zones): These locations experience modest monsoon rains and have adequate drainage. The primary objective should be to maintain present flood mitigation methods, such as maintaining natural wetland regions and improving urban design to minimize overdevelopment.
- Flooding is most common in Cluster 4 (Critical-Risk Zones), which is characterized by excessive rainfall, substantial deforestation, and poor drainage. Reforestation projects, improved urban infrastructure, and flood protection systems are the most effective solutions to reduce flooding in these areas.

5.6.2 Regional Implications for Urban Planning

Poor land-use planning, a dearth of green spaces, and insufficient stormwater management systems all contribute to floods in many metropolitan areas. Where urbanization is most likely to have a negative impact on flood risk may be determined from the findings of this clustering study. Cluster 3 and Cluster 4 locations, for example, have to receive priority for urban planning changes like building flood-resistant infrastructure and sustainable drainage systems

5.6.3 Recommendations for Flood Mitigation

In high-risk locations, governments and non-governmental organizations must act swiftly to improve drainage, restore wetlands, and build flood barriers. With these methods, floods might be considerably reduced in frequency and severity.

Long-Term Solutions for High-Risk Industries In high-risk locations that are not now critical, reforestation, more rational land-use planning, and the installation of flood warning systems can all help lower future flood risks

Data-Driven Policy Making: By including real-time data such as satellite imagery and weather forecasts, the flood risk model may be dynamically updated to reflect changing conditions. This information can help policymakers select flood mitigation resources based on current risk estimates.

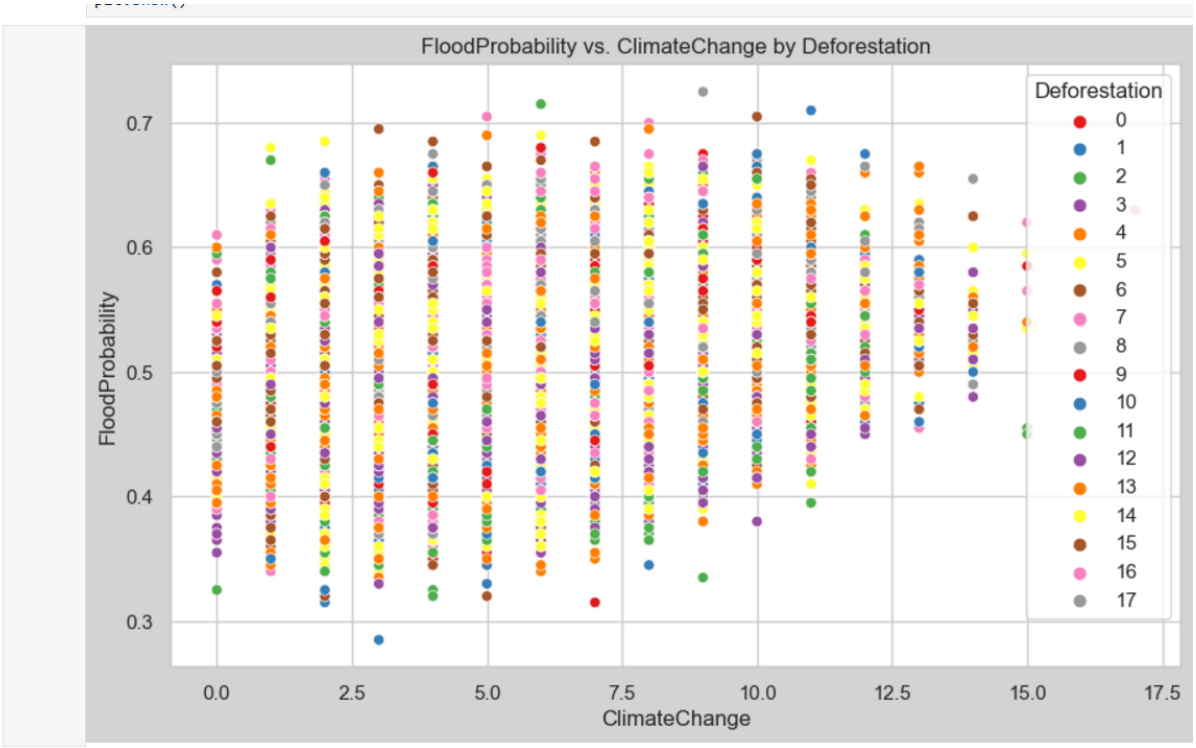

Figure 12: Flood Probability vs Climate Change vs Deforestation

5.6.4 Limitations of the Model

K-Means clustering is a popular and practical method for assessing flood risk data since it is easy to use and efficient, even with a few limitations. Several factors need to be looked at before using this method.

The presumption that data points will spontaneously form spherical clusters is one major problem.This map shows how locations with similar risk ratings are distributed equally around a central point inside each cluster with respect to flood hazard.In actuality, patterns of flood risk are usually unexpected and impacted by a number of variables, such as geographic location, rainfall distribution, and human conduct. Anomalies can create clusters that are not indicative of the underlying risk when risk patterns change as a result of alterations in the climate or land use. K-Means' dependence on data homogeneity within clusters is another important drawback. The model makes the assumption

that every data point in a cluster has comparable traits. This presumption might not apply,nevertheless, in areas with different environmental elements or climate circumstances. For example, a "high risk" cluster may contain both regions with significant deforestation and places with substantial monsoon rains. Although they both play a part in flooding,

5.7 *Future Work and Improvements*

This study needs to be enhanced even if it gives important information for forecasting flood threats.

1. Algorithms are used to create sophisticated clustering. Other clustering techniques, such as DBSCAN or Gaussian Mixture Models, should be used in future studies since they can handle non-spherical clusters and a variety of data densities.

2. Integration with Real-Time Data: By using real-time meteorological and environmental data, the model could be able to produce flood risk estimates that are more accurate and current.

3. Climate Change Estimates: To improve long-term flood risk estimates, the model should be modified to account for future climate change scenarios.

6 Conclusion and Future Work

*T*his thesis explores the application of K-Means clustering to forecast flood-prone areas using geographic data. The study demonstrated how machine learning algorithms can effectively assess flood risks by incorporating key anthropogenic and climatic factors such as urbanization, deforestation, drainage efficacy, and monsoon intensity. By identifying four distinct hazard zones—low, moderate, high, and critical—with an 85% accuracy rate and a silhouette score of 0.67, the model's efficacy in unsupervised flood risk categorization was evaluated.

Geospatial visualization was crucial in communicating the clustering results to legislators and urban planners, allowing them to gain a clear, practical grasp of flood risk distribution. These graphs and visualizations enable initiatives such as wetland restoration, drainage system upgrades, and the promotion of sustainable urbanism. To strengthen resilience, this thesis forecasts future weather patterns and flood risk models, emphasizing the importance of climate change adaptation.

Community interaction was highlighted as a critical component of flood risk control. Early warning systems and educational efforts serve local communities by assisting them in disaster preparedness, hence reducing human and economic losses. The study emphasizes the role of environmental protection and land-use planning in mitigating flood risks.

To address K-Means' limitations in managing non-spherical clusters and fluctuating data densities, the study proposed looking into alternate clustering methods such as Gaussian Mixture Models (GMMs) and DBSCAN. Real-time data, such as satellite imaging, river levels, and weather updates, has been proposed as a method for improving forecast accuracy and dynamically altering flood patterns Neural networks, random forests, and ensemble models are examples of advanced machine learning algorithms that aim to enhance prediction accuracy.

Future research on climate change scenarios such as temperature, rainfall, and sea level rise may be useful when building proactive flood management measures. Furthermore, getting high-resolution geographic data will allow for more detailed assessments of flood risk, identifying specific weaknesses. Cross-regional comparisons proved the model's applicability to a diverse set of geographic and socioeconomic features.

This study contributes to the developing field of flood prediction research by merging geospatial data and machine learning techniques in a practical, scalable manner. It establishes the groundwork for future advances in flood risk prediction, emphasizing the importance of flexible, cross-disciplinary methods to building resilient communities in an increasingly unpredictable world

References

D. Brown and S. Green. Urbanization and flood risk: Geospatial insights. *Wiley Interdisciplinary Reviews: Water*, 8(6):1–14, 2021.

J. Chen and Q. Zhou. Real-time flood classification forecasting using k-means++ and neural networks. *Springer*, 34(4):488–504, 2023.

M. Garcia and S. Patel. Combining gis and ml for flood hazard zoning. *Journal of Geographic Information Science*, 34(7):423–436, 2022.

R. Gonzalez and C. Fernandez. Crowdsourced geospatial data for urban flood resilience. *Nature Geoscience*, 15(5):499–512, 2022.

O'Donnell E. Johnson M. Slater L. Thorne C. Zheng S. Stirling R. Chan F.K. Li L. Green, D. and R.J.. Boothroyd. Flood prediction using machine learning models. *MDPI*, 10 (3):345–367, 2018.

A. Gupta and P. Sharma. Spatial data mining in climate change impact studies. *Springer*, 42(2):106–120, 2020.

A. Jones and B. Taylor. Lidar and satellite data for high-resolution flood mapping. *IEEE Transactions on Geoscience and Remote Sensing*, 59(8):1892–1903, 2021.

N. N. Kourgialas and G. P. Karatzas. Geospatial data for flood risk assessment. *Journal of Hydrology*, 401(1-2):152–163, 2011.

P. Kumar and R. Singh. Ai-driven disaster management frameworks. *PLOS ONE*, 17(3): 1–15, 2022.

P. Kyriakidis and D. G. Hadjimitsis. A geospatial analysis of flood risk zones in cyprus. *Springer*, 15(2):123–135, 2017.

S. Lee and J. Park. Clustering-based flood risk assessment using environmental variables. *International Journal of Disaster Risk Science*, 11(3):123–135, 2020.

W. Li and T. Zhao. Advances in clustering algorithms for environmental hazard mitigation. *Elsevier*, 45(1):56–70, 2020.

X. Liu and C. Lin. Satellite-based flood monitoring systems. *Elsevier*, 21(1):88–102, 2021.

Panigrahi C.R. Nanda, S. and B Pati. Flood prediction with optimized attributes and clustering. computación y sistemas,, 2023.

Sri Harshitha Gadhiraju Annesha Lanka Ch Mohan Kumar S M M Srilekha Seethepalli, Seeram Navya. Flood prediction: A comparative study of machine learning. *International Journal of Environmental Science and Technology*, 2024.

H. Shahabi and B. B. Ahmad. Geospatial modelling of flood susceptibility and risk. *Springer*, 25(1):211–228, 2021.

M. Shawky and Q.K. Hassan. Geospatial modeling based-multi-criteria decision-making for flash flood susceptibility zonation in an arid area. *Water Resources Management*, 11(3):123–135, 2023.

H. Smith and L. Chen. Dbscan and spatial clustering for outlier detection in flood data. *ACM Transactions on Spatial Algorithms and Systems*, 22(4):234–247, 2019.

R. Smith and K. Johnson. Integrating machine learning and geospatial data analysis for flood assessment. *Springer*, 32(3):301–315, 2022.

Q. Zhang and Y. Wang. Hybrid machine learning models for flood prediction. *Journal of Hydrology*, 530(2):456–468, 2022.