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PREDICTION OF FLOOD BY USING ARTIFICIAL INTELLIGENCE IN THE CASE OF DIRE DAWA WATERSHED, AWASH BASIN, ETHIOPIA

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Declaration

I, Habte Kinfe, the undersigned, declare that this thesis entitled: “Prediction of flood by using artificial intelligence in case of Dire Dawa watershed, awash basin, Ethiopia is my original work. I have undertaken the research work independently with the guidance and support of the research supervisor. This study has not been submitted for any degree or diploma program in this or any other institution and all sources of materials used for the thesis have been duly acknowledged.

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This is to certify that the thesis prepared by Habte Kinfe "Prediction of flood by using artificial intelligence in case of Dire Dawa, Ethiopia" and submitted in partial fulfillment of the requirements for the Degree of Masters in Remote Sensing and Geo informatics complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Acronyms

AI	Artificial intelligence
ANN	Artificial neural network
BPN	Back Propagation Neural Network
DDAC	Dire Dawa Administrative Council
DL	Deep Learning
DNN	Deep Neural Network
DT	Decision Tree
ERA5	European environmental Reanalysis data
XGBoost,	Extreme Gradient Boosting
KNN	K-Nearest Neighbor
LNREG	Linear Regression
LR	Logistic Regression
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multilayer Perceptron
MPE	Mean Percentage Error
NARX	Nonlinear Autoregressive Network with Exogenous Inputs
RBF	Radial Basis Functions
ReLU	Rectified Linear Unit
RF	Random Forest

RMSE	Root Mean Square Error
SRO	Surface runoff
SVC	Support Vector Classifier
SVM	Support Vector Machine
TP	Total Precipitation

Abstract

In the present century, floods are one of the foremost destroying and costly risks around the world. Its contribution can be ascribed to variables like climate change impacts on the hydrologic cycle, land-use changes and increased density of residence activities in flood-prone areas. However, Flood is a complex event to model and predict for the future. Recently Machine Learning/ Artificial Neural Network (ML/ANN) enhanced the accuracy of weather related event prediction. In Dire Dawa, Ethiopia, flood is forecasted by conventional methods and this method is less accurate and cannot predict the flood hazard effectively. Therefore, this study aims to improve flood prediction accuracy in the area by using Artificial Intelligence(AI) such as; SVM (Support Vector Machines), MLP (Multi-layer perceptron),and KNN (KNeighborsClassifier). In this study, data were downloaded from Copernicus European environmental Reanalysis data Agency (ERA5), preprocessed and trained by using python language. Hourly precipitation and runoff data for 31 years were used for the training of algorithms. Out of these data, 75% were used for training and 25% for testing and validation while doing the machine learning process. The result shows that SVM was found to be the robust performing algorithm with Mean Squared Error of 0.0005046, and R^2 of 99.949% compared to MLP (99.947%) and KNN (99.939 %). These methods are useful for the prediction and recommended for the policy makers to consider the AI method for the flood prone areas of the country.

Key words: Flood, Flood prediction, Remote Sensing, Dire Dawa, Artificial Intelligence

Chapter One

1.1 Introduction

Flood is overflowing a great body of water over land not usually submerged (Taiwo et al, 2019). Of all weather-related natural disasters, floods are the most common and widespread natural severe weather event which are estimated to affect 250 million people around the world every year, also costing billions of dollars in impact (Matias, 2018). Currently, floods and consequences all over the world are becoming too frequent and a threat to sustainable development in human settlements (Nwigwe and Emberga, 2014).

Flood is one of the most natural hazards worldwide both in terms of the frequency of occurrence and the damage to human lives, the environment, and economic assets (Jonkman 2005; Doocy et al. 2013). The occurrence of floods relies on meteorology, topography, land use, soil type, and antecedent moisture conditions (Funk 2006; Youssef et al. 2016; Agbola et al. 2012).

In the present century, floods are one of the foremost destroying and costly risks around the world, its contribution can be ascribed to variables like climate change impacts on the hydrologic cycle, land-use changes, and increased density of residence activities in flood-prone areas. To mitigate the adverse impacts of floods, the plan and implementation of hazard administration procedures are fundamental. Since floods are common and cannot be avoided, flood hazard evaluation plays a vital role in flood catastrophe administration and decision making (Jiang et al. 2009).

In Ethiopia, flooding is a common occurrence. In the last few decades, the frequency and magnitude of earthquakes have increased dramatically. Flooding is becoming more common as a result of both climate change and land use changes (particularly deforestation). In the Awash Valley, it is estimated that almost all of the area (200,000 - 250,000 ha) delineated for irrigation development is exposed to flood during high flows of the river (Kefeyalew, 2003).

In Ethiopia, the risk of urban floods has become a serious problem in recent years. They are primarily related to poorly design urban drainage systems and land use plans. Coupled with this, the lack of early warning systems and systemic responses to flood disasters at the national and local levels further exacerbates the severity of the problem (Amare and Okubay 2019).

Flood risk has been in history affecting Dire Dawa city since the establishment of the city. Even though proper records on urban floods of Dire Dawa city were patchy and insufficient, previous information revealed that the first damaging flood risk was recorded in 1945. Since then flood has been affecting the city many times. Different authors have described the causes of this type of hazard in Dire Dawa city with respect to geomorphology, hydrology, and land-use changes within the urban boundary (Yonas 2015; Girma and Bhole 2015; Alemayehu 2007).
In cities and suburbs, rooftops prevent some rainfall from being absorbed by the soil. Thus, it can increase the amount of runoff flowing into low-lying areas or storm drain systems (ResearchClue, 2020).

Establishing rapid and accurate flood prediction methods is essential, however, a complicated and challenging task (Guo et al., 2021). Conventionally, hydrodynamic models have been used for applications such as flood inundation simulations, and assessment of mitigation and adaptation measures (Wolfs and Willems, 2013; Wang et al., 2021; Li et al., 2019). Different AI techniques for flood predictions include Artificial Neural Networks, Ensemble Neural Networks, Backpropagation networks, Radial Basis Function Networks, General Regression Neural Networks, Genetic Algorithms, Multilayer Perceptron, and Fuzzy clustering. Applying AI techniques along with a physical understanding of the environment can significantly improve the prediction skill for multiple types of high-impact floods (Preetipadma, 2020).

As outlined above, recently ML/AINN enhanced the accuracy of weather-related event prediction. So far, AINN/ML has not been introduced for flood prediction in Ethiopia. It is believed that AINN/ML will offer a very good base for research and operational forecasting. This accurate daily, sub-seasonal seasonal weather forecast and hazard prediction method could predict effectively to address the needs of farmers and pastoral communities. Thus, this study investigates the most applicable AI techniques that can be applicable in agro-pastoral areas of Ethiopia. The main aim of this study is to improve flood predicting accuracy to give an early warning for the people who are likely to be affected in the Awash River basin.

1.2 Objectives:

General Objective

The general objective of this research is to improve flood prediction accuracy in the Awash River sub-basin, Dire Dawa by using Artificial Intelligence.

1.2.1 Specific Objectives

- ✓ Describing trends of Precipitation and Surface runoff
- ✓ Evaluating AI techniques for flood prediction at the Awash River sub basin
- ✓ Identifying the best predicting model

1.3 Research questions

- What looks like trends of predicting parameters?
- What looks like predicting performance of each model?
- Which model is the best predicting model?

1.4 Statement of the problem

A flood predicting early warning system is an important tool to give appropriate reliable information about the incoming flood to vulnerable communities. In Ethiopia, flood prediction and early warning systems are not well advanced. Nowadays the Government established flood control management to minimize flood risk in the Awash River basin. Nevertheless, there still are problems with increasing flood damage in this area (Mekonnen, 2016). The Awash River Basin has been highlighted as a highly inhabited, economically productive area with significant irrigation potential. This basin is home to pastoralists, agro pastoralists, and farmers. Flooding, on the other hand, is a frequent concern for those who live near the river's flow. There has been a significant loss of human life and property. Such a disastrous event can be mitigated with the help of an accurate and early forecast. Rainfall onset and secession, as well as the length of rainy days, are critical for agricultural productivity in the area. Therefore, this research provides accurate seasonal predictions for pastoralists and farmers, and residents to use in making knowledge-based decisions, as well as timely seasonal and extreme weather forecasts, in order to boost productivity and avoid potential climate-related dangers. Thus, lessons learned in this study area can be scaled up to other areas of the country. In this area, flood is predicted by conventional methods. This way is less accurate and cannot predict the flood hazard effectively. Nowadays artificial intelligence is better for predicting different natural phenomena. This research tried to predict floods by using different artificial intelligence techniques.

1.5 Significance of the study

Ethiopia is one of the poorest countries in the world whose economy is highly dependent on rain-fed agriculture which is sensitive to the variability of rainfall. Not only agriculture but also other sectors like health (Malaria) and energy (hydropower) are also sensitive to the intra-annual variability of rainfall in the country. It is well known that Ethiopia is frequently affected by flood risks. Farmers and pastoral communities are one of the most affected segments of society. This study is basically significant too; 1. Improve the predicting capability of a flood, 2. Identifying the best predicting model, 3. Protect the livelihood of the communities around the Awash River basin from extreme flooding events from early prediction.

1.6 Limitations of the study

The limitation of the study was the lack of full and documented flood occurrence data for the study area. Unorganized data was obtained from the national disaster management commission and Dire Dawa disaster management office.

1.7 Organization of the thesis

This study is organized into six chapters. The first chapter includes an introduction (background of the study), statements of the problem, objectives of the study (general and specific objectives), research questions, the significance of the study, the scope of the study, limitations of the study, and organization of the paper, and the second chapter is about literature review. The third chapter is about a description of the study area, research method, sources of data, models, data analysis and chapter four includes results, and chapter five is about the discussion. Finally, the last chapter includes conclusions and recommendations.

Chapter Two

2. Literature review

This part of the research presents a review of related literature on the concept and definition of flooding, flood prediction, and artificial intelligence. Literature was reviewed in order to provide the study with a conceptual framework to explain theories underlying the study to further define the problem and thereby to identify previous research studies on flood prediction.

Predicting various hydrological phenomena is of significant concern in the field of hydrology and critical for water resource management and disaster management for every year, severe storms across the globe create significant public and financial losses, as well as fatalities, particularly in places prone to monsoon weather and regions with poor expansion of water conservation scheme s (Jiang et al., 2013; Wang et al., 2015). Flood prediction and forecasting act as essential practices to control flood events across the globe (Young 2002; Campolo et al. 2003; Moore et al. 2005; Rath et al., 2017; Panigrahi et al., 2018).

Table 1. 1: Flood-induced risks in Dire Dawa watershed since 2006

Village/city	Human loss	Livestock loss	Property loss	Remarks
Metokomia	2	Not stated	Not stated	9026 people were displaced
Biftu Gada	5	11	10ha crops	
Dire Dawa city	339	Not stated	200 houses, roads and bridges	
Lja Anani	2	21	178ha crop	
Harala Balina	4	27	80 ha crops and 40 houses	
Lazaret	22	900	Not stated	
Shinile	Not stated	200	3 houses	
Total	374	1100	268 ha crops ,243 houses	

Source; compiled from Dire Dawa city Flood assessment unpublished report (2006-2016)

2.1 Flood prediction by using artificial intelligence

Prediction of hydrological processes has a great advantage in the management of watersheds (Firat and Gu¨ngo¨r 2007). Prediction and estimation of river flow, particularly during floods is one of the most important aspects of these investigations (Wu et al. 2012). The outcome of these predictions enables the officials to cut the created damages and take the necessary mitigations in advance for controlling and preventing floods (Aronica and Candela 2007). Different AI techniques for weather predictions include Artificial Neural Networks, Ensemble Neural Networks, Backpropagation Networks, Radial Basis Function Networks, General Regression Neural Networks, Genetic Algorithms, Multilayer Perceptron, and Fuzzy clustering. Applying AI methods along with a physical understanding of the environment can significantly improve the prediction skill for different types of high-impact weather." This type of weather includes events like severe thunderstorms, floods, droughts, and hurricanes (Preetipadma, 2020).

Flood prediction and its mitigation or management are one of the greatest challenges facing the world today. Floods have become more frequent and severe due to the impact of global climate change and human alterations in the natural environment. All flood predicting systems serve specific purposes and in most cases, they are designed to prevent, minimize, or mitigate people's suffering and to limit economic losses. The forecast of flooding would benefit greatly from the use of hydrological models, which are designed to simulate the flow processes of surface or subsurface water. Flood models are mainly used in flood forecasting and early warning systems. Both systems require reliable real-time hydro-meteorological data and lag time. The utility of forecasting depends largely on the relationship between the desired lead time at that point and the lag time of the hydrological response (Lettenmaier and Wood, 1993; Werner et al., 2005).

According to Matreata (2006), the desirable characteristics of a good flood prediction system are:

• Timeliness: If enough lead time (the period between making a prediction and the event occurring) is available and the suggested model's predictions are accurate, evacuation of the affected population may be possible.

• Accuracy: refers to the accuracy of prediction, both in terms of the magnitude and timing of the flood or drought peak, as well as the resulting water levels - the more accurate the forecast, the more effective flood control, and damage mitigation measures may be undertaken.

• Reliability: refers to the flood predicting system’s overall long-term reliability, not only the accuracy of a forecast for a specific flood. The system's long-term reliability is usually determined by its performance in two areas.

2.1.1 Artificial intelligence (AI)

Artificial Intelligence was born in the 1950s when a number of pioneers from the emerging field of computer science started asking whether computers could be made to “think” —a question we are still examining today. A brief description of the field can be as follows: an effort to perform the intellectual tasks that people usually do. Thus, AI is a common field that combines machine learning with the in-depth learning, but that also includes many methods that do not involve learning. Early chess programs, for example, included only the rules with strict code developed by the programmers, and they did not qualify as machine learning. For a long time, many experts believed that human-made artificial intelligence could be achieved by having programmers manually create a large enough set of clear rules to manipulate information. This approach is known as symbolic AI and has been a major paradigm in AI from the 1950s to the late 1980s. It reached its peak of popularity during the development of professional programs in the 1980s. While symbolic AI seemed to be suitable for solving well-defined, logical problems, such as playing chess, it was still difficult to find clear rules for solving complex, mysterious problems, such as image classification, speech recognition, and language translation. A new way to replace symbolic AI emerged: machine learning (Chollet, 2018).

Artificial intelligence (AI) is a broad topic with many problem settings and approaches, and there is not one single definition of AI (Stuart, 2016). One of its many definitions and one that is useful in the context here is “The study of the computations that make it possible to perceive, reason, and act.” (Winston, 1992).

2.1.2 Artificial Neural Networks (ANNs)

An artificial neural network (ANN) can be seen as a replica of the human brain consisting of numerous neuron cells. ANN consists of layers of artificial neurons lined up in a 2- dimensional manner. These neural networks are competent in functioning like the human brain and perform educated decisions to solve several problems. It can be seen that ANNs can give accurate results on time series data. Supervised and unsupervised learning are the two types of learning techniques used for training artificial neural networks (ANN). Among these, supervised learning is generally used for forecasting floods because of the massive dataset available for discharge, precipitation, and several other parameters used for predicting floods (Mosavi et al., 2018).

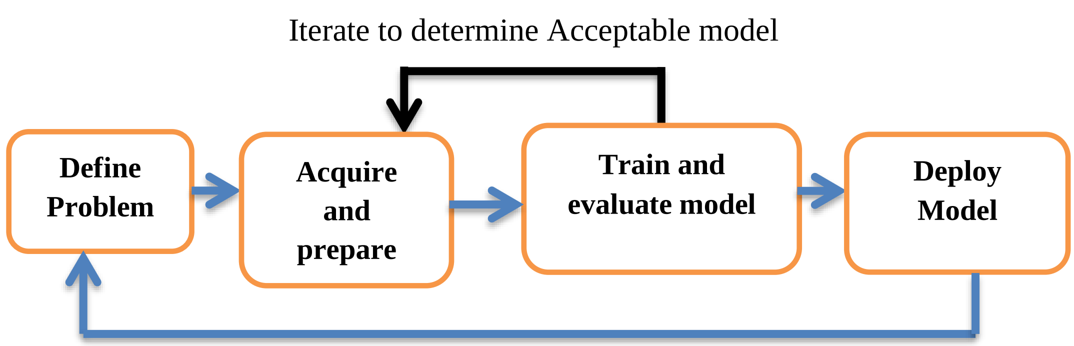
Artificial neural networks (Gereon 2018) have an input layer, at least one hidden layer, and an output layer. In a process called feature hierarchy, each layer performs specific sorts and order types. A neural network deals with unlabeled or unstructured data, which is one of the significant uses.

2.1.3 Machine learning (ML)

ML means the art of "learning" from data. Learning can be different things, from finding structure in the data to making predictions. Independently of the methods used, ML is often divided into different categories which cover fundamentally different approaches and problem settings. They are classified as supervised learning, unsupervised learning, and reinforcement learning. Supervised learning deals with learning linkage between pairs of inputs and outputs. This includes problems like time series forecasting (the connection between the values at two different points in time) and the connection between two or more physical observations, but also more abstract problems like image recognition (the connection between an image and the label of an image)(Scher 2020).

Increasing quantities of data, collectively with extra computing energy and better ML algorithms to analyze the statistics are causing modifications in nearly everything in our lives. This style is predicted to proceed as extra facts become available, computing electricity increases and ML algorithms improve. Flood hazards and have impact on assessments are additionally being influenced by this trend, specifically in areas such as the development of mitigation measures, emergency response preparation, and flood restoration planning (Bonafilia et al., 2020; Wagenaar et al., 2020).

With computational development and algorithms enhancements, ML has emerged as a preferred instrument to delve into non-linear systems and discover robotically generated predictions of floods. Computational algorithms such as neural networks have been majorly used to estimate flood in threatened areas of a river and its impact backyard of the particular area. It is predicted that in the future greater purpose come to be and many method models and typical observation strategies will be changed by means of ML. Examples of this include the use of ML on far flung sensing facts to estimate exposure or on social media data to improve flood response. Some enhancements might also require new data collection efforts, such as for the modeling of flood damages or defense disasters (Zehra, 2020).



(Tsakiri et al, 2018)

Figure 2. 1 Machine learning process

2.1.4 Deep learning (DL)

Deep Learning (DL) refers to neural networks that have more than one hidden layer, so-called deep neural networks. Deep networks suffer from the vanishing-gradient problem, therefore they have long been thought infeasible to train. However, recent advances in activation functions and weight initialization, together with the use of computing potential of graphical processing units have made them usable. Deep ANN architectures are superior to shallow (only one hidden layer) architectures in many applications. One of the reasons for this is that the first layers learn to extract features, meaning relevant portions and transformations of the data, and the following layers then learn to use these features for classification or regression (Scher 2020).

2.2 Models Used For Flood Prediction

In the assessment of conventional statistical models, ML algorithms have been used for prediction with larger accuracy. Ortiz-García et al. (2014) defined how the ML technique should efficiently model complex hydrological phenomena such as floods. Many machine learning algorithms had been stated as advantageous for both short-term and long-term flood prediction. Besides, it used to be shown that the overall performance of ML ought to be elevated through hybridization with different ML Methods, gentle computing techniques, numerical simulations, and/or bodily models. Those kinds of purposes provided more sturdy and environment-friendly model models that can effectively examine complex flood systems in an adaptive manner (Mosavi et al., 2018).

The selection of suitable machine learning algorithms to apply in flood modeling and prediction is often based on data availability, quantity and quality, study objectives, and the scope of the study (Obarein et al, 2019).

Recent research on flood prediction leverage on the predictive power of several machine learning algorithms that learn patterns from historical data. Over time, machine learning algorithms such as Decision Tree (DT), Random Forest (RF), Linear Regression (Linreg) Logistic Regression (LR), Extreme Gradient Boosting (XGBoost), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM) have been implemented in flood prediction which in turn yields a reliable outcome (Obarein et al, 2019).

2.2.1 Support Vector Machines (SVM)

Support Vector Machines (SVM) come under supervised machine learning algorithms. Support vector machines framework the data at a larger dimension with the help of Kernel functions implicitly and project a plane to classify the data from each other. Support vector regression is useful for real value function estimation. The data is commonly normalized for training support vector machine models (SVM) (Ghorpade et al., 2021). The discharge data and flood data are used to train the support vector machine model with RBF Kernel to predict water levels.

Support vector machines are maximum-margin classifiers, which means they discover the hyperplane that has the biggest opposite separation between the hyperplane and the closest tests on either side. How to unravel the numerous names utilized to refer to support vector machines. When a preparing set is given, an SVM preparing calculation builds a demonstration that relegates modern illustrations to the categories, making it a non-probabilistic double straight classifier (Ramalingam et al., 2020).

The supervised vector machine is primarily associated with learning algorithms that analyze the data used to study regression and taxonomy. A trained database is selected as an example, each of which is labeled to fit one or two classifications. The SVM training algorithm basically develops a binary, nonlinear linear classification (Gereon 2018; Sankaranarayanan and Mookherji, 2019), creating an example naming model for one class or another. SVC predicts the newer data and the class they belong to considering the distance of these classes from the line. The basic idea is to perform linear regression to find a decision function for a given sample x,

$$\sum_{i \epsilon SV} y_i \alpha_i K(x_i, x) + b \quad \text{(Eq 1)}$$

The term αi is called the dual coefficients which are upper-bound by C, and b is an independent term that has to be estimated. K (xi, x) is the kernel where, x is the input vector (Crammer and Singer 2001)

2.2.2 Multilayer perceptron (MLP)

A multilayer perceptron (MLP) is a class of feed-forward artificial neural networks (ANN). The term MLP is used vaguely, sometimes loosely to refer to any feed-forward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptron (with threshold activation). Multilayer perceptron is sometimes referred to as neural networks, especially when they have a single hidden layer (Ramalingam et al., 2020). For some surprising and credible reason, such multi-layer networks are rarely referred to as multilayer cognitions (MLPs), regardless of whether they are composed of sigmoid neurons (Gereon 2018).

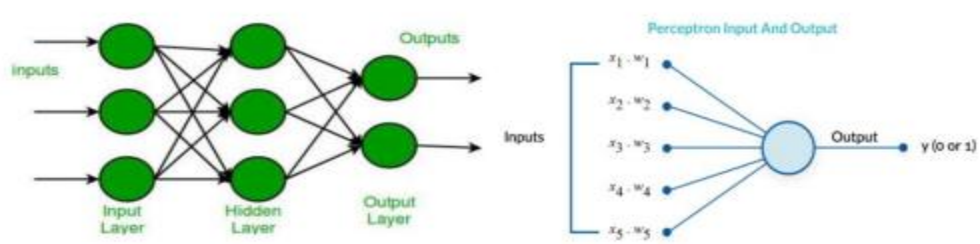


Figure 2. 2 Multilayer Perceptron structure

2.2.3 K-Nearest Neighbor (KNN)

The KNN algorithm is a sort of supervised machine learning method that is being used to solve both classification and regression predicting problems. The KNN approach uses feature similarity to forecast the values of new data points, which means that the new data point will be assigned a value based on how closely it resembles the points in the training set. According to (Miah et al, 2022), the K nearest neighbor (KNN) is a non-parametric algorithm that can be used for regression predictive problems. The KNN method assumes the resemblance between the new data and the existing data and places the new data in the category that is most comparable to the existing categories. The KNN algorithm calculates the distance between a new data point and all previous data points in the training set. KNN is a supervised classification algorithm that functions by first storing all the data and classifying new data points based on distance functions with respect to the stored data. Distance from the testing point to each training point (Madhuri et al, 2021)

$$\text{Distance} = (x_{\text{train}} - x_{\text{test}})^p \qquad \text{(Eq 2)}$$

Where p is the Minkowski metric (p ϵ [1, 2, 3, 4]), xtrain is a training data point and xtest is the data point whose class we wish to predict.

2.3. Activation function

The activation function (or transfer function) is a mathematical relationship that decides whether a node or neuron could be fired or not using input for computing single value output so that each output (y) is moved forward to the next layer of nodes in the layers as input (x) by calculating the weighted (w) sum of input and biases (b) for each node in the process of training a neural network (S. M. Noor, et al., 2017; C. Szegedy, et al., 2015):

$$y = w1.\ X1 + w2.\ X2 + \ldots + wn.\ xn + b \qquad \text{(Eq 3)}$$

The activation function α uses as a transformation tool to convert the linear inputs into the on-linear output so that the neural network learns patterns in data and predicts results (Goodfellow et al., 2016), as given by the formula:

$$y = \alpha.\ (W1.\ x1 + w2.\ x2 + \ldots + wn\ .\ xn + b) \qquad \text{(Eq 5)}$$

There are different types of activation functions, like sigmoid, ReLU, and tanh. (V. Nair and G. E. Hinton, 2010). In this study, the Rectified Linear Unit (ReLU), Minkowski, and Sigmoid Function was used in the different architectures

2.4 Limitations of Conventional flood prediction Methods

Floods are among the most negative natural disasters and account for nearly half of all weather-related disasters, affecting 2.3 billion people. Improved response to mitigate and control flood danger can be radically assisted through satellite observation, which can be used in the mitigation, response, and restoration levels of the catastrophe cycle (IPCC, 2012).

Conventional models have long been used to predict hydrological events, such as storm rainfall/runoff shallow water conditions, hydraulic models of flow, and similar world circulation phenomena, including the coupled results of atmosphere, ocean, and flood. Although those models show exquisite capabilities for predicting a numerous range of flooding scenarios, they frequently require quite a number kinds of hydro-geomorphological monitoring datasets, subsequently requiring intensive computation which prohibits non-permanent prediction of the flood. Furthermore, the development of physically-based models often requires in-depth information and information regarding hydrological parameters and is not dependable due to inherent systematic errors (Mosavi et al., 2018).

In flood prediction, standard techniques of predicting hazard variables can involve a chain of hydrologic and hydraulic models describing the physical processes. Therefore the use of a process model may additionally not constantly be possible or integral in the training stage of a disaster. ML strategies have the viability to enhance the accuracy as properly as limit calculating time and model improvement cost. The ML model is becoming very interesting (Wagenaar et al., 2020). Meanwhile, there is an unavoidable need for conceptualization and simplification of the physical model; the applicable calibration and validation techniques also are truly challenging (Wu et al., 2018).

2.5 Model selection and prediction

The model selection or algorithm selection stage is the most exciting and the main part of machine learning. It is the phase where we select the model which performs best for the data set at hand. Model selection is the process of identifying one final machine learning model from among a collection of candidate machine learning models for a training dataset. Model selection is a process that can be applied across different types of models. Different kinds of machine learning algorithms are used to predict floods. They are SVM (support vector machine), Random forest, KNN, and Decision tree, etc.(Sandhya and Shejina, 2021).

Chau et al., (2005) employed two hybrid models based on recent artificial intelligence technology, namely, the genetic algorithm-based artificial neural network and the adaptive-network-based fuzzy inference system, for flood forecasting in a channel reach of the Yangtze River in China. They observed that the performance of both hybrid algorithms was more accurate than the linear regression model.

2.6. Training and testing the network

The aim of the training process is to reduce the error between the ANN output and the real data by changing the weight values based on a BP algorithm. An effective ANN model can predict target data from a given set of input data. Once the minimal error is achieved and training is completed, the FF algorithm is applied by ANN to generate a classification of the whole data set (Paul & Das, 2014)

2.7. Model performance evaluation

In order to demonstrate the performance of the proposed models, both the individual and conceptual models were evaluated in terms of a series of various performance measures. Diverse quantitative performance indicators were evaluated; root means square error (RMSE), mean absolute error (MAE), mean percentage error (MPE), and correlation coefficient (R). Detailed formulations can be found in (Napolitano et al., 2010) and (Yaseen et al., 2018). RMSE indicates overall agreements in actual units with the deviations squared so the assessment is biased in favor of higher magnitude events. The relative error is a relative measure of the error relative to the observed record while the (R) value describes the proportion of the variance in the observed dataset that can be explained by the model.

The output of the system was tested to match the target given to the system. If not, then the learning algorithm increased by providing a new network structure or learning. The outcomes of flood prediction through the selected strategies are evaluated with the RMSE (Root Mean Squared Error) and Mean Squared Error (MSE). Mathematically, RMSE and MSE are expressed as (Wang and Lu, 2018).

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2} \ \ and \ \ MSE = \frac{1}{n}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2$$

where $\hat{y}_k$ is the prediction value, y_k is the actual value, and n is the data number.

(Eq 6)

$$R^2 = \left(\sum_{i=1}^{n}(y_{io} - y_{mean})^2\right) - \sum_{i=1}^{n}(y_{io} - y_i)^2) /\left(\sum_{i=1}^{n}(y_{io} - y_{mean})^2\right)$$

(Eq 7)

Note that both RMSE and MSE express the average model prediction error in the unit of the observed variable. The MSE parameter is used when data contains unexpected values that must be considered, i.e. the value is too high or too low. The value of both parameters can range from 0 to ∞ and ignores the direction of the error. Prediction results are obtained well if both values are close to zero.

Where, yi and yio are the predicted and the actual values of the output respectively, y mean is the mean of the actual value and n is the total number of observations. The minimum error refers to the performance validity of the computer model. The R^2 value is within the range of 0 to 1. Once the coefficient R^2 is equal to one the model is perfect but if it is equal to 0.5 or below the model is poor. Zero value of MSE means an ideal model (Aczel, 1989; Gareth et al., 2013; Iqbal, 1986).

Chapter Three

Research Methodology

In this chapter, the methods of collecting, and analyzing data, and the modeling to be done is discussed. This research focuses on using Artificial intelligence to analyze data and come up with the best model of prediction. And also an essential role in implementing this research study according to the scope of the study is presented.

3.1 Description of the study area

The Awash River basin is the most important river basin in Ethiopia, with a total area of 114,123 km^2. According to 2016 estimates, there are 18.6 million inhabitants (Awash Basin Authority, 2018). The city of Dire Dawa is located in the Great Rift Valley of East Africa between latitudes $9^o25'$−$9^o45'$N and longitudes $41^o40'$−$42^o10'$E, covering a total area of 698.5 km^2 (Figure 3.1). It borders Somali in the north, east, and west, and Oromia in the south and southwest. The city is located at the foot of the surrounding mountains and is drained by a tributary of five major rivers: the Dechatu, Goro, Ragahea, Butsuji, and Mercajabdu rivers. The largest river, Dechatu, runs through the center of the city. All of these rivers come from the southern mountains and originate in the districts of the Oromia provinces (Kombolcha, Haramaya, Kersa, Meta). The basin of Dire Dawa includes the surrounding districts of the provinces of Oromia and Somalia. Based on the 2013 Ethiopia Forecast Statistics Report, the city of Dire Dawa is estimated to have a population of approximately 466,000 with a CAGR of 2.7% (CSA, 2013). The city is regularly flooded as it is surrounded by various mountains and drained by several major river tributaries. Flash floods from the surrounding mountains reportedly recalled the elderly and flooded the surrounding mountains in 1945, 1968, 1977, 1983, 1985, 1995, 2003, 2005, 2006, and 2010, There was a large flood in 2016. The most devastating of these was the 2006 flood, which killed 339 people and evacuated 9027 (Erena and Worku, 2018).

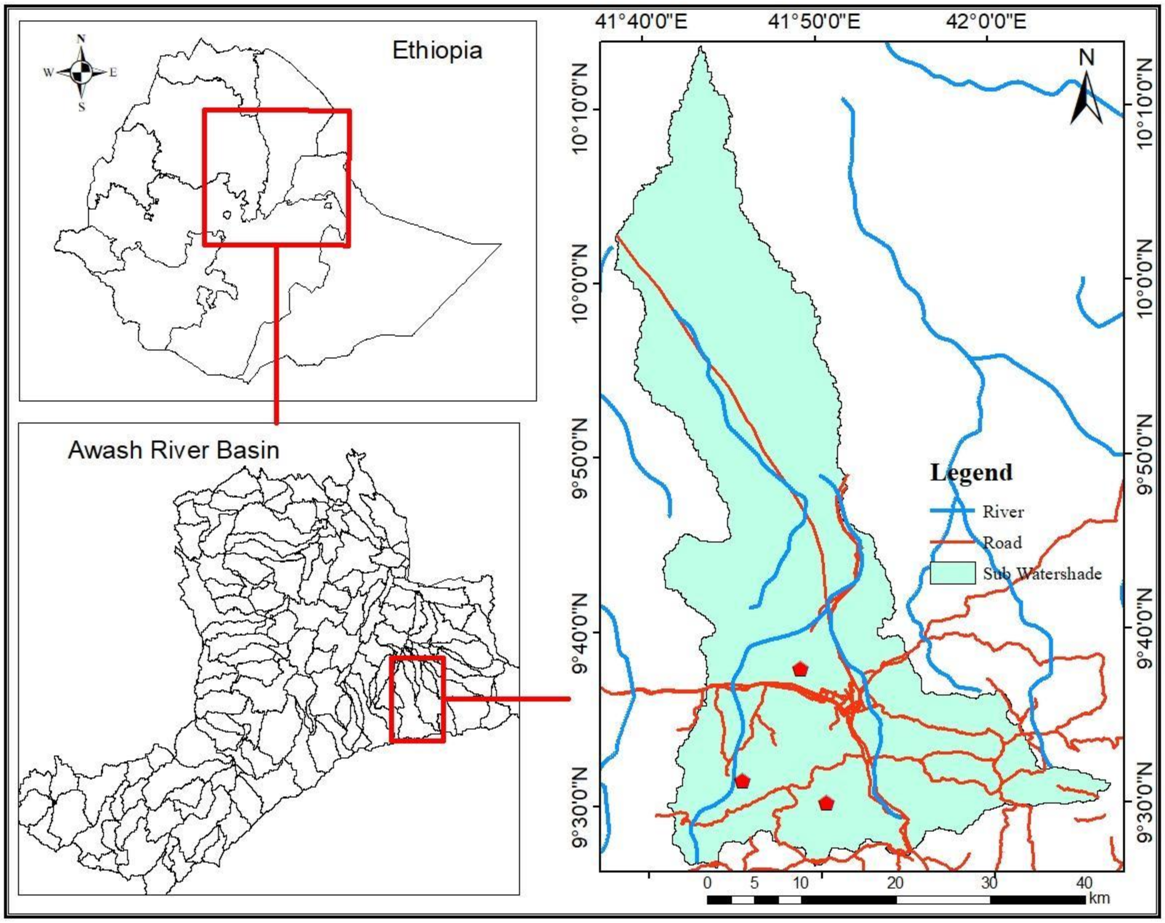


Figure 3. 1 Location map of the study area

3.1.1 Climate and Topography

Rainfall

The monthly rainfall data analysis shows that, during the years from 1952 to 2017, the maximum value of monthly rainfall is 271.9 mm, and the mean average was 92.1mm. An increase in rainfall intensity, in association with other factors such as land-use change, and increased population settlement along the river bank in the downstream area has contributed to raising the risk level of flash floods in the city of Dire Dawa to the point that floods caused severe socio-economic consequences in the town and rural kebeles of Dire Dawa (Wahaj, and Mikyas 2021).

Temperature

Dire Dawa administrative council is situated in the kola agro-climatic region; because of its tropical location, Dire Dawa is experiencing high temperatures throughout the year with minor seasonal variations. Temperature timely increases northward from a somewhat temperate type along the mountainside of the city at its southernmost point (Amante and Tesega, 2014). The average annual temperature of Dire Dawa is about 25.4°C. The mean maximum temperature is 31.4°C, and also its average minimum temperature is about 18.2°C (Fazzini et al., 2015). The area has two rain seasons; that is, a small rain season from March to April, and a big rain season that extends from August to September. According to Fazzini et al. (2015), the average annual rainfall that the region gets from these two seasons is about 611 mm. The variability of annual precipitation in Dire Dawa during the last 30-year period is a bit larger than neighboring stations (Rediat, 2012).

Elevation

As shown in figure 3.2, the altitude of Dire Dawa ranges from 1000 to 1600 meters above sea level. Mountain heights in the basin range up to 2400 meters above sea level. Dangago is the highest mountain at the top of the Continental Divide.

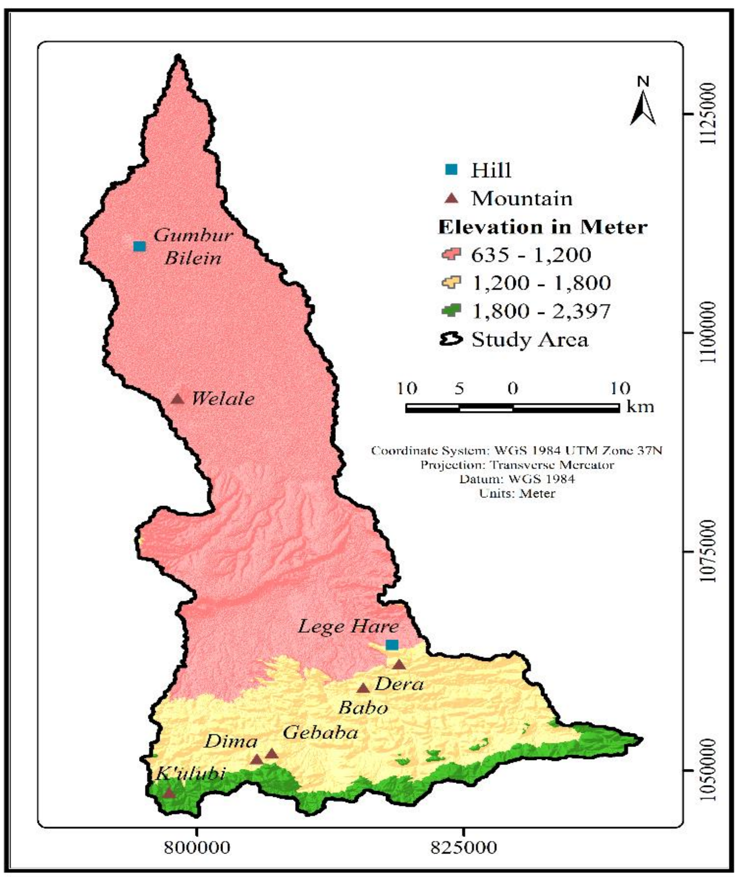


Figure 3. 2 Elevation map

3.1.2 Geology

The geology of Dire Dawa embraces various metamorphic, volcanic, and sedimentary rocks. The metamorphic rock, which mainly includes gneisses and migmatites, represents the oldest rock types in the area. They are large of the pre-Cambrian origin or crystalline basement complexes. They are mainly exposed in the escarpment zone and limited out crop occur near Dire Dawa. Very limited crops of volcanic rocks are exposed in the immediate area of the town. However, significant out crops of the extrusive lava flow (mainly basalt) and a few small out crops of intrusive can be observed in the bordering areas within the Dire Dawa watershed. Sedimentary rocks of the area include various sandstone, limestone, alluvial sediments, and travertine. The alluvial sediments are composed of sand, silt, and clay with minor wadi gravel. They occupy nearly the entire low-lying flat alluvial plain. The travertine is exposed in limited areas within the town and its vicinity (WWDSE, 2004; Abbate et al., 2015). A geological map of the area is shown in figure 3.3.

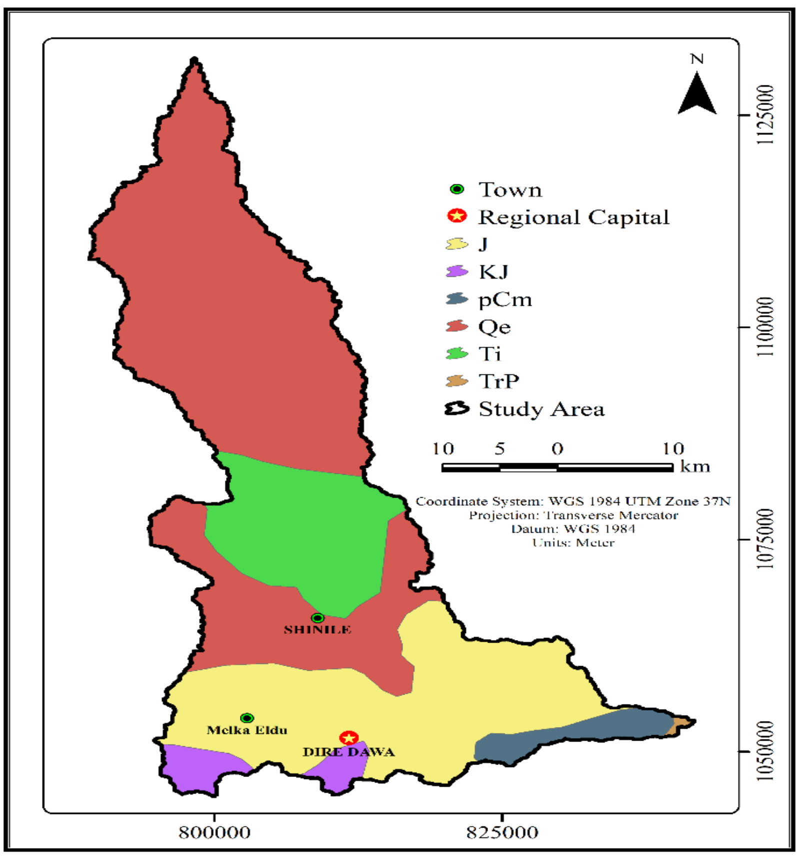


Figure 3. 3 Geology map

3.1.3 Land-use and land-cover

The land use types in the study area are classified into six classes (Figure 3.4). These are shrub land, grassland, cropland, wetland, built-up, and sparse vegetation as indicated in map

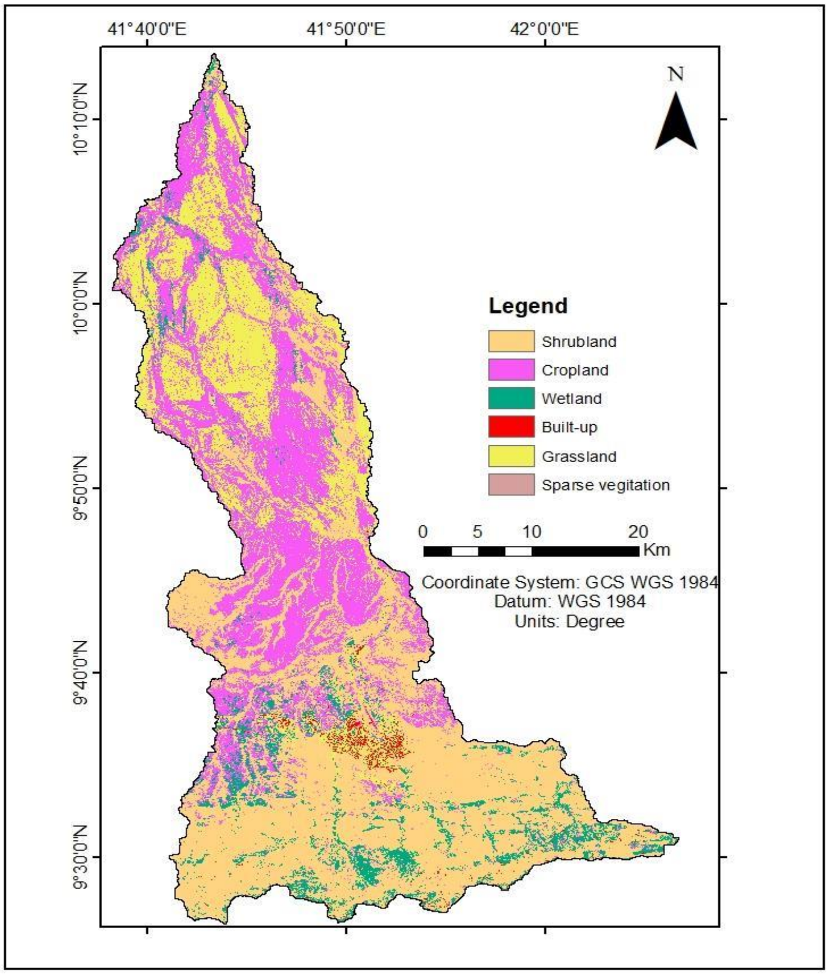


Figure 3. 4 Land use Land cover map

3.1.4 Drainage density

As shown in Figure 3. 5, there are few intermittent and perennial streams pre dominate the natural water flow system of Dire Dawa. According to the study made by the agricultural development office of Dire Dawa administrative council (DDAC) in the year 2000, the region has over 130 springs with different water discharging capacities and over 44 perennial and intermittent streams. The most important intermittent and perennial streams that drain the Dire Dawa region are

Dechatu, Butiji, Lega Hare, Dube, Goro and Elbah (WWDSE, 2004). All the rivers originate from the southern highland catchments of Kulibi, Dengego and Alemaya. The city is bounded by Lege Hare in the east and by Goro Rivers in the west. Dechatu and Butugi rivers pass through the middle of the city (Ephrem, 2006). The first three passes pass the town of Dire Dawa and the others are flowing to the west side of the town. The intermittent streams except Lega Hare start from the escarpment zone and flow northwards into the alluvial plain. Among the main intermittent streams in the Dire Dawa region, Dechatu is the major one where most of the precipitation as run-off from the south drains into it. Although this stream is dry for the most part of the year, it carries very large flows in the rainy season, which sometimes causes flash flooding that results in damage in the town, mainly because it passes through the middle of the town. Most of the runoff from Dechatu and the other streams spread in the low lying and flat topographic areas north of the town contributing a lot to the groundwater (WWDSE, 2004). Dire Dawa is vulnerable to flood hazards, which originates from uphill areas, especially Meta, Kersa, and Alemaya (Eleni, 2011

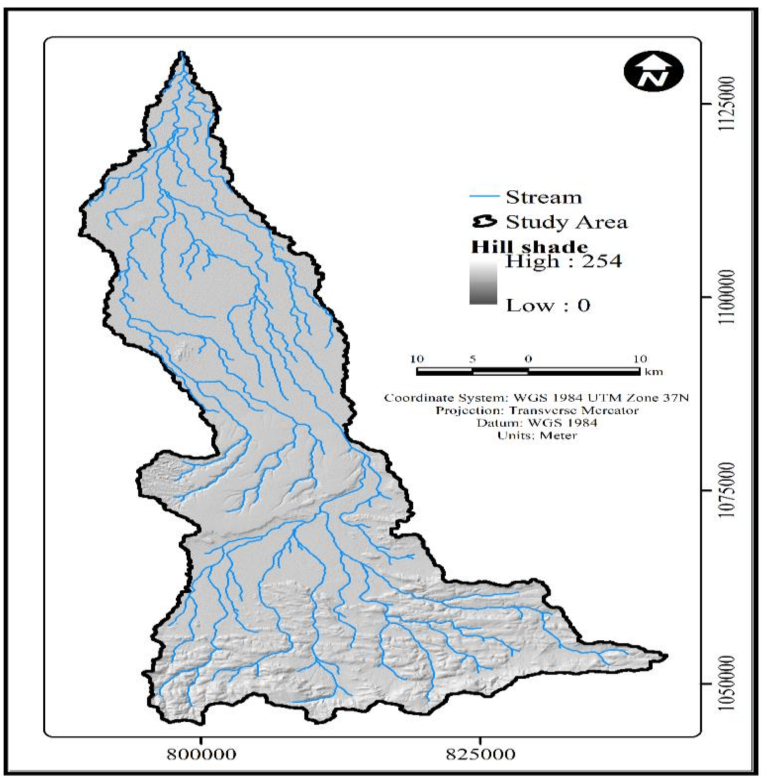


Figure 3. 5 Stream map

3.2 Data source

Data used for the study were collected from different sources. Hourly precipitation and surface runoff data are downloaded from Copernicus ERA5. Historical flood occurrence data is collected from the National Disaster management commission, the Dire Dawa disaster management office, and the OCHA report. Those data are utilized for calibration (training) and testing application for the proposed models by splitting them into two. The data which was collected from Ethiopia meteorological authority and the ministry of water and energy are not sufficient for the study because of a lack of consistency, and a lack of recent data such as runoff. To solve this constraint instead of station data satellite data is used for the study. The data was clipped for the time frame that was relevant to the model. Satellite imageries used for the study as presented in table 3.1.

Table 3. 1: Data description

Type of data	Source	Purpose
Precipitation (1990-2021)	ERA5	For training models to predict flood
Surface runoff(1990-2005)	ERA5	For training models to predict flood
Historical flood data	National Disaster Management Commission, Dire Dawa city Disaster management office, and OCHA report	For training models to predict flood
Shapefiles attributes of administrative institute boundaries, roads, rivers of	Ethiopia space science and geospatial	Study area description
Population data	Central statistical agency	Study area description
Digital elevation model 30M	USGS	Topography

3.2.1 Description of ERA5 Data

ERA5-Land is a reanalysis dataset providing a consistent view of the evolution of land variables over several decades at an enhanced resolution compared to ERA5. ERA5-Land has been produced by replaying the land component of the ECMWF ERA5 climate reanalysis. Reanalysis combines model data with observations from across the world into a globally complete and consistent dataset using the laws of physics. Reanalysis produces data that goes several decades back in time, providing an accurate description of the climate of the past.

ERA5-Land uses as an input to control the simulated land fields ERA5 atmospheric variables, such as air temperature and air humidity. This is called atmospheric forcing. Without the constraint of atmospheric forcing, the model-based estimates can rapidly deviate from reality. Therefore, while observations are not directly used in the production of ERA5-Land, they have an indirect influence through the atmospheric forcing used to run the simulation. In addition, the input air temperature, air humidity, and pressure used to run ERA5-Land are corrected to account for the altitude difference between the grid of the forcing and the higher resolution grid of ERA5-Land. This correction is called 'lapse rate correction'.

The ERA5-Land dataset, as with any other simulation, provides estimates which have some degree of uncertainty. Numerical models can only provide a more or less accurate representation of the real physical processes governing different components of the Earth System. In general, the uncertainty of model estimates grows as we go back in time, because the number of observations available to create a good quality atmospheric forcing is lower. ERA5-land parameter fields can currently be used in combination with the uncertainty of the equivalent ERA5 fields.

The temporal and spatial resolutions of ERA5-Land make this dataset very useful for all kinds of land surface applications such as flood or drought forecasting. The temporal and spatial resolution of this dataset, the period covered in time, as well as the fixed grid used for the data distribution at any period, enable decision makers, businesses, and individuals to access and use more accurate information on land states.

3.3. Methodology

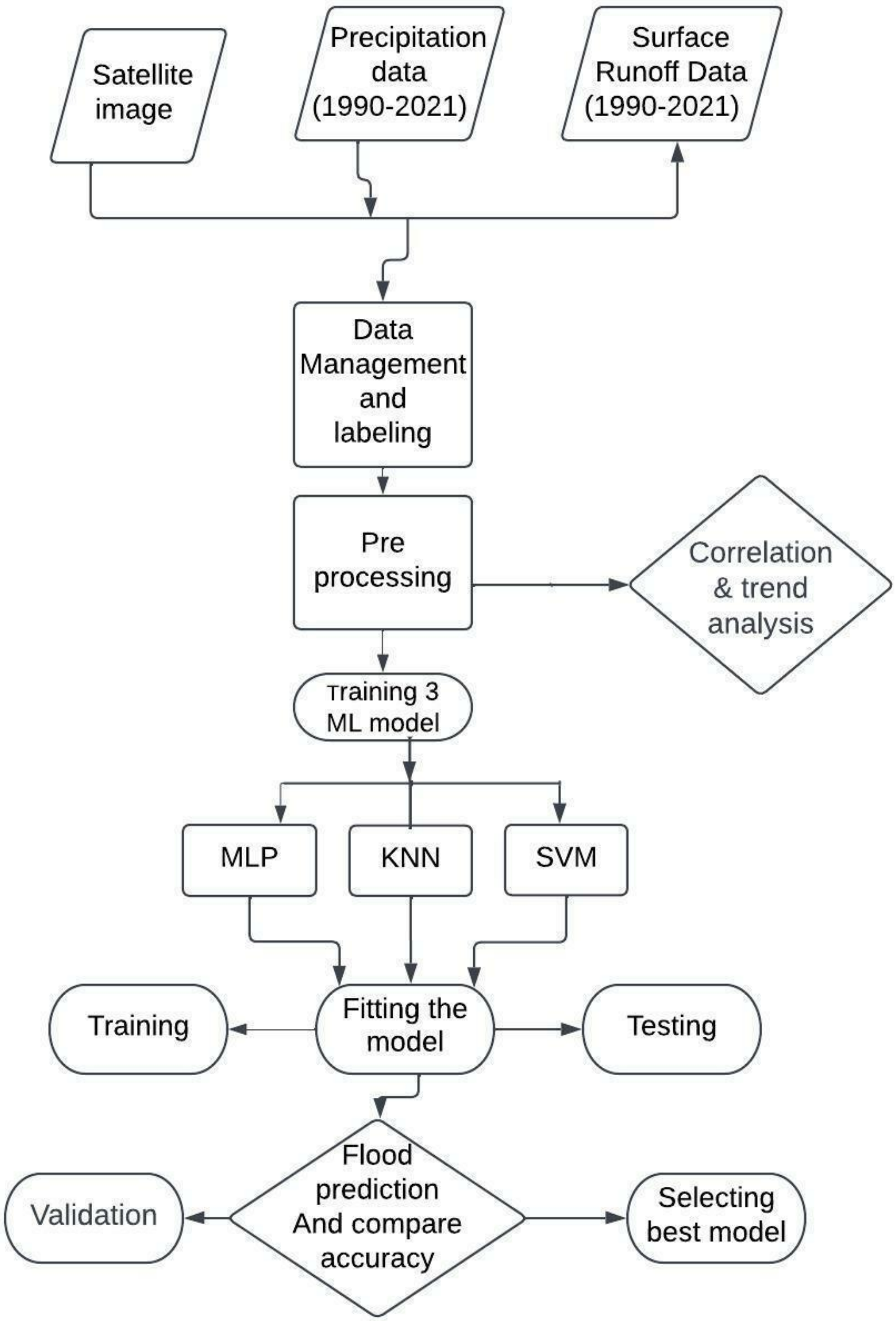


Figure 3. 7 Methodology flow chart employed in this study

3.3.1 Data Pre-processing

Downloaded NETCDF satellite data is converted to CSV (Comma Separated Values) format in ARCGIS. In this part, raw data is processed and arranged for prediction. Import Libraries, such as Numpy and Pandas libraries imported for processing the dataset. Numpy is the critical bundle for scientific computing with python. A panda is an open- supply high-performance library for data manipulation and analysis. The prepared information is compiled into a CSV file and imported by using pandas. Removal of information with missing values is done. Instead of lacking values, we are placing null values. The following libraries are imported (Sandhya and Shejina, 2021).

Sklearn; Sklearn is a library for python which features algorithms like SVM, Random forest etc for machine learning analysis. It is used to build models.

NumPy; in python, we used the NumPy library for scientific computing. It is a core library that provides tools and high performance for a given array of objects.

Panda; Panda library is an open-source library that is used to make an analysis of data and to use it easily. It provides high performance and easy-to-use data structure.

Matplotlib is a python library used to create plots and graphs. It provides a variety of bar charts, histograms and error charts

Seaborn; Seaborn library is based on data visualization like matplotlib. It's used to represent statistical plotting.

3.3.1.1 Dataset Cleaning and Feature Engineering

The discipline of cleaning up data is an essential one. It's a technique for removing incomplete or irrelevant data from a dataset by finding and correcting any inaccuracies. Feature engineering is a machine learning preprocessing procedure that converts raw data into features that may be used to build a predictive model using a machine learning model. It primarily seeks to enhance the models' performance. It aids in better representing an underlying problem to predictive models, which improves the model's accuracy for unobserved data. While the feature engineering process identifies the most effective predictor variables for the model, the predictive model contains predictor variables and an outcome variable

3.3.1.2 Feature Encoding and Feature Scaling

In machine learning algorithms, only numerical values can be used. Therefore, the categorical values of the relevant attributes must be converted to numerical values and this process is referred to as feature encoding. Analysis of the sample data and the selection of features that make a machine learning model correct is facilitated by a process called feature scaling. Machine learning models like linear and Multi-layered perceptron, KNN, Support Vector Classifier, etc require the data to be scaled.

Correlational analysis

The Flood predicting parameters correlation is done by using statistical methods. The **Pearson correlation coefficient (*r*)** is the most common way of measuring a linear correlation. It is a number between –1 and 1 that measures the strength and direction of the relationship between two variables (Shaun 2022).

3.3.2 Model Description

Application of the Machine Learning Models For this research, the researcher has used a Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Multi-layer perceptron (MLP) for predicting our data. The data has been split into a 75:25 ratio for training and testing the models. Firstly the models have been implemented on the whole dataset which consists of data from 1990-2021. The models implemented for this study are described below.

K nearest neighbor

K nearest neighbor (KNN) is a non-parametric algorithm that can be used for regression predictive problems. The KNN method assumes the resemblance between the new data and the existing data and places the new data in the category that is most comparable to the existing categories. The KNN algorithm calculates the distance between a new data point and all previous data points in the training set. There are a variety of distance functions for calculating the distance but Euclidean is the most widely utilized method.

Support Vector Classifier

The Support Vector Classifier (SVC) is a machine learning algorithm that uses both regression and classification. The structural Risk Minimization Principle is roughly implemented in this way. The SVC, in contrast to other models, aims to fit the best line within a threshold value rather than to reduce the error between real and predicted values.

Multilayer perceptron

A multilayer perceptron (MLP) is an artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input and output layers.

3.4 Materials

Table 3. 2: Materials

Item	**Purpose**
I. HPC and internet facility	downloading satellite imageries, running of models
4 twin-nodes (8 servers) with 64 CPUs and 96 GB ram 1 twin-node with 16CPUs and 12GB ram as spare	For downloading satellite imageries, running of models
Aster node with 4 CPUs and 8TBs hard disk, a high-speed infinity band networking switch	Preprocessing and storing of data
A Gigabit Ethernet switch Internet facility.	Training algorithms. Data preprocessing and downloading of satellite data
312 TB storage hard disc and 960 processer	Storing of meteorological data
ARCGIS	Preparing study area map, stream flow, elevation map and land use and land cover map
PYTHON 3.6	For programming

3.5. Model evaluation

The selected meteorological parameters were trained and tested in this study to determine which combinations of parameters have the best correlation with the highest accuracy and should be used as the model's input. The data being trained spans thirty-one years, with 75% of it being used for training and 25% for testing. The system's output is checked to see if it matches the target it was given. The results of flood prediction using the chosen approaches are examined by R^2 (accuracy score) and Mean Squared Error (MSE). Mathematically, R^2 and MSE are expressed as (Wang and Lu, 2018).

Chapter Four

Result

This chapter deals with the presentation and interpretation of results. The data trained and predicted was analyzed and interpreted in line with the objective of the study which was; the prediction of floods in three AI algorithms. It gives the empirical findings and results following the application of these models using the techniques indicated in the third chapter.

4.1 Feature encoding

As shown in table 4.1, the dataset that is used in this research has two attributes that have string type data which are - 'total precipitation, surface runoff' and 'Flood'. As machine learning models give better results for numerical values, the string-type data are encoded. The attribute contains all the names of the stations from where the hourly rainfall and surface runoff data have been collected. In this dataset, the attribute 'Flood' has two unique values, 'YES' and 'NO' and to encode these values, binary encoding is used. After encoding the values of the feature 'Flood', the value 'YES' is replaced by 1, and the value 'NO' is replaced by 0.

Table 4. 1: Feature encoding

	time	latitude	longitude	sro	tp	Flood
0	1990-01-01	9.69	41.680000	0.0	2.987640e-06	No
1	1990-01-01	9.69	41.779999	0.0	1.991760e-06	No
2	1990-01-01	9.69	41.880001	0.0	9.958790e-07	No
3	1990-01-01	9.69	41.979999	0.0	9.958790e-07	No
4	1990-01-01	9.59	41.680000	0.0	9.958790e-06	No

	time	latitude	longitude	sro	tp	Flood
0	1990-01-01	9.69	41.680000	0.0	2.987640e-06	0
1	1990-01-01	9.69	41.779999	0.0	1.991760e-06	0
2	1990-01-01	9.69	41.880001	0.0	9.958790e-07	0
3	1990-01-01	9.69	41.979999	0.0	9.958790e-07	0
4	1990-01-01	9.59	41.680000	0.0	9.958790e-06	0

4.2 Trends and correlational results of predicting parameters

The correlation between precipitation and runoff is often intertwined and complicated, and it is obvious that flow data at a given time involves some information about the past rainfall record because the change in flow data generally are the result of past rainfall events (Seifi & Riahi-Madvar, 2012). Figure 4.1, shows the trends of precipitation and surface runoff data over the last thirty-one years. It is plotted by using matplotlib.pyplot library of python.

4.2.1 Trends of hourly precipitation

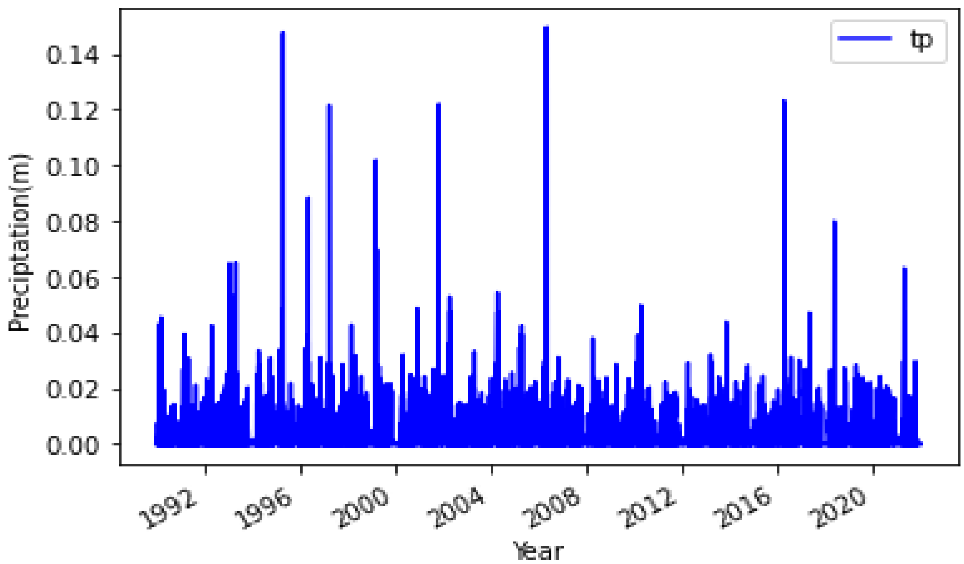


Figure 4. 1 Hourly precipitation trend of the year between (1990-2020)

By using a simple regression model to look at the trends of thirty-one years' precipitation. There is the seasonal fluctuation of precipitation from time to time and year to year. As indicated in the graph above, trends of precipitation in Dire Dawa vary from time to time. Within thirty-one years it indicated that flood occurring times have relatively higher amounts of precipitation. Higher amounts of precipitation lead to floods.

4.2.2 Trends of surface runoff

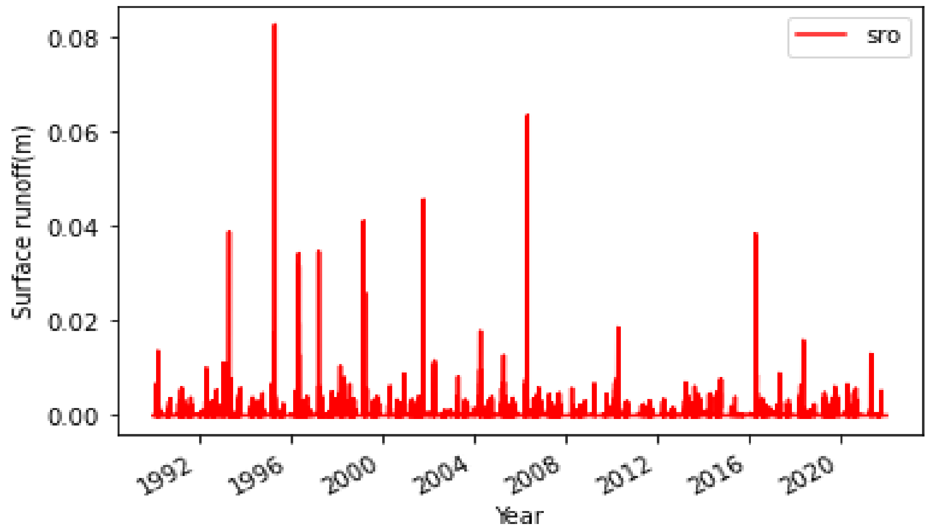
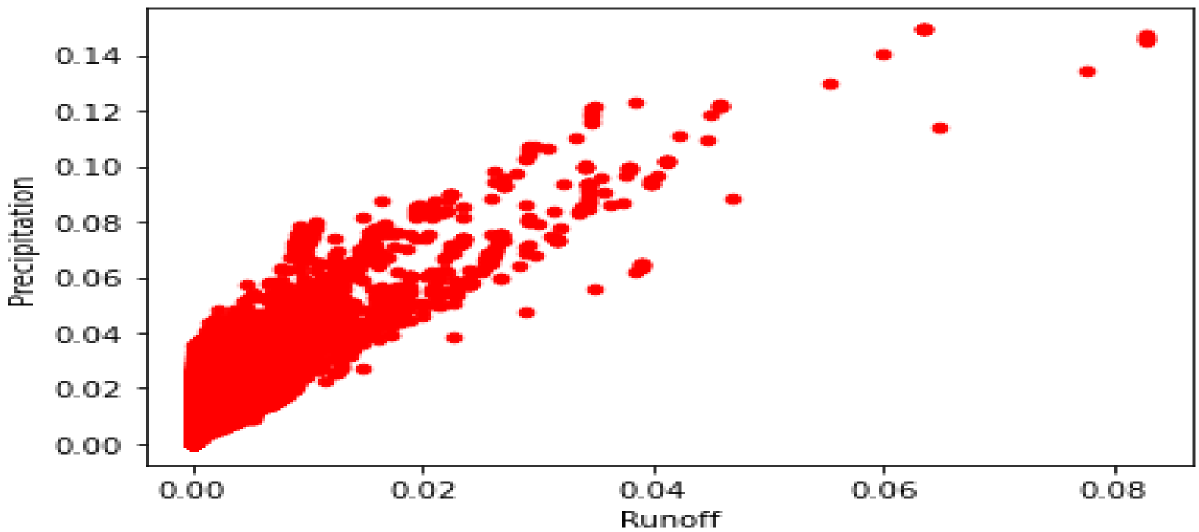


Figure 4. 2 Hourly Surface runoff between the years 1990-2021

Surface runoff is a portion of rainfall that enters the stream immediately after the rainfall. It occurs when all losses are satisfied and rainfall is still continued and the rate of rainfall intensity is greater than the filtration rate. As indicated in the above graph, trends in surface runoff vary from time to time, the peak surface runoff reaches up to 0.09 m in 1996, if there is peak surface runoff it probably leads to flooding. A peak runoff with increasing event magnitude, as it often occurs due to a higher relevance of surface and near-surface flow paths and greater surface flow depths, will increase the flood frequency curve with a return period (Rogger et al., 2012).

4.2.3 Correlation between precipitation and surface runoff

Figure 4.3 describes the correlation between run hourly precipitation and surface runoff between the years 1990-2021, it implies that both of them have direct proportionality. The precipitation data and river flow have significant correlations for the prediction of the flood. Because this study aimed to predict floods at a given time using previous rainfall data and surface runoff. It is evident that the fall has the highest relationship with river flow at a given time.



r= 0.769438

Figure 4. 3 Correlation between precipitation and surface runoff

Pearson correlation test was conducted to know the degree of relationship between surface runoff and total precipitation for the last thirty-one years. Based on the results of correlation analysis, these variables are shown in figure 4.3 both variables are highly correlated with R=0.7694

4.3 Flood prediction models evaluation

For the prediction, three different types of models have been used. The algorithms are K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Multilayer Perceptron (MLP). Their accuracy of prediction is described below;

4.3.1 SVM Prediction Accuracy

Table 4. 2: Accuracy Report of Support Vector Machine

Evaluation	Result
Mean squared error	$5.04(10^{-4})$
accuracy score	$99.949(10^{-2})$
r2_score	$5.05(10^{-4})$
R^2	99.949

As indicated in the table above Support vector machine algorithm has higher accuracy with low mean squared error. It implies the model prediction with respect to its training and testing data is interesting. On the other hand, SVM takes more time for a prediction.

4.3.2 KNN Prediction Accuracy

Table 4. 3: Accuracy Report of K-Nearest Neighbors

Evaluation	Result
Mean squared error	$6.148(10^{-4})$
accuracy score	$99.938(10^{-2})$
r2_score	0.174
R^2	99.938

From the table above, K-Nearest Neighbors (KNN) has an accuracy score of $99.938(10^{-2})$, Mean squared error, and r2_score $6.148(10^{-4})$ and 0.174 respectively. The prediction time of this model is better than SVM but not faster as MLP.

4.3.3 MLP Classifier Prediction Accuracy

Table 4. 4: Accuracy Report of Multilayer Perceptron

Evaluation	Result
Mean squared error	$5.2398(10^{-4})$
accuracy score	$99.947(10^{-2})$
r2_score	$5.2424(10^{-4})$
R^2	99.947

From the table above, Multi-Layer perceptron has an accuracy score of $99.947(10^{-2})$, Mean squared error, and r2_score $5.2398(10^{-4})$ and $5.2424(10^{-4})$ respectively. This model takes a small time for prediction as compared to the rest of other models used in this study. Root mean square (R^2) is used to check the performance of the model. Each method is estimated from the model's predicted values and the observed values.

4.4 Comparison of three models

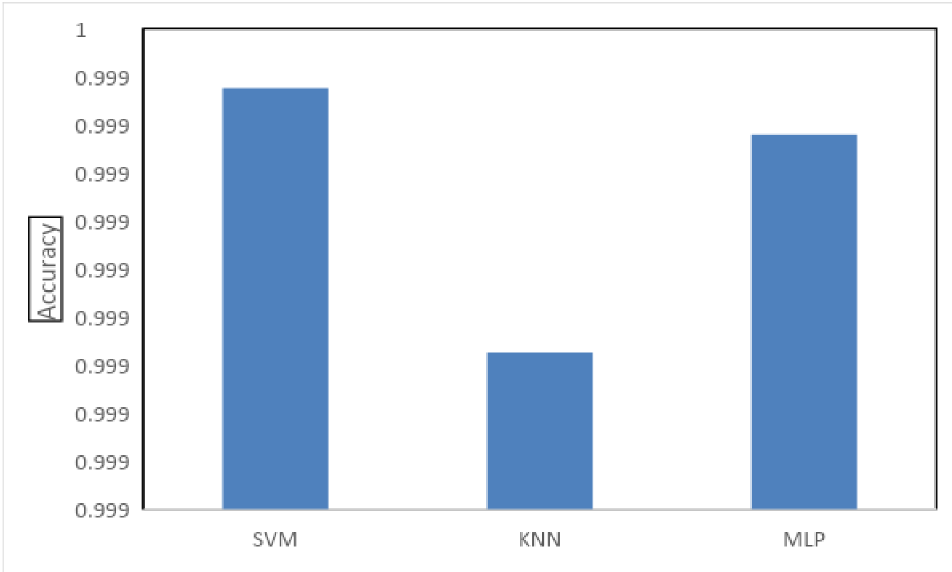


Figure 4. 4 Comparison of three models

Fig illustrates the accuracy score of the KNN, MLP, and KNN. It can be clearly seen that SVM outperforms the other algorithms with an accuracy score of 0.99949. The MLP comes second with an accuracy score of 0.99947 followed by KNN with accuracies of 0.99938. It is shown that SVM gives the best prediction with very few inaccurate results compared to other algorithms.

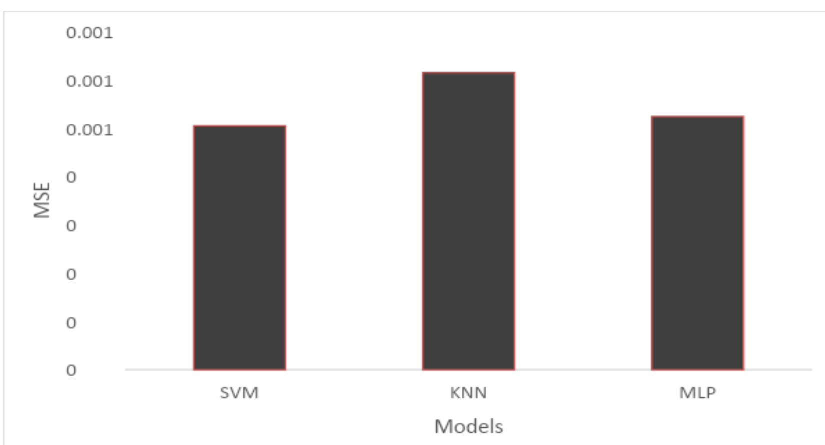


Figure 4. 5 MSE of three models

As indicated in the above figure, the mean square error of the KNN, MLP, and KNN. It can be clearly seen that KNN has a mean square error of 0.0006148. The MLP comes second with an accuracy score of 0.0005239 followed by SVM which is 0.0005046. It is shown that SVM found the best prediction with very low root means squares compared to other algorithms.

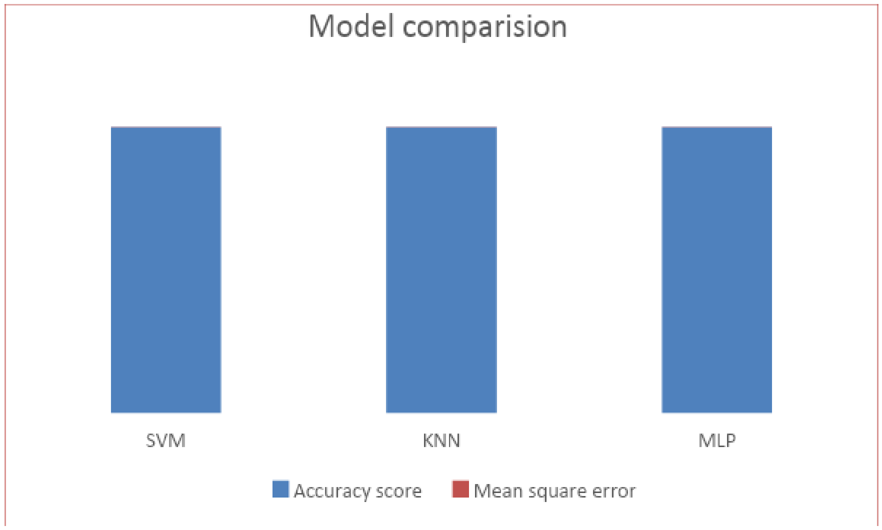


Figure 4. 6 MSE And Accuracy score of three models

The graph above compares the comparison of accuracy between MLP, SVM, and KNN algorithms. It can be observed that the accuracy values of SVM are comparatively more efficient when compared to MLP and KNN. In addition to this mean squared error of each model is presented. From the two determinants, we can conclude that Support Vector Machine algorithms have efficient performance compared to K nearest Neighbour and Multilayer Perceptron Algorithms. This statement can be further supported by table 4.5, which compares the accuracy percentage of all three algorithms with the Support Vector Machine having the highest percentage of 99.949%.

Table 4. 5: Comparison of three models

Models	Transfer function	Accuracy score	Mean square error	Prediction Accuracy (R^2)
SVM	RBF	99.949 (10^{-2})	5.05(10^{-4})	99.949
KNN	Minkowski	99.939 (10^{-2})	6.14 (10^{-4})	99.938
MLP	RELU	99.947 (10^{-2})	5.24 (10^{-4})	99.947

Table 4.5 provides the summary performance of each model. The performance results of each model are presented in tabular form. The measures used to evaluate performance included the

activation function, accuracy score, Mean square error, and Prediction Accuracy respectively obtained during the training of the network.

4.5. Models validation

K-Fold cross-validation is used to analyze prediction performance and to check the overfitting and underfitting of these models in the study. As shown using the plot, variations between the predicted and observed values. It indicates that all three models predicted the given phenomena properly and there is no overfitting and underfitting. This accuracy in figure 4.7 shows an overall agreement between our predicted flood and the observed flood for 1990 to 2021. Predictions are within a reasonable level of error and accurately represent future values.

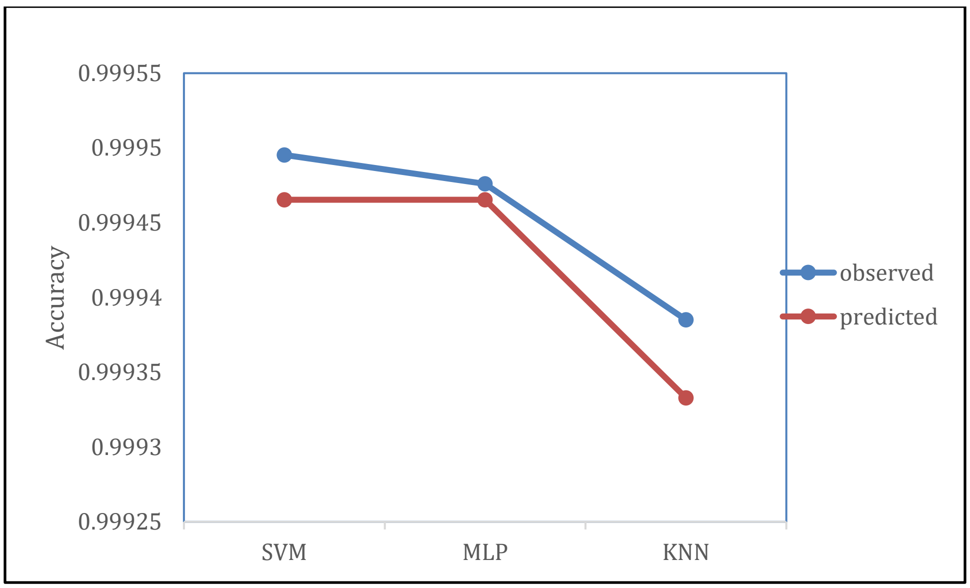


Figure 4. 7 Model validation

Chapter Five

Discussion

The Python package running on a notebook was used to implement the algorithms on the data. Common parameters of each algorithm were used in training and testing the model. At the completion of the learning process, the trained model was evaluated to see how well the algorithms were able to learn from the data. Precipitation and runoff are identified as appropriate input variables. Changes in surface runoff are mainly determined by the variation of precipitation. Greater A greater of precipitation means larger changes in surface runoff. Runoff generation over the land surface is closely related to precipitation (Mohamadi & Kavian, 2015).

The correlation coefficient is used in statistics to provide information in terms of the strength of a linear relationship between precipitation and surface runoff. In this study, the correlation coefficient of predicting parameters was calculated.

A historical record along the years 1990 to 2021 of remote sensing data (Hourly precipitation, surface runoff) and historical flood event has been used for modeling as input variables and probability of flood occurrence as output in order to assess the performance of those methods in flood prediction in Dire Dawa. Initially, data were pre-processed by avoiding noise and normalizing data. For better performance of the models during the training process optimization algorithm was used to minimize the loss value or error of the network by updating the network weights iteratively based on training data. RELU, Sigmoid, and Minkowski transfer functions and different architectures on account of no general rule that is reliable to determine the numbers of nodes and layers in the network were adopted.

Given the Dire Dawa‟ historical rainfall and surface runoff patterns, it was expected that the data would contain a great proportion of zero rainfall values compared to non-zero values. Stated differently, the non-zero rainfall values were sparsely distributed in the data. This condition caused neural networks to lapse into learning a zero output mapping since the trained network would then correctly predict the majority of outputs. To obviate this situation, consecutive instances of zero rainfall were substituted by a single zero value. This approach is reasonable since flooding cannot occur if there is no preceding rainfall and runoff. A number of scaling methods were considered in preparing the data for training and testing. Since the neural network employed RELU is used for multilayer perceptron, RBF is for Support vector machine, and minkowski is adopted for K nearest Neighbour algorithm as activation function, the output of the network would be constrained to the unscaled range of [0, . . . , 1]. In order to evaluate those outputs with desired values, it was thus necessary to scale the target values to the same range.

Trends of flood-triggering factors are described properly. In addition, the correlation, between precipitation and surface runoff has been determined. Based on this, both parameters have direct proportionality as an increase in precipitation there is a chance of high surface runoff.

When the amount of data increases, the accuracy of prediction also increases, in this study attributes of data are above two million. It indicates that higher accuracy of prediction is a result of datasets. Prediction time is assessed in this study, at the same operating system and the same dataset with the same device MLP prediction is faster than KNN and SVM. The same study by (Shi et al. 2016) reported that SVM accuracy of 0.928, this implies that my research found satisfactory accuracy results as compared to previous findings. However, this study is, about the comparison of three models, when we compare the result of those models from previous findings three of them have promising prediction accuracy. (Hema 2021) Also conducted on flood prediction by using MLP it found an accuracy score of 0.933, as compared to the current finding accuracy of MLP is better. On the other hand, the SVM algorithm takes more time than the two algorithms in the study.

(Hung et al., 2009) their recent works show that a model with improved performance on the training set does not always provide better performance during testing. In this study, the accuracy of the training set and the validation set were observed and recorded during the training process. After training the models, each model prediction performance was assessed. Finally based on model evaluation criteria SVM is identified as the best predictive model.

According to a research work (Sankaranarayanan 2019) that was carried out in India, in recent years, a number of machine learning algorithms have been used to anticipate floods by taking into account variables such as rainfall and humidity as well as temperature and water velocity. Specifically, Deep Neural Network (DNN) and other machine learning algorithms (Support Vector Machine, K-Nearest Neighbor, and Naive Bayes) are compared for accuracy and error in this paper’s flood prediction. This paper claims that it took temperature and rainfall as parameters and a confusion matrix was developed to figure out the best way to detect floods. He founds the ML methods the accuracy rate of SVM is 85.57%, Na¨ıve Bayes has 87.01% accuracy, and KNN has 85.73% of accuracy on the other hand as compared to this research which used predicting parameters, precipitation, and surface runoff instead of humidity and temperature then the result of this paper is outstanding.

Overall, the results show that hourly rainfall and surface runoff data variables can be used to predict impending floods. The results also indicated that the RELU, Sigmoid, and minkowski activation function was appropriate for the network architectures considered in this study. Publications for neural network flood prediction employed dedicated sensor networks that involved a number of meteorological parameters or considered, shorter predictive periods such as a few hours (Mandal 2005, Fan et al., 2002). While the percentage accuracy of the results reported in that work is not as high as this, this approach is a reasonable technique to apply for flood prediction, even if a limited number of variables are available.

Chapter Six

Conclusion and Recommendation

6.1. Conclusion

Floods can be devastating in certain years due to high rainfall and upstream water movement. Floods in 2003, 2005, 2006, 2010, and 2016 are examples of the intensity of floods in Dire Dawa in terms of duration and damage. The 2006 floods have also emerged as one of these natural catastrophes, as the shocks are being felt by a vast number of people over an extended period of time.

This study attempts to predict floods by using AI models in Dire Dawa, Ethiopia. Predicting the hazard and evaluating the model were the major tasks. SVM, KNN, and MLP, methods were applied. The most important thing to learn is how to better manage floods while causing the least amount of harm to people's lives and property, as well as how to lessen flood-induced vulnerability. And for that, it is important to have an idea of a flood that is about to hit beforehand, so that necessary precautions can be taken. There are various factors that need to be kept in mind in order to predict the occurrence of a flood. For example, rainfall, the water level of the river basins, the geographical structure of the said location etc. This research has achieved very high accuracy rates to predict floods, by correlating some of the aforementioned factors or more and by using different methods. Climate is ever-changing and with it as time goes on, other factors dependent on it also change. So, over time, the amount of rainfall and water level also have changed. Additionally, the population has also increased over the years and with the number of housing structures. Due to this changing geographical structure of the area with time, the drainage system of the area is changing as well. Runoff is dependent on the drainage system, as the rainwater collects and discharges on a nearby river. So, all the factors that a flood occurrence is related to, are related to one another. This research was done by taking time to collect these data for the respected location and finding the correlation between the factors. Since these actors change over a long time period. Finally in this research, the models gave higher accuracy. Also, due to time constraints, only the precipitation and surface runoff data along with flood occurrence was used for prediction.

6.2. Recommendation

Based on the findings which are obtained from this study, the researcher has drawn the following recommendations;

Using artificial intelligence for flood prediction as well as other catastrophic event is mandatory for better accuracy and preparedness

Remote sensing data are more consistent and easily accessible for time series analysis of different climate variables.

Further improvements have to include the model for better prediction performance by including other relevant features such as climatic data (e.g. Temperature, humidity) and topographical data could be in the course of training the model.

Predicting floods in the study area by using other AI models and comparing the result with that algorithm is necessary

It is necessary to automate this process by showing the prediction results in web or desktop applications.

Adding various other parameters to improve efficiency is mandatory such as loss of life, infrastructure, and Economic crisis

The government has to give high attention to flood hazard prediction and early warning systems

Researchers should have to align satellite data with meteorological station data and compare their accuracy

A blending of physical forecasting models with Artificial intelligence is necessary

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ANNEX

Python codes

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import mean_squared_error , accuracy_score , confusion_matrix
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
import seaborn as sns
```

```
dataset1 = pd.read_excel('C:/Users/user/Desktop/MSC Thesis 2021/1990-2021.xlsx')
dataset1.tail()
```

```
dataset2 = pd.read_excel('C:/Users/user/Desktop/MSC Thesis 2021/2000-2004.xlsx')
dataset2.head()
```

```
dataset3 = pd.read_excel('C:/Users/user/Desktop/MSC Thesis 2021/2005-2009.xlsx')
dataset3.head()
```

```
dataset4 = pd.read_excel('C:/Users/user/Desktop/MSC Thesis 2021/2010-2014.xlsx')
dataset4.head()
```

```
dataset5 = pd.read_excel('C:/Users/user/Desktop/MSC Thesis 2021/2015-2019.xlsx')
dataset5.head()
```

```
dataset6 = pd.read_excel('C:/Users/user/Desktop/MSC Thesis 2021/2020-2021.xlsx')
dataset6.head()
```

```
merge1=pd.merge(dataset1,dataset2, how='outer')
```

```
merge1.head()
```

```
merge2=pd.merge(merge1,dataset3, how='outer')
merge3=pd.merge(merge2,dataset4, how='outer')
```

```
merge4=pd.merge(merge3,dataset5, how='outer')
```

```
dataset=pd.merge(merge4,dataset6, how='outer')
```

```
dataset.tail()
```

```
dataset.drop(dataset.columns[len(dataset.columns)-1], axis=1, inplace=True)
dataset.head()
```

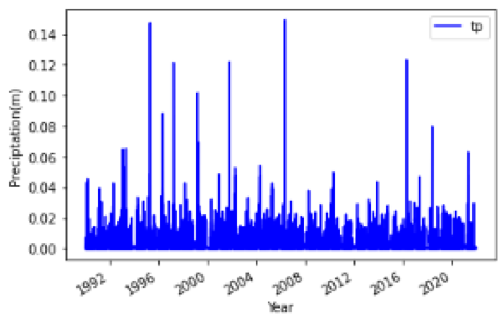
```
dataset.tail()
```

```
dataset.info()
```

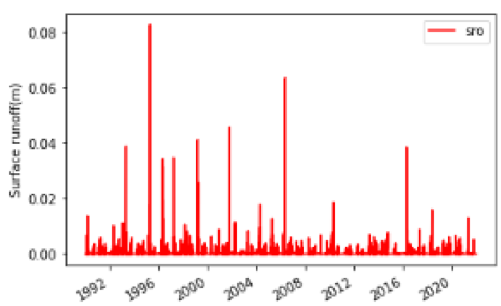
```
dataset[['sro','tp']].hist(figsize=(15, 9),bins=16,linewidth='1',edgecolor='k',grid=False)
plt.show()
```

```
dataset.plot(kind='scatter', x='sro', y='tp', color='red')
plt.xlabel("Runoff")
plt.ylabel("Precipitation")
plt.show()
```

```
dataset.plot(x='time', y='tp', color='blue')
plt.xlabel("Year")
plt.ylabel("Preciptation(m)")
plt.show()
```




```
dataset.plot(x='time', y='sro', color='red')
plt.xlabel("Year")
plt.ylabel("Surface runoff(m)")
plt.show()
```



```
dataset.info()
```

```
np.isnan(dataset.all())
```

```
np.isfinite( dataset.all())
```

```
np.isfinite( dataset.all())
```

```
np.isfinite( dataset.all())
```

```
dataset = dataset.dropna()
```

```
dataset = dataset.reset_index()
```

```
dataset['Flood'].replace(['Yes','No'],[1,0],inplace=True)
dataset.head()
```

```
#Now let's seperate the data which we are gonna use for prediction
x = dataset.iloc[:,1:-1]
x.head()
```

```
y = dataset.iloc[:,-1]
y.head()
```

```
SVM.fit(x_train, y_train)
```

```
y_test.-plot(figsize=(14,5))
```

```
SVM.predicted1 = SVM.predict(x_test)
print("prediction result:".predicted)
```

```
y_train.plot(figsize=(14,5))
```

```
SVM.predict(x_test)
```

```
y_test
```

```
SVM.score(x_test,y_test)
```

```
SVM_pred = SVM.predict(x_test)
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
KNN = neighbors.KNeighborsClassifier(n_neighbors = 2, metric = "minkowski", p =3)
```

```
 KNN.fit(x_train,y_train)
```

...

```
KNN.score(x_test,y_test)
```

...

```
Multilayer perceptron
```

...

```
from  sklearn.neural_network import MLPClassifier
```

```
MLP = MLPClassifier(hidden_layer_sizes=(2,3), max_iter=10000, activation='relu')
```

```
MLP.fit(x_train,y_train)
```

...

```
MLP_pred = MLP.predict(x_test)
```

```
MLP.predict(x_test)
```

...

```
y_test
```

...

```
MLP.score(x_test,y_test)
```

```python
r2_score(y_test,MLP_pred)
```

...

```python
from sklearn.metrics import classification_report,confusion_matrix
```

```python
print(classification_report(y_test,MLP_pred))
```

...

```python
#Let's predict chances of flood
MLP_predict = MLP.predict(x_test)
print('predicted chances of flood')
print(MLP_predict)
```

...

```python
KNN_predict = KNN.predict(x_test)
print('predicted chances of flood')
print(KNN_predict)
```

```
predicted chances of flood
[0. 0. 0. ... 0. 0. 0.]
```

```python
print(classification_report(y_test,KNN_predict))
```

...

```python
SVM_predict = SVM.predict(x_test)
print('predicted chances of flood')
print(SVM_predict)
```

...

```python
print(classification_report(y_test,SVM_predict))
print(confusion_matrix(y_test,SVM_predict))
```

...

```
from sklearn.neighbors import KNeighborsClassifier
```

```
KNN = neighbors.KNeighborsClassifier(n_neighbors = 2, metric = "minkowski", p =3)
```

```
 KNN.fit(x_train,y_train)
```

...

```
KNN.score(x_test,y_test)
```

...

```
Multilayer perceptron
```

...

```
from  sklearn.neural_network import MLPClassifier
```

```
MLP = MLPClassifier(hidden_layer_sizes=(2,3), max_iter=10000, activation='relu')
```

```
MLP.fit(x_train,y_train)
```

...

```
MLP_pred = MLP.predict(x_test)
```

```
MLP.predict(x_test)
```

...

```
y_test
```

...

```
MLP.score(x_test,y_test)
```

```python
from sklearn import preprocessing
minmax = preprocessing.MinMaxScaler(feature_range=(0,1))
minmax.fit(x).transform(x)
```

...

```python
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=0)
```

```python
x_train.head()
```

...

```python
y_train.tail()
```

...

```python
x_train = x_train.astype(np.float)
```

```python
y_train = y_train.astype(np.float)
```

```python
from sklearn.preprocessing import StandardScaler
```

```python
sc = StandardScaler()
```

```python
x_train = sc.fit_transform(x_train)
```

```python
x_test = sc.fit_transform(x_test)
```

```python
from sklearn.svm import SVC
```

```python
SVM = SVC(kernel= "rbf", random_state =2)
```

```python
In [73]: from sklearn.metrics import accuracy_score,recall_score,roc_auc_score,confusion_matrix
         print("\naccuracy score: %f"%(accuracy_score(y_test,SVM_predict)*100))
         print("recall score: %f"%(recall_score(y_test,SVM_predict)*100))
         print("roc score: %f"%(roc_auc_score(y_test,SVM_predict)*100))
```

...

```python
In [75]: SVM_predict = SVM.predict(x_test)
         print("Mean squared error",mean_squared_error(y_test,SVM_predict))
         print("accuracy_score",accuracy_score(y_test,SVM_predict))
         print("r2",r2_score(y_test,SVM_predict))
         print("RMSE",mean_absolute_error(y_test,SVM_predict))
```

...

```python
In [327]: from sklearn.metrics import accuracy_score,recall_score,roc_auc_score,confusion_matrix
          print("naccuracy score: %f"%(accuracy_score(y_test,MLP_pred)*100))
          print("recall score: %f"%(recall_score(y_test,MLP_pred)*100))
          print("roc score: %f"%(roc_auc_score(y_test,MLP_pred)*100))
```

...

```python
In [328]: from sklearn.metrics import accuracy_score,recall_score,roc_auc_score,confusion_matrix
          print("naccuracy score",accuracy_score(y_test,MLP_pred))
          print("recall score",recall_score(y_test,MLP_pred))
          print("roc score",roc_auc_score(y_test,MLP_pred))
```

...

```python
In [329]: MLP_pred = MLP.predict(x_test)
          print("Mean squared error",mean_squared_error(y_test,MLP_pred))
          print("accuracy_score",accuracy_score(y_test,MLP_pred))
          print("r2",r2_score(y_test,MLP_pred))
          print("RMS",mean_absolute_error(y_test,MLP_pred))
```

...

```python
In [330]: from sklearn.metrics import accuracy_score,recall_score,roc_auc_score,confusion_matrix
          print("\naccuracy score: %f"%(accuracy_score(y_test,KNN_predict)*100))
          print("recall score: %f"%(recall_score(y_test,KNN_predict)*100))
          print("roc score: %f"%(roc_auc_score(y_test,KNN_predict)*100))
```

```
In [331]: KNN_predict = KNN.predict(x_test)
          print("Mean squared error",mean_squared_error(y_test,KNN_predict))
          print("accuracy_score",accuracy_score(y_test,KNN_predict))
          print("r2",r2_score(y_test,KNN_predict))
          print("RMS",mean_absolute_error(y_test,KNN_predict))
```

...

```
In [ ]: Comparing all the prediction models¶
```

```
In [198]: models = []
          from sklearn.neighbors import KNeighborsClassifier
          from  sklearn.neural_network import MLPClassifier
          from sklearn.svm import SVC
          models.append(('SVM', SVC()))
          models.append(('KNN', KNeighborsClassifier()))
          models.append(('MLP', MLPClassifier()))
```

```
In [199]: names = []
          scores = []
          for name, model in models:
              model.fit(x_train, y_train)
              y_pred = model.predict(x_test)
              scores.append(accuracy_score(y_test, y_pred))
              names.append(name)
          tr_split = pd.DataFrame({'Name': names, 'Score': scores})
          print(tr_split)
```

ERA5 Data downloading Command

```
        import cdsapi

c = cdsapi.Client()

c.retrieve(
    'reanalysis-era5-land',
    {
        'variable': [
            'surface_runoff', 'total_precipitation',
        ],
        'year': [
            '1990', '1991', '1992',
```

```
            '1993', '1994', '1995','1996','1997', '1998','1999',

'2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007', '2008', '2009',
'2010','2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018', '2019',
'2020', '2021'],

        'month': [

            '01', '02', '03',

            '04', '05', '06',

            '07', '08', '09',

            '10', '11', '12',

        ],

        'day': [

            '01', '02', '03',

            '04', '05', '06',

            '07', '08', '09',

            '10', '11', '12',

            '13', '14', '15',

            '16', '17', '18',

            '19', '20', '21',

            '22', '23', '24',

            '25', '26', '27',

            '28', '29', '30',

            '31',

        ],

        'time': [

            '00:00', '01:00', '02:00',

            '03:00', '04:00', '05:00',
```

```
            '06:00', '07:00', '08:00',

            '09:00', '10:00', '11:00',

            '12:00', '13:00', '14:00',

            '15:00', '16:00', '17:00',

            '18:00', '19:00', '20:00',

            '21:00', '22:00', '23:00',

        ],

        'area': [

            9.75, 41.68, 9.49,

            42.02,

        ],

        'format': 'netcdf',

    },

    'download.nc')
```