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USING MACHINE LEARNING ALGORITHMS TO MOD FLOOD DISASTER WITH CLIMATIC PARAMETERS: A CASE STUDY OF MONROVIA, LIBERIA

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NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

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M.Sc. THESIS

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M.Sc. THESIS

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February 2023

Approval

We certify that we have read the thesis submitted by Ansumana Abraham Bility titled **"Using Machine Learning Algorithms to Model Flood Disaster With Climatic Parameters: A Case Study Of Monrovia, Liberia"** and in our combined opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Environmental Sciences and Engineering

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Abstract

Flooding has emerged as one of the deadliest disasters confronting developing counties and developed states. In this thesis, three subclasses of Artificial Neuron Networks (ANNs) were employed; 1) Elman Feedforward Neuron Network, 2) Multipeceptron Feedforward Neuron Network and 3) Cascade Neuron Network to predict the incidence of flooding in Liberia's capital, Monrovia. Five input parameters considered climatological variables influencing flooding in the study area, including rainfall, temperature, soil moisture, and wind speed. Runoff was treated as the output variable—two transfer functions, TANSIG and LOGSIG, with varying numbers of neurons ranging from 10 to 25. The study uses a uniform layer (2) throughout the training and testing phases to ensure speed and easiness in prediction. Of the 40yrs (1980-2020) satellite climatological data used in this study, 70% (28yrs) were used for the training stage, while the remainder, 30% (12yrs), was used for the validation (testing) phase. For model accuracy, the coefficient of determination, $R^{2,}$ and the Root Mean Square, RMSE, were used. The results indicate that the Cascade Neuron Network is the best to model floods in the study area based on the evaluation technique. The cascade-1 model produced an R^2 value for the testing phase of 0.515101. This value is the highest of the 18 models trained and simulated. A distant second is an Elman-3 model with an R^2 value of 0.377333. The least-performing model was the FFBNN. This research is the first of its kind in the study area (Liberia); it's recommended that further research be carried out incorporating other flood-inducing variables other than the ones used in this paper to abreast national and international policymakers with the data required to make sound decisions regarding flood mitigation and prevention.

Table of Content

Acknowledgment -- v

Abstract -- vi

Table of Content -- vii

List of Tables -- **ix**

List of Figures -- **ix**

Chapter 1: Introduction

1.1 The current state of flooding globally -- 1

1.2 Flooding in Liberia -- **1-2**

1.3 Problem Statement -- **2**

1.4 Aim of the study -- **3**

1.5 Significance of the study -- **3**

1.6 Scope of the thesis -- 3

Chapter 2: Literature Review

2.1 Introduction -- **4**

2.2 Theoretical Framework -- **4**

2.3 Supervised Learning --- **4-5**

2.4 Unsupervised Learning -- **5**

2.5 Reinforcement Learning -- **5-6**

2.6 Interdisciplinary Application of ANNs -- **6-7**

2.7 Application of ANNs in Flood Modeling ------------------------------------ **7-20**

Chapter 3: Methodology

3.0 Methodology -- 21

3.1 Description of Study Area -- **22**

3.2 Data type and source -- **23-24**

3.3 Simulation models -- **24**

3.3.1 Artificial Neuron Networks -- **24**

3.3.1.1 Multipecertron Feedforward Neuron Network -------------------------- **24-26**

3.3.1.2 Cascade Neuron Network --- **26-27**

3.3.1.3 Elman Neuron Network -- **28**

3.4 Training and Testing -- **29-30**

3.5 Model Accuracy Evaluation -- **30-31**

3.5.1 Mean Square Error -- **31**

3.5.2 Root Mean Square Error -- **31**

3.5.3 R- square -- **31-32**

3.6 Input and Output Variables --- 32-33

Chapter 4: Results and Discussion

4.1 Results -- **34-40**

4.2 Discussion --- **40-42**

Chapter 5: Conclusion and Recommendation

5.1 Conclusion -- **43**

5.2 Recommendation -- **43**

References --- **44-52**

Appendix A --

Appendix B --

Appendix C --

List of Tables

Table 1: Climatic Overview (Monrovia) 22
Table 2: Evaluation **of the CFNNs with corresponding Statistical results for Training with all five inputs** 33
Table 3: Evaluation of CFNNs at testing with all five inputs given the statistical performance (Testing) 33
Table 4: Evaluation of the Elman Neuron Network models with statistical performances with all five inputs (Training) 34
Table 5: Elman Neuron Network model evaluation with the statistical performance results in 34
Table 6: Evaluation of the Feedforward Multipercetron Neuron Network models with statistical performances with all five input variables (Training) 35
Table 7: Evaluation of Feedforward Neuron Network at testing with all five inputs given the statistical performance (Testing) 36
Table 8: Best Model for Training Data (R square Value) 36
Table 9: Best Model for Training (RMSE value) 37
Table 10: Best Models for Testing dataset (R square Value) 37
Table 11: Best Model for testing dataset (RMSE value) 38

List of Figures

Figure 1: Order of the Research Methodology 20
Figure 2: Map of Study Area 21
Figure 3: Design of Multilayer Perceptron (Sun et al. 2016) 24
Figure 4: CFNN Model schematics (Hayder et al., 2020; Tengeleng & Armand, 2014) 26
Figure 5: Schematic of the Elman Neural Network (Jai et al., 2019) 27
Figure 6: General Flowchart of the Models (FMLP, CFNN & GRNN 28
Figure 7: Input and Output Variables 31
Figure 8: General Model Layer Architecture 32
Figure 9: Actual VS Predicted value of Runoff 39
Figure 10: Input Variables Intensity Graph 40

Chapter I
Introduction

1.1 The current state of flood disasters globally

Flooding has emerged as one of the deadliest disasters confronting not only developing counties but developed states as well. Since the year 1990, flooding has become the natural disaster that occurs the most frequently. Worldwide, there were a total of 9,924 natural disasters recorded between the years 1990 and 2019, with floods accounting for 42% of those disasters (Voh, 2020). There were 432 disasters reported in 2021, which is significantly more than the average of 357 disasters each year over the period 2001–2020. With 223 separate flood occurrences, these disasters far outnumbered the average yearly flood total of 163 for the period 2001-2020 (*2021 Disasters in Numbers - World*, 2022). Though floods can happen in any country, most of the world's flood-vulnerable population — 89% — resides in low and medium-income nations (*1.47 billion People Face Flood Risk Worldwide*, 2020). The complexities in flood disasters in these low-income countries encompass not just the lack of policy infrastructure to curb or avert its potential danger but the absence of technological innovation to accurately predict the incidence. Flood is ranked number one in the global disaster index, costing about 70 billion in life and property damages annually. The risk of damage caused by flood disasters can be minimized with the proper technological infrastructure to forecast its incidence.

1.2 Flooding in Liberia

Due to the country's low economic output, rapid population growth, high unemployment, and massive rural-urban migration, a significant proportion of the country's population are faced with increasing disaster vulnerability. Of these disasters, flooding remains the most devastating in terms of economic and social losses. There are about 4.2 million inhabitants in Liberia; of those, 320,000 are at risk from coastline erosion, 2.1 million from windstorms, and 2.2 million from flooding. Furthermore, the risks of such natural disasters in the country are anticipated to rise as a result of climate change (*Building Resilience to Flooding and Coastal Erosion in Liberia - Liberia*, 2022). The population in Monrovia is on an unprecedented increase. Consequently, the problems of poor wetland management, improper waste disposal, coastal encroachment, and the birth of largely unplanned urban sprawls arise. The ongoing global climate crisis further worsens the crisis- which led to rising sea levels, increased ocean tides, and routine coastal erosion. Discussion. Liberia's expansive and rich coastline zone is being threatened by sea level rise and attendant coastal flooding and erosion (Profile, 2008).

1.3 Problem statement

Monrovia's low elevation and high rainfall intensity are compelling factors that put a significant proportion of urban dwellers at constant risk of flood disasters. Over 4.2 million people are living in Liberia, and 320,000 are in danger from coastal erosion, 2.1 million from windstorms, and 2.2 million from flooding. In addition, climate change is expected to increase the dangers of such natural disasters in the country (Building Resilience to Flooding and Coastal Erosion in Liberia - Liberia, 2022). There has been a dramatic growth in the number of people living in Monrovia. Wetland management issues, garbage management issues, coastal encroachment issues, and unplanned urban sprawl are all results. The global climate catastrophe, which has already caused higher sea levels, stronger tides, and regular erosion of coastlines, has only exacerbated the situation. However, due to increasing poverty and the constant threat of climate change, most developing nations, including Liberia, continue to lag behind in accurate data sourcing that informs real-time policy formulation and implementation.

1.4 Aim of the study

On a yearly basis, hundreds of slums and urban sprawl inhabitants are displaced from their flood-prone homes, infested with vector diseases like cholera and skin ratches, and properties damaged as a result of fluvial and coastal flooding in Liberia's capital, Monrovia. This thesis aims to use a subclass of artificial intelligence known as machine learning to model and predict the incidence of flooding in Monrovia in order to inform policy actions that prevent or minimize the adverse impacts of this disaster. The research's focus is to gather and use 40yrs of satellite data for Monrovia, considering rainfall, maximum temperature, minimum temperature, windspeed, and soil moisture as inputs and runoff as output to enhance flood forecasting using three machine learning models: Elman Neural Network, Cascade Feedforward Neural Network, and Multipercetron Feedforward Neural Network.

1.5 Significance of the study

Flooding is unarguably the most raging of all disasters in Liberia. The complexities in flood disasters encompass not just the lack of policy infrastructure to curb or avert its potential danger but the absence of technological innovation to accurately predict the incidence. Flood is ranked number one in the global disaster index, costing about 70 billion in life and property damage annually. One effective way of dealing with flood disasters is flood forecasting. The current study offers huge potential for flood prediction and prevention to aid researchers, government, and non-governmental organizations in transitioning flood disaster management from intervention to prediction and prevention to minimize the damage.

1.6 Scope of the thesis

This thesis is divided into five (5) separate but complementing chapters. Chapter one focuses on the background, objective, and significance of the study. Chapter two is the literature review component of the research, where published materials in the form of journal articles, books, and other authoritative sources are consulted and referenced. Chapter three lays out the roadmap of the research; the methodology. This part touches on specific materials and models used for this paper. Chapter four is the result and discussion section. This part endeavors to display, interpret, and discuss the result of the experiments and different tests carried out during the research. Chapter five is the final or concluding segment of the paper. This chapter summarizes the major takeaways from the research results, states the researcher’s position relevant to the topic, and recommends workable solutions.

Chapter II

2.0 Literature Review

2.1 Introduction

The complexities in flood disasters encompass not just the lack of policy infrastructure to curb or avert its potential danger but the absence of technological innovation to accurately predict the incidence. Flood is ranked number one in the global disaster index, costing about 70 billion in life and property damage annually. Researchers over the years have developed and modified cost-effective and accurate ways to enhance flood forecasting. Machine learning, a subcategory of Artificial Intelligence, AI, has emerged as the leading tool for analyzing and predicting natural disasters such as floods. The goal of the study was to gather and use 40yrs of satellite data for Monrovia, considering rainfall, maximum temperature, minimum temperature, windspeed, and soil moisture as inputs and runoff as output to enhance flood forecasting using three machine learning models: Elman Feedforward Neural Network, Cascade Feedforward Neural Network, and Multipeceptron Feedforward Neural Network.

2.2 Theoretical framework

Machine learning is a subcategory of Artificial Intelligence AI concerned with learning from data to improve execution tasks. Historical data is at the core of the learning and prediction exercise carried out by machine learning algorithms. To draw broad conclusions from specific examples is one of the primary goals of a learner (Sra et al., 2012). The machine learning concept has been used across fields, and the results have proven remarkable. Machine learning has proven to be an effective tool in engineering since its popularization in the 1990s. Machine learning can be broken down into three subclasses: Supervised, Unsupervised, and Reinforcement. Below is a schematic of the machine diagram.

2.3 Supervised Learning

supervised machine learning refers to a process where the tasks often include learning a function that connects an input to an output based on sample input-output pairs (. During the supervised learning process, the training data are presented alongside annotations that correctly instruct the algorithm on how to answer the questions (Konkoi, 2014). In the circumstances like these, the objective is to arrive at a description of these cases so that evaluations can be performed on brand-new instances in the future (Smith & Frank, 2016). Marsland (2011, p.6) further explained that the algorithm is given a training set of examples and appropriate replies (targets). Then, using this training set as a foundation, it generalizes itself to respond appropriately to potential inputs. Supervised Learning can be further broken down into Regression and Classification. In regression scenarios, the goal is to predict or estimate values close to a value designed or proposed by supervision (human). On the other hand, classification entails predictions that have discrete values. We could employ a color filter to detect if a sample is black or white. We may be dealing with a binary problem in this instance. There may be multi classes as well.

2.4 Unsupervised Learning

Unlike supervised Learning, this machine learning involves no prior information or input and output criteria. Portugal et al. (2018) and Celebi & Aydin (2016) concluded that there is no concept of a training set in supervised machine learning algorithms. They are given some information about the actual world, and it is up to them to figure out what they can learn from that information on their own. The model tries to make sense of a trunk of historical data without any human intervention or labeling, as in the case of supervised Learning—the machine self-categorizes data into clusters with some identified characteristics. Class discovery is another name occasionally used to refer to unsupervised machine learning (Gentleman & Carey, 2008).

2.5 Reinforcement Learning

This group sort of forms a midpoint between supervised and unsupervised Learning. In this learning method, the machine learns from mistakes and improves based on the supervisor's reaction. When the answer is wrong, the algorithm is told, but it is not suggested how to fix it. Reinforcement learning (RL) is the study of how both natural and artificial systems can learn to predict the results of their actions and change their behavior to get the best results in situations where their actions can move them from one state or situation to the next and also lead to rewards and punishments (Dayan & Niv, 2008; Sutton, 1999). It has to try out different options until it figures out how to find the correct answer. Reinforcement learning is sometimes called "learning with a critic" because the monitor grades the answer but doesn't suggest how to improve it (Marsland, 2011, p. 7). The approach is based more on trial and error. For instance, a series of images of objects may be displayed for the machine to recognize and name. If the device gets the correct label, a correction maybe is awarded, but if it gets the wrong answer, a failing mark may be awarded. The machine then learns based on the feedback and improves future responses.

2.6 Related research in the application of machine learning across different disciplines

Ibrahim & Abdulazeez (2021) reviewed papers that applied machine learning algorithms like Independence Bayes, binary logistic regression, maximum margin classifier, K-NN, K-means clustering, decision tree, and random forest; for the identification and prediction of diseases in the help sector. The study evaluating nineteen articles on illness prediction models showed that various algorithms, such as the Maximum margin classifier, K-NN, random forest, and the decision tree, offer good accuracy for prediction.

Cai et al. (2018) used "the USDA's Common Land Units (CLUs) to aggregate spectral information" for each field based on Landsat image data stacks to overcome the cloud pollution issue while exploiting a machine learning model that uses Deep Neural Network (DNN) and high-performance" compiling Various crop-type classification tests were conducted to determine what information is most beneficial for training the machine learning model and the way various spatial and temporal aspects affect the crop-type classification performance. Over Champaign County, Illinois, the tests used 1322 Landsat multi-temporal scenes spanning 2000 to 2015, including data from all six optical spectral bands. Classification of maize and "soybean across all CLU fields in Champaign County from 2000 to 2015 had a comparatively high Overall Accuracy (i.e., the number of corrected categorized fields divided by the total number of areas) of 96 percent when compared to USDA's Crop Data Layer (CDL). This method achieved a 95 percent overall accuracy for corn and soybeans in the latter part of July of the same year. The methodology described in this work has the potential to accurately, economically, and seasonally classify field-level crop kinds on a broad geographic scale, such as the Corn Belt in the United States.

Grace and Suganya (2020) used machine learning to predict rainfall to improve agricultural production in India. Multiple linear regression is the foundation of this approach. To make the forecast, the authors gathered data from publicly available sources, with 70% of the data used for training and 30% for testing purposes. The researchers found that predicting rainfall in India with multiple linear regression yields better accuracy, MSE, and correlation outcomes than previous approaches.

In the distant learning improvement in the era of uncertainties like the global pandemic (Villegas-Ch et al., 2020) explored the possibility of integrating machine learning and data analysis in learning management systems. According to the authors, the model's ability to make better resources and activities makes learning online a quality model with the ability to respond quickly, even before an event occurs, such as dropout. Students who drop out of a university save money that can be used to create virtual labs, which has been one of the most vulnerable areas in online education and has been made particularly notable by the pandemic of Online Learning.

2.7 Related works in flood prediction with machine learning models

Based on a thirty-three-year (33) rainfall dataset, Lewal, Yassin & Zakari (2021) developed a machine learning algorithm that can forecast floods in Kebbi state so that it can be applied to other high flood-risk states in Nigeria. Three machine learning algorithms: Decision Tree, Logistic Regression, and Support Vector Classification (SVR) were evaluated and compared on Accuracy, Recall, and Receiver Operating Characteristics (ROC).

Using a variety of machine learning models, Syeed et al. (2022) helped reduce flood disaster risks and contribute to policy recommendations by predicting floods accurately, such as Binary Logistic Regression, KNN, Support Vector Classifier, and Decision Tree.

Mali et al. (2019) did a study to use Bayesian networks (BN) and other Machine Learning (ML) approaches such as Decision Tree (DT), k-Nearest Neighbours (kNN), and Support Vector Machine (SVM) for flood risk projection in Kuala Krai, Kelantan, Malaysia. The data spans five years, from 2012 to 2016, and includes 1,827 observations. Each model's performance was compared in regards to reliability, precision, recall, and measure. The results indicated that DT with the SMOTE approach outperformed the others, obtaining 99.92% accuracy. Furthermore, the SMOTE approach is quite effective in dealing with an imbalanced dataset.

Hashi et al. (2021) propose a novel and robust model for real-time flood detection systems based on machine learning algorithms and deep learning. Random Forest, Naive Bayes J48, and Convolutional Neural Networks can detect and measure floods with potential humanitarian consequences before they occur. Researchers initially identified and selected scientific information for this study. This phase was important for observing the watershed and collecting data from the riparian community. Next, we implemented a river level sensor that relays real-time data to the flood protection device for data mining. This sensor helped me. A normal high or dangerous water level has been detected. After converting analog data to digital, a machine learning algorithm determines if a critical condition exists. Finally, exchange data. Data was sent to the core control unit (microcontroller PIC). The PIC classifier provided correct data. After receiving high-precision data, it was monitored and managed from any GSM-enabled location. This study shows that the bootstrap aggregation algorithm outperforms all other machine learning models in terms of classification accuracy, achieving 98.7% accuracy. Naïve Bayes and J48 scored 84.2% and 88.4% respectively. However, in terms of precision and recall, we obtained an accuracy of 87% by adopting deep learning techniques. Artificial intelligence, data mining, and deep learning benefit from the anti-flooding capabilities of the proposed method.

Hkhalaf et al. (2018) conducted a study to evaluate the potential of empirical datasets for classifying flood severity. Various machine learning techniques are used to achieve this goal. In this work, we attempted to address the problem of flood mitigation by presenting a new flood dataset consisting of 2,000 annotated flood events. In this dataset, outcome severities are categorized according to three target groups representing different degrees of flood severity. The study also described several machine learning methods for estimating flood severity and grouped the results into three categories: Normal, Abnormal, and High Risk. As a result, according to extensive research, flood data processing should be improved using artificial intelligence algorithms. Their use has made the classification system more accurate. In general, neural network architectures have worked well in a variety of applications. Nevertheless, the study found that the random forest classifier outperformed the benchmark model.

Nti et al. (2021) aimed to assemble hybrid robust machine learning algorithms, namely his LSTM, XGBoost, RF, and extreme extra trees, to implement effective flood forecasting models. In this study, the authors examine the ability of his ML computing paradigm to develop flood forecasting models. Four alternative flood forecasting models implemented using four state-of-the-art ML algorithms: Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Highly Randomized Trees (Extra Trees) it was done. Several statistical performance evaluators are used to evaluate the effectiveness of custom-designed models. Experimental results demonstrate the potential of the developed model for accurate and efficient flood forecasting. This is the first study to use a combination of environmental factors in Ghana and machine learning algorithms to create an intelligent flood model to help stakeholders make informed decisions.

Kumberge et al. (2021) attempted to develop India's most effective multi-regional flood detection model. This study used three different machine learning algorithms. Decision trees, random forests, gradient boosting. These three were introduced to identify the most accurate in predicting floods and ensure early action to prevent flood disasters. The metric used to evaluate machine learning algorithms is accuracy. displayed proportionally. The accuracy of the decision tree algorithm was 94.4%. The gradient boosting algorithm had an accuracy of 87.9%, and the random forest algorithm had an accuracy of 92.4%. Therefore, the decision tree algorithm was chosen for the model.

Baalaji & Sandhya (2020) aim to develop an early warning system for floods by first training a forecasting model using a dataset containing rainfall records from all Indian states. Neural networks are used to simulate the complex mathematical formulas of flooding processes, offering improved performance and cost-effective solutions. The best flood forecasting methods are compared using MLP, logistic regression, support vector machines, and K Nearest Neighbor. Accuracy estimates are obtained using the classification report and confusion matrix parameters. The proposed system uses MLP to analyze data sets, train forecasting models, and a graphical user interface to produce real-time flash flood forecasts. This study compares the accuracy results of logistic regression, support vector machines, K-nearest neighbors, and multilayer perceptron algorithms. Based on the calculated values, the researchers found that support vector machines and multi-layer perceptrons gave relatively good results. Further comparisons led to the conclusion that multi-layer perceptrons have the highest accuracy.

Maspo et al. (2020) conducted research to evaluate existing machine learning (ML) methods for flood prediction and evaluate the parameters used for flood prediction; Evaluation is based on a review of previous research papers. To this end, the authors have divided the document into two parts: the first part identifies flood forecasting methods using ML techniques, and the second part identifies flood prediction parameters that have been used as input parameters for flood forecasting models. The main contribution of this paper is to identify the latest machine learning (ML) techniques for flood forecasting and to identify important parameters to be used as model inputs for flood researchers and managers. Flood prediction results can be used as a guide to evaluating ML methods for early flood forecasting. Over the past 5 years, the study compared and evaluated several machine learning models in flood prediction and parameters. The results show that ANN is the most popular ML method for flood prediction.

Mosabi etc. (2018) demonstrated the "state of the art for flood forecasting" of ML models and sought to contribute to the most appropriate models. In this work, we examined the literature assessing the robustness, accuracy, effectiveness, and speed of machine learning models to provide an overview of many machine learning techniques used in the field. Performance comparison of ML models provides a complete investigation and explanation of different strategies. This paper presents long-term and short-term flood forecasting strategies. We also examine trends in improving flood forecasting models. Hybridization, data decomposition, algorithm ensembles, and model optimization are reported to be the most effective tactics for improving ML methods. This research helps hydrologists and climate scientists choose the best ML method for a given forecasting task.

Khan et al. (2020) used machine learning models and longer lead-time regression techniques to build a regional-scale flood forecasting model that estimates the likelihood of Bangladesh experiencing monsoon floods. The model predicts flooding around three of his BWDB measurement stations in Manikganj, Bangladesh. Previous studies used data quality that required additional processing. On the ground, Bangladesh may not have such a framework. This work focused on the simplest forecasting model for longer lead-time local-scale flood forecasting that required fewer data and could be used by local governments and non-governmental organizations (NGOs). This study used LASSO regression techniques, decision trees, naive Bayes, support vector machines (SVM), logistic regression, and artificial neural networks (ANN). Input parameters included water level and temporal precipitation data. Random forest was the best classifier model for predicting flood severity with 83% accuracy, followed by the bagging classifier with 79% accuracy. These accuracies are supported by high precision and recall values derived from individual models. This survey will help disaster management teams to accurately assess flood severity and take preventive measures.

Islam et al. (2021) examined and compared the capabilities of ANN, SVM, RF, RS, and Dagging models to predict flood vulnerability maps in the Teesta River Basin in Bangladesh and identify flood impact factors for flood vulnerability mapping. I rated it.
In this study, we used two new hybrid ensemble models, Dagging and Random Subspace (RS), Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM), to simulate the Teesta River Basin. We generated flood vulnerability maps estimated in, northern Bangladesh.12 flood impact parameters and 413 current and past flood locations in a GIS environment were integrated into these models. was used to determine the relationship between events and flood impact parameters. Freidman, Wilcoxon signed ranks, t-pair tests, and receiver operating characteristic curves (ROC) were used to validate and compare the predictive ability of these models. The area under the curve (AUC) of ROC was significantly greater than 0.80 for all models. The Dagging model performed best in flood vulnerability modeling, followed by RF, ANN, SVM, RS", and various benchmark models. Help local authorities, and policymakers to mitigate floods, and associated hazards and implementation of effective harm mitigation techniques to reduce future harm.

Arora et al. (2021) presented new advanced models for forecasting flood-sensitive zones in the 'Middle Ganga Plain of India', namely ANFIS (standalone) and genetic algorithms (GA), differential evolution (DE), and particle swarms. Optimization (PSO)". Based on a highly detailed flood inventory for the region and 12 flood control factors such as curvature, land use/land cover, and topography, we developed an advanced new hybrid model called Adaptive

Neuro-Fuzzy Inference System "ANFIS" and ANFIS. Three ensembles based on the metaheuristic model used were constructed. A flood sample was used to build a 70-part flood inventory dataset. 30 classes for creating training and validation datasets. The Area Under Receiver Operating Characteristic Curve (AUROC) and 11 other cutoff-dependent model evaluation metrics showed that ANIFS-GA outperformed the other three, with a success rate of AUC=0.922 and a prediction of AUC=0.922. I came to the conclusion that it is the model rate. 0.924. ANFIS-GA was found to be the most accurate during training (0.886) and validation (0.883).

Rani et al. (2020) developed a real-time flood monitoring and warning system to reduce flood injuries. For this system, the researcher used his Raspberry Pi with three rain sensors, three water sensors, and both water and rain sensors. The system uses IoT to predict floods and alert the right people. It also sounds like an alarm alerting surrounding villages of possible flooding. The system also determines how long it will take for the tide to reach the desired area. A rain sensor measures rainfall in millimeters, and a water flow sensor measures the water level in a body of water. Researchers have found that implementing a flood monitoring and warning system reduces the level of flood stress and increases the length of time floods occur.

More time and support for people evacuating areas and those working on flood protection structures.

El Haddad et al. (2020) used four data mining/ I used a machine learning model. Using high-resolution satellite imagery (Sentinel-2 and Astro Digital) (according to flood episodes), historical documents, and intensive fieldwork, he divided the flooded areas into two groups. Training (239 flood sites, 70%) and validation (103%). Nine parameters were identified that influence flooding.

Slope angle, slope length, elevation, distance from major wadis, land use/land cover, lithologic unit, curvature, slope direction, and terrain wetness index. The model evaluated the relationship between flood impact factors and flood inventory maps (BRT, FDA, GLM, and MDA). Results were compared to a validation flood site not used in modeling. Model accuracy was calculated using success (training data) and prediction rate (validation data) curves, ROC, and AUC (AUC). According to the results of this study, the AUCs of success rate and prediction rate for BRT, GLM, and MDA models are 0.783, 0.958, 0.821, and 0.83, respectively. The flood vulnerability maps were then classified into five categories ranging from low to very high. Flood vulnerability mapping using the BRT, FDA, GLM, and MDA models was fairly accurate. As a result of this study, the future development of this region may be influenced by the vulnerability map developed.

Ke and associates. (2020) studied the application of ML techniques to predict the occurrence of floods due to urban storms in Shenzhen city, China. Using machine learning (ML) methods, researchers used precipitation thresholds to classify floods and non-flood events in a study of the Chinese city of Shenzhen to construct building resilience of the city in the face of frequent rain-induced flooding in a future climate. Several precipitation thresholds can be found in the plane covered by the two main components of the ML model, giving binary results (flood or no flood). The study concluded that ML models can find the precipitation-induced flood baseline as a line designed in a plane stretched by two principal components. This gives a binary result (flood or no flood). Compared with the traditional empirical critical rain curve, the proposed models, especially the subspace discriminant analysis algorithm, can better classify flood and non-flood events according to rainfall intensity. various resolutions. This significantly increases the ACC to 96.5% and reduces the false alarm rate to 25%. They further suggest that these models could also be used in other urban watersheds.

In a study, Rasheed et al. (2022) proposed a prototype ML-based framework for flood warning and peak flood forecasting, based on the recent success of ML models for runoff forecasting. The strategy they proposed consisted of a) a long short-term memory (LSTM) model that classifies storm events as flood/non-flood at the 90th flow percentile threshold and b) a prediction model for flood peaks. Predict flood peaks using histogram-based gradient-boosting regressors and random forests. These decision tree models are interpretable, which is their strength. It is used to geographically separate static and dynamic sources of flood peak response. The study covered 18 hydroclimate zones in the United States. The results show strong regional dependence of prediction performance and critical flood predictions, highlighting the heterogeneity of hydrological activity in the basin and its impact on flood prediction. Researcher evaluations of flood peak drivers have revealed different relationships between dynamic and static predictors for flood peaks of varying severity. Low to moderate flooding favored static catchment features over dynamic predictors such as precipitation, but precipitation caused the most important flood spikes. In most unsurveyed basins, the proposed peak flood prediction model outperformed state-of-the-art LSTM models.

In a study by Motta et al. (2021) used a combination of machine learning and his GIS method to create an accurate flood vulnerability map of the Silavati River Basin based on 12 different theories about the causes of flooding in the region. RF, NB, and XGB (Extreme Gradient Boosting) are his three ensemble machine learning models used in the study of the Silavati River FSM (Tropical Rivers, India). Over 500 historical flood points and field observations were used to generate the training and validation datasets. These include rainfall, elevation, slope, curvature, curvature index, current index, sediment transport index, terrain roughness index, terrain wetness, soil clay content, distance from rivers, drainage density, land use, and included factors such as land cover. Five parameters, including elevation, DD, precipitation, DFR, and SC, were the most influential in determining the flood vulnerability of the study basins, regardless of the model. 36.08% of the basins are classified as very high FSM. Compare three models (ROC) using the multicollinearity diagnostic test, kappa index, MAE (mean absolute error), RMSE (mean squared error), Pearson's correlation coefficient, and receiver operating characteristic (ROC) and verified. RF (84.7%) took first and second place, followed by XGB (83.1%) and (82.1%) models respectively. The RF model outperforms other models in terms of FSM performance.

Andaryani et al. (2021) evaluated the integration of multiple machine learning algorithms to generate a flood sensitivity map, FSM, for the Ajichay River basin in northwestern Iran. The researchers used three artificial neural networks with different activation functions (sigmoid (S), linear (L), interaction (-C), and typicality (-T)) to evaluate the predictability of automatic hard and soft supervised learning classifiers in FSM. They studied the Ajichay River basin in northwestern Iran by integrating these models to estimate the probability of flooding. For the networks, spatial data on ten parameters affecting flooding were provided (elevation, slope, direction, curvature, flow intensity index, topographic moisture index, and lithology). , land use, rainfall, and distance to the river). The FSMs generated from the outputs of the model were trained and evaluated using data from the flood inventory of the Ajichay River basin. Their results show that elevation has the most influence on the model to generate FSM, while curvature has the least effect. Model validation using TOC with AUC (AUC). MLP-S (92.1%) has the highest success rate, while FART-T has the lowest rate (75.8%). The validation throw rates for

MultiLinear Perceptron-S, MLPL, FART-C, FART-T, SOM-C, and SOM-T FSM were 90.1%, 89.6%, 71.7%, and 70.8, respectively. %, 83.8%, and 81.1%. . . The integration of hardware and software-supervised machine learning classifiers with MLP-S and MLP-L-enabled functions demonstrates high flood forecasting capabilities for effective flood risk planning and management. fruit. MLP-S is a promising method for predicting the spatial expansion probability of flooding.

Shirzadi et al. (2020) used Bayesian belief network models and extreme learning machines (GA-BN-NN) to design and test a new ensemble learning model for predicting high-flooded zones in the Haraz basin. A new ensemble learning model developed by researchers was used to predict vulnerability to flash floods in Haraz, Iran. Backpropagation structures augmented by Extreme Learning Machines (ELM) and Genetic Algorithms (GA) are incorporated into a new model called GA-BN-NN. A database of 194 floodplains with 10 impact variables was analyzed with his SVM. As a benchmark model, the proposed model is an artificial neural network (ANN) algorithm with multi-layer perceptron functions (MLP-BP) optimized with a genetic algorithm (GA) and a mixed frog-jumping algorithm (ESTV-MLP). compared. Statistical measures such as sensitivity, specificity, precision, F1 measure, Jaccard coefficient, and mean squared error are used to determine the fitness and accuracy of the training and test datasets, respectively, in relation to the statistical measures. I rated it. According to the results, all 10 variables are related to flooding. Nevertheless, the angle of repose had the highest average value (AM = 9.7) and therefore had the greatest impact on flooding. The results show that the GA-BN-NN model outperforms the SFRAMLP, MLP-BP, and GA-MLP ensemble learning models in terms of goodness of fit and prediction accuracy (AUC = 0.966). As a result, this study concludes that the proposed risk management model can be used in flood-prone regions around the world.

Chobin et al. (2019) Conducted a survey for the purpose of research. i) the ability of the CART, MDA, and SVM methods to predict flood vulnerability, and investigated. (i.e., SVM), iii) assessing the importance of flood-related factors in flood vulnerability mapping, and iv) using and applying ensemble modeling approaches to flood vulnerability mapping. In this study, two new algorithms, Multivariate Discriminant Analysis (MDA) and Classification Regression Trees (CART), along with a well-known technique, Support Vector Machines (SVMs), are used to flood using ensemble modeling. Create a vulnerability map. Using these models, flood inventory maps, and flood control variables, flood vulnerability maps were created (elevation, slope, orientation, curvature, distance from river, terrain wetness index, drainage density, soil depth, soil hydrological group, and land use).). , petrology). The Iranian watershed Kiyavchai was investigated. In this study, we proposed a methodology for flood vulnerability assessment where only models with N80 curacy can be used in ensemble modeling. Jackknife tests determined the significance of factors. A prediction accuracy of 89% was achieved with MDA, followed by SVM (88%) and his CART (0.83%). Slope percentage was an important factor in flood risk mapping, as was drainage and distance from the river.

Teherany et al. (2015) tested and evaluated the ability of the support vector machine technique to predict the occurrence of floods in different geographical locations using different kernel functions. This project studies the Kuala Terengganu Basin in Malaysia. Documentation and field surveys were used to map Terengganu's flood inventory. The training and test sets of flood inventory data are randomly generated. These characteristics include elevation, slope, curvature (SPI), flow intensity index (SPI), topographic moisture index (TWI), distance from the river, geology, use/layer land cover (LULC), soil, and surface runoff. The resilience of the SVM model was investigated using linear, polynomial, RBF, and GIS kernels. Four flood zone maps were created. A probability-frequency (FR) model was used to test and compare the SVM results. The AUC verified the accuracy of the flood sensitivity maps. The study shows that the forecast rate curves for flood sensitivity maps generated by SVM-LN, SVM-PL, SVM-RBF, and SVM-SIG are 84.63%, 83.92%, and 84 respectively. , 97%, and 81.88%. The accuracy of FR is 61.43%. Cohen's kappa index was used to analyze the harmonic factors on the flood sensitivity map. All conditioning factors favorably impact the flood analysis in the present case study, with the exception of surface runoff, which reduces accuracy. Altitude and slope affect all types of winds. SVM is a reliable and effective tool for flood sensitivity assessment. Flood sensitivity maps help mitigate floods.

Nachappara. (2020) investigated creating a flood vulnerability map for the Austrian province of Salzbury. The researchers used two multi-criteria decision analysis (MCDA) models (AHP and ANP) and two machine learning models (random forest and support vector machine) to generate maps (SVM). In this paper, using the Dempster-Shafer theory (DST), he compared CMDA and ML models for flood vulnerability. Evaluate the use of DST to determine results based on location, slope, slope orientation, terrain wetness index (TWI), current intensity, NDVI, geology, precipitation, land cover, distance to road, drainage distance, etc. We optimized the flood vulnerability map obtained as. After accurately evaluating the flood vulnerability map using AUC (area under the receiver operating characteristic curve), the SVM (AUC = 87.8%) is the model's ANP (AUC = 86.6%) and AHP (AUC = 85.9%). flood density. As a result, the ML model outperformed the MCDA model in terms of accuracy. For both ML (AUC = 88.3%) and MCDA models (AUC = 87.3%), DST may further improve accuracy. However, the ensemble of all four models shows the best accuracy (AUC = 89.3%).

A study by Elsafi (2014) to predict the flow of the Nile at the Dongola station in Sudan using an artificial neural network (ANN) as a model used an ANN model to simulate how the river flows at a certain location within the reach of the river depending on how the river flows in upstream places. ANN used different methods to make flood forecasts. Between 1965 and 2003, data from stations along the Blue Nile, White Nile, Main Nile, and Atbara rivers were used to determine the flood potential of Dongola Station. To avoid unnecessary duplication, the performance of each scenario was tested, and the structure with the fewest layers and neurons was chosen. Compared to more complex models, ANN has the advantage of simplicity. Therefore, the ANN technique is the best choice for flood forecasting when data is scarce or difficult to collect. By reducing the time required to analyze data, neural networks (ANNs) can reduce the cost of analyzing topographic and hydrological information.

Rezaeianzadeh et al. (2014) studied his MLP network and his application of ANFIS for peak runoff forecasting, using geographically distributed precipitation and area-weighted average precipitation as inputs to the network. Researchers used artificial neural networks, adaptive neuro-fuzzy inference systems, multiple linear regression, and multiple nonlinear regression to predict his maximum daily flow in the Khosrow Sirin watershed in Fars Province, Iran. Did. A multilayer perceptron topology model was developed using data from four weather stations. The simulations used precipitation data, area-weighted averages, and staggered prior runoff of 1 and 2 days. We used R2 and root mean square to evaluate model performance. Results showed that area-weighted precipitation as input to ANNs and MNLR and spatially distributed precipitation as input to ANFIS and MLR yielded more accurate predictions (e.g., maximum

RMSE 2.0 m3 s-1 reduction). MNLR outperformed ANN, ANFIS and MLR ($R2 = 0.81$ and $RMSE = 0.145$ m3 s-1) to predict maximum daily flow ($R2 = 0.81$ and $RMSE = 0.145$ m3 s-1).

Paul & Das (2014) conducted a study to determine suitable input parameters for an optimized ANN and build the most effective network architectures for next-day river-level prediction. Using artificial neural networks (ANNs), researchers have developed a model to predict river flooding. This model uses precipitation and current river-level data to estimate river levels. Only two of the many factors that affect water levels are considered. Nonlinear tasks such as flood forecasting require the use of ANNs. Predict flooding using feed-forward (FF) and back-propagation (BP) techniques for multi-linear perceptron (MLP)-based ANNs. Statistical analysis results show that the data fit the model very well. Here we report simulation results for expected and actual water levels. The results show that the proposed model can accurately predict the height of flood levels 24 hours in advance.

Tabbusum & Dar (2021) conducted a study to improve flood forecasting systems in regions where data quality, availability, and reliability are low and access to complex models is limited. In this work, we explored a new computational paradigm based on artificial intelligence (AI) to better understand the current flow. The flood prediction model was developed by combining artificial neural networks (ANN), fuzzy logic, and the adaptive neuro-fuzzy inference system 'ANFIS'. method. Several statistical performance evaluators were used to measure the performance of the generated models. Flood simulations in the study area were used to assess the model's ability to predict and withstand extreme weather events. A model was built with a total of 12 different inlets. We build fuzzy models using two fuzzy inference systems (Mamdani and Sugeno) and train ANFIS models (hybrid and backpropagation). The ANFIS model with an NSE of 0.968, an R2 of 97.066%, an MSE of 0.00034, a mean squared error (RMSE) of 0.018, a mean absolute error (MAE) of 0.0073, and a combined accuracy (CA) of 0.018% uses the hybrid training algorithm. The model developed by using has the best performance metric, indicating that the developed model can be used for flood forecasting. The significance of this work lies in the fact that the flood model was created using a combination of numerous inputs and AI algorithms. Thanks to this research, it was discovered that models based on AI algorithms can be used by many state, regional, and national flood control agencies to predict floods.

Puttinaovarat & Horkaew (2020) integrate meteorological, hydrological, geographic, and crowdsourced big data into an adaptive machine learning framework to propose an innovative flood forecasting system. This research paper presents a novel flood forecasting method that integrates crowdsourcing, meteorological, hydrological, and other data sources into a machine learning framework. This data was collected from various big data platforms (APIs) using Web APIs. Machine learning techniques were used to drive the prediction mechanism. Decision Trees, Random Forests, Naive Bayes, Artificial Neural Networks, Support Vector Machines, and Fuzzy Logic were evaluated to find the best fit for the job. We find that the proposed method can accurately predict flooding at specific locations and timeframes based on both subjective and objective evaluations. The MLP ANN configuration for this system has proven to be the most effective in benchmark studies, with 97.93, 0.89, 0.01, and

0.10 for the other four indicators.

Liong and Sivapragasam (2002) used machine learning models to predict flood stages in Dhaka, Bangladesh. They used SVM (Support Vector Machine), an innovative regression technique based on statistical learning theory. Structural risk minimization is a fundamental premise of SVM, not empirical risk minimization, which is a fundamental principle of traditional regression analysis. The forecasting capabilities of SVM are demonstrated using flood data from Dhaka, Bangladesh. The results are compared with those of the ANN-based model for predictions from 1 to 7 days. The most significant water level errors predicted from SVM over ANN are 9.6 cm, 22.6 cm, 4.9 cm, and 15.7 cm, respectively, at 4-7 derivative days. The results show several advantages of using supervised learning models (SVMs) instead of artificial neural networks (ANNs). B. You are more likely to choose a meaningful training set, improving your ability to arrive at a good network architecture. This shows that SVM can make good predictions.

Chapter III

3.0 Methodology

The methodology section of this thesis is generally categorized into 1) general and specific description of the study area, 2) explanation of both input and output parameters, 3) data and data source, and 4) definition and scoping of three families of the models (ANNs: Feedforward Multilayer Perceptron (FMLP), Elman Neural Network (ENN), and Cascade Forward based Neural Network (CFBNN).

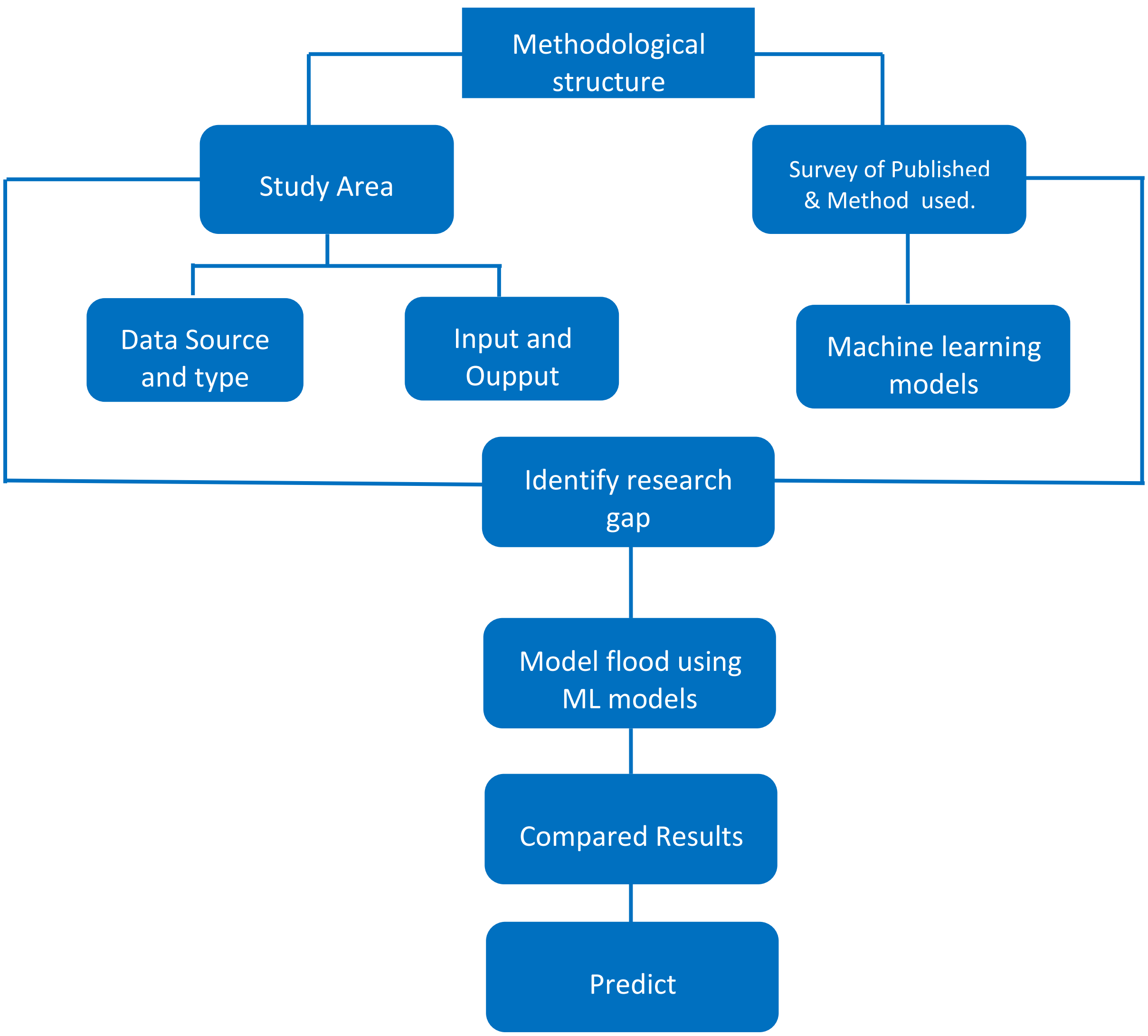

Figure 1: Order of the Research Methodology

3.1 Description of the Study Area

Liberia's capital and largest city, Monrovia, is located in Montserrado County and serves as the country's administrative, commercial, and financial center ((UN-Habitat - A Better Urban Future | UN-Habitat, undated). About two million people live in the city. Monrovia, Monrovia is located along the coast of the Meslard Peninsula between the Atlantic Ocean and the Meslard River, whose estuary offers vast natural areas. It has a tropical monsoon climate according to the Köppen climate classification (Am). With an average annual rainfall of 4,624 millimeters (182.0 inches), it is the wettest capital city in the world. In addition to its 10 m (33 ft) elevation along Monrovia's coast, the city is heavily drained by Stockton Creek, the main river that connects central Monrovia to Bushrod Island. These features, combined with the city's incredible rainfall rate, make it a breeding ground for flooding during the wet season.

Therefore, this research is essential.

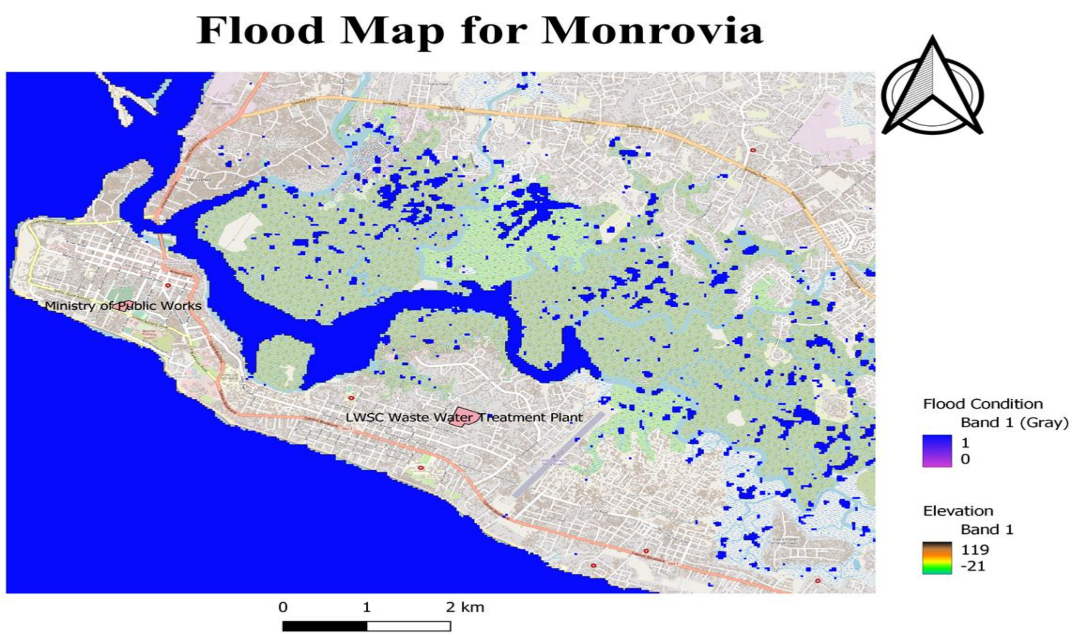

Figure 2: Map of Study Area

Table 1: Climatic Overview (Monrovia)

Latitude (N)	6.3156
Longitude (W)	10.8074
Min Temp (□C)	23
Max Temp (□C)	27
Elevation (m)	10
Area (km^2)	194.2

3.2 Data Type and Source

The data used for this research is satellite-based. The source is TerraClimate

(https: http://climatetoolbox.org/tool/data-download). 40 climate data were obtained from 1980 to 2020. The data includes flood predictor variables such as precipitation, soil moisture, maximum and minimum temperatures, wind speed, and runoff. The reason for choosing satellite data is that it has a slight access advantage over real data. Observatory-based observations from multiple networks, such as the Global Historical Climate Network, SNOTEL, and RAWS, provided adequate validation for TerraClimate. Additionally, TerraClimate's improved geographical realism made the validation results slightly better than those obtained with the original CRU Ts 4.0 data, especially the error measures. (TerraClimate - Climatology Lab, undated). The study area has severe data access restrictions, with no coordinated weather reporting system. In an age of increasingly scarce resources, most researchers have turned to use terrestrial climate data to predict climatological events. TerraClim uses climate-assisted interpolation to generate monthly datasets of precipitation, maximum and minimum temperatures, wind speed, vapor pressure, and solar radiation. This is done by combining high spatial resolution climatological normals from the coarser time-varying resolution WorldClim dataset (i.e. monthly). Data from other sources (Abatzoglou et al. 2019). Wiwoho & Atsushi (2019) describe the use of Terraclimate data, suggesting that TerraClimate monthly runoff data are available worldwide and consequently in data-poor locations despite the limitations imposed by runoff data. He pointed out that it can be used to complement local water resource assessments. Liberia is a data-poor region, so the use of deracinating data provides more opportunities for improving flood forecasts.

3.3 Simulation Models

The models (Machine learning) discussed here are used for training and testing the input and output data to establish a relationship and make the prediction process easier.

3.3.1 Artificial Neural Networks (ANNs)

Artificial neural networks combine input and output signals using models that mimic how living brain networks respond to sensory stimuli (Maspo et al., 2020). Artificial Neural Networks (ANNs) can be taught to recognize and generalize relationships between sets of inputs and outputs with appropriate instructions (Sulafa, 2014). Neurons are connected like nodes by a network of cells that connect inputs to outputs through hidden layers. The network takes in data and later trains it via the input to identify patterns with hidden layers and produce (predict) the output. The input layer is the core processor of the network. Most computations are done in hidden layers. The output layer is where predictions, or results, are output from the network. Artificial neural networks are a leading tool for cross-industry forecasting. In many fields, including business, medicine, and engineering, ANNs have proven effective in solving problems that are otherwise impossible to understand, explain, or measure (Dawson et al. ., 2006). Due to the inherent nature of ANNs, it is not necessary to have a deep understanding of how the system works for these models to successfully map inputs and outputs (Rezaeiazadeh et al., 2013; Kisi, 2004). . ANN has several subcategories.

3.3.1.1 Multilayer Perceptron (MLP)

This type of ANN contains an input layer, a hidden layer, and an output layer of neurons. Each neuron has multiple inputs (from the outside world or previous layers) and multiple outputs (to other neurons) (from subsequent layers or networks). A neuron uses an activation function to compute its output response from the weighted sum of its inputs (logistic sigmoid in this case). In a unidirectional network, data enters an input layer (predictors), travels through hidden layers, and exits an output layer (predictors). Error backpropagation is used to train the network by changing the weights connecting neurons. By feeding the network a set of training instances (predictors and their associated predictors), the entire network can be trained to adjust weights and make predictions. The network must repeat this process in order to learn to model connectivity. In FFNN, data moves from input nodes to hidden nodes (if any) and then to output nodes, but not vice versa (Abiodun et al., 2018). Figure 3.3 shows a feedforward multilayer perceptron (FFMLP).

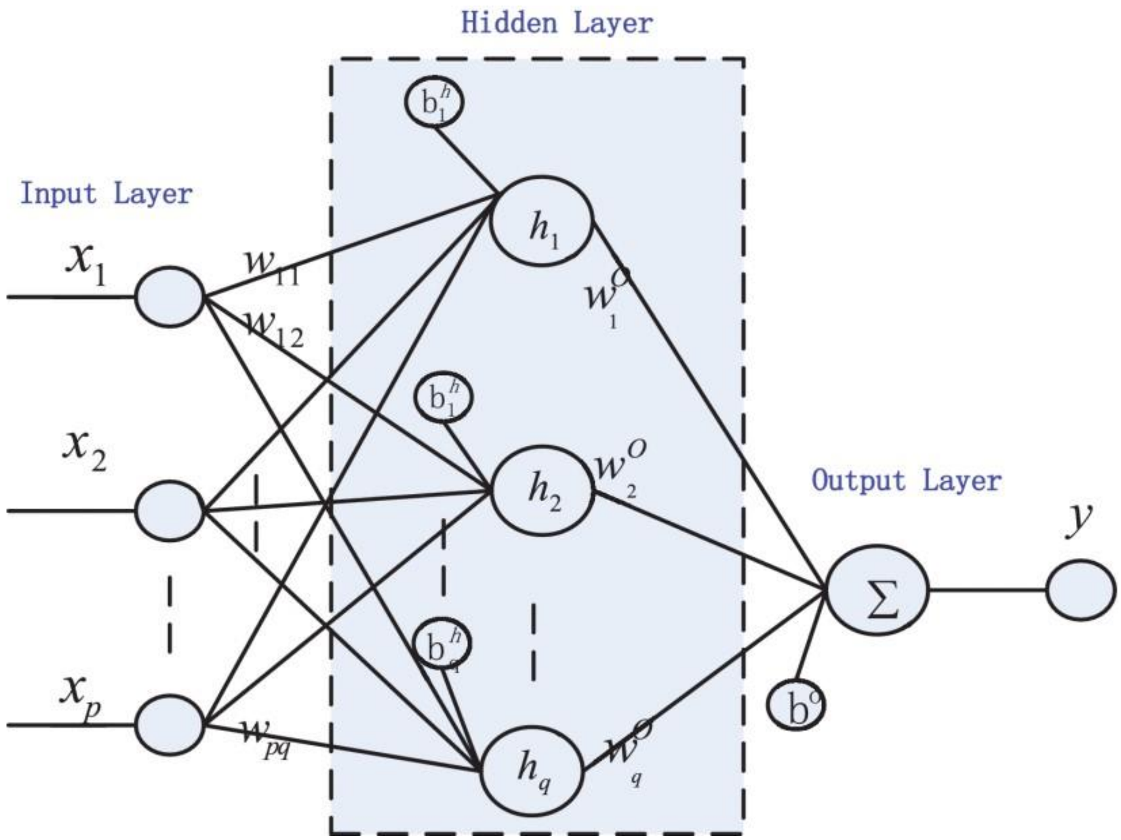

Figure 3: Design of Multilayer Perceptron (Sun et al. 2016)

As the figure above shows, inputs are fed to the network through the input layer, where processing begins in a feed-forward mechanism. The data leaves the input layer to the output layer through the hidden layer, where most of the learning occurs. This sequence of forwardness, with intermittent backpropagation for checking and correcting errors, mimicked after the human brain, makes the Artificial Neural Network a near-perfect prediction model used in almost all research fields.

Why FMLP?

Several studies on river flooding and other hydrological models suggest that feedforward neural networks are effective predictive tools. This is due to the ease of handling and processing nonlinear inputs using sophisticated perceptrons and sigmoid neurons in neural networks. Latt (2015), "Application of Feedforward Artificial Neural Networks in Muskingum Flood Routing:

A black-box prediction approach for natural river systems”. FMLP models outperform competing flood management approaches using widely accepted benchmark data measured by metrics such as a sum of squares, efficiency factor, peak flow error, and time-to-peak error. I was. In societies such as Liberia with low data accuracy, Thirumalaiah & Deo (1998) found that the application of neural networks does not require a priori knowledge of the underlying processes, and the underlying problem is well defined. Effective even if you don't. I see clearly.

3.3.1.2 Cascade Forward Neural Network (CFNN)

Like all other forms of artificial neural network models, CFNNs are designed to mimic the structure of the human brain, allowing for robust processing of inputs. It is similar to a feedforward multilayer perceptron (FMLP). However, they differ in certain areas, such as A CFNN that connects the input to neurons in the next hidden layer, allowing it to accept nonlinear input-output relationships without completely removing linear relationships (Hayder et al., 2020; Warsito et al., 2018). The layers of a CFNN model are connected to each other, the layers below and above are connected via weighted connections, and the model can use one or more hidden layers with different transfer functions (Larestani et al., 2022). . Expression is different. Input layers affect all subsequent layers (Devi et al., 2016). CFNNs optimize weights and biases using a variety of training algorithms. Computational neural networks use neurons, which are essentially small computers. Weights assigned to neurons strengthen neurons (Nami & Deyhimi, 2011). Arguably, considering an appropriate number of hidden layers facilitates the training process of cascaded ANNs (Esfe & Toghraie, 2021). Below (Figure 3.4) is a sketch of a Cascade Forward Neural Network (CFNN).

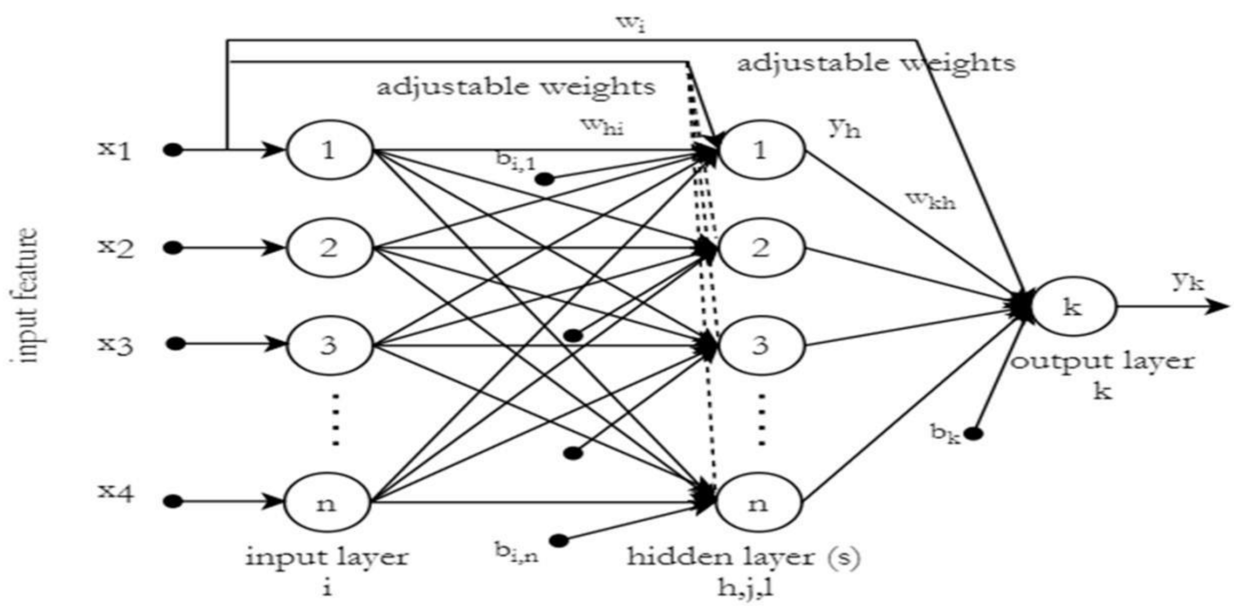

Figure 4: CFNN Model schematics (Hayder et al., 2020; Tengeleng & Armand, 2014)

Why CFNN?

Cascade neural networks, like feedforward neural networks, are very good at predicting hydrological features in areas with severe data deficiencies. Cascading ANNs, like feedforward ANNs, can be trained (via training, testing, and validation phases) to recognize specific logical relationships between inputs and outputs. Hader et al. (2020) used a cascade forward neural network to model the river flow of the Kelantan River in Malaysia. They found that using CFNN yielded acceptable prediction accuracy during model testing, with regression coefficient (R2), root means square error (RMSE), and mean percent error (MPE) values of 0.88, 191.1 cms, and 0.09%. .

3.3.1.3 Elman Neural Network (ENN)

Elman neural networks are simplified models of recurrent neural networks based on feedforward connections. It has short-term memory because it remembers the previous state and can pass the output of the hidden layer on the next iteration (Liu et al., 2018; Wang et al., 2014). The network consists of four layers. ie:

1) the input layer, which is considered the primary layer where the input variables are fed, 2) the hidden layer where most of the work in the network is done, 3) the context layer, and 4) the output layer. The connections between the input layer, hidden layer, and output layer can be

viewed as a feedforward network. This section resembles a traditional multilayer neural network (Ren et al., 2018). The context layer mainly acts as a one-step delay operator that provides a feedback function by remembering the instantaneous value of the output of the hidden layer (Jai et al., 2019). Elman neural networks are better at predicting time series data accurately than other models (Li et al., 2019; Xiaowei et al., 2009). By using a context layer, the outputs of the hidden layers are directly connected to the corresponding inputs of the hidden layers. To create dynamic modeling, this strategy becomes sensitive to historical data (Yan et al., 2021). Below (Figure 3.5) is a typical Elman neural network schematic.

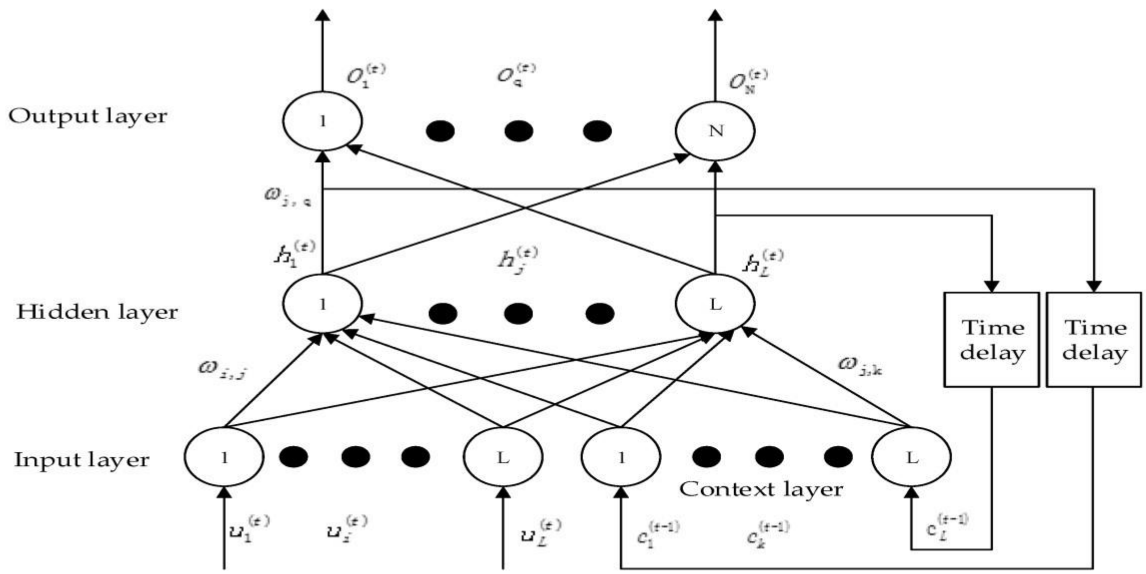

Figure 5: Schematic of the Elman Neural Network (Jai et al., 2019)

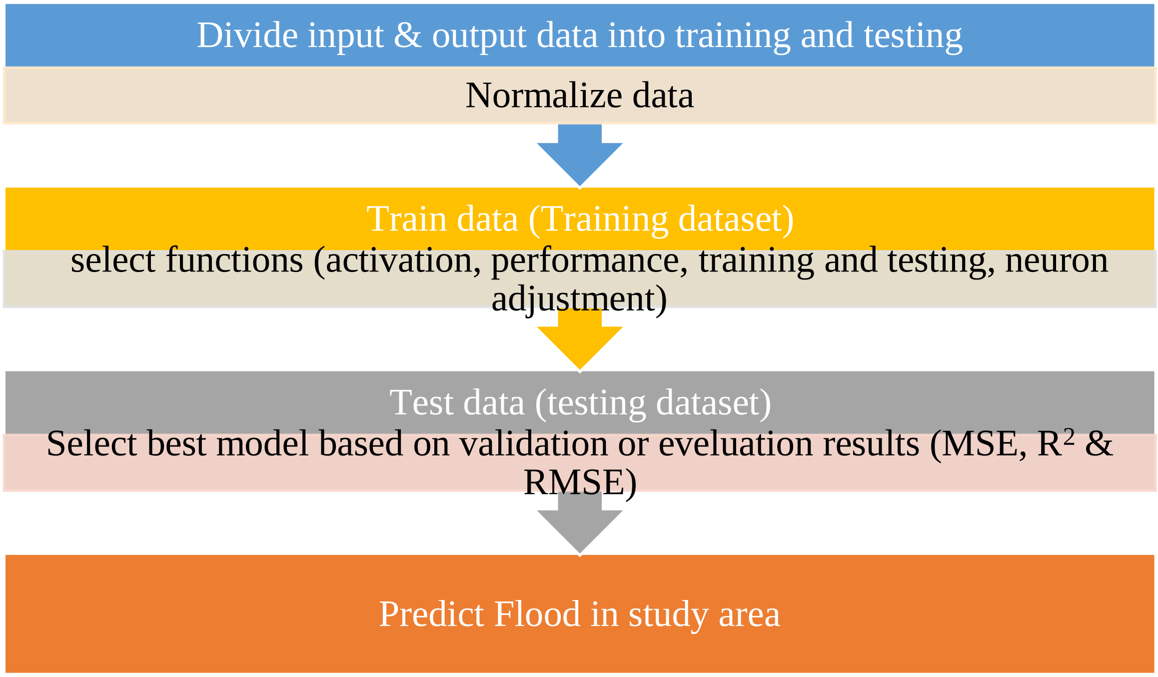

Figure 6: General Flowchart of the Models (FMLP, CFNN & GRNN

3.4 Training and Testing

To use the ANN algorithm, we need to normalize the data and split it into training and test data. Training data is a dataset used to train machine learning algorithms to record patterns or trends in specific time series data. During the training phase, the machine learns something new. This process of splitting the data into training and testing is often called out-of-sample testing. After the training phase, tests are run to determine the accuracy of the model. When working with time-series data, it is recommended to use old data for the training phase and new data for the testing phase. The goal of training an artificial neural network is to fine-tune the connection weights so that its inputs and outputs closely match the relationships between respective structures in the training data (Keong et al., 2016). Different activation functions are used during the training and testing phases of neural networks. How a node or group of nodes in a particular layer of a neural network transforms a weighted sum of inputs into output is defined by that layer's activation function. In this work, we use a sigmoidal activation function, which has proven robustness. The value ranges from 0 to 1 and the function defines it as:

$$y = 1/(1 + e^ - x) \tag{3.1}$$

There are many training algorithms for neural networks. Predicting which training algorithm will give the best results is a difficult task (Sundar et al., 2012). However, in this work, we use the gradient descent backpropagation function as the training function. When using GD, the weights are arranged so that the square root of the error derivative for each weight is equal to one. As a type of BP, GD is the easiest to implement (Cömert & KOCAMAZ, 2017). 40 years of data (1980 to 2020) are split into training and testing datasets by 70% and 30% ratios respectively. The data are normalized by the formula:

$$x = \frac{x - x_{m_i n}}{x_{m_i x} - x_{max}} \tag{3.2}$$

where X represents the ser of observed values or first number in the data, X_{min} is the minimum value in the dataset, and X_{max} represents the largest number or point in the dataset.
The data were normalized to make the range between -1 and +1 so that machine learning models could understand easily.

3.5 Model Accuracy Evaluation

During the training and testing stages of various models with input and output variables, statistical methods are used to determine the model's error bars and predictive accuracy. We use the mean squared error (MSE) and the root means squared error (RMSE) as measures of error and the R-squared value for prediction accuracy.

3.5.1 Mean Square Error (MSE)

Mean squared error is a statistical tool used to determine how close or far the predicted values are to the actual values. Values are between 0 and positive infinity (0-□). The smaller the value, the more accurately the model can predict the output. The value is calculated using the formula:

$$\text{MSE} = \frac{1}{n} \sum_{i=0}^{n} (a_a , i - a_{p,}, i)^2 \tag{3.3}$$

where n is the number of counts or samples, i for variables, a_a is the actual value, and a_p is the predicted value.

3.5.2 Root Mean Square Error (RMSE)

Like the MSE, the RMSE is a statistical measure of how closeness or farness of predicted variables to the real or actual variable. The RMSE shows how tightly the data clusters around the regression line. Like the MSE, smaller values show a better fit of the model for predicting the output. The RMSE is computed using the formula:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=0}^{n} (a_a , i - a_{p,}, i)2} \tag{3.4}$$

3.5.3 R-square

An r-squared analysis of certainty shows the correlation between the dependent and independent variables. R-Squared measures how well the independent variables predict the variance of the dependent variable. Values range from 0 to 1. The closer the Rsquare value is to 1, the more accurately the model describes the relationship between the explanatory and response variables. The closer the problem is to 0, the less accurate the model is at determining relationships from the regression trend line. R-squared values are given as percentages.

The R-squared equation is defined as

$$R^2 = 1- \frac{\sum_{i=0}^{n}(a_a,i-a_p,i)2}{\sum_{i=0}^{n}(a_a,i-a_p,i)2} \tag{3.5}$$

3.6 Input and Output Variables

Several climatological variables have been used in research pertaining to flood forecasting globally. To accurately simulate the hydrological processes during a flood, rainfall data is a crucial input variable in rainfall-runoff modeling (Wu et al., 2019). When analyzing a region's hydrology and climate, rainfall is the most important factor to consider (Hamed et al., 2021). Of the essential flood prediction variables, the study selects and uses five input variables (precipitation, windspeed, minimum temperature, maximum temperature, and soil moisture) to predict the output variable (Runoff). Given that no previous study has been carried out in the study area, comparing variables by other researchers is impossible. The selected input variables all seem to have an impact on runoff. Rainfall being the chief contributor to flash floods in the area is received in high proportion year-round. Due to Monrovia's low elevation (approx. 10m), Windspeed increases ocean tides, thus, exacerbating coastal floods in the slum habitats of the city. Maximum and minimum temperature are utility climatological variables that influence the hydrological cycle, consequently impacting flooding incidences. The soil moisture, or the amount of water available in the soil, is integral in flood forecasting scenarios. If the water limit in the ground exceeds what the soil can hold, it leads to runoff and subsequent flooding. The figure below details the input and output variables used in this study and maps their relationship:

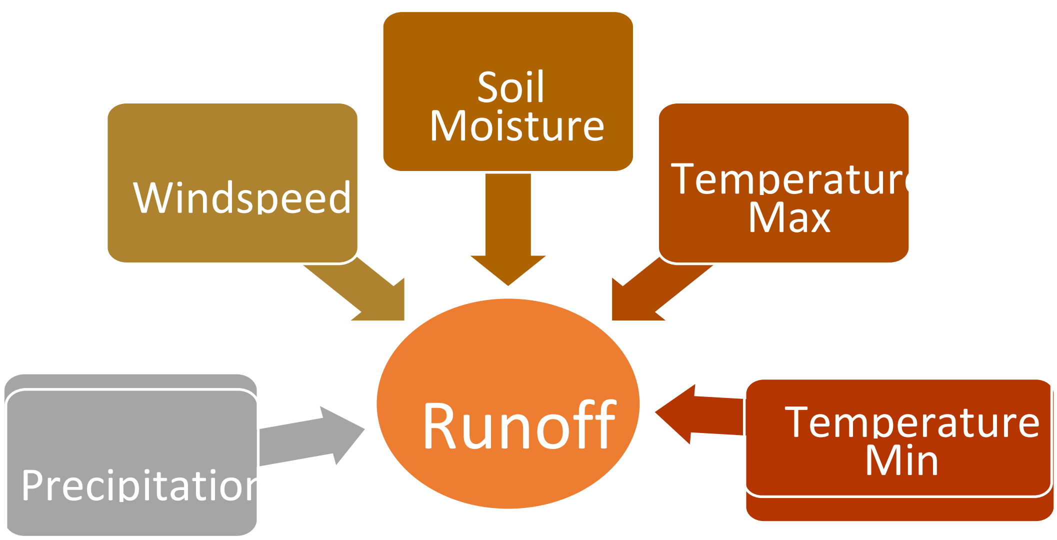

Figure 7: Input and Output Variables

Chapter IV
4.0 Results and Discussion

This chapter of the thesis presents the results from the different data analyses using the selected models. The results are presented separately for each model. A total of 18 models were trained and tested; 6 from each ANNs model were selected for the study. The most appropriate model is selected based on the maximum R^2 value and the least RMSE value. Also, to ease the training period and model performance, we selected a uniform layer for all models (2 layers) while alternating all other conditions, including the number of neurons and transfer function. Figure 4.1 shows the general layer architecture for all the models used in this study.

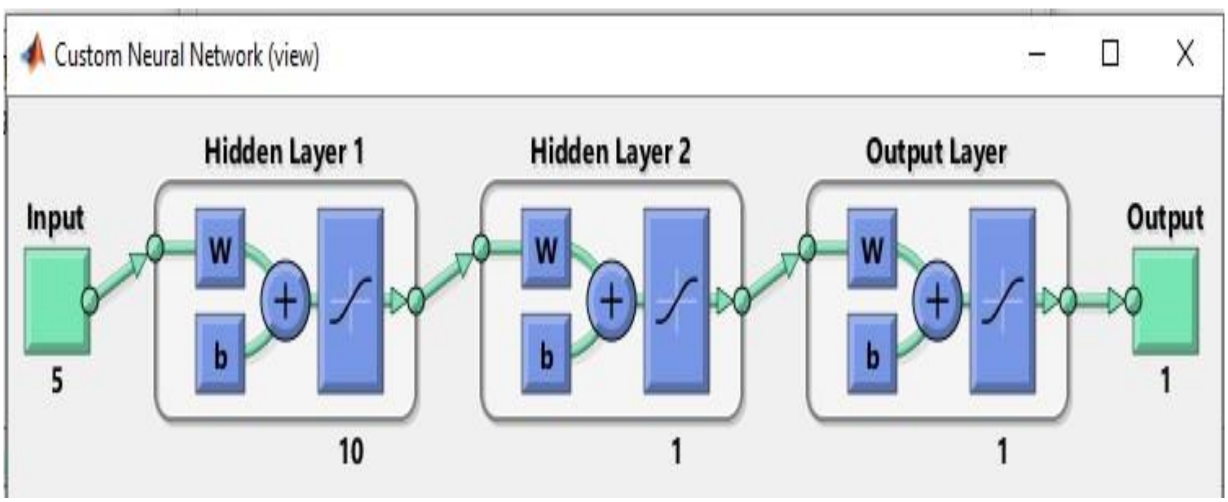

Figure 8: General Model Layer Architecture

4.1 Results

Cascade Feedforward Neuron Networks with all five inputs

All five input parameters were fed to the network architecture and tried several times using alternating transfer functions with varying numbers of neurons to determine the best model for forecasting flood. The accuracy of the models was measured using the R^2 and MSE values. The CAS-5 recorded the highest R2 value, 57.2%, of the six cascade models trained and simulated for the training phase. In terms of RMSE value, CAS-1 produced the most negligible value, 0.039412. Table 4.1 displays all six models with their corresponding statistical values.

Table 2: Evaluation of the CFNNs with corresponding statistical results for Training with all five inputs

TRAINING DATA					
Model	#Layer	#Neurons	Transfer Function	R	RMSE
CAS1	2	10	TRANSIG	0.304301	0.039412
CAS2	2	12	TRANSIG	0.513484	0.080584
CAS3	2	15	TRANSIG	0.468897	0.062016
CAS4	2	18	LOGSIG	0.311731	0.082654
CAS5	2	20	LOGSIG	0.571614	0.098464
CAS6	2	25	LOGSIG	0.445304	0.092811

Table 4.2 shows the result for the testing stage of the cascade network analyses with matching statistical values. For the testing phase, the CAS-1 model was the best in terms of the coefficient of determination, 0.515101211. The CAS-3 produced the best Root Mean Square Error value, 0.068528.

Table 3: Evaluation of CFNNs at testing with all five inputs given the statistical performance (Testing)

TESTING DATA					
Model	#Layer	#Neuron	Transfer Fn	R square	RMSE
CAS1	2	10	TANSIG	0.515101211	0.104795
CAS2	2	12	TANSIG	0.218779062	0.106285
CAS3	2	15	TANSIG	0.15579065	0.068528
CAS4	2	18	LOGSIG	0.467701769	0.148414
CAS5	2	20	LOGSIG	0.220331122	0.175418
CAS6	2	25	LOGSIG	0.38757512	0.11573

To discover which of the five input parameters produces the most accurate flood prediction model, the network design was run through a series of iterations in which alternate transfer functions were applied to different numbers of neuronal connections. The R^2 and RMSE values served as the yardsticks for determining how accurate the models were. For the training phase, Elman-1 had the highest R^2 value, 0.670939. The Elman-5, 0.056034, is the least, thus the best model for predicting flood. Table 4.3 summarizes the six ENN models with corresponding statistical values.

Table 4: Evaluation of the Elman Neuron Network models with statistical performances with all five inputs (Training*)*

TRAINING DATA					
Model	#Layer	#Neurons	Transfer Function	R_2	RMSE
ENN1	2	10	TRANSIG	0.670939	0.089628
ENN2	2	12	TRANSIG	0.487991	0.064425
ENN3	2	15	TRANSIG	0.394586	0.067532
ENN4	2	18	LOGSIG	0.545304	0.070924
ENN5	2	20	LOGSIG	0.379894	0.056034
ENN6	2	25	LOGSIG	0.548861	0.081477

For testing, though seemingly insignificant, Elman-3 had the highest R^2 value, 0.377333. The Root Mean Square Error was suitable for the Elman-5, recording 0.074159. Table 4.4 shows the result for the Elman network with the statistical performance results.

Table 5: Elman Neuron Network model evaluation with the statistical performance results

TESTING DATA					
Network	#Layer	#Neuron	Transfer Function	R_2	RMSE
ENN1	2	10	TRANSIG	0.281649	0.224372
ENN2	2	12	TRANSIG	0.139584	0.061516

ENN3	2	15	TRANSIG	0.377333	0.084549
ENN4	2	18	LOGSIG	0.241963	0.08662
ENN5	2	20	LOGSIG	0.328079	0.074159
ENN6	2	25	LOGSIG	0.222026	0.074495

For the feedforward neural network, the same five inputs were used, varying the transfer functions between TANSIG and LOGSIG, neurons spanning from 10 to 25, with a layer constant of 2. The model accuracy evaluation was conducted using the statistical coefficient of determination, R^2, RMSE, and MSE values to determine the best model for predicting flood. Of the six FFBNN models trained and simulated, the FFBNN-6 recorded the highest value, 0.615387, for the training phase, corresponding to the LOGSIG transfer function. The least RMSE value is 0.069712, corresponding to FFBNN-3. Table 4.5 shows a summary of the results for the FFBNN models with the statistical evaluations.

***Table 6*: Evaluation of the Feedforward Multipercetron Neuron Network models with statistical performances with all five input variables (Training)**

TRAINING DATA					
Model	#Layer	#Neuron	Transfer Fn	R square	RMSE
FFB1	2	10	TANSIG	0.538124	0.11675
FFB2	2	12	TANSIG	0.514109	0.078954
FFB3	2	15	TANSIG	0.538225	0.069712
FFB4	2	18	LOGSIG	0.421066	0.092256
FFB5	2	20	LOGSIG	0.589046	0.08475
FFB6	2	25	LOGSIG	0.615387	0.114785

For testing, the FFBNN-5 produced the highest R^2 value, 0.328919. FFBNN-5 gives the best RMSE value, 0.082873. Table 4.6 displays the testing results for all six FFBNN models.

Table 4.6

Table 7: : Evaluation of Feedforward Neuron Network at testing with all five inputs given the statistical performance (Testing)

TESTING DATA					
Model	#layer	#neuron	Transfer Fn	R square	RMSE
FFN1	2	10	TANSIG	0.193861	0.222464
FFN2	2	12	TANSIG	0.290088	0.117746
FFN3	2	15	TANSIG	0.200115	0.082873
FFN4	2	18	LOGSIG	0.328919	0.122503
FFN5	2	20	LOGSIG	0.230033	0.126581
FFN6	2	25	LOGSIG	0.143347	0.198418

Of all the training results, Table 4.7 indicate, based on the R^2 value, the Elman-1 model, TANSIG transfer function, and 10 neurons performed best with a score of 0.670939; followed by the FFBNN- 6, R^2 value of 0.615387, the LOGSIG transfer function, and 25 neurons. Table 4.7 summarizes the result based on R square value.

Table 8: : Best Model for Training Data (R square Value)

Best Model for Training Data (R square Value)				
Model	#Layer	#Neuron	Transfer Fn	R square
Elman 1	2	10	TANSIG	0.670939
FFB 6	2	25	LOGSIG	0.615387
Cascade	2	20	LOGSIG	0.571614

Based on Root Mean Square Error, the results show that the Cascade-1 model performed better than the others, recording 0.039412, followed by Elman-5, 0.0.56034. Table 4.8 gives an overview of the results based on RMSE value.

Table 9: Best Model for Training (RMSE value)

Best Model for Training (RMSE value)				
Model	#Layer	#Neuron	Transfer Function	RMSE
Cascade 1	2	10	TANSIG	0.039412
FFB 3	2	15	TANSIG	0.069712
Elman 5	2	20	LOGSIG	0.056034

The testing results suggest that model CAS-1, with transfer function TANSIG and 10 neurons; produced the best coefficient of determination value of 0.515101. This is followed by the Elman3 model, which recorded an R^2 value of 0.377333. The Feedforward multipercetron Neuron Network recorded the least R^2, 0.328919. The table below, Table 4.9, summarizes the findings based on R^2 values for the testing phase.

Table 4.9:

Table 10: Best Models for Testing dataset (R square Value)

Best Models for Testing dataset (R square Value)				
Model	#Layer	#Neuron	Transfer Function	R_2
Cascade 1	2	10	TANSIG	0.515101
Elman 3	2	15	TANSIG	0.377333
FFB 4	2	18	LOGSIG	0.328919

Based on the RMSE, the Elman-2 model performed best for the testing phase with a value of 0.061516, followed by the CAS-3 model, 0.068528, and lastly, the FFBNN-3 with an RMSE score of 0.082873. Table 4.10 captures the best models based on RMSE values for the testing phase.

Table 11: Best Model for testing dataset (RMSE value)

Best Model for testing dataset (RMSE value)				
Model	#Layer	#Neuron	Transfer Function	RMSE
Elman 2	2	12	TANSIG	0.061516
Cascade 3	2	15	TANSIG	0.068528
FFB 3	2	15	TANSIG	0.082873

4.2 Discussion

From the analysis, the Cascade Feedforward Neuron Network demonstrated the most robustness in terms of statistical coefficient of determination. With all five inputs fed to the network architecture, the CAS-1, with ten neurons, two hidden layers, and a TANSIG transfer function, gave 51.5%, followed by the Elman-3 model with an R^2 value of 37.8%. The Feedforward Neuron Network produced the least R^2 value of the three models. The Cascade Feedforward Neuron Network's superior robustness can be attributed to the fact that its Layers are connected to each other and the layers below and above. In terms of Root Mean Square Error analysis, the Elman-2 model performed best for the testing phase with a value of 0.061516, followed by the CAS-3 model, 0.068528, and lastly, the FFBNN-3 with an RMSE score of 0.082873. Table 4.10 captures the best models based on RMSE values for the testing phase. Of all the training results, Table 4.7 indicate, based on the R^2 value, the Elman-1 model, TANSIG transfer function, and 10 neurons performed best with a score of 0.670939; followed by the FFBNN- 6, R^2 value of 0.615387, the LOGSIG transfer function, and 25 neurons. Table 4.7 summarizes the result based on the R square value. Figure 4.2 displays the relationship between the real value and predicted runoff values. The scatter plot demonstrates a positive correlation.

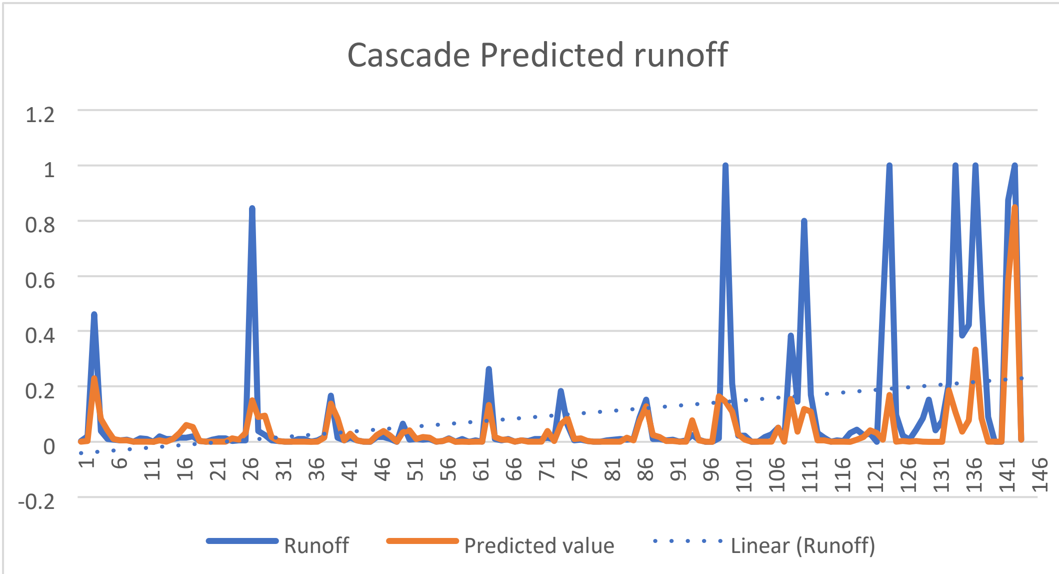

Figure 9: Actual VS Predicted value of Runoff

4.3 Input Sensitivity Analysis

Five input variables were selected for this flood prediction modeling. The variables were chosen based on their presumed relationship to the output variable. An input intensity analysis was conducted using the Minitab 17 software data analysis tool to determine the variable with the most impact on flooding in the study area. The multiple linear regression model was employed with rainfall, windspeed, soil moisture, minimum temperature, and maximum temperature as independent variables, while runoff was considered the response variable. Of all five input variables: rainfall, windspeed, soil moisture, and maximum and minimum temperature, rainfall recorded the highest intensity influencing flooding in the study area, followed by windspeed and soil moisture. High torrential downpour creates inundation, thus increasing the soil moisture content. The coastal location of Monrovia also makes it susceptible to wind-induced coastal flooding. Maximum and minimum temperatures had a somewhat negligible impact on flood incidence. However, their impact is conditional on the season- during the rainy seasons, low temperature reduces evaporation.

In summary, the five selected input variables all impact runoff and, consequently, flooding. Below in figure 4.3, a scatter plot diagram explains the relationship between actual and predicted runoff values.

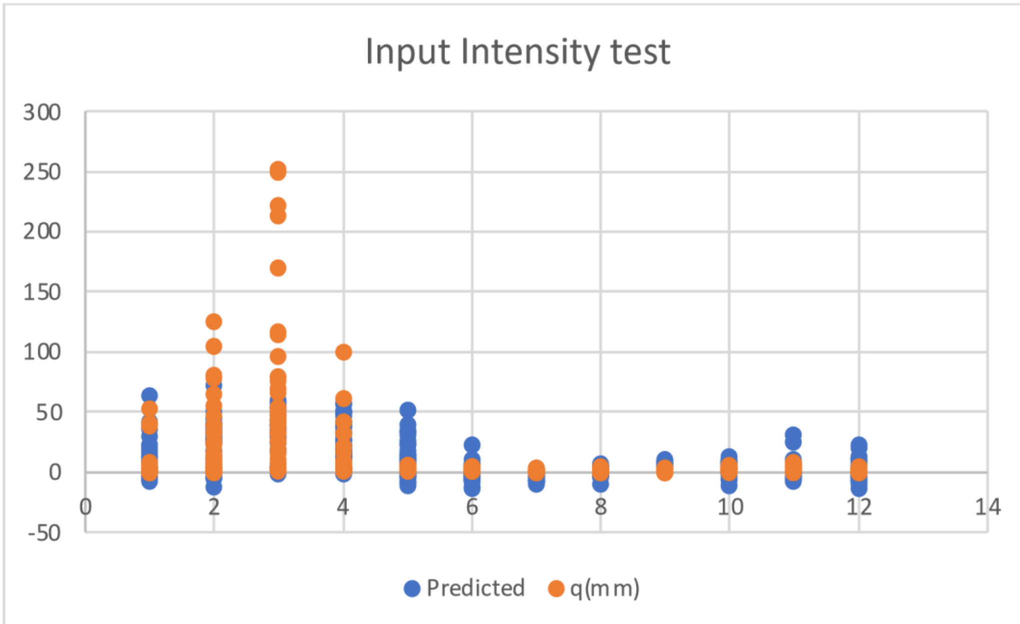

Figure 10: Input Variables Intensity Graph

Chapter V

5.0 Conclusion and Recommendation

5.1 Conclusion

Flooding continues to be the most devastating disaster undermining viable urban planning in the developing world. Coastal cities are even more vulnerable, considering their low elevation. Monrovia is regarded as one of the wettest cities globally, with rainfall averaging annually at approximately 4600mm. In addition to this massive rainfall potential, the city is drained by small and large rivers, creating marshes and swamplands. This research aimed at modeling floods using machine learning algorithms to ensure better policy planning to prevent flood disasters' dangers. In the current study, we suggested the application of a subclass of artificial intelligence known as machine learning to model floods using real-time analysis tools to ensure the minimization of flood events and the succeeding threats to lives and properties. Three Artificial Neuron Networks were employed in the current study: Feedforward Multipercetron Neuron Network, Elman Neuron Network, and Cascade Feedforward Neuron Network.

The results indicate that the Cascade Neuron Network is the best to model floods in the study area based on the evaluation technique. The cascade-1 model produced an R^2 value for the testing phase of 0.515101. This value is the highest of the 18 models trained and simulated. A distant second is an Elman-3 model with an R^2 value of 0.377333. The least-performing model was the FFBNN. This research is the first of its kind in the study area (Liberia); it’s recommended that further research be carried out incorporating other flood-inducing variables other than the ones used in this paper to abreast national and international policymakers with the data required to make a sound decision regarding flood mitigation and prevention.

5.2 Recommendation

For further study on flooding in the study area, this paper also recommends the consideration of incorporating software engineering for the development of flood-detection mobile applications based on the results of the models used in this paper to aid private citizens and national government actors to foresee, prepare, and possibly avert the devastating impacts of flood disasters.

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63

APPENDIX A

ACTUAL DATA

Yr	Mon	PPT	ws	tmax	tmin	soil	Runoff
1980	1	0.63539	0.487395	0.077659	0.085355	0.583333	0
1980	2	0.330605	0.256303	0.230445	0.383648	1	0.096864
1980	3	0.416247	0.680672	0.303039	0.427673	1	0.276697
1980	4	0.234887	0.554622	0.557681	0.628032	0.857966	0.00794
1980	5	0.664987	0.44958	0.603545	0.708446	0.90304	0.02104
1980	6	0.31801	0.352941	0.655037	0.766846	0.724843	0.009925
1980	7	0.147355	0.394958	0.86072	0.880054	0.355346	0.004764
1980	8	0.117128	0.483193	0.820484	0.761006	0.177149	0.003573
1980	9	0.248741	0.403361	0.730163	0.739892	0.108491	0.00794
1980	10	0.15806	0.222689	0.563872	0.544025	0.075996	0.005161
1980	11	0.43136	0.441176	0.299381	0.460018	0.303459	0.013497
1980	12	0.646725	0.441176	0.24789	0.41195	0.724319	0.019452
1981	1	0.243073	0.184874	0.227349	0.416442	0.872117	0.007543
1981	2	0.501889	0.403361	0.25408	0.362983	1	0.135371
1981	3	0.423174	0.428571	0.411367	0.436208	1	0.102422
1981	4	0.392947	0.756303	0.463984	0.549865	0.950734	0.012306
1981	5	0.358942	0.386555	0.571187	0.683738	0.842243	0.011116
1981	6	0.501259	0.722689	0.62915	0.760108	0.75	0.015879
1981	7	0.169395	0.491597	0.833146	0.799191	0.37631	0.005161
1981	8	0.0233	0.306723	0.973832	0.893531	0.184486	0.000794
1981	9	0.178841	0.306723	0.768993	0.705301	0.101153	0.005558
1981	10	0.410579	0.382353	0.4713	0.530997	0.166143	0.0131
1981	11	0.412469	0.415966	0.348621	0.484277	0.360063	0.0131
1981	12	0.678212	0.529412	0.184581	0.329739	0.531971	0.007543
1982	1	0.629093	0.747899	0.124086	0.212489	0.531971	0
1982	2	0.493073	0.676471	0.188239	0.279874	0.704403	0.007543
1982	3	0.410579	0.621849	0.335397	0.451033	1	0.675268
1982	4	0.50063	0.743697	0.420371	0.461815	1	0.029774
1982	5	0.198363	0.57563	0.609173	0.638814	0.716981	0.006352
1982	6	0.155542	0.302521	0.776027	0.891734	0.425052	0.004764
1982	7	0.273929	0.432773	0.841306	0.880503	0.20021	0.008734
1982	8	0.125315	0.403361	0.896455	0.895777	0.109539	0.00397
1982	9	0.292191	0.432773	0.72341	0.732255	0.058176	0.009131
1982	10	0.489924	0.323529	0.481148	0.551213	0.204927	0.015482
1982	11	0.373426	0.352941	0.211874	0.336029	0.333857	0.006749
1982	12	0.475441	0.411765	0.150535	0.288859	0.387317	0.002382
1983	1	0.422544	0.584034	0.26027	0.398473	1	0.02898
1983	2	0.539673	0.407563	0.306415	0.459119	1	0.321556
1983	3	0.586272	0.466387	0.391953	0.525606	1	0.198491
1983	4	0.232997	0.483193	0.484806	0.495058	0.853249	0.007543
1983	5	0.273929	0.62605	0.664041	0.683288	0.593816	0.008734

1983	6	0.36335	0.52521	0.710186	0.794699	0.41457	0.011513
1983	7	0.323048	0.47479	0.785594	0.851303	0.239518	0.010322
1983	8	0.167506	0.247899	0.933315	0.965409	0.128931	0.005161
1983	9	0.238035	0.39916	0.669387	0.64735	0.069706	0.007543
1983	10	0.248741	0.197479	0.532077	0.556155	0.0587	0.00794
1983	11	0.702771	0.638655	0.308104	0.494609	0.487421	0.022231
1983	12	0.491814	0.277311	0.008723	0.051662	0.487421	0
1984	1	0.314232	0.394958	0.181204	0.268643	0.561321	0.003176
1984	2	0.271411	0.420168	0.246764	0.36478	1	0.048432
1984	3	0.592569	0.44958	0.355374	0.491914	1	0.383486
1984	4	0.309194	0.634454	0.430219	0.507637	0.932914	0.009925
1984	5	0.400504	0.781513	0.550647	0.622192	0.809748	0.012703
1984	6	0.403023	0.47479	0.675014	0.760557	0.654612	0.012703
1984	7	0.082494	0.365546	0.903208	0.855795	0.251572	0.002779
1984	8	0.108942	0.361345	0.919246	0.898922	0.134172	0.003573
1984	9	0.197103	0.491597	0.675295	0.668014	0.072851	0.006352
1984	10	0.280227	0.42437	0.460045	0.477538	0.066038	0.008734
1984	11	0.652393	0.697479	0.265898	0.440252	0.449161	0.020246
1984	12	0.526448	0.386555	0.078784	0.133872	0.449161	0
1985	1	0.080605	0	0.037141	0.113208	0.449161	0
1985	2	0.280227	0.437209	0.133089	0.138365	0.449161	0
1985	3	0.297229	0.395349	0.320203	0.33558	1	0.097658
1985	4	0.214736	0.706977	0.524761	0.561096	0.883124	0.010322
1985	5	0.304156	0.446512	0.665166	0.685984	0.655136	0.009528
1985	6	0.276448	0.609302	0.758301	0.784367	0.373166	0.008734
1985	7	0.021411	0.4	1	0.934412	0.183438	0.000794
1985	8	0.229219	0.404651	0.834187	0.837376	0.100629	0.007146
1985	9	0.491184	0.35814	0.602673	0.654088	0.09696	0.015482
1985	10	0.246222	0.618605	0.46843	0.504942	0.082809	0.00794
1985	11	0.375315	0.362791	0.116325	0.178347	0.082809	0
1985	12	0.110202	0.106977	0	0	0.082809	0
1986	1	0.561083	0.562791	0.180029	0.312558	0.395178	0.013497
1986	2	0.671914	0.302326	0.208223	0.328837	0.993187	0.026201
1986	3	0.332494	0.344186	0.407342	0.51907	1	0.313617
1986	4	0.222922	0.55814	0.462261	0.503721	0.854822	0.007146
1986	5	0.314861	0.55814	0.63583	0.693488	0.646751	0.009925
1986	6	0.074937	0.362791	0.845521	0.871628	0.277254	0.002382
1986	7	0.151763	0.483721	0.797651	0.790233	0.145702	0.004764
1986	8	0.149244	0.288372	1	0.938605	0.079665	0.004764
1986	9	0.422544	0.269767	0.622124	0.684186	0.065514	0.013497
1986	10	0.119018	0.097674	0.583776	0.535349	0.035115	0.003573
1986	11	0.593199	0.525581	0.233333	0.390698	0.387841	0.018261
1986	12	0.146096	0.093023	0.114454	0.238605	0.396751	0.000397
1987	1	0.262594	0.269767	0.114454	0.16093	0.396751	0

1987	2	0.25	0.390698	0.260177	0.354419	0.754717	0.018658
1987	3	0.314861	0.534884	0.363422	0.465116	0.820231	0.012306
1987	4	0.2267	0.572093	0.602655	0.608372	0.642034	0.007146
1987	5	0.360202	0.460465	0.69115	0.733488	0.463312	0.011513
1987	6	0.287154	0.367442	0.816224	0.828372	0.234277	0.009131
1987	7	0.383501	0.4	0.841888	0.890233	0.12631	0.011909
1987	8	0.071159	0.344186	0.884071	0.82	0.068134	0.002382
1987	9	0.003149	0.172093	0.858702	0.716279	0.031447	0
1987	10	0	0.083721	0.630678	0.473953	0.005765	0
1987	11	0.18268	0.186047	0.316814	0.431628	0.02935	0.005955
1987	12	0.427939	0.4	0.115339	0.215349	0.053983	0.001191
1988	1	0.417826	0.376744	0.106785	0.182326	0.053983	0
1988	2	0.167509	0.395349	0.279056	0.327907	0.602725	0.026995
1988	3	0.497472	0.832558	0.353982	0.387907	0.81499	0.019849
1988	4	0.384956	0.423256	0.519764	0.571163	0.767296	0.012306
1988	5	0.353982	0.525581	0.626844	0.66093	0.59434	0.011116
1988	6	0.285714	0.376744	0.735103	0.816279	0.395178	0.009131
1988	7	0.159292	0.451163	0.887906	0.845581	0.190776	0.005161
1988	8	0.004425	0.423256	0.927729	0.826977	0.104298	0.000397
1988	9	0.218078	0.376744	0.755752	0.683721	0.055031	0.007146
1988	10	0.091656	0.144186	0.666372	0.642791	0.022013	0.003176
1988	11	0.692162	0.744186	0.274041	0.446512	0.431866	0.021834
1988	12	0.220607	0.260465	0.135103	0.228372	0.447065	0.000794
1989	1	0.603034	0.637209	0.152802	0.263256	0.552411	0.004367
1989	2	0.23641	0.232558	0.038938	0.011163	0.552411	0
1989	3	0.621997	0.539535	0.297935	0.413953	1	0.456133
1989	4	0.17952	0.590698	0.537758	0.578605	0.829665	0.006749
1989	5	0.435525	0.567442	0.60885	0.656744	0.707547	0.013894
1989	6	0.178887	0.52093	0.782596	0.832558	0.385744	0.005558
1989	7	0.046776	0.330233	0.894985	0.843721	0.187631	0.001588
1989	8	0.584071	0.251163	0.827729	0.857674	0.138365	0.018658
1989	9	0.117573	0.237209	0.789676	0.704651	0.075472	0.00397
1989	10	0.238938	0.283721	0.523599	0.542791	0.057652	0.007543
1989	11	0.370417	0.562791	0.312684	0.48093	0.204403	0.011909
1989	12	0.209229	0.04186	0.161652	0.312093	0.253669	0.002382
1990	1	0.561315	0.855814	0.20767	0.382326	0.651468	0.019055
1990	2	0.224399	0.669767	0.198525	0.242791	0.699686	0.003176
1990	3	0.216182	0.269767	0.39882	0.406977	0.765199	0.013894
1990	4	0.510114	0.483721	0.555457	0.601395	0.743187	0.016276
1990	5	0.594185	0.423256	0.585251	0.670233	0.720126	0.018658
1990	6	0.225032	0.604651	0.713569	0.825581	0.458595	0.007146
1990	7	0.104298	0.330233	0.936873	0.915814	0.210168	0.003573
1990	8	0.180152	0.190698	0.908555	0.941395	0.114256	0.005955
1990	9	0.001896	0.093023	0.900295	0.790698	0.061321	0

1990	10	0.493679	0.72093	0.473156	0.538605	0.133648	0.015482
1990	11	0.599874	0.818605	0.30649	0.485116	0.444444	0.019055
1990	12	0.319216	0.548837	0.036578	0.032558	0.444444	0
1991	1	0.328066	0.246512	0.10531	0.174419	0.444444	0
1991	2	0.23957	0.27907	0.334513	0.431628	1	0.03811
1991	3	0.391909	0.502326	0.301475	0.369767	1	0.074236
1991	4	0.312263	0.739535	0.473746	0.50093	0.900943	0.009925
1991	5	0.592288	0.525581	0.552212	0.634884	0.88522	0.018658
1991	6	0.420986	0.362791	0.649558	0.744651	0.732704	0.013497
1991	7	0.057522	0.353488	0.890855	0.861395	0.294025	0.001985
1991	8	0.123894	0.269767	0.957522	0.925116	0.15304	0.00397
1991	9	0.015803	0.218605	0.826844	0.711628	0.083857	0.000794
1991	10	0.099874	0.311628	0.555752	0.473488	0.041929	0.003176
1991	11	0.719975	0.395349	0.238348	0.420465	0.501048	0.022628
1991	12	0.257901	0.395349	0.193805	0.358605	0.620021	0.006749
1992	1	0.279393	0.35814	0.19764	0.347442	0.773585	0.00794
1992	2	0.313527	0.060465	0.316224	0.454419	0.980084	0.0131
1992	3	0.085967	0	0.469027	0.508837	0.841195	0.002779
1992	4	0.453224	0.558824	0.535988	0.594884	0.802935	0.014291
1992	5	0.107459	0.495098	0.742773	0.698605	0.417715	0.003573
1992	6	0.185209	0.294118	0.855162	0.893023	0.198113	0.005955
1992	7	0.212389	0.191176	0.851327	0.901395	0.108491	0.006749
1992	8	0.259166	0.284314	0.933923	0.875814	0.057128	0.008337
1992	9	0.252845	0.519608	0.70767	0.675349	0.024109	0.00794
1992	10	0.144121	0.176471	0.563127	0.586512	0	0.004764
1992	11	0.485461	0.220588	0.215929	0.396279	0.275972	0.014688
1992	12	0.2067	0.529412	0.101475	0.175814	0.275972	0
1993	1	0.291403	0.240196	0.042478	0.066512	0.275972	0
1993	2	0.145386	0.112745	0.114159	0.143721	0.275972	0
1993	3	0.343236	0.196078	0.329794	0.417674	0.875866	0.031759
1993	4	0.714286	0.5	0.444543	0.564186	1	0.130607
1993	5	0.359039	0.406863	0.70708	0.802791	0.781034	0.011513
1993	6	0.307838	0.573529	0.704425	0.816744	0.556739	0.009925
1993	7	0.350822	0.259804	0.721534	0.813488	0.412893	0.011116
1993	8	0.137168	0.284314	0.838053	0.829767	0.186468	0.004367
1993	9	0.016435	0.156863	0.775516	0.660465	0.094299	0.000794
1993	10	0.14981	0.029412	0.576401	0.591628	0.062334	0.004764
1993	11	0.219975	0.210784	0.20413	0.186977	0.085242	0.001588
1993	12	0.347661	0.323529	0.158997	0.340465	0.24081	0.006749
1994	1	0.339444	0.29902	0.250737	0.410233	0.661694	0.019452
1994	2	0.237674	0.367647	0.160472	0.233953	0.684603	0.001191
1994	3	0.161188	0.382353	0.416814	0.410233	0.695258	0.012306
1994	4	0.317952	0.406863	0.526254	0.623256	0.615344	0.010322
1994	5	0.290139	0.318627	0.660472	0.750233	0.428343	0.009131

1994	6	0.21555	0.446078	0.753392	0.78	0.201385	0.006749
1994	7	0.069532	0.387255	0.969027	0.923256	0.102291	0.002382
1994	8	0.01201	0.303922	0.951917	0.908837	0.046883	0.000397
1994	9	0.082174	0.142157	0.840118	0.777674	0.011188	0.002779
1994	10	0.554362	0.465686	0.518879	0.547442	0.135322	0.017467
1994	11	0.770544	0.583333	0.189971	0.350698	0.529568	0.017864
1994	12	0.525284	0.411765	0.149853	0.280465	0.639851	0.004764
1995	1	0.499368	0.338235	0.170501	0.268837	0.818327	0.007543
1995	2	0.347029	0.446078	0.29292	0.37814	1	0.499405
1995	3	0.530341	0.514706	0.345723	0.416744	1	0.175863
1995	4	0.366625	0.460784	0.450737	0.517674	0.941929	0.011513
1995	5	0.221239	0.382353	0.651032	0.712558	0.669686	0.007146
1995	6	0.520228	0.397059	0.687316	0.825581	0.566862	0.016276
1995	7	0.195954	0.485294	0.870206	0.904651	0.241343	0.006352
1995	8	0.238306	0.406863	0.835693	0.799535	0.120938	0.007543
1995	9	0.249684	0.093137	0.802065	0.784186	0.058604	0.00794
1995	10	0.53603	0.460784	0.445428	0.540465	0.233351	0.01707
1995	11	0.732617	0.735294	0.318289	0.493023	0.694726	0.023025
1995	12	0.54488	0.372549	0.154572	0.292558	0.806606	0.004764
1996	1	0.70354	0.416667	0.125664	0.229767	0.875866	0.002779
1996	2	0.776233	0.578431	0.163717	0.164186	0.971763	0.00397
1996	3	0.282554	0.328431	0.313569	0.393953	1	0.992457
1996	4	0.766119	0.617647	0.478761	0.576279	1	0.24216
1996	5	0.517699	0.52451	0.526254	0.636279	0.948322	0.016276
1996	6	0.158028	0.328431	0.732743	0.784186	0.581247	0.005161
1996	7	0.038559	0.294118	0.943953	0.897209	0.227491	0.001191
1996	8	0.03287	0.431373	0.929499	0.874419	0.114544	0.001191
1996	9	0.175727	0.25	0.689676	0.68186	0.054342	0.005558
1996	10	0.541087	0.367647	0.50295	0.557209	0.210975	0.01707
1996	11	0.761062	0.29902	0.240708	0.384186	0.710176	0.023422
1996	12	1	0.563725	0.086431	0.165581	0.710176	0
1997	1	0.650968	0.411765	0.10767	0.196744	0.773042	0.002382
1997	2	0.352258	0.318627	0.2	0.306047	1	0.311235
1997	3	0.597419	0.769608	0.313569	0.412093	1	0.880905
1997	4	0.645806	0.514706	0.419764	0.46	1	0.167924
1997	5	0.328387	0.308824	0.654572	0.713023	0.796484	0.010322
1997	6	0.217419	0.416667	0.69823	0.795814	0.535429	0.006749
1997	7	0.281935	0.318627	0.859587	0.841395	0.271177	0.008734
1997	8	0.067742	0.294118	0.935103	0.906977	0.134257	0.002382
1997	9	0.233548	0.29902	0.773746	0.775349	0.066063	0.007146
1997	10	0.564516	0.529412	0.511504	0.558605	0.216303	0.017467
1997	11	0.436129	0.343137	0.29764	0.425116	0.451785	0.013497
1997	12	0.32129	0.240196	0.157522	0.291628	0.515717	0.002779
1998	1	0.572903	0.563725	0.176106	0.285581	0.705381	0.00794

1998	2	0.24	0.401961	0.29115	0.426977	1	0.158793
1998	3	0.267742	0.279412	0.359882	0.455349	0.996271	0.009131
1998	4	0.277419	0.235294	0.510324	0.533953	0.876399	0.008734
1998	5	0.730323	0.362745	0.638348	0.728837	0.92488	0.022628
1998	6	0.204516	0.397059	0.715929	0.813953	0.627064	0.006352
1998	7	0.287097	0.147059	0.965782	0.995349	0.313266	0.009131
1998	8	0.077419	0.284314	0.984956	0.890698	0.151838	0.002382
1998	9	0.269677	0	0.862832	0.812558	0.075653	0.008337
1998	10	0.157419	0.121212	0.508555	0.507442	0.046883	0.005161
1998	11	0.852903	0.606061	0.310619	0.517674	0.586042	0.026201
1998	12	0.726452	0.661616	0.148968	0.268372	0.692062	0.004367
1999	1	0.393548	0.494949	0.218289	0.384186	1	0.211195
1999	2	0.699355	1	0.254277	0.396279	1	0.414053
1999	3	0.291613	0.545455	0.349853	0.406977	0.98455	0.009925
1999	4	0.165161	0.491979	0.461947	0.431628	0.79382	0.005161
1999	5	0.230323	0.561497	0.571681	0.573023	0.561002	0.007146
1999	6	0.271613	0.513369	0.691445	0.763721	0.359084	0.008337
1999	7	0.026452	0.417112	0.852507	0.788372	0.168887	0.000794
1999	8	0.273548	0.272727	0.923009	0.934419	0.085242	0.008337
1999	9	0.005806	0.304813	0.769322	0.631163	0.036228	0.000397
1999	10	0.362581	0.379679	0.538053	0.502791	0.030368	0.011116
1999	11	0.56129	0.609626	0.354867	0.526512	0.336708	0.017467
1999	12	0.541935	0.470588	0.19115	0.390233	0.651572	0.014688
2000	1	0.433548	0.438503	0.147198	0.282326	0.727224	0.003176
2000	2	0.583871	0.272727	0.223599	0.371163	1	0.260024
2000	3	0.421935	0.454545	0.345133	0.433953	1	0.161572
2000	4	0.292903	0.491979	0.537463	0.543256	0.855088	0.009131
2000	5	0.473548	0.502674	0.60708	0.68186	0.709643	0.014688
2000	6	0.238065	0.57754	0.746018	0.793023	0.388918	0.007543
2000	7	0.036129	0.31016	0.899115	0.846512	0.178476	0.001191
2000	8	0.023226	0.433155	0.936283	0.832093	0.09057	0.000794
2000	9	0.404516	0.331551	0.704425	0.688372	0.049014	0.012703
2000	10	0.352258	0.122995	0.49941	0.52186	0.048482	0.011116
2000	11	0.348387	0.096257	0.138348	0.218605	0.073522	0.001191
2000	12	0.288387	0.144385	0.064602	0.188372	0.073522	0
2001	1	0.295484	0.122995	0.10826	0.249302	0.11561	0.001588
2001	2	0.221935	0.106952	0.139528	0.193023	0.157698	0.001985
2001	3	0.303226	0.454545	0.354277	0.41814	0.928077	0.040095
2001	4	0.486452	0.459893	0.425369	0.503256	0.960575	0.015482
2001	5	0.276129	0.609626	0.685546	0.674884	0.632392	0.008734
2001	6	0.289677	0.395722	0.70118	0.772558	0.392648	0.009131
2001	7	0.126452	0.315508	0.885841	0.869302	0.180075	0.00397
2001	8	0.020645	0.235294	0.984366	0.920465	0.091103	0.000794
2001	9	0.063871	0.235294	0.841003	0.769767	0.039957	0.001985

2001	10	0.525161	0.57754	0.50708	0.551628	0.110815	0.016276
2001	11	0.518065	0.502674	0.320649	0.482326	0.364411	0.015879
2001	12	0.450323	0.540107	0.147198	0.29907	0.444326	0.003573
2002	1	0.448387	0.572193	0.176696	0.337674	0.713372	0.011909
2002	2	0.275484	0.470588	0.235398	0.286512	0.9691	0.012703
2002	3	0.483226	0.673797	0.235693	0.293488	1	0.216753
2002	4	0.244516	0.604278	0.465487	0.487907	0.981886	0.014688
2002	5	0.251613	0.502674	0.577876	0.645116	0.738945	0.00794
2002	6	0.338065	0.363636	0.751622	0.826512	0.484283	0.010322
2002	7	0.042581	0.390374	0.946608	0.927907	0.20618	0.001588
2002	8	0.167097	0.320856	0.886726	0.807907	0.104422	0.005161
2002	9	0.084516	0.240642	0.767552	0.709302	0.048482	0.002779
2002	10	0.144516	0.085561	0.5	0.390698	0.018647	0.004764
2002	11	0.287097	0.315508	0.295575	0.387442	0.126798	0.009131
2002	12	0.443871	0.395722	0.19292	0.431163	0.392115	0.0131
2003	1	0.88	0.283422	0.210619	0.440465	1	0.031759
2003	2	0.352258	0.219251	0.225369	0.308372	1	0.128622
2003	3	0.723226	0.727273	0.357522	0.479535	1	0.302104
2003	4	0.414194	0.326203	0.448968	0.547907	0.971763	0.012703
2003	5	0.329677	0.28877	0.598525	0.677674	0.777304	0.010322
2003	6	0.050323	0.390374	0.79292	0.832558	0.339371	0.001588
2003	7	0.029032	0.385027	0.994985	0.947907	0.161428	0.001191
2003	8	0.108387	0.272727	0.970206	0.91814	0.081513	0.003573
2003	9	0.194194	0.342246	0.800295	0.765116	0.034097	0.005955
2003	10	0.14129	0.524064	0.60472	0.631163	0.002131	0.004367
2003	11	0.369677	0.59893	0.215339	0.255814	0.109217	0.005558
2003	12	0.577419	0.208556	0.158997	0.335814	0.339904	0.009925
2004	1	0.562581	0.406417	0.064602	0.189767	0.339904	0
2004	2	0.305806	0.122995	0.217404	0.33814	0.958444	0.026598
2004	3	0.194194	0.641711	0.442773	0.492558	1	0.126241
2004	4	0.248387	0.304813	0.548083	0.552558	0.832179	0.00794
2004	5	0.655484	0.390374	0.597345	0.69907	0.816196	0.020246
2004	6	0.191613	0.28877	0.755162	0.845116	0.492808	0.005955
2004	7	0.047097	0.368984	0.936283	0.946047	0.208311	0.001588
2004	8	0.358065	0.278075	0.911799	0.969767	0.105487	0.011116
2004	9	0.18129	0.229947	0.69115	0.755814	0.049014	0.005558
2004	10	0.345161	0.315508	0.541003	0.596744	0.042088	0.010719
2004	11	0.370968	0.224599	0.279646	0.406047	0.213639	0.011513
2004	12	0.297419	0.283422	0.206195	0.382326	0.37187	0.008337
2005	1	0.214194	0.304813	0.130973	0.23907	0.390517	0.000794
2005	2	0.034839	0.13369	0.282301	0.263256	0.433671	0.005558
2005	3	0.426452	0.593583	0.39705	0.453023	0.533831	0.015482
2005	4	0.301935	0.540107	0.486136	0.547907	0.444859	0.009528
2005	5	0.655484	0.304813	0.623599	0.735814	0.421417	0.020246

2005	6	0.227742	0.379679	0.683776	0.790698	0.226425	0.007146
2005	7	0.08129	0.42246	0.927434	0.90186	0.114012	0.002779
2005	8	0.042581	0.320856	0.952802	0.886047	0.054342	0.001588
2005	9	0.10129	0.208556	0.728024	0.70186	0.016516	0.003176
2005	10	0.408387	0.176471	0.522124	0.635349	0.05594	0.012703
2005	11	0.405806	0.481283	0.218879	0.391628	0.267448	0.011909
2005	12	0.551613	0.278075	0.083776	0.170698	0.267448	0
2006	1	0.765161	0.807487	0.260472	0.472093	1	0.163954
2006	2	0.232258	0.663102	0.219174	0.252093	1	0.044859
2006	3	0.360645	0.42246	0.320354	0.413953	1	0.127829
2006	4	0.487742	0.486631	0.482891	0.575349	0.991476	0.015085
2006	5	0.322581	0.352941	0.661947	0.70093	0.741609	0.009925
2006	6	0.391613	0.28877	0.766372	0.886512	0.524241	0.012306
2006	7	0.016774	0.304813	0.981711	0.973953	0.21577	0.000794
2006	8	0.04129	0.262032	0.933333	0.862326	0.109217	0.001588
2006	9	0.170968	0.090909	0.789676	0.74186	0.051145	0.005558
2006	10	0.16	0.181818	0.510029	0.519535	0.022376	0.005161
2006	11	1	1	0.274336	0.42093	0.659563	0.030965
2006	12	0.473997	0.45614	0.141003	0.270233	0.710709	0.002382
2007	1	0.346954	0.403509	0.123304	0.193023	0.736814	0.001191
2007	2	0.440565	0.426901	0.209145	0.38	1	0.220723
2007	3	0.381872	0.555556	0.4059	0.517674	1	0.13418
2007	4	0.256315	0.473684	0.476991	0.53814	0.841236	0.007146
2007	5	0.248886	0.327485	0.667847	0.693488	0.551412	0.006749
2007	6	0.248886	0.473684	0.752802	0.851163	0.281833	0.006749
2007	7	0.063893	0.356725	0.984366	0.982791	0.139052	0.001985
2007	8	0.083952	0.403509	0.917404	0.880465	0.068727	0.002382
2007	9	0.082467	0.380117	0.746903	0.716279	0.026105	0.002382
2007	10	0.377415	0.51462	0.497935	0.562791	0.020778	0.010322
2007	11	0.610698	0.321637	0.266372	0.364186	0.327651	0.016276
2007	12	0.739227	0.596491	0.158702	0.298605	0.473628	0.006352
2008	1	0.526003	0.695906	0.112979	0.149767	0.473628	0
2008	2	0.352897	0.567251	0.248378	0.354419	1	0.154029
2008	3	0.444279	0.643275	0.29056	0.376279	1	0.178642
2008	4	0.237741	0.555556	0.413864	0.422326	0.855088	0.006749
2008	5	0.273403	0.48538	0.642773	0.714884	0.614811	0.007543
2008	6	0.337296	0.526316	0.720649	0.781395	0.363879	0.009131
2008	7	0.037147	0.479532	0.918584	0.893023	0.170485	0.001191
2008	8	0.283061	0.508772	0.911504	0.913488	0.085775	0.007543
2008	9	0.10104	0.169591	0.770796	0.709302	0.036761	0.002779
2008	10	0.116642	0.385965	0.528909	0.54093	0.004262	0.003176
2008	11	0.606984	0.432749	0.330973	0.494419	0.283431	0.016276
2008	12	0.748143	0.391813	0.076991	0.122791	0.283431	0
2009	1	0.587667	0.432749	0.135103	0.249302	0.368673	0.003573

2009	2	0.303863	0.251462	0.202655	0.314419	0.805008	0.019055
2009	3	0.763001	0.637427	0.259882	0.346047	1	0.462088
2009	4	0.479941	0.479532	0.461062	0.501395	1	0.038904
2009	5	0.415305	0.625731	0.658997	0.67814	0.744273	0.011116
2009	6	0.268202	0.397661	0.755752	0.835814	0.4374	0.007146
2009	7	0.161961	0.245614	0.946903	0.930698	0.193394	0.004367
2009	8	0.260773	0.356725	0.918879	0.92093	0.098029	0.007146
2009	9	0.022288	0.280702	0.839528	0.785581	0.044219	0.000794
2009	10	0.424963	0.602339	0.432153	0.487442	0.063399	0.011513
2009	11	0.367013	0.637427	0.309145	0.414884	0.16569	0.009925
2009	12	0.355126	0.146199	0.035693	0.097209	0.16569	0
2010	1	0.48737	0.315789	0.206195	0.389302	0.58764	0.018658
2010	2	0.22734	0.064327	0.279646	0.419535	0.726159	0.009925
2010	3	0.343239	0.479532	0.382006	0.404186	0.706446	0.009528
2010	4	0.592868	0.795322	0.457817	0.52186	0.706979	0.015879
2010	5	0.553492	0.561404	0.542478	0.593953	0.630794	0.015085
2010	6	0.692422	0.415205	0.668732	0.797674	0.572722	0.018658
2010	7	0.083952	0.432749	0.889381	0.850698	0.225892	0.002382
2010	8	0.043091	0.432749	0.892035	0.871163	0.114012	0.001191
2010	9	0.282318	0.274854	0.735398	0.776279	0.054342	0.007543
2010	10	0.479198	0.204678	0.536283	0.612093	0.11561	0.0131
2010	11	0.55052	0.409357	0.215044	0.320465	0.350027	0.011513
2010	12	0.812779	0.497076	0.132743	0.262326	0.433138	0.003573
2011	1	0.555721	0.51462	0.157522	0.266047	0.576452	0.005955
2011	2	0.667905	0.590643	0.157522	0.210698	0.680341	0.004367
2011	3	0.690193	0.74269	0.315929	0.441395	1	0.845971
2011	4	0.505944	0.877193	0.364897	0.43814	1	0.038507
2011	5	0.753343	0.614035	0.552507	0.62186	1	0.02501
2011	6	0.234027	0.461988	0.654277	0.763256	0.719233	0.006352
2011	7	0.076523	0.385965	0.850442	0.808372	0.289291	0.001985
2011	8	0.034918	0.374269	0.965782	0.892093	0.141716	0.001191
2011	9	0.043834	0.274854	0.864897	0.772093	0.070325	0.001191
2011	10	0.377415	0.28655	0.50708	0.609767	0.069259	0.010322
2011	11	0.419019	0.830409	0.271091	0.325116	0.211508	0.010719
2011	12	0.158247	0.187135	0.151622	0.22093	0.22163	0.000794
2012	1	0.640416	0.719298	0.19115	0.239535	0.350559	0.005955
2012	2	0.430163	0.497076	0.216224	0.330698	0.742142	0.018261
2012	3	0.65899	1	0.334808	0.433953	1	0.166336
2012	4	0.540119	0.66443	0.509145	0.579535	0.986681	0.014688
2012	5	0.225854	0.738255	0.601475	0.635814	0.676612	0.005955
2012	6	0.543834	0.704698	0.685251	0.804186	0.546617	0.014688
2012	7	0.161961	0.234899	0.941888	0.945581	0.220565	0.004367
2012	8	0.011887	0.369128	0.983776	0.894884	0.111348	0.000397
2012	9	0	0.127517	0.838348	0.74186	0.052744	0

2012	10	0.635215	0.704698	0.517699	0.568372	0.169419	0.01707
2012	11	0.652303	0.563758	0.30472	0.489767	0.499734	0.017467
2012	12	0.497028	0.677852	0.178466	0.366047	0.695791	0.009528
2013	1	0.397474	0.322148	0.09646	0.184651	0.695791	0
2013	2	0.228826	0.469799	0.254277	0.372093	1	0.065105
2013	3	0.210253	0.637584	0.372271	0.427907	0.956313	0.00794
2013	4	0.340267	1	0.453982	0.497209	0.846564	0.009131
2013	5	0.305349	0.371429	0.670501	0.69814	0.607885	0.008337
2013	6	0.401189	0.428571	0.741593	0.830698	0.403836	0.010719
2013	7	0.015602	0.485714	0.99233	0.955349	0.183271	0.000397
2013	8	0.14636	0.242857	0.964602	0.964186	0.092701	0.00397
2013	9	0.498514	0.578571	0.771976	0.869302	0.058071	0.013497
2013	10	0.052006	0.164286	0.49233	0.463721	0.018647	0.001588
2013	11	0.379643	0.485714	0.248968	0.359535	0.170485	0.009925
2013	12	0.304606	0.335714	0.09705	0.135349	0.170485	0
2014	1	0.368499	0.5	0.161652	0.31907	0.304742	0.005955
2014	2	0.648588	0.864286	0.1059	0.195814	0.342035	0.001588
2014	3	0.703566	0.928571	0.347493	0.423256	1	0.262803
2014	4	0.352155	0.928571	0.488791	0.519535	0.87853	0.009925
2014	5	0.175334	0.5	0.669617	0.705116	0.549814	0.004764
2014	6	0.332838	0.471429	0.723894	0.814419	0.322856	0.009131
2014	7	0.057949	0.492857	0.99233	1	0.155035	0.001588
2014	8	0.18945	0.257143	0.943953	0.994247	0.077784	0.005161
2014	9	0.101783	0.4	0.80472	0.801055	0.031966	0.002779
2014	10	0.363299	0.542857	0.610324	0.714765	0.019712	0.009925
2014	11	0.481426	0.878571	0.235693	0.330297	0.223229	0.011116
2014	12	0.745171	0.478571	0.182891	0.365772	0.570059	0.014688
2015	1	0.420505	0.171429	0.169322	0.331735	0.739478	0.007146
2015	2	0.483655	0.407143	0.328319	0.449185	1	0.184597
2015	3	0.502229	0.478571	0.448378	0.522052	1	0.060341
2015	4	0.17682	0.621429	0.50649	0.504314	0.778903	0.004764
2015	5	0.300892	0.335714	0.701475	0.772771	0.527437	0.008337
2015	6	0.145617	0.414286	0.888791	0.980825	0.216303	0.00397
2015	7	0.053492	0.542857	0.946608	1	0.109217	0.001588
2015	8	0.02526	0.55	0.953982	0.968116	0.051678	0.000794
2015	9	0.191679	0.257143	0.745428	0.743961	0.014385	0.005161
2015	10	0.30312	0.3	0.619174	0.711111	0	0.008337
2015	11	0.416048	0.728571	0.244248	0.361836	0.141685	0.010719
2015	12	0.824666	0.6	0.160767	0.327053	0.353392	0.008734
2016	1	0.499257	0.4	0.162242	0.338164	0.584792	0.009528
2016	2	0.268945	0.65	0.327434	0.458937	1	0.088527
2016	3	0.661961	0.95	0.39233	0.507246	1	0.153235
2016	4	0.332095	0.378571	0.587021	0.657005	0.84628	0.009131
2016	5	0.376672	0.621429	0.660767	0.782609	0.606127	0.010322

2016	6	0.190936	0.571429	0.80236	0.888889	0.265317	0.005161
2016	7	0.244428	0.571429	0.876106	0.942029	0.117068	0.006749
2016	8	0.055721	0.457143	0.938053	0.937198	0.044311	0.001588
2016	9	0.166419	0.385714	0.734513	0.768116	0	0.004367
2016	10	0.907132	0.557143	0.501475	0.68599	0.380453	0.024216
2016	11	0.309064	0.621429	0.386431	0.555556	0.451132	0.008337
2016	12	0.639673	0.45	0.050147	0.091787	0.451132	0
2017	1	0.47474	0.307143	0	0	0.451132	0
2017	2	1	0.664286	0.090909	0.161111	0.754279	0.011909
2017	3	0.903566	0.871429	0.285714	0.455556	1	1
2017	4	0.676661	0.864286	0.37987	0.511111	1	0.210632
2017	5	0.353323	0.4	0.62013	0.694444	0.748205	0.022066
2017	6	0.341977	0.692857	0.733766	0.85	0.440641	0.021063
2017	7	0	0.5	1	1	0.170624	0
2017	8	0.008177	0.35	1	1	0.06847	0.001003
2017	9	0.274734	0.207143	0.76431	0.787709	0.011596	0.018054
2017	10	0.408013	0.714286	0.468013	0.463687	0.003313	0.026078
2017	11	0.831562	0.8	0.222222	0.385475	0.418001	0.052156
2017	12	0.839738	0.142857	0	0.128492	0.454997	0.004012
2018	1	0.603434	0.5	0.136519	0.329609	1	0.383149
2018	2	0.514309	1	0.09215	0.122905	1	0.144433
2018	3	0.45462	0.571429	0.276451	0.318436	1	0.798395
2018	4	0.698283	0.785714	0.423208	0.50838	1	0.170512
2018	5	0.503679	0.142857	0.713311	0.843575	0.805632	0.032096
2018	6	0.249387	0.714286	0.723549	0.832402	0.477084	0.016048
2018	7	0	0.5	0.989761	0.960894	0.180011	0.001003
2018	8	0.055281	0.571429	0.962457	0.938547	0.07344	0.005015
2018	9	0.014851	0.285714	0.723549	0.681564	0.014357	0.002006
2018	10	0.500825	0	0.467577	0.50838	0.081171	0.032096
2018	11	0.709571	0.428571	0.187713	0.307263	0.433462	0.044132
2018	12	0.571782	0.571429	0.098976	0.256983	0.648813	0.025075
2019	1	0.407591	0.714286	0.122867	0.268156	0.880729	0.029087
2019	2	0.79703	0.428571	0	0	0.880729	0
2019	3	0.279703	0.642857	0.083019	0	1	0.483936
2019	4	0.883663	0.928571	0.426415	0.406015	1	1
2019	5	0.419142	0	0.656604	0.736842	0.76974	0.097378
2019	6	0.084983	1	0.762264	0.864662	0.324682	0.022472
2019	7	0.028053	0.6	0.920755	0.917293	0.134732	0.007491
2019	8	0.188119	0.4	0.996226	1	0.049696	0.044944
2019	9	0.367162	0.2	0.739623	0.631579	0	0.086142
2019	10	0.668317	0.1	0.335849	0.112782	0.122679	0.153558
2019	11	0.171617	0.3	0.086792	0.082707	0.126618	0.041199
2019	12	0.363861	0.5	0.030189	0.045113	0.283624	0.074906
2020	1	1	1	0.033962	0.045113	0.797974	0.209738

2020	2	0.715258	1	0.090566	0.037594	1	1
2020	3	0.335277	0.833333	0.2	0.112782	1	0.384615
2020	4	0.413994	0.833333	0.392453	0.338346	1	0.423077
2020	5	1	1	0.581132	0.586466	1	1
2020	6	0.496107	1	0.686792	0.736842	0.809564	0.511111
2020	7	0.087875	0.8	0.924528	0.909774	0.272417	0.088889
2020	8	0	0.8	1	1	0.094791	0
2020	9	0	0	1	1	0	0
2020	10	0.71374	1	1	1	0	0.875
2020	11	1	1	1	1	0	1
2020	12	0.418766	0.378151	0.208497	0.362084	0.68239	0.008734

APPENDIX B

Training Data Results

cas1	cas2	cas3	cas4	cas5	cas6
1.89E-03	2.17E-03	0.009368	0.065881	5.98E-10	0.032874
0.01537	0.22234	0.099661	0.098281	0.080925	0.235385
0.128693	0.189376	0.261844	0.17247	0.650676	0.223893
3.27E-02	0.01147	0.02183	0.035346	0.000338	0.046498
0.060939	2.66E-02	0.103606	0.160661	0.002526	0.069357
0.015797	7.24E-03	0.019787	0.022752	3.06E-08	0.039077
0.004748	9.30E-03	0.010117	9.11E-04	5.07E-06	0.032954
0.00152	1.55E-02	0.011448	3.01E-04	7.55E-07	0.038303
0.001427	0.009342	0.012382	3.70E-04	4.75E-09	0.053103
3.06E-07	0.004287	0.00897	1.22E-04	3.87E-10	0.041149
5.76E-04	0.005876	0.00829	4.15E-03	2.4E-08	0.045035
4.97E-02	6.36E-03	0.011657	0.081207	2.62E-06	0.056266
4.26E-03	0.065225	0.05874	0.037024	9.73E-08	0.116231
0.063498	0.226145	0.118214	0.18129	0.133438	0.222146
0.056292	0.144998	0.140966	0.156368	0.03853	0.156093
0.05538	0.0558	0.099403	0.125804	0.045144	0.11947
2.73E-02	1.81E-02	0.030219	0.046919	3.07E-06	0.05253
0.035738	1.47E-02	0.028273	0.073903	0.007629	0.045855
0.005288	0.008947	0.009965	1.42E-03	4.12E-06	0.034361
0.001533	0.00773	0.010079	1.20E-04	0.002348	0.032567
0.000279	6.26E-03	0.010627	1.87E-04	2.09E-07	0.052212
1.68E-04	5.52E-03	0.010077	1.63E-03	1.2E-09	0.045159
2.52E-03	0.005667	0.007466	4.82E-03	2.33E-09	0.044435
0.025083	5.63E-03	0.006896	0.05318	9.7E-07	0.038654
0.014175	5.39E-03	0.019937	0.072747	2.74E-07	0.041164
1.93E-02	0.009994	0.031293	0.076031	2.75E-07	0.047546
0.126491	0.181471	0.228142	0.162357	0.482716	0.201669

0.116734	0.152671	0.21822	0.232589	0.063125	0.188845
1.39E-02	3.21E-03	0.006961	0.013994	2.62E-05	0.031358
4.71E-03	1.24E-02	0.009319	1.24E-03	1.09E-06	0.033832
0.005789	1.41E-02	0.015573	8.07E-04	5.32E-07	0.039778
0.002112	0.012491	0.013036	1.80E-04	1.85E-06	0.031073
0.000997	0.008866	0.015623	3.88E-04	1.58E-08	0.056478
1.04E-03	6.16E-03	0.010137	2.81E-03	5.77E-11	0.04764
9.00E-06	3.25E-03	0.009672	3.20E-03	7.01E-10	0.039535
6.14E-05	3.22E-03	0.009215	0.008212	2.33E-09	0.039227
0.13458	0.232157	0.220428	0.173888	0.184245	0.229991
0.071	0.268975	0.135043	0.162025	0.239251	0.224645
0.091241	2.07E-01	0.153818	0.181781	0.215788	0.203816
2.21E-02	1.49E-02	0.031488	0.043432	4.65E-05	0.054602
0.011982	3.53E-03	0.006474	1.23E-02	0.002938	0.032157
0.012834	1.85E-02	0.013162	6.13E-03	1.77E-05	0.040672
0.007094	1.69E-02	0.015653	1.48E-03	3.33E-07	0.043968
4.10E-03	1.24E-02	0.012971	2.05E-04	0.000215	0.037278
8.20E-05	0.006414	0.01217	2.94E-04	1.88E-09	0.052724
5.69E-07	0.005897	0.008739	1.99E-04	1.61E-10	0.041173
4.38E-02	3.09E-02	0.011056	6.56E-02	0.000266	0.045358
9.66E-07	1.50E-03	0.008082	0.015289	4.1E-12	3.63E-02
4.49E-04	0.001102	0.015742	0.010954	6.29E-11	0.031861
0.034106	0.2172	0.153722	0.114435	0.036766	0.213554
0.09029	0.235301	0.143958	0.186038	0.185937	0.218637
0.059944	4.55E-02	0.071735	0.085939	0.007339	0.093873
0.024552	1.48E-02	0.018822	0.077177	0.001003	0.051806
0.030864	0.007083	0.016494	0.02795	4.36E-07	0.036319
0.002286	9.16E-03	0.009613	2.78E-04	7.55E-05	0.034155
0.002269	1.10E-02	0.012129	1.70E-04	2.76E-05	0.030886
1.40E-04	1.31E-02	0.012879	2.99E-04	8.58E-08	0.051553
1.85E-06	0.005199	0.011794	5.30E-04	2.69E-08	0.04432
0.0278	0.022816	0.011761	5.53E-02	0.000629	0.04654
1.29E-05	2.51E-03	0.008344	0.017033	3.42E-11	0.0332
3.09E-09	0.0077	0.009682	0.000805	1.03E-14	4.67E-02
2.20E-06	0.000708	0.019987	0.007116	2.14E-11	2.87E-02
0.02502	0.153054	0.149123	0.138847	0.143197	0.187489
0.021926	1.23E-02	0.026092	0.044108	0.000949	0.053834
0.02419	0.003794	0.009751	1.76E-02	2.16E-07	0.03549
0.006863	1.48E-02	0.013181	3.60E-03	0.022996	0.037213
0.001746	6.50E-03	0.012196	1.44E-04	0.001116	0.025005
0.003178	0.012801	0.014753	3.15E-04	1.96E-07	0.043911
1.44E-03	8.63E-03	0.01724	1.39E-03	1.48E-09	0.052578
6.65E-06	0.015888	0.014146	8.05E-04	0.000247	0.048353
2.40E-07	9.39E-03	0.016521	0.002167	3.63E-09	0.035577

4.96E-09	0.007957	0.008706	0.000266	1.59E-10	2.27E-02
0.001661	8.86E-03	0.011515	2.07E-02	9.97E-07	0.039563
0.035129	0.093998	0.06536	0.165042	0.02719	0.212424
0.029925	0.173087	0.115876	0.09696	0.15522	0.150984
2.55E-02	1.55E-02	0.028034	0.04127	6.69E-05	0.053645
0.022746	4.34E-03	0.007557	1.83E-02	6.74E-05	0.033589
2.08E-03	0.011248	0.007834	3.14E-04	2.89E-06	0.033054
0.001761	1.67E-02	0.01205	3.16E-04	8.66E-08	0.040674
0.003756	1.26E-02	0.01599	1.38E-04	0.003657	0.030023
2.32E-04	7.92E-03	0.014253	6.34E-04	2.08E-10	0.052071
3.90E-08	5.87E-03	0.009325	5.78E-05	1.49E-09	0.037535
0.007335	1.08E-02	0.008995	2.07E-02	3.24E-06	0.041485
2.01E-08	0.006433	0.008429	0.000908	2.6E-13	3.57E-02
1.22E-07	0.001746	0.010964	0.00327	2.59E-10	3.16E-02
4.37E-03	0.013047	0.031876	0.027564	3.28E-08	0.049724
3.01E-02	0.02054	0.031748	0.051647	1.95E-05	0.059118
0.010852	3.22E-03	0.005714	1.19E-02	3.05E-05	0.032617
0.018336	1.23E-02	0.010554	7.92E-03	9.66E-07	0.042983
0.006638	1.15E-02	0.013387	9.25E-04	5.47E-07	0.047467
0.008667	1.43E-02	0.021403	8.69E-04	9.45E-07	0.046121
0.00051	1.13E-02	0.011602	8.54E-05	7.2E-06	0.034336
4.04E-06	5.44E-03	0.009266	3.46E-05	1.74E-05	0.044491
5.54E-09	0.005031	0.013015	2.47E-05	2.52E-09	0.037921
4.15E-08	7.20E-03	0.013145	9.77E-05	6.56E-12	0.035115
5.89E-07	1.72E-02	0.017607	0.002668	2.53E-08	0.040547
3.93E-07	1.64E-02	0.017267	0.002722	8.53E-09	0.037723
5.30E-04	0.004678	0.015408	0.006929	6.44E-10	0.031877
0.028476	0.056996	0.052161	0.139466	0.002162	0.082543
3.40E-02	0.008619	0.017984	0.046789	1.41E-06	0.048402
0.025823	5.57E-03	0.007722	1.86E-02	4.82E-05	0.037329
0.008712	0.014102	0.010272	2.70E-03	1.74E-08	0.042914
0.003218	1.18E-02	0.013588	3.88E-04	4.96E-06	0.033668
0.000542	1.09E-02	0.012222	8.22E-05	2.36E-05	0.025326
0.000179	6.83E-03	0.013919	2.22E-04	3.45E-08	0.053609
2.33E-07	0.004733	0.008003	4.47E-05	2.79E-08	0.042505
0.030174	1.98E-02	0.014033	6.95E-02	0.003343	0.050344
7.55E-07	0.002012	0.011341	0.00281	1.27E-10	0.035198
1.52E-02	0.004718	0.014054	0.055847	2.64E-07	0.03664
1.85E-07	0.000648	0.013377	0.008316	2.42E-11	4.91E-02
0.150123	0.287195	0.166054	0.246814	0.37097	0.249938
1.97E-02	0.007851	0.016439	0.025691	7.65E-05	0.041561
0.045898	6.82E-03	0.012142	0.051848	8.09E-05	0.03834
0.004437	1.15E-02	0.009182	1.74E-03	3.64E-07	0.032612
0.001151	1.00E-02	0.008966	1.41E-04	5.68E-05	0.034077

0.019047	1.05E-02	0.034722	2.24E-03	2.86E-06	0.033264
4.69E-05	5.36E-03	0.009581	9.55E-05	1.31E-06	0.049685
8.81E-07	4.99E-03	0.00939	2.26E-04	2.73E-11	0.043289
5.06E-05	0.010278	0.009946	2.32E-03	1.07E-05	0.051746
1.14E-08	0.009112	0.008094	0.00042	1.86E-12	0.028423
0.013944	0.049946	0.02972	0.086854	4.37E-05	0.082199
5.04E-03	0.0063	0.04136	0.034606	2.67E-10	0.042162
2.72E-03	1.07E-02	0.036237	0.022304	7.24E-08	0.061471
0.066118	9.71E-03	0.016812	0.078708	7.22E-06	0.049059
0.065974	0.012996	0.029039	0.082004	3.01E-06	0.050851
0.005066	1.06E-02	0.008813	3.98E-03	4.79E-05	0.033823
0.003121	8.97E-03	0.011223	2.46E-04	0.000296	0.033683
3.14E-03	1.13E-02	0.012241	1.85E-04	0.000126	0.041711
4.07E-05	0.006008	0.008638	3.91E-05	9.96E-05	0.04978
0.001203	4.24E-02	0.020847	6.71E-03	0.001276	0.0481
1.43E-02	0.057949	0.013404	5.64E-02	0.005985	0.062206
1.23E-06	0.001186	0.025511	0.0113	1.21E-11	2.95E-02
6.33E-07	1.54E-03	0.009116	0.005005	1.23E-10	3.50E-02
0.012835	0.167841	0.116206	0.084647	0.065036	0.186978
0.08195	0.186553	0.171469	0.174769	0.047156	0.193271
0.034614	2.21E-02	0.046958	0.084437	0.001943	0.07333
0.080489	3.13E-02	0.058511	0.148745	0.001936	0.075755
0.024692	8.79E-03	0.026671	0.038426	8.27E-09	0.043381
0.002126	8.85E-03	0.008353	2.96E-04	7.12E-05	0.034301
0.003225	1.02E-02	0.012295	1.80E-04	0.001172	0.036001
1.87E-05	6.33E-03	0.008636	5.16E-05	5.54E-06	0.044762
1.22E-07	4.63E-03	0.012067	9.68E-05	3.85E-10	0.041799
2.68E-02	1.02E-02	0.004651	0.035107	1.83E-07	0.044558
1.44E-03	0.004294	0.016261	0.010499	4.29E-10	0.03549
5.45E-03	1.58E-02	0.03687	0.031488	1.09E-07	0.059374
1.72E-03	9.87E-02	0.049964	0.05669	1.98E-06	0.202802
2.43E-04	0.025252	0.05591	0.012205	1.93E-08	1.07E-01
0.060903	1.31E-02	0.019071	0.081119	6.58E-05	0.050547
0.002639	8.97E-03	0.005842	1.16E-03	2.88E-06	0.036775
3.65E-03	1.12E-02	0.010875	3.58E-04	7.29E-06	0.041264
2.38E-03	9.15E-03	0.011612	2.10E-04	1.14E-05	0.045862
0.004183	1.13E-02	0.018605	2.23E-04	0.000248	0.039366
1.67E-04	1.21E-02	0.018139	3.66E-04	1.45E-05	0.057008
1.13E-07	0.005991	0.008445	5.61E-05	1.41E-09	0.039147
7.96E-06	6.28E-03	0.006773	2.80E-03	4.23E-13	0.041796
4.33E-07	0.003386	0.020315	0.00215	2.37E-09	3.68E-02
2.75E-08	3.77E-03	0.008917	0.00272	4.46E-10	2.60E-02
5.29E-09	0.005256	0.008373	0.000608	4.13E-12	2.51E-02
0.005496	3.43E-02	0.055739	0.056895	8.11E-06	0.10891

0.106042	1.72E-01	0.138943	0.25518	0.173484	0.19214
0.020021	6.94E-03	0.031867	0.035099	4.13E-08	0.042428
0.0124	7.47E-03	0.011158	9.79E-03	7.96E-05	0.031861
0.008801	1.11E-02	0.014113	4.09E-03	1.75E-07	0.052685
1.76E-03	1.01E-02	0.009269	2.30E-04	6.87E-06	0.043773
2.91E-06	4.33E-03	0.008231	4.90E-05	9.29E-07	0.050163
9.45E-08	6.70E-03	0.008415	7.11E-05	2.64E-09	0.038114
2.46E-08	4.71E-03	0.016051	4.99E-04	1.41E-09	0.026577
5.55E-07	4.26E-03	0.009864	1.51E-03	1.24E-10	0.041941
3.93E-03	0.004076	0.017804	0.016208	2.3E-10	0.042947
7.72E-04	0.002939	0.0273	0.017982	1.66E-10	0.043695
1.94E-03	7.12E-03	0.017344	0.01131	2.04E-07	0.039555
1.59E-02	7.31E-03	0.00795	0.013539	2.48E-09	0.041541
0.006988	0.012674	0.00877	3.09E-03	2.87E-09	0.051586
0.003362	0.015559	0.010663	5.78E-04	1.48E-08	0.04611
0.001851	9.95E-03	0.013659	1.17E-04	0.000132	0.024748
6.59E-04	1.13E-02	0.011112	5.09E-05	0.000118	0.027217
1.78E-05	0.005904	0.009443	4.64E-05	6.42E-06	0.04732
0.002348	1.41E-02	0.018477	4.33E-03	7.21E-05	0.046332
0.051468	7.18E-03	0.005861	0.078264	2.43E-05	0.042253
7.25E-03	9.87E-04	0.011591	0.039466	7.43E-10	0.038647
1.40E-02	0.004638	0.030583	0.090566	9.23E-07	0.074982
0.054484	0.198786	0.159867	0.144855	0.103834	0.194973
0.117622	0.204303	0.170616	0.214863	0.091747	0.202161
5.51E-02	6.63E-02	0.081158	0.096514	0.006019	0.097354
1.27E-02	0.004239	0.010176	0.010486	1.26E-08	0.034102
0.028074	2.38E-02	0.031169	2.83E-02	1.03E-08	0.03922
0.003718	1.21E-02	0.014428	7.66E-04	1.52E-06	0.031969
0.003551	1.17E-02	0.015039	3.72E-04	6.51E-07	0.045564
2.34E-04	6.02E-03	0.011662	1.67E-04	5.43E-06	0.050355
0.006244	1.06E-02	0.011941	5.89E-03	2.6E-06	0.046648
4.86E-02	0.077618	0.015826	0.15668	0.005473	0.081378
2.17E-02	0.004536	0.025341	0.088567	4.22E-07	0.072239
5.23E-02	0.011944	0.02949	0.161401	1.03E-05	0.1114
1.87E-01	0.096664	0.045531	0.336762	0.000229	0.203775
0.019965	0.181275	0.132421	0.105906	0.575153	0.193938
0.110246	2.06E-01	0.159391	0.361313	0.171256	0.198588
0.068564	0.056414	0.08949	0.129705	0.048701	0.101267
0.006262	5.16E-03	0.00981	3.60E-03	4.19E-07	0.032649
0.001889	0.008004	0.009242	1.65E-04	0.000915	0.036537
0.00097	1.06E-02	0.012312	1.08E-04	1.04E-05	0.025034
1.22E-05	0.004893	0.009191	1.21E-04	1.45E-08	0.04925
0.003942	7.94E-03	0.012462	4.37E-03	2.26E-08	0.047793
3.38E-02	0.004227	0.007795	0.070163	2.75E-07	5.32E-02

0.108	1.48E-03	0.005781	0.204679	4.84E-05	5.91E-02
2.11E-02	0.002205	0.015701	0.111414	4.92E-08	0.060986
0.021462	0.193329	0.102268	0.131808	0.201241	0.238218
0.153665	3.64E-01	0.264194	0.276325	0.525244	0.274306
0.123933	0.175087	0.132888	0.26183	0.009263	0.189465
1.33E-02	0.008608	0.027664	0.033634	1.4E-07	0.048722
0.00949	8.13E-03	0.007784	4.33E-03	6.62E-09	0.032674
0.007555	1.01E-02	0.014218	1.06E-03	1.67E-05	0.046724
1.72E-03	1.01E-02	0.010477	1.17E-04	0.000212	0.032804
0.000657	0.007013	0.01228	2.08E-04	7.36E-08	0.052453
0.017076	1.70E-02	0.017221	8.18E-03	0.000415	0.04634
2.62E-03	3.09E-03	0.00809	7.60E-03	1.55E-10	0.043041
8.30E-05	1.92E-03	0.010189	0.005417	2.95E-11	0.040039
2.76E-02	0.00433	0.017434	0.084396	3.17E-07	0.045437
0.032922	0.203277	0.146418	0.092576	0.122667	0.191858
0.014235	0.160592	0.108993	0.08648	0.042548	0.171883
6.39E-03	2.66E-02	0.052333	0.046072	1.72E-06	0.080285
0.04522	2.34E-02	0.132926	0.179566	0.000145	0.058634
0.010583	4.65E-03	0.010432	6.93E-03	5E-08	0.030526
0.010932	0.012404	0.029411	1.35E-03	0.005094	0.04269
0.002157	0.008868	0.012009	1.33E-04	0.004412	0.033736
5.04E-04	5.66E-03	0.014544	2.20E-04	0.000173	0.041553
4.52E-08	0.006373	0.009881	8.27E-05	1.46E-10	0.034836
8.65E-02	2.66E-02	0.010952	0.117281	0.001684	0.056351
0.062012	0.007968	0.011665	0.124957	1.03E-05	0.056678
0.095808	0.270107	0.177597	0.151003	0.030251	0.239251
0.151954	0.300818	0.186707	0.313417	0.373737	0.366386
0.061772	0.115499	0.140961	0.121001	0.017033	0.148364
7.17E-03	9.42E-03	0.021566	0.02505	8.08E-06	0.045891
0.006316	0.004934	0.005387	8.11E-03	2.4E-05	0.036295
0.007163	1.88E-02	0.00903	2.50E-03	3.62E-07	0.043736
0.00062	1.30E-02	0.009208	1.32E-04	1.27E-06	0.032072
0.005899	1.31E-02	0.017819	2.96E-04	9.4E-05	0.037969
9.29E-07	0.006606	0.01046	4.39E-05	2.42E-07	0.042795
5.06E-06	0.007088	0.014297	7.02E-04	1.83E-08	0.046324
1.77E-02	3.15E-02	0.010889	1.73E-02	4.33E-05	0.046972
2.15E-02	0.003168	0.011949	0.041436	4.65E-08	0.043632
8.84E-03	0.002515	0.022311	0.050635	1.83E-09	0.047749
0.025869	1.57E-01	0.069312	0.136523	0.182699	0.229237
0.0743	0.20018	0.162317	0.154799	0.18381	0.184099
3.56E-02	0.012442	0.028547	0.053619	2.79E-05	0.051654
0.051588	8.76E-03	0.016409	0.05503	1.52E-05	0.041852
0.005739	1.35E-02	0.010351	2.88E-03	0.000198	0.036363
9.92E-04	9.88E-03	0.008768	1.21E-04	8.01E-05	0.034642

0.000656	1.10E-02	0.013592	8.77E-05	2.59E-05	0.025098
0.000667	7.29E-03	0.018254	5.90E-04	7.12E-09	0.055202
4.52E-07	1.34E-02	0.009151	3.91E-04	8.85E-11	0.035915
2.86E-08	1.00E-02	0.009139	0.000685	4.44E-12	0.027951
2.20E-08	7.35E-03	0.008527	0.000479	5.02E-12	2.99E-02
2.46E-08	7.11E-03	0.00864	0.000474	1.83E-12	0.02936
8.92E-09	0.006105	0.008916	0.000452	4.82E-12	2.46E-02
0.035353	7.11E-02	0.087749	0.090799	0.004006	0.105755
0.073565	1.05E-01	0.104187	0.140534	0.014965	0.130716
0.016511	0.002643	0.006942	1.54E-02	0.000858	0.030336
0.008705	1.45E-02	0.009026	2.76E-03	5.11E-09	0.046528
0.002398	1.06E-02	0.010439	2.23E-04	3.18E-05	0.037533
1.12E-03	1.01E-02	0.010498	6.48E-05	0.001988	0.032552
4.99E-05	0.007241	0.009708	5.58E-05	4.78E-06	0.042569
0.001596	1.93E-02	0.020643	4.41E-03	0.000582	0.049069
9.30E-03	9.92E-03	0.008144	1.15E-02	9.63E-07	0.043442
6.41E-04	2.93E-03	0.013455	0.013251	3.9E-08	0.037594
1.81E-02	0.006377	0.025874	0.0549	4.43E-08	0.048987
0.024159	0.129098	0.122636	0.128203	0.000366	0.170978
0.156279	0.198083	0.186755	0.247593	0.014026	0.230888
0.057548	5.68E-02	0.094076	0.09039	0.004649	0.102077
2.29E-02	5.05E-03	0.00983	0.020157	3.22E-06	0.035452
0.01409	1.21E-02	0.015165	6.94E-03	5.41E-08	0.03906
0.001889	7.96E-03	0.010532	1.86E-04	0.000107	0.027755
0.001703	0.009778	0.013178	1.79E-04	3.48E-05	0.041542
1.09E-05	0.005643	0.009021	6.48E-05	3.11E-07	0.046261
1.12E-08	0.00947	0.015226	8.59E-05	4.76E-11	0.032351
3.08E-07	4.56E-03	0.012357	6.33E-04	4.99E-11	0.037749
8.35E-04	4.48E-03	0.007716	5.15E-03	2.38E-09	0.047336
0.051104	1.18E-01	0.052865	0.170096	0.001708	0.191494
0.009236	0.137277	0.084047	0.108319	0.484774	0.242719
0.132	0.411382	0.167842	0.34784	0.320282	0.291283
2.64E-02	0.126025	0.086718	0.096738	0.032632	0.124446
1.18E-02	9.84E-03	0.025144	0.03119	9.34E-08	0.048669
1.68E-03	1.28E-02	0.006148	3.89E-04	2.2E-07	0.031491
0.001837	7.11E-03	0.012237	1.30E-04	0.00084	0.024861
0.002233	1.16E-02	0.013166	1.07E-04	0.001105	0.031862
0.000327	8.25E-03	0.013595	1.49E-04	9.69E-08	0.049959
3.42E-06	0.014694	0.013298	1.58E-04	1.86E-07	0.057509
1.96E-06	1.63E-02	0.02465	3.64E-03	3.06E-06	0.038671
2.40E-05	7.03E-03	0.004531	5.42E-03	2.36E-11	0.040166
4.21E-06	1.24E-02	0.007652	0.01118	2.35E-09	0.038044
3.31E-03	0.07367	0.062309	0.062209	2.92E-05	0.21543
0.050323	0.069333	0.107034	0.079585	0.023629	0.118473

9.71E-03	1.25E-02	0.036807	0.035265	9.66E-07	0.058806
0.058502	1.76E-02	0.063631	0.116142	9.96E-06	0.055275
5.78E-03	1.04E-02	0.011339	2.42E-03	1.43E-06	0.035795
0.002066	8.30E-03	0.010034	1.89E-04	7.48E-05	0.028922
0.009736	1.50E-02	0.02212	5.65E-04	3.05E-05	0.036409
3.84E-05	0.005601	0.008685	1.13E-04	2.33E-08	0.049094
8.12E-06	6.54E-03	0.01133	4.16E-04	2.23E-11	0.049211
1.07E-06	5.47E-03	0.009678	1.25E-03	3.7E-13	0.038337
1.16E-05	0.004326	0.008792	1.92E-03	3.82E-12	0.04205
2.84E-07	2.41E-03	0.011199	0.002117	2.24E-10	0.033853
1.5E-07	0.004034	0.012508	0.00071	6.34E-13	0.039268
1.22E-02	0.007763	0.008141	2.64E-02	1.3E-05	0.034827
5.65E-03	1.37E-02	0.005984	6.20E-03	1.73E-06	0.041659
0.032343	1.20E-02	0.025805	2.20E-02	5.44E-09	0.049261
2.90E-03	1.44E-02	0.0082	6.13E-04	3.07E-10	0.051132
0.001649	1.10E-02	0.013133	1.46E-04	7.44E-06	0.026593
0.000834	0.011267	0.012284	6.53E-05	0.00018	0.02769
2.20E-06	0.005127	0.008743	5.40E-05	1.06E-07	0.04592
7.30E-06	1.16E-02	0.01029	5.12E-04	1.02E-10	0.043053
2.00E-05	0.005612	0.010569	3.49E-03	1.57E-07	0.046825
6.30E-07	1.15E-02	0.006287	0.007495	4.76E-10	0.032141
0.126655	0.484322	0.139659	0.324168	0.938159	0.367677
0.032994	1.12E-01	0.150001	0.147809	2.2E-05	0.212528
0.052971	2.02E-01	0.154557	0.135576	0.259298	0.186771
0.07637	1.13E-01	0.13138	0.139712	0.076802	0.135795
1.85E-02	5.27E-03	0.019578	0.027758	1.84E-08	0.041897
0.013939	0.016524	0.029611	1.13E-02	4.55E-07	0.038
2.38E-03	6.79E-03	0.009833	1.49E-04	0.001956	0.03372
8.13E-04	9.80E-03	0.01	8.01E-05	0.000325	0.034531
3.28E-05	0.005295	0.009598	9.60E-05	2.45E-06	0.053162
7.40E-08	0.006019	0.00951	7.95E-05	1.49E-10	0.037177
0.099627	5.66E-03	0.023281	0.309165	0.027094	0.170297
9.89E-03	0.001768	0.01887	0.054616	1.52E-09	0.044946
2.32E-03	0.00206	0.025563	0.044765	1.63E-10	0.051348
0.075999	0.286246	0.141058	0.152709	0.053279	0.245331
0.09801	0.149346	0.177278	0.128625	0.183828	0.160351
2.73E-02	1.59E-02	0.028646	0.040522	4.72E-05	0.052709
0.008105	0.006634	0.009356	5.69E-03	1.85E-08	0.042397
0.004791	1.78E-02	0.01099	1.26E-03	1.2E-08	0.040712
0.002484	0.008441	0.012664	1.39E-04	0.000396	0.026357
0.001236	1.24E-02	0.013593	1.08E-04	4.86E-06	0.028447
1.48E-05	0.010101	0.010862	7.65E-05	6.66E-09	0.046136
1.92E-05	0.009281	0.016241	8.38E-04	2.63E-05	0.056531
5.41E-04	8.60E-03	0.006217	1.09E-02	3.36E-09	0.04101

0.02729	7.14E-03	0.007117	6.41E-02	5.67E-06	0.040006
7.59E-04	0.005425	0.024883	0.038721	1.9E-08	3.27E-02
0.089717	0.193373	0.186263	0.162887	0.012342	0.215448
0.145538	0.190648	0.226351	0.20431	0.195167	0.217283
2.04E-02	1.83E-02	0.036105	0.052435	2.89E-05	0.059308
0.017957	4.94E-03	0.007178	1.09E-02	2.79E-07	0.034066
0.010677	0.018724	0.012584	3.95E-03	2.45E-05	0.042881
0.001115	9.93E-03	0.011769	1.78E-04	3.26E-06	0.025198
0.005009	0.017029	0.022666	5.23E-04	4.83E-05	0.034119
5.89E-06	0.004879	0.008849	6.01E-05	6.15E-07	0.048525
3.22E-07	0.006021	0.010944	8.91E-05	7.37E-11	0.048417
0.005699	1.36E-02	0.009358	9.88E-03	3.78E-07	0.04661
7.37E-06	4.29E-02	0.006986	0.03056	1.07E-08	3.16E-02
0.304301	0.513484	0.468897	0.311731	0.571614	0.445304
0.039412	0.080584	0.062016	0.082654	0.098464	0.092811

ffb1	ff2	ff3	ff4	ff5	ff6
3.04E-13	9.27E-03	0.001974	4.49E-02	0.000923	1.94E-06
0.09391	1.69E-01	0.180397	0.158044	0.207387	0.096985
0.006193	2.59E-01	0.230617	0.284398	0.251783	2.77E-01
0.007232	1.91E-02	0.012445	0.074284	0.005482	7.86E-03
0.020603	0.031246	0.015738	0.118768	0.010452	2.17E-02
0.009909	0.007232	0.003448	0.045158	0.005881	1.16E-02
0.00434	3.06E-04	0.004368	0.017929	4.47E-03	2.95E-03
0.003495	7.97E-05	0.004404	0.009746	2.19E-03	0.003303
0.007553	1.24E-04	0.007054	0.01554	9.05E-04	9.65E-03
0.004538	3.98E-04	0.008606	0.014352	2.22E-04	4.54E-03
0.014043	6.16E-03	0.009468	0.028642	1.10E-04	0.017972
0.017315	0.013497	0.017146	9.22E-02	0.005228	0.019693
0.000143	4.21E-02	0.047922	0.084078	0.048698	8.68E-03
0.316186	1.88E-01	0.146109	0.194593	0.245024	1.36E-01
0.101343	0.141131	0.119763	0.155341	0.161009	1.45E-02
0.001339	0.05973	0.068704	0.19943	0.018847	1.49E-02
0.011772	1.85E-02	0.007329	0.06923	0.009227	1.12E-02
0.01557	5.81E-03	0.003943	0.064557	0.006021	1.71E-02
0.004853	3.21E-04	0.00303	0.013351	6.04E-03	3.64E-03
0.001677	1.05E-04	0.004825	0.011279	3.69E-03	0.001326
0.005144	1.11E-04	0.005677	0.0131	8.65E-04	5.72E-03
0.013297	2.80E-03	0.012359	0.018289	0.000136	1.52E-02
0.013351	5.06E-03	0.006645	0.026278	1.89E-04	1.75E-02
0.011296	0.007001	0.0122	5.32E-02	0.000638	0.011539
5.73E-11	9.35E-03	5.62E-03	4.74E-02	0.000512	0.00027

1.62E-07	1.07E-02	4.86E-03	5.98E-02	0.001082	4.33E-02
0.096777	2.19E-01	0.226234	0.260236	0.2455	6.75E-01
0.030567	0.226287	0.21084	0.250485	0.167948	2.94E-02
0.005628	0.007727	0.002934	0.033757	0.00258	7.63E-03
0.004666	5.41E-04	0.005788	0.030723	2.17E-03	4.64E-03
0.00852	9.73E-05	0.006892	0.016394	4.86E-03	7.47E-03
0.003839	5.63E-05	0.005787	0.010518	2.34E-03	3.56E-03
0.009116	1.27E-04	0.009028	0.014574	0.000781	8.54E-03
0.015945	3.26E-03	0.013423	0.02057	2.16E-04	1.32E-02
0.008369	7.30E-03	0.004662	0.030596	8.52E-05	3.33E-03
0.003543	4.92E-03	0.005256	4.08E-02	8.37E-05	1.84E-04
0.030623	2.61E-01	0.235096	0.269508	0.262861	0.028317
0.88932	2.10E-01	0.173836	0.213512	0.324898	0.321614
0.198039	2.18E-01	0.169041	0.208471	0.221828	1.98E-01
0.007591	2.22E-02	0.012997	0.072285	0.007346	3.92E-03
0.008195	0.001929	0.001316	0.019316	0.003662	7.72E-03
0.011688	0.000364	0.003616	0.022514	0.004262	1.08E-02
0.01031	1.29E-04	0.006873	0.018815	0.004183	0.010403
0.005048	8.61E-05	0.006761	0.019378	4.75E-03	6.01E-03
0.007103	1.79E-04	0.00727	0.01288	5.45E-04	5.84E-03
0.007475	8.49E-04	0.013547	0.01762	1.87E-04	0.008521
0.020594	0.005641	0.02745	5.63E-02	0.000557	2.73E-02
7.72E-06	5.50E-03	0.002217	4.49E-02	5.75E-05	3.50E-05
0.000477	6.09E-03	2.26E-03	0.032578	0.000132	1.56E-04
0.62251	0.188786	0.216589	0.180329	0.164961	0.048556
0.452952	2.23E-01	0.176554	0.211786	0.299987	3.84E-01
1.69E-13	4.99E-02	0.04688	0.158589	0.019679	1.05E-02
2.37E-15	1.16E-02	0.00791	0.083679	0.004916	1.17E-02
0.012956	0.002723	0.001921	0.0367	0.005501	1.24E-02
0.002728	1.42E-04	0.004514	0.012847	3.88E-03	0.001887
0.003399	6.81E-05	0.005361	0.011338	2.97E-03	2.92E-03
0.00581	1.28E-04	0.00607	0.011983	0.00059	4.61E-03
0.008557	1.92E-03	0.00882	0.01437	5.23E-05	8.50E-03
0.016416	0.005455	0.027124	4.18E-02	0.000322	1.96E-02
3.44E-06	4.65E-03	2.39E-03	4.45E-02	9.37E-05	5.2E-06
2.49E-05	5.66E-03	0.004283	0.034076	7.9E-06	7.59E-05
6.15E-05	5.35E-03	2.44E-03	0.034118	2.48E-05	1.03E-06
0.095709	1.58E-01	0.180947	0.140374	0.201647	4.12E-01
0	0.019214	0.013371	0.096018	0.002502	7.26E-03
0.009222	3.26E-03	0.001406	0.034303	0.005277	9.16E-03
0.008467	0.000239	0.002906	0.012665	0.005617	6.48E-03
0.001675	9.07E-05	0.00491	0.008454	5.31E-03	1.32E-03
0.006931	7.32E-05	0.00686	0.013334	1.85E-03	6.75E-03
0.016062	1.11E-03	0.021777	0.021931	0.000687	1.57E-02

0.007435	1.36E-03	0.005248	0.010677	4.75E-05	0.009949
0.000143	1.09E-02	1.07E-02	0.02477	1.94E-05	5.18E-07
3.19E-05	9.40E-03	9.93E-03	0.031493	6.85E-06	3.52E-06
0.01446	4.77E-03	0.009209	4.06E-02	0.00013	2.69E-03
0.022509	0.078967	0.083094	0.137407	0.04922	2.65E-02
0.313882	1.09E-01	0.120953	0.149875	0.103992	2.25E-05
0.001014	2.32E-02	0.014274	0.083709	0.005287	7.78E-03
0.009701	2.95E-03	0.00152	0.030065	0.003959	9.18E-03
0.002645	1.72E-04	0.004835	0.015936	2.18E-03	2.70E-03
0.004487	7.20E-05	0.005184	0.010962	1.54E-03	5.28E-03
0.004409	6.13E-05	0.005868	0.012103	5.50E-03	4.61E-03
0.013836	7.52E-04	0.024392	0.024154	8.39E-04	1.26E-02
0.003484	3.25E-04	0.010201	0.013474	1.91E-04	4.68E-03
0.018315	4.79E-03	0.015491	4.02E-02	0.000224	1.89E-02
5.2E-05	7.47E-03	3.37E-03	0.031764	2.71E-05	3.28E-06
8.56E-05	6.23E-03	3.74E-03	0.035554	1.88E-05	8.40E-06
0.018865	1.38E-02	7.32E-03	0.047666	0.004395	1.83E-02
0.000111	2.30E-02	0.013233	0.091318	0.016448	1.54E-02
0.006489	3.24E-03	0.00144	0.025314	0.002224	6.50E-03
0.011426	5.53E-04	0.002436	0.026641	0.004053	1.33E-02
0.008886	1.39E-04	0.005895	0.02164	4.50E-03	9.43E-03
0.012539	1.06E-04	0.011714	0.020572	0.005904	1.29E-02
0.002526	5.85E-05	0.005059	0.009843	1.27E-03	2.25E-03
0.001347	8.04E-05	0.004929	0.009838	5.70E-04	8.03E-04
0.00126	1.72E-04	0.006223	0.008977	1.96E-04	1.11E-04
0.005532	5.20E-03	0.007144	0.026477	1.59E-05	3.67E-04
0.003169	1.23E-02	1.42E-02	0.023507	1.9E-05	9.18E-05
0.0005	1.19E-02	1.29E-02	0.023725	1.94E-05	2.13E-06
0.02704	6.02E-03	2.08E-03	0.024488	0.000266	6.04E-05
0.018839	3.44E-02	0.026713	0.098555	0.031458	1.93E-02
0.012087	8.36E-03	0.003053	0.062665	0.009058	1.41E-02
0.011082	1.57E-03	0.001296	0.028751	0.003792	1.22E-02
0.008865	3.51E-04	0.004683	0.029198	0.003219	8.62E-03
0.004649	7.96E-05	0.004834	0.010451	4.14E-03	0.003406
0.001411	5.10E-05	0.004849	0.007707	2.52E-03	1.69E-03
0.006378	1.05E-04	0.006207	0.011002	7.64E-04	7.17E-03
0.002931	1.60E-04	0.007804	0.014195	2.86E-04	3.45E-03
0.012751	0.006047	0.035391	0.037667	0.000351	2.17E-02
0.000112	7.06E-03	3.23E-03	0.033702	3.05E-05	2.42E-06
1.12E-13	7.03E-03	0.005722	4.93E-02	0.000472	1.59E-03
1.08E-05	5.42E-03	0.004097	0.041506	1.59E-05	1.30E-04
0.455835	2.43E-01	0.213256	0.24591	0.349394	4.56E-01
0.00451	1.72E-02	0.010218	0.064864	0.002705	7.48E-03
0.013936	3.85E-03	0.001739	0.042124	0.006051	1.43E-02

0.005272	3.45E-04	0.003703	0.014978	0.003909	5.44E-03
0.002062	9.92E-05	0.004728	0.012058	2.30E-03	1.70E-03
0.018736	3.68E-04	0.028635	0.042933	0.006727	6.88E-02
0.003465	1.01E-04	0.005513	0.012269	6.82E-04	0.002978
0.007138	8.20E-04	0.011058	0.01668	1.62E-04	6.93E-03
0.012035	5.85E-03	0.010348	0.021863	3.23E-05	7.24E-03
0.002381	8.13E-03	0.004531	0.028434	5.39E-05	1.03E-03
0.018465	0.010791	0.014064	0.080516	0.000814	0.018785
4.41E-16	7.57E-03	0.003147	0.053516	0.000149	2.60E-03
0.089493	1.07E-02	0.007697	0.045345	0.008215	3.45E-05
0.016169	5.36E-03	0.002887	0.061024	0.008319	8.97E-02
0.018717	0.003464	0.003941	0.067739	0.006866	1.91E-02
0.006813	6.46E-04	0.003467	0.016617	0.003155	7.10E-03
0.003265	1.11E-04	0.005087	0.014045	4.59E-03	0.00259
0.005416	9.68E-05	0.007137	0.023298	3.49E-03	6.18E-03
0.001356	8.84E-05	0.005182	1.45E-02	6.30E-04	7.46E-04
0.01614	1.92E-03	0.014349	0.008888	3.12E-05	1.47E-02
0.001085	0.004109	0.027261	0.030144	0.000188	2.00E-02
2.04E-08	5.23E-03	0.002378	0.042182	4.04E-05	4.70E-06
0.000101	5.51E-03	3.36E-03	0.036164	4.13E-05	3.97E-05
3.88E-02	1.35E-01	0.202855	0.136579	0.18476	3.78E-02
0.509598	2.09E-01	0.191707	0.199358	0.283144	7.46E-02
7.24E-14	2.94E-02	0.022002	0.123953	0.006163	1.29E-03
0.019284	3.25E-02	0.015397	0.111071	0.01502	1.73E-02
0.013562	5.57E-03	0.002827	0.049505	0.006337	1.40E-02
0.002248	2.12E-04	0.004543	0.014495	3.21E-03	0.001741
0.003742	8.88E-05	0.005447	0.015423	4.77E-03	3.69E-03
0.001522	8.80E-05	0.004865	0.010737	6.37E-04	8.64E-04
0.003001	3.45E-04	0.005222	0.010561	1.53E-04	4.45E-03
0.019802	0.005909	0.01959	5.66E-02	0.000599	5.00E-02
0.008245	7.35E-03	3.41E-03	0.039511	0.000391	7.40E-03
0.001898	1.53E-02	0.010053	0.055838	0.004107	4.87E-03
1.78E-12	9.56E-02	0.082385	0.129587	0.151126	1.62E-01
6.48E-13	1.90E-02	0.05155	0.052644	0.006651	1.23E-06
0.014036	1.16E-02	0.004629	0.070564	0.010415	3.54E-02
0.003178	4.98E-04	0.002739	0.013684	0.002966	4.33E-03
0.005531	1.14E-04	0.006213	0.020989	3.09E-03	5.32E-03
0.006447	1.12E-04	0.00822	0.025304	2.28E-03	6.04E-03
0.007878	7.58E-05	0.00729	0.014938	4.60E-03	9.56E-03
0.007651	1.05E-04	0.007601	0.010722	0.00058	7.99E-03
0.004258	3.75E-04	0.010543	0.016722	1.84E-04	3.40E-03
0.01462	6.72E-03	0.01094	0.030071	2.31E-04	1.47E-02
3.5E-05	9.42E-03	6.94E-03	0.025171	1.3E-05	5.07E-06
8.4E-05	6.54E-03	7.16E-03	0.038248	7.81E-06	6.02E-06

4.43E-05	6.69E-03	4.04E-03	0.032926	1.12E-05	1.02E-06
0.031418	3.21E-02	2.35E-02	0.094373	0.085915	3.21E-02
0.624116	2.31E-01	0.144573	0.208052	0.128177	1.54E-01
0.01141	1.14E-02	0.003576	0.04446	0.006027	1.35E-02
0.009662	1.43E-03	0.002635	0.023961	0.004256	7.63E-03
0.011215	4.70E-04	0.006705	0.038781	0.003152	1.35E-02
0.004066	1.10E-04	0.005302	0.017836	1.79E-03	3.11E-03
0.001514	1.07E-04	0.005245	0.011743	4.17E-04	0.001191
0.004362	4.24E-04	0.013707	0.01627	1.79E-04	7.40E-03
0.000622	7.47E-03	4.76E-03	0.02414	2.27E-05	5.46E-07
0.006458	9.12E-03	0.008261	0.034943	3.46E-05	7.64E-03
0.017899	0.007844	0.004477	0.044728	0.004287	1.93E-02
5.22E-05	8.39E-03	0.004082	0.034278	0.00018	1.40E-04
0.012489	5.93E-03	0.003457	0.032532	0.001228	7.16E-05
0.00984	2.61E-03	0.002365	0.042549	0.002565	7.74E-03
0.008975	5.31E-04	0.004941	0.034593	0.00192	8.75E-03
0.006442	1.18E-04	0.005419	0.015646	1.52E-03	7.87E-03
0.002537	5.11E-05	0.005364	0.008822	3.36E-03	0.002207
0.001575	4.92E-05	0.00509	0.009709	1.52E-03	1.85E-03
0.002736	8.84E-05	0.005735	0.014142	5.70E-04	0.001644
0.017842	2.73E-03	0.016315	0.015202	0.000149	1.80E-02
0.014395	0.010063	0.020832	6.32E-02	0.000744	1.80E-02
6.35E-05	6.75E-03	3.68E-03	4.56E-02	0.000805	1.33E-04
0.007969	0.018288	0.00818	0.060814	0.005996	5.51E-03
0.635838	1.90E-01	0.197077	0.185694	0.260915	4.99E-01
0.175461	2.33E-01	0.186298	0.208514	0.359451	2.88E-01
0.012997	5.90E-02	0.045062	0.125659	0.044667	4.46E-03
0.006421	4.81E-03	0.002909	0.038414	0.004484	6.82E-03
0.016944	1.01E-03	0.004452	0.041129	0.004621	1.54E-02
0.005872	1.00E-04	0.005611	0.011933	5.48E-03	0.004393
0.007142	8.10E-05	0.005936	0.012933	2.10E-03	7.62E-03
0.007539	1.69E-04	0.010936	0.023962	1.51E-03	0.007116
0.017371	3.76E-03	0.013595	0.02174	0.000145	1.61E-02
5.35E-13	0.017659	0.028795	0.112777	0.007183	0.022627
0.004368	1.79E-02	0.009148	0.072791	0.004387	4.58E-04
0.001033	0.022481	0.016789	0.082054	0.007826	1.63E-06
0.004012	3.79E-02	0.04235	0.122845	0.081986	2.20E-07
0.992367	0.153415	0.19663	0.146781	0.237284	5.00E-01
0.241362	2.83E-01	0.147937	0.250888	0.088618	2.42E-01
0.01576	0.062027	0.041005	0.14385	0.021201	1.34E-02
0.004536	2.46E-03	0.003867	0.032231	3.21E-03	4.38E-03
0.001929	1.41E-04	0.004868	0.01414	3.32E-03	1.53E-03
0.001863	5.10E-05	0.005017	0.008119	2.74E-03	0.002165
0.005138	1.58E-04	0.0077	0.015356	4.74E-04	0.004929

0.017464	3.01E-03	0.012694	0.020491	2.66E-04	1.72E-02
0.004442	1.40E-02	0.022762	7.13E-02	0.002505	2.31E-02
0.000122	0.022087	1.77E-02	5.81E-02	0.001664	1.39E-06
1.3E-07	0.013694	0.005376	0.054346	0.003425	1.8E-06
0.309447	1.68E-01	0.153089	0.13934	0.112066	3.11E-01
0.174818	3.62E-01	0.316263	0.32892	0.516078	6.31E-01
0.167169	2.22E-01	0.146504	0.187215	0.22313	9.34E-01
0.010234	0.013122	0.004099	0.052076	0.007275	1.03E-02
0.006456	1.35E-03	0.003357	0.029228	0.002952	6.87E-03
0.008624	1.60E-04	0.005091	0.024255	7.40E-03	8.30E-03
0.002496	7.76E-05	0.005158	0.012735	2.58E-03	2.35E-03
0.007044	1.13E-04	0.007687	0.016775	1.00E-03	6.84E-03
0.018124	2.37E-03	0.012173	0.016655	0.000219	2.08E-02
0.013743	5.71E-03	0.004307	2.86E-02	5.24E-04	0.037505
0.000654	6.62E-03	3.07E-03	0.031053	0.000237	0.000305
9.24E-12	1.15E-02	6.13E-03	5.92E-02	0.002056	7.52E-03
0.158908	1.59E-01	0.226474	0.180733	0.192184	0.158854
0.008503	0.121159	0.162617	0.137558	0.160189	9.87E-03
0.008497	0.026816	0.016788	0.079447	0.01544	4.92E-06
0.019615	3.15E-02	0.018573	0.120818	0.009166	5.22E-02
0.006003	0.004077	0.003805	0.032358	3.90E-03	6.92E-03
0.008928	2.56E-04	0.008668	0.03732	7.64E-03	0.008777
0.002611	8.62E-05	0.004934	0.011947	4.43E-03	2.04E-03
0.008172	1.89E-04	0.013281	0.029913	2.39E-03	0.008948
0.004537	7.32E-04	0.010932	0.01658	1.03E-04	3.75E-03
0.03	0.01317	0.031557	0.102283	0.00107	2.61E-02
0.000215	1.63E-02	1.13E-02	7.59E-02	0.003385	5.19E-03
0.177894	0.233884	0.216969	0.247964	0.182504	0.211336
0.414132	4.30E-01	0.338731	0.39683	0.345421	4.14E-01
0.009039	1.20E-01	0.130964	0.184801	0.098425	1.30E-02
0.006412	1.39E-02	0.00753	0.049201	0.002217	4.59E-03
0.006618	0.001464	0.001248	0.020403	0.001277	4.20E-03
0.008359	2.82E-04	0.003887	0.0194	0.002122	9.04E-03
0.001723	8.06E-05	0.0045	0.009436	1.99E-03	2.28E-03
0.008523	8.46E-05	0.009113	0.019565	6.56E-03	0.008867
0.001373	8.25E-05	0.004664	0.007628	5.64E-04	7.67E-04
0.011471	1.29E-03	0.013887	0.012574	0.000104	1.64E-02
0.018135	3.79E-03	0.018164	0.030393	0.000131	1.83E-02
0.009563	0.007408	0.008609	6.64E-02	0.001326	1.54E-02
6.73E-07	9.49E-03	0.004081	0.053375	0.001008	3.76E-03
0.261533	1.22E-01	0.097086	0.167281	0.106104	2.60E-01
0.015651	1.87E-01	0.177249	0.191634	0.290941	1.62E-01
0.009222	1.95E-02	0.008394	0.069559	0.009068	9.66E-03
0.015262	3.80E-03	0.002227	0.04881	0.006326	1.70E-02

0.007158	3.03E-04	0.003119	0.014235	0.004221	6.67E-03
0.001886	9.74E-05	0.004776	0.012318	2.07E-03	1.56E-03
0.001674	4.60E-05	0.00499	0.007538	2.56E-03	1.79E-03
0.013091	3.06E-04	0.015446	0.017827	0.001151	1.32E-02
0.01116	2.06E-03	0.019679	0.017272	1.36E-04	1.23E-02
0.000279	7.28E-03	6.74E-03	0.029483	3.33E-05	4.53E-07
8.66E-05	9.08E-03	9.51E-03	0.032503	8.90E-06	2.95E-06
0.000365	8.48E-03	0.007697	0.032409	1.87E-05	2.62E-05
0.00015	7.47E-03	5.09E-03	0.030391	1.79E-05	6.22E-06
4.93E-06	7.06E-02	0.065808	0.125843	0.081493	1.89E-03
0.021279	1.03E-01	0.069212	0.151701	0.105734	1.03E-01
0.008193	0.002892	0.001162	0.02087	0.004537	9.19E-03
0.00897	3.66E-04	0.004259	0.028107	0.002489	9.27E-03
0.0038	9.67E-05	0.005184	0.015125	2.80E-03	3.08E-03
0.001672	6.99E-05	0.005066	0.011921	2.32E-03	1.88E-03
0.002363	7.66E-05	0.005144	0.011612	6.64E-04	1.49E-03
0.017058	2.29E-03	0.017391	0.012091	6.74E-05	5.70E-03
0.016827	4.69E-03	0.012055	0.032566	1.96E-04	1.69E-02
0.004372	4.82E-03	0.004588	4.41E-02	5.12E-05	0.002168
1.79E-13	9.73E-03	5.63E-03	6.89E-02	0.000916	0.011674
0.013798	1.38E-01	0.117991	0.133857	0.050882	0.001659
0.216905	2.70E-01	0.163891	0.239573	0.248062	2.17E-01
1.69E-13	0.046088	0.056681	0.159515	0.012597	1.62E-02
0.007445	0.008257	0.003071	0.044389	0.004211	7.75E-03
0.010705	0.000656	0.003497	0.03205	0.005008	9.99E-03
0.00204	1.05E-04	0.004945	0.010264	4.09E-03	1.80E-03
0.004824	7.71E-05	0.005245	0.012131	2.13E-03	3.72E-03
0.002765	9.60E-05	0.005502	0.012089	5.06E-04	2.21E-03
0.00406	8.06E-04	0.008856	0.013989	5.38E-05	5.02E-05
0.008747	7.53E-03	0.00671	0.023797	3.13E-05	7.80E-03
0.013596	5.83E-03	0.010096	4.30E-02	1.65E-04	7.14E-01
0.033704	6.46E-02	0.163944	0.095216	0.02035	3.20E-02
0.001056	1.47E-01	0.132599	0.116674	0.151933	1.29E-01
0.303468	3.52E-01	0.266242	0.352727	0.429252	3.02E-01
0.015679	7.83E-02	0.050134	0.132527	0.057906	6.81E-06
0.010294	1.03E-02	0.004413	0.058642	0.007381	7.31E-03
0.002164	2.93E-04	0.004587	0.016913	1.53E-03	3.39E-03
0.001812	7.67E-05	0.005062	0.008856	4.69E-03	1.56E-03
0.003365	6.45E-05	0.005466	0.012282	3.27E-03	3.30E-03
0.00572	8.13E-05	0.006446	0.012254	8.37E-04	5.52E-03
0.004245	1.81E-04	0.005951	0.01215	3.03E-04	2.66E-03
0.010577	1.11E-02	0.008645	0.01206	1.93E-05	2.19E-05
0.009657	4.45E-03	0.010411	3.41E-02	2.81E-04	2.36E-03
7.83E-06	4.39E-03	5.87E-03	4.88E-02	4.08E-05	5.98E-07

8.72E-14	8.64E-02	0.086704	0.091173	0.087262	2.59E-02
1.74E-06	4.49E-02	0.055958	0.182026	0.00912	1.26E-01
0.008018	1.80E-02	0.009332	0.064151	0.010372	5.74E-05
0.020046	0.00868	0.007951	0.092992	0.008986	1.92E-02
0.005646	8.97E-04	0.004838	0.033224	2.94E-03	4.82E-03
0.002145	1.10E-04	0.005127	0.011669	3.56E-03	2.05E-03
0.011678	1.07E-04	0.014699	0.025632	1.02E-02	9.89E-03
0.005449	1.57E-04	0.008921	0.020673	4.63E-04	3.25E-03
0.011039	1.11E-03	0.018389	0.019257	2.15E-04	6.13E-03
0.011682	7.94E-03	0.00809	0.024892	9.88E-05	3.50E-03
0.009107	7.97E-03	0.004534	0.030995	1.20E-04	5.92E-03
0.000167	7.56E-03	3.90E-03	0.035632	1.82E-05	1.91E-06
0.000134	3.50E-03	1.51E-03	0.018452	4.06E-05	2.01E-06
0.013469	3.12E-03	0.002729	0.025767	0.000524	1.49E-02
0.009263	1.39E-03	0.002301	0.020032	0.000396	9.96E-03
0.02037	0.001007	0.009105	0.051983	1.68E-03	2.05E-02
0.006964	1.88E-04	0.007319	0.024414	0.000801	1.00E-02
0.002789	5.15E-05	0.005393	0.008904	2.83E-03	2.66E-03
0.002023	5.04E-05	0.005134	0.009353	1.80E-03	1.93E-03
0.003171	1.13E-04	0.006414	0.013539	3.98E-04	2.59E-03
0.013398	1.98E-03	0.031511	0.02375	2.84E-04	0.01265
0.012776	7.53E-03	0.009397	0.031543	4.74E-05	1.48E-01
5.22E-06	4.74E-03	5.84E-03	4.03E-02	5.73E-05	3.05E-06
0.164563	3.43E-01	0.285999	0.47102	0.259295	0.163928
0.045099	0.191517	0.063416	0.184681	0.023198	0.000226
0.127714	1.76E-01	0.188798	0.182823	0.281335	1.28E-01
0.012098	1.08E-01	0.087766	0.164462	0.046616	1.87E-02
0.00991	0.007679	0.0024	0.045924	0.00688	1.00E-02
0.012718	0.000953	0.00535	0.035518	0.004916	1.22E-02
0.001645	1.43E-04	0.005158	0.013314	3.72E-03	0.001719
0.001973	7.50E-05	0.004952	0.011831	1.85E-03	1.58E-03
0.004946	1.39E-04	0.008296	0.018863	7.98E-04	0.005462
0.004643	6.93E-04	0.010254	0.017092	1.08E-04	4.34E-03
0.031412	0.05066	0.039067	0.102152	0.009028	0.031057
2.12E-08	8.97E-03	3.67E-03	5.27E-02	0.000912	4.88E-04
7.1E-09	0.008934	0.003632	0.041709	0.000325	0.003586
0.220337	2.09E-01	0.186675	0.227635	0.17	2.21E-01
1.95E-05	0.130126	0.161362	0.215048	0.108766	1.34E-01
0.00833	2.13E-02	0.011465	0.07546	0.009217	4.26E-03
0.007316	0.001199	0.002404	0.035102	0.003433	4.94E-03
0.007689	1.57E-04	0.006094	0.019111	0.002449	8.79E-03
0.002474	6.73E-05	0.005542	0.010406	4.42E-03	2.40E-03
0.00284	4.53E-05	0.005489	0.008951	1.90E-03	2.82E-03
0.002774	7.45E-05	0.005269	0.010652	5.63E-04	2.21E-03

0.012248	1.71E-03	1.86E-02	0.013936	5.63E-05	0.009587
0.018678	5.00E-03	0.009967	0.02863	3.54E-04	1.63E-02
0.010174	8.35E-03	0.015834	5.47E-02	0.000624	0.006372
0	5.89E-03	2.61E-03	3.80E-02	0.000203	0.000419
0.153948	0.23173	0.184345	0.23381	0.164622	1.54E-01
0.024024	2.72E-01	0.215836	0.256862	0.307122	1.79E-01
7.82E-08	0.026241	0.015915	0.08306	0.006741	3.09E-03
0.008255	0.002473	0.001905	0.031013	0.003555	8.60E-03
0.01072	2.64E-04	0.003806	0.019609	0.003864	1.09E-02
0.00195	6.57E-05	0.004916	0.007927	3.84E-03	2.44E-03
0.008873	4.26E-05	0.009325	0.009561	4.17E-03	5.96E-03
0.003117	1.08E-04	0.006205	0.01356	4.78E-04	0.002722
0.003542	4.31E-04	0.005579	0.013175	1.29E-04	0.002659
0.019287	4.97E-03	0.020112	0.032715	1.78E-04	0.150819
6.5E-05	8.61E-03	6.88E-03	4.00E-02	0.000372	1.11E-05
0.538124	0.514109	0.538225	0.421066	0.589046	0.615387
0.11675	0.078954	0.069712	0.092256	0.08475	0.114785

enn1	enn2	enn3	enn4	enn5	enn6
0.00085	7.45E-04	1.03E-02	3.29E-04	1.10E-02	0.000255
0.096852	0.118875	0.155483	0.114262	0.090961	2.31E-01
0.276651	0.23998	0.173885	0.227458	1.48E-01	0.364602
7.19E-03	1.14E-02	6.19E-02	5.83E-03	2.13E-02	0.000361
0.021207	0.023534	0.086643	0.008066	0.05465	1.88E-03
0.009873	0.002506	2.46E-02	1.48E-03	0.015973	8.48E-06
0.004461	1.60E-03	4.79E-03	2.01E-03	1.77E-02	4.21E-07
0.003714	0.003438	2.88E-03	2.97E-03	9.61E-03	2.27E-06
0.0073	5.01E-03	2.53E-03	5.17E-03	1.25E-02	3.37E-06
0.004613	4.72E-03	2.02E-03	5.13E-03	1.11E-02	9.19E-05
0.013365	1.62E-02	3.66E-03	3.26E-03	2.24E-02	8.85E-04
6.01E-06	0.02048	2.37E-02	1.58E-02	3.47E-02	4.44E-03
0.046707	0.021453	0.065591	0.007255	3.67E-02	4.53E-02
0.135248	0.199582	0.157866	0.227481	0.118671	0.210145
0.102143	8.94E-02	1.58E-01	1.50E-01	6.73E-02	0.090406
1.15E-02	7.40E-02	1.27E-01	3.41E-02	7.60E-02	1.28E-02
1.14E-02	8.11E-03	5.28E-02	3.87E-03	2.72E-02	1.41E-04
1.62E-02	7.39E-03	3.22E-02	8.71E-04	0.030034	8.40E-05
0.005144	1.47E-03	4.89E-03	1.21E-03	0.012429	5.10E-07
0.001926	2.86E-03	2.92E-03	4.22E-03	1.03E-02	7.01E-07
0.005311	3.71E-03	2.28E-03	5.12E-03	8.44E-03	9.23E-06

0.012804	1.15E-02	2.63E-03	6.17E-03	1.81E-02	3.66E-04
0.012811	1.55E-02	4.20E-03	3.34E-03	1.74E-02	9.77E-04
0.003843	4.94E-03	8.47E-03	3.95E-03	1.68E-02	8.43E-04
0.001703	1.55E-03	9.35E-03	7.48E-04	1.49E-02	5.31E-04
0.003736	8.02E-03	2.17E-02	1.73E-03	2.30E-02	2.27E-03
0.675317	0.225797	0.170973	0.19452	1.31E-01	2.60E-01
3.06E-02	1.60E-01	1.81E-01	1.76E-01	1.10E-01	0.112259
0.006024	3.75E-03	2.37E-02	1.17E-03	9.46E-03	3.68E-05
0.004553	0.001915	6.35E-03	2.75E-03	2.27E-02	1.09E-06
0.008163	2.93E-03	3.23E-03	3.69E-03	0.021547	1.90E-07
0.003813	3.51E-03	2.68E-03	4.96E-03	0.014075	4.55E-07
0.008715	6.55E-03	2.41E-03	5.95E-03	1.23E-02	2.46E-06
0.015582	8.55E-03	2.79E-03	9.31E-03	1.90E-02	3.91E-04
0.017048	8.73E-03	3.58E-03	4.82E-04	1.79E-02	6.22E-04
3.07E-08	4.66E-03	4.30E-03	8.09E-04	1.61E-02	4.59E-04
0.02959	0.251912	0.168426	0.238356	0.145449	3.07E-01
0.321616	0.273742	0.161344	0.275299	1.60E-01	0.333204
1.16E-01	2.55E-01	1.67E-01	2.02E-01	1.60E-01	0.154694
7.27E-03	1.04E-02	5.73E-02	7.33E-03	0.015024	1.38E-03
0.008407	2.79E-03	1.18E-02	6.08E-04	9.56E-03	2.72E-06
0.011296	2.98E-03	5.78E-03	1.34E-03	2.05E-02	3.58E-07
0.009807	3.14E-03	3.58E-03	3.15E-03	2.39E-02	1.95E-07
0.004887	0.004658	2.70E-03	6.72E-03	0.019223	2.69E-07
0.006976	6.78E-03	2.28E-03	5.50E-03	1.00E-02	1.66E-05
0.007218	4.93E-03	2.00E-03	5.96E-03	1.53E-02	2.19E-04
0.021927	0.015043	7.86E-03	2.67E-02	2.28E-02	6.06E-04
6.68E-07	5.84E-04	5.57E-03	5.26E-04	1.07E-02	1.46E-04
0.000914	6.18E-03	8.63E-03	1.81E-04	0.011186	9.07E-04
0.222244	0.115059	0.162458	0.116311	7.97E-02	1.27E-01
3.83E-01	2.74E-01	1.66E-01	2.55E-01	1.65E-01	0.242825
1.09E-02	5.42E-02	1.07E-01	3.06E-02	5.08E-02	1.01E-02
0.004185	1.18E-02	4.61E-02	2.14E-03	2.88E-02	1.68E-04
0.012884	0.002529	1.62E-02	8.29E-04	0.014949	1.98E-06
0.002985	2.13E-03	3.43E-03	2.94E-03	1.22E-02	7.29E-07
0.003477	3.29E-03	2.73E-03	4.80E-03	0.013466	4.64E-07
0.005677	0.009171	2.43E-03	4.93E-03	1.01E-02	1.16E-05
0.008227	1.63E-02	2.20E-03	3.36E-03	1.56E-02	2.23E-04
0.020663	1.07E-02	6.82E-03	1.54E-02	2.02E-02	9.24E-04
1.33E-05	1.15E-03	5.04E-03	5.33E-04	1.09E-02	2.14E-04
0.000887	0.003136	5.01E-03	9.26E-05	1.09E-02	3.22E-04
1.42E-06	3.20E-03	4.92E-03	6.97E-05	8.74E-03	2.48E-04
0.097637	0.062566	0.156859	0.121769	4.81E-02	9.70E-02
0.006805	0.015689	0.075781	0.010692	0.022994	0.000818
9.52E-03	1.90E-03	1.56E-02	8.89E-04	8.99E-03	4.91E-06

0.008348	0.002395	5.10E-03	1.14E-03	1.70E-02	3.31E-07
0.001878	2.36E-03	3.08E-03	3.61E-03	1.28E-02	3.27E-07
0.006707	4.09E-03	2.59E-03	5.08E-03	1.42E-02	4.55E-07
0.015613	8.83E-03	2.49E-03	9.63E-03	1.81E-02	1.69E-05
0.007049	2.43E-02	2.55E-03	3.52E-03	1.44E-02	6.97E-05
0.000662	2.24E-03	1.98E-03	4.25E-04	3.64E-02	1.32E-04
0.001059	2.62E-03	1.48E-03	1.61E-04	3.64E-02	7.37E-05
0.01394	4.63E-03	4.89E-03	1.95E-03	1.54E-02	5.06E-04
0.026421	1.26E-01	1.48E-01	1.02E-01	1.32E-01	1.17E-01
8.40E-03	8.44E-02	1.59E-01	1.13E-01	7.98E-02	9.06E-02
0.007023	0.014627	0.059293	0.007898	1.91E-02	1.33E-03
0.009783	3.23E-03	1.55E-02	7.73E-04	1.19E-02	4.5E-06
0.002741	2.22E-03	3.86E-03	3.33E-03	1.57E-02	1.27E-06
0.004481	0.004026	2.82E-03	3.77E-03	1.22E-02	1.66E-06
0.004531	4.60E-03	2.40E-03	5.82E-03	1.31E-02	2.38E-07
0.013208	6.86E-03	2.27E-03	9.18E-03	1.80E-02	2.24E-05
0.003671	3.06E-03	1.80E-03	5.78E-03	1.02E-02	1.10E-04
5.99E-05	8.53E-03	4.85E-03	6.87E-03	1.74E-02	7.24E-04
0.001333	0.005109	4.20E-03	8.85E-05	1.53E-02	5.41E-04
0.002479	3.87E-03	3.90E-03	1.06E-04	1.15E-02	2.72E-04
0.000374	0.009557	0.02844	0.001214	1.59E-02	4.55E-03
0.01096	0.022122	0.045621	0.005956	2.81E-02	0.005253
0.006901	3.68E-03	1.47E-02	8.14E-04	7.48E-03	2.47E-05
0.011318	0.002646	6.39E-03	1.18E-03	1.32E-02	7.86E-07
0.008697	0.002903	3.25E-03	3.43E-03	1.77E-02	2.98E-07
0.011935	0.004798	2.83E-03	5.42E-03	2.32E-02	1.14E-07
0.002697	4.00E-03	2.31E-03	5.38E-03	8.16E-03	2.84E-06
0.00163	3.59E-03	1.93E-03	6.64E-03	4.60E-03	2.97E-05
0.001572	0.002843	1.62E-03	4.49E-03	5.91E-03	5.26E-05
0.004984	9.63E-03	1.87E-03	5.19E-04	3.20E-02	5.90E-04
0.000104	1.99E-03	2.05E-03	7.14E-04	4.33E-02	1.42E-04
3.36E-05	1.73E-03	1.96E-03	6.96E-04	0.041136	1.24E-04
0.016736	0.00534	1.11E-02	2.19E-04	7.68E-03	1.12E-03
0.01908	0.020506	0.049223	0.013383	3.49E-02	1.50E-02
0.012368	0.006863	0.030451	0.002483	1.61E-02	0.000281
1.12E-02	3.44E-03	1.13E-02	8.18E-04	1.01E-02	4.05E-06
0.008595	0.002368	5.23E-03	2.01E-03	1.98E-02	6.29E-07
0.004788	2.47E-03	3.04E-03	3.08E-03	1.34E-02	3.59E-07
0.001624	0.003393	2.50E-03	4.07E-03	7.38E-03	2.07E-06
0.006457	5.08E-03	2.19E-03	5.29E-03	8.11E-03	7.12E-06
0.003028	3.40E-03	1.89E-03	7.87E-03	8.54E-03	4.61E-05
0.021703	9.19E-03	6.78E-03	2.20E-02	2.04E-02	7.75E-04
0.002029	5.25E-03	5.01E-03	8.01E-05	1.19E-02	4.92E-04
0.000368	3.07E-03	9.50E-03	1.22E-03	1.58E-02	7.19E-04

8.11E-07	1.51E-03	7.51E-03	1.43E-04	8.04E-03	1.73E-04
0.456233	0.293482	0.171003	0.302061	0.172163	3.77E-01
0.005514	0.009171	0.050741	0.004833	1.47E-02	0.000369
0.014117	4.90E-03	2.18E-02	9.89E-04	1.44E-02	7.82E-06
0.005257	1.89E-03	5.40E-03	1.36E-03	1.86E-02	5.75E-07
0.002277	2.73E-03	2.92E-03	4.11E-03	0.010164	1.86E-06
0.01872	0.011799	2.70E-03	7.66E-03	2.50E-02	9.11E-08
0.003733	3.45E-03	2.12E-03	5.84E-03	6.99E-03	1.72E-05
0.006897	7.41E-03	2.06E-03	5.17E-03	1.43E-02	1.60E-04
0.011087	2.05E-02	3.18E-03	2.69E-03	2.83E-02	5.28E-04
0.00186	0.005448	2.67E-03	1.82E-04	3.04E-02	6.37E-04
1.98E-02	8.74E-03	1.77E-02	5.13E-03	0.036095	8.56E-03
0.001686	5.03E-03	2.03E-02	1.78E-04	1.23E-02	1.02E-03
0.015267	0.004026	0.029898	0.002615	8.71E-03	3.67E-03
0.016672	0.007893	2.65E-02	2.15E-03	1.75E-02	4E-05
0.0192	0.007718	2.30E-02	2.37E-03	2.08E-02	1.76E-05
0.006542	2.59E-03	7.29E-03	9.60E-04	2.29E-02	7.37E-07
0.003415	2.67E-03	3.18E-03	4.01E-03	1.53E-02	3.67E-07
0.005233	0.005277	2.55E-03	7.66E-03	1.77E-02	3.75E-07
0.001603	0.003992	2.08E-03	8.23E-03	5.69E-03	2.05E-05
0.015527	0.026347	3.21E-03	8.46E-03	1.76E-02	7.51E-05
0.019143	1.39E-02	7.12E-03	1.01E-02	2.26E-02	9.82E-04
0.001379	8.56E-04	4.98E-03	1.33E-04	9.50E-03	1.01E-04
0.0032	3.35E-03	4.70E-03	2.05E-04	0.0114	3.31E-04
0.037583	0.059704	0.158857	0.117999	5.75E-02	1.43E-01
7.44E-02	1.43E-01	1.62E-01	1.94E-01	8.76E-02	0.156228
6.73E-06	0.025416	0.086079	0.01497	3.32E-02	2.59E-03
0.019247	0.027491	0.076002	0.008466	4.87E-02	0.000851
0.013568	0.003279	2.49E-02	1.33E-03	1.71E-02	6.5E-06
0.002486	1.91E-03	3.92E-03	2.75E-03	1.27E-02	9.97E-07
0.003874	0.003695	2.74E-03	5.30E-03	1.44E-02	3.42E-07
0.001799	3.13E-03	2.14E-03	5.85E-03	5.36E-03	2.63E-05
0.003257	8.43E-03	1.88E-03	3.26E-03	8.40E-03	5.53E-05
0.022661	0.006907	7.12E-03	1.87E-02	1.84E-02	8.37E-04
0.009101	9.25E-03	1.26E-02	3.40E-04	1.57E-02	1.88E-03
0.008046	0.013669	0.032544	0.001293	2.34E-02	6.22E-03
4.01E-06	2.51E-02	1.31E-01	7.15E-02	6.10E-02	0.316161
0.001162	1.24E-03	5.51E-02	9.59E-03	8.52E-03	9.11E-03
0.014764	1.30E-02	4.08E-02	2.74E-03	2.39E-02	1.28E-04
0.003568	2.30E-03	5.44E-03	1.05E-03	7.73E-03	6.61E-06
0.005393	0.003265	3.07E-03	4.96E-03	1.86E-02	4.64E-07
0.006135	0.005117	2.49E-03	7.80E-03	1.75E-02	5.98E-07
0.007815	0.00534	2.28E-03	6.06E-03	1.27E-02	2.12E-07
0.007437	0.010111	2.34E-03	5.57E-03	9.30E-03	5.25E-06

0.004146	4.67E-03	1.85E-03	6.60E-03	1.23E-02	9.43E-05
1.01E-05	0.005868	3.04E-03	2.66E-03	2.75E-02	7.57E-04
1.11E-06	0.004227	3.04E-03	5.32E-05	1.81E-02	1.53E-04
0.002408	1.66E-03	2.50E-03	3.06E-04	1.61E-02	1.07E-04
0.001353	4.90E-03	2.53E-03	7.51E-05	1.73E-02	2.42E-04
0.001952	1.29E-02	6.37E-02	1.50E-02	0.028827	4.54E-02
0.378728	0.20491	0.176917	0.17505	1.70E-01	9.22E-02
0.011411	0.002409	0.035635	0.001373	1.69E-02	1.23E-05
0.00937	2.17E-03	1.07E-02	7.38E-04	1.94E-02	8.98E-07
0.010879	0.00284	5.30E-03	2.63E-03	2.06E-02	6.37E-07
0.00416	0.002978	2.86E-03	4.78E-03	1.27E-02	1.79E-06
0.00181	2.65E-03	2.10E-03	6.39E-03	5.35E-03	3.76E-05
0.004358	2.58E-03	1.92E-03	8.31E-03	1.35E-02	1.55E-04
0.00187	7.23E-03	1.72E-03	8.17E-05	2.74E-02	2.20E-04
0.011242	7.50E-03	2.88E-03	3.87E-04	3.20E-02	4.52E-04
0.018388	0.011151	1.55E-02	1.60E-03	0.017111	3.99E-03
0.001229	5.24E-03	1.77E-02	1.50E-04	1.21E-02	1.43E-03
5.15E-03	4.19E-03	1.92E-02	1.34E-03	0.006001	7.44E-04
9.78E-03	4.99E-03	1.25E-02	1.47E-03	1.24E-02	9.06E-05
0.008742	0.002615	5.62E-03	2.25E-03	1.64E-02	3.98E-06
0.006276	3.73E-03	3.11E-03	3.54E-03	1.51E-02	1.53E-06
0.002666	3.36E-03	2.61E-03	4.90E-03	1.22E-02	3.66E-07
0.001675	4.61E-03	2.31E-03	6.65E-03	9.06E-03	1.38E-06
0.002904	0.004466	1.95E-03	8.13E-03	6.99E-03	1.67E-05
0.017707	1.35E-02	2.73E-03	1.32E-02	1.62E-02	1.06E-04
0.022103	0.004775	9.09E-03	6.74E-03	1.88E-02	8.30E-04
0.001255	6.46E-03	1.35E-02	1.18E-03	1.81E-02	1.22E-03
1.15E-05	0.016721	0.042803	0.003658	0.030982	5.45E-03
0.499348	0.12689	0.16049	0.164363	8.23E-02	0.149234
0.175615	0.211439	0.165156	0.260832	0.116723	0.232038
0.012914	0.046066	0.10818	0.0329	4.86E-02	0.01296
0.006677	0.001808	0.017671	0.001294	0.009966	1.67E-05
0.016742	0.004492	1.04E-02	1.24E-03	2.20E-02	8.58E-07
0.005717	2.06E-03	3.65E-03	2.77E-03	0.022051	2.13E-07
0.007088	3.72E-03	2.59E-03	4.42E-03	1.22E-02	5.18E-07
0.007417	0.004963	2.08E-03	8.54E-03	1.17E-02	4.27E-06
0.017043	1.57E-02	3.24E-03	1.11E-02	1.93E-02	3.04E-04
0.023047	0.018771	2.38E-02	2.21E-02	4.83E-02	4.91E-03
0.005054	0.018306	0.040059	0.004135	3.75E-02	5.12E-03
0.002102	0.012684	0.069188	0.00315	5.77E-02	0.006256
0.039845	2.13E-02	1.46E-01	9.71E-03	0.088341	0.034553
1.69E-01	7.51E-02	1.58E-01	1.25E-01	0.061579	1.49E-01
4.17E-03	1.73E-01	1.92E-01	1.52E-01	1.66E-01	8.98E-02
0.017226	0.064337	0.119195	0.020303	7.60E-02	3.40E-03

0.004802	0.001195	1.15E-02	1.39E-03	1.02E-02	5.18E-06
0.002154	2.58E-03	3.28E-03	4.07E-03	0.012148	7.50E-07
0.002016	0.003207	2.66E-03	4.28E-03	1.01E-02	8.66E-07
0.005087	4.20E-03	2.11E-03	6.81E-03	9.90E-03	2.66E-05
0.017298	9.54E-03	2.91E-03	1.14E-02	1.73E-02	1.95E-04
0.023468	6.79E-03	2.09E-02	1.51E-02	2.78E-02	2.02E-03
8.32E-05	2.86E-03	2.93E-02	2.33E-04	2.41E-02	1.24E-03
0.003781	0.004245	3.28E-02	9.90E-04	2.82E-02	1.50E-03
0.311258	0.107386	0.154867	0.08321	7.89E-02	1.23E-01
5.10E-01	2.55E-01	1.88E-01	3.38E-01	1.91E-01	0.528887
0.166946	0.179388	0.170042	0.236904	1.16E-01	8.34E-02
1.04E-02	2.44E-03	3.76E-02	2.24E-03	0.014114	2.65E-05
0.006407	0.001901	9.38E-03	1.22E-03	0.015315	2.28E-06
0.008628	0.00251	3.45E-03	2.97E-03	1.65E-02	2.39E-07
0.002626	3.60E-03	2.68E-03	5.53E-03	0.012164	7.17E-07
0.006825	4.64E-03	2.28E-03	6.43E-03	1.18E-02	2.98E-06
0.018029	1.65E-02	3.27E-03	1.07E-02	1.57E-02	5.88E-05
0.014366	0.011528	5.43E-03	2.55E-03	1.40E-02	1.44E-03
0.003102	6.43E-03	6.84E-03	2.59E-04	1.31E-02	9.49E-04
0.205567	8.04E-03	2.15E-02	2.34E-03	0.024566	2.15E-03
0.159033	0.115405	0.164403	0.135083	8.01E-02	1.26E-01
0.00532	0.056081	0.153805	0.113786	0.059296	0.133791
1.04E-02	4.50E-03	6.47E-02	1.02E-02	1.69E-02	0.004981
0.020578	0.025797	0.099803	0.011017	5.53E-02	3.85E-03
0.006076	0.001463	1.49E-02	1.17E-03	1.36E-02	3.08E-06
0.00879	0.004299	4.02E-03	4.45E-03	0.027597	2.03E-07
0.002917	3.34E-03	2.66E-03	4.55E-03	1.04E-02	4.68E-07
0.008191	0.006013	2.10E-03	9.20E-03	1.19E-02	1.56E-06
0.00455	3.91E-03	1.84E-03	4.13E-03	1.44E-02	2.52E-04
0.025186	0.009067	1.29E-02	4.13E-02	3.39E-02	4.17E-04
2.76E-06	3.54E-03	2.24E-02	1.99E-03	2.93E-02	2.47E-03
0.031429	0.24422	0.164474	0.196298	1.42E-01	2.32E-01
0.414019	0.11127	0.222979	0.383568	0.326071	0.4981
0.010545	0.085518	0.148991	0.111507	6.06E-02	0.053912
5.20E-03	6.01E-03	3.76E-02	3.47E-03	7.75E-03	0.000633
0.006965	0.004823	9.45E-03	8.11E-04	6.72E-03	3.50E-05
0.008077	3.68E-03	4.77E-03	1.74E-03	1.82E-02	1.17E-06
0.001931	0.003116	2.82E-03	3.53E-03	8.37E-03	4.85E-06
0.008173	0.005575	2.47E-03	6.56E-03	1.86E-02	1.70E-07
0.001647	0.004299	1.95E-03	5.16E-03	4.54E-03	2.68E-05
0.01122	1.15E-02	2.07E-03	5.95E-03	1.25E-02	1.89E-04
0.009544	2.34E-02	4.59E-03	1.14E-02	2.25E-02	4.81E-04
0.015508	1.61E-02	1.51E-02	4.57E-03	2.74E-02	2.68E-03
0.002383	1.07E-02	2.34E-02	1.14E-03	2.39E-02	2.31E-03

0.259978	0.182119	0.152405	0.193303	1.39E-01	2.05E-01
0.161559	0.161516	0.161183	0.191213	9.87E-02	0.188584
0.009278	9.23E-03	5.77E-02	5.64E-03	1.63E-02	0.000577
0.015381	0.005195	2.19E-02	1.16E-03	1.69E-02	7.91E-06
0.007048	0.00246	5.38E-03	1.17E-03	1.77E-02	5.29E-07
0.002095	2.85E-03	2.86E-03	4.46E-03	0.009801	2.22E-06
0.001903	0.003462	2.46E-03	4.13E-03	7.55E-03	1.42E-06
0.01274	6.57E-03	2.24E-03	7.48E-03	1.25E-02	3.34E-06
0.010772	4.27E-03	1.90E-03	6.24E-03	1.95E-02	6.78E-04
0.003347	0.002657	1.71E-03	3.92E-04	4.53E-02	2.35E-04
0.002635	2.46E-03	1.75E-03	3.42E-04	5.35E-02	1.58E-04
0.00272	3.73E-03	1.92E-03	2.84E-04	4.83E-02	2.60E-04
0.002014	5.08E-03	1.94E-03	1.30E-04	3.10E-02	2.52E-04
0.0402	0.040484	0.097701	0.034869	4.01E-02	2.87E-02
5.89E-03	9.18E-02	1.24E-01	6.93E-02	7.65E-02	0.036378
8.58E-03	2.09E-03	1.42E-02	5.95E-04	8.04E-03	2.60E-06
0.008737	0.002671	5.08E-03	1.94E-03	0.017262	1.23E-06
0.003908	3.01E-03	2.90E-03	4.52E-03	0.013512	7.14E-07
0.001845	4.52E-03	2.42E-03	6.66E-03	0.009644	9.09E-07
0.002556	4.04E-03	2.08E-03	6.63E-03	6.77E-03	1.34E-05
0.016706	2.12E-02	2.86E-03	1.12E-02	1.67E-02	7.91E-05
0.01637	1.87E-02	4.53E-03	7.42E-03	1.96E-02	8.92E-04
0.00386	5.32E-03	5.59E-03	5.85E-04	1.63E-02	5.40E-04
0.011921	1.46E-02	2.23E-02	2.01E-03	2.92E-02	3.16E-03
0.000298	0.052172	0.130653	0.04138	4.78E-02	4.16E-02
0.216941	0.159853	0.171371	0.224332	1.15E-01	0.201124
1.60E-02	5.52E-02	1.50E-01	8.04E-02	4.15E-02	0.010155
0.007659	4.68E-03	2.68E-02	1.53E-03	1.29E-02	6.05E-05
0.010508	0.001965	7.15E-03	1.36E-03	1.75E-02	4.33E-07
0.002178	2.40E-03	3.29E-03	3.74E-03	1.48E-02	4.25E-07
0.005031	3.66E-03	2.39E-03	4.81E-03	9.50E-03	9.31E-07
0.002942	3.75E-03	2.06E-03	6.50E-03	7.06E-03	2.36E-05
0.004439	3.87E-03	1.60E-03	1.31E-03	1.19E-02	3.67E-04
0.008322	1.19E-02	2.24E-03	5.35E-04	2.78E-02	5.34E-04
0.013696	1.34E-02	4.75E-03	2.11E-03	2.55E-02	1.03E-03
0.031845	0.063716	0.166045	0.10316	2.68E-01	1.58E-01
0.013605	0.070868	0.150522	0.075687	6.47E-02	0.15778
0.30197	0.269567	0.19669	0.279839	2.32E-01	0.234221
1.03E-02	5.14E-02	1.29E-01	5.77E-02	6.98E-02	0.031861
1.04E-02	2.96E-03	3.28E-02	2.49E-03	1.55E-02	7.31E-05
0.002278	2.06E-03	4.68E-03	2.57E-03	1.45E-02	3.75E-06
0.001973	2.69E-03	2.96E-03	4.21E-03	0.013461	3.27E-07
0.003502	4.55E-03	2.39E-03	6.10E-03	1.16E-02	4.16E-07
0.005667	4.90E-03	2.19E-03	6.07E-03	9.31E-03	3.38E-06

0.004039	1.71E-02	2.26E-03	5.58E-03	1.01E-02	1.93E-05
6.04E-06	0.005672	2.46E-03	2.96E-04	2.42E-02	1.92E-04
0.005893	0.003157	3.52E-03	3.32E-03	2.01E-02	5.40E-04
0.000387	1.43E-03	3.66E-03	1.11E-03	1.60E-02	1.98E-04
0.000967	0.033219	0.114622	0.023284	4.85E-02	1.27E-01
0.126059	0.075325	0.173757	0.131639	5.09E-02	0.015275
0.007815	0.003332	0.047764	0.005123	1.14E-02	0.001051
0.020926	0.012692	0.044453	0.004367	3.42E-02	0.000152
0.005645	0.001612	7.83E-03	2.00E-03	1.67E-02	1.55E-06
0.002227	2.56E-03	3.36E-03	4.22E-03	0.016721	4.28E-07
0.011031	0.006545	2.65E-03	6.81E-03	2.66E-02	1.21E-07
0.005118	4.47E-03	2.20E-03	8.21E-03	1.30E-02	1.99E-05
0.010422	8.46E-03	2.16E-03	7.55E-03	1.69E-02	1.51E-04
0.011362	0.008036	2.59E-03	1.14E-03	2.76E-02	8.25E-04
0.001777	1.02E-02	4.14E-03	4.07E-04	2.03E-02	9.24E-04
0.001745	5.91E-03	4.12E-03	7.60E-05	1.46E-02	4.02E-04
0.000658	3.69E-03	4.83E-03	6.23E-05	6.43E-03	7.18E-04
0.013107	1.37E-02	8.22E-03	1.84E-03	1.01E-02	6.97E-04
9.14E-03	1.04E-02	5.79E-03	1.40E-03	0.010286	1.11E-04
0.020707	0.009942	5.32E-03	5.98E-03	2.16E-02	1.33E-06
0.00651	0.004129	3.33E-03	4.48E-03	2.06E-02	3.97E-06
0.002871	3.20E-03	2.70E-03	4.58E-03	0.012751	4.57E-07
0.00218	4.35E-03	2.30E-03	5.92E-03	0.008776	1.07E-06
0.003241	4.01E-03	1.97E-03	7.50E-03	7.92E-03	2.98E-05
0.012575	5.98E-03	2.13E-03	1.07E-02	2.45E-02	3.33E-04
0.011225	1.11E-02	3.36E-03	1.06E-03	2.64E-02	5.77E-04
0.000188	1.27E-03	2.74E-03	1.53E-03	1.76E-02	1.78E-04
0.42845	0.220491	0.20935	0.27391	0.384926	4.10E-01
0.044809	0.066147	0.168578	0.074729	5.78E-02	0.031437
0.12812	0.132298	0.160004	0.169738	0.086585	0.169978
1.55E-02	1.15E-01	1.57E-01	6.85E-02	9.47E-02	0.01605
0.010207	0.001897	0.026095	0.001436	0.011064	1.17E-05
0.012362	0.002776	8.59E-03	1.56E-03	2.23E-02	4.39E-07
0.001768	2.83E-03	3.40E-03	4.84E-03	0.01598	4.00E-07
0.002185	3.76E-03	2.44E-03	5.73E-03	8.75E-03	1.85E-06
0.005064	0.00394	2.01E-03	8.32E-03	8.93E-03	1.69E-05
0.004581	5.33E-03	1.84E-03	4.29E-03	1.41E-02	1.88E-04
0.027498	1.60E-03	3.08E-02	1.80E-02	5.58E-02	3.60E-03
0.003478	8.66E-03	2.11E-02	1.12E-03	2.30E-02	1.81E-03
2.01E-06	5.75E-03	2.46E-02	4.11E-04	1.70E-02	1.36E-03
0.220651	0.256164	0.161065	0.200999	1.46E-01	2.37E-01
0.140709	0.176535	0.168809	0.120595	1.07E-01	0.089268
7.94E-03	1.23E-02	5.29E-02	6.06E-03	0.019711	0.001377
7.57E-03	1.60E-03	9.03E-03	1.30E-03	8.61E-03	9.72E-06

0.00724	3.08E-03	4.02E-03	2.79E-03	0.024968	4.43E-07
0.002525	3.22E-03	2.89E-03	5.26E-03	0.016674	2.75E-07
0.002921	3.89E-03	2.46E-03	5.22E-03	1.07E-02	7.03E-07
0.002839	0.005705	2.16E-03	5.83E-03	7.50E-03	1.71E-05
0.011488	2.25E-02	2.39E-03	7.30E-03	1.72E-02	1.27E-04
0.001454	0.005004	3.54E-03	7.94E-03	1.50E-02	6.47E-04
0.008798	3.46E-03	7.09E-03	3.00E-03	1.54E-02	5.47E-04
1.48E-07	1.11E-03	6.61E-03	3.66E-04	1.08E-02	2.50E-04
0.154213	0.162371	0.166018	0.175789	1.05E-01	1.48E-01
0.178597	0.202751	0.170604	0.251908	0.122875	0.28146
7.91E-03	1.39E-02	5.85E-02	8.30E-03	0.01696	0.002408
0.00831	2.68E-03	1.31E-02	9.06E-04	0.01183	5.26E-06
0.010387	3.10E-03	4.85E-03	1.61E-03	0.01912	3.74E-07
0.00207	0.002552	3.08E-03	3.44E-03	0.013184	5.62E-07
0.008475	3.16E-03	2.78E-03	4.76E-03	0.018941	1.19E-07
0.003304	3.60E-03	1.98E-03	7.34E-03	0.007194	2.71E-05
0.003473	1.32E-02	2.01E-03	4.41E-03	0.011091	4.82E-05
0.019106	0.01224	3.63E-03	2.33E-02	0.023455	6.48E-04
0.005665	0.001766	3.22E-03	1.67E-03	0.01136	1.42E-04
0.670939	0.487991	0.394586	0.545304	0.379894	0.548861
0.089628	0.064425	0.067532	0.070924	0.056034	0.081477

APPENDIX C

Testing Data Results

cas1	cas2	cas3	cas4	cas5	cas6
8.24E-05	9.19E-03	0.007855	0.015047	1.33E-08	0.038884
3.66E-03	0.013536	4.45E-02	0.038266	1.61E-06	0.080738
0.229454	0.404279	0.110129	0.348339	0.147238	0.286574
0.081976	0.126762	0.142361	0.163928	0.0143	0.145125
0.040503	0.005488	1.45E-02	0.058257	0.000212	0.034661
0.009456	0.012495	1.09E-02	3.33E-03	3.95E-08	0.036752
0.004454	0.010163	1.29E-02	2.83E-04	0.001321	0.04074
0.005735	0.01419	1.82E-02	3.41E-04	1.58E-05	0.036323
5.15E-05	0.00948	9.29E-03	4.71E-05	2.12E-06	0.03785
2.57E-05	0.01503	0.018019	2.31E-03	0.00024	4.82E-02
1.1E-05	0.014612	0.013979	2.99E-03	0.000101	4.65E-02
2.18E-08	7.28E-03	0.005977	0.001734	3.16E-10	2.58E-02
5.70E-03	1.84E-03	0.009367	0.017236	3.06E-10	0.042972
6.21E-04	0.008373	3.39E-02	0.011751	2.72E-11	0.082519
1.08E-02	0.005583	1.77E-02	0.036149	2.02E-07	0.038601
3.10E-02	0.064561	1.75E-02	0.144032	0.00074	0.058133
0.060692	0.014529	0.011854	0.072188	0.000152	0.044643
0.054206	0.041909	5.83E-02	0.059375	1.8E-06	0.036058

0.001959	0.010413	1.04E-02	2.84E-04	5.9E-06	3.10E-02
0.000909	0.01215	0.011345	1.17E-04	9.88E-07	2.75E-02
5.20E-04	6.44E-03	0.0126	2.47E-04	1.74E-08	5.48E-02
9.90E-05	1.04E-02	0.011509	1.25E-03	3.11E-11	4.26E-02
2.53E-04	6.07E-03	0.008371	1.10E-02	1.86E-08	0.039887
0.011577	1.11E-02	0.004467	5.63E-02	1.29E-06	0.040222
8.16E-03	0.001707	0.011546	0.041165	9.08E-09	0.034008
3.19E-02	0.003539	1.20E-02	0.113647	1.06E-06	0.041003
0.150901	0.443958	2.01E-01	0.319712	0.601037	0.302154
0.089569	0.256518	0.283979	0.233948	0.183076	0.246092
0.093593	0.112693	1.83E-01	0.357479	0.117288	0.148311
0.017615	0.004464	0.010566	0.014258	6.65E-08	0.032566
0.001869	0.010669	8.07E-03	3.37E-04	7.35E-06	0.035464
0.001407	0.008698	0.011742	1.13E-04	0.000385	2.62E-02
1.26E-04	0.008739	0.009875	6.34E-05	1.41E-05	0.039068
1.38E-05	6.90E-03	0.010292	5.39E-04	6.36E-12	0.04864
2.55E-05	0.059464	0.025282	1.19E-02	0.000482	4.19E-02
1.39E-08	0.004906	1.00E-02	0.00047	2E-11	0.02673
0.001335	8.52E-03	0.020044	5.30E-02	1.29E-05	0.036288
1.61E-02	0.005677	2.70E-02	0.059762	2.77E-08	0.047268
0.137918	0.302365	0.174646	0.331512	0.140387	0.327741
0.084554	0.084912	1.46E-01	0.207922	0.060237	0.139898
0.005377	0.003171	0.005849	1.64E-02	0.002651	0.032285
0.029379	0.042807	3.29E-02	3.71E-02	0.127681	0.037679
4.91E-03	0.009951	0.012865	3.37E-04	0.001242	0.042523
0.001081	0.008648	0.012222	8.20E-05	0.000777	2.40E-02
6.90E-06	0.005307	8.14E-03	3.49E-05	6.24E-06	4.80E-02
0.023889	2.31E-02	0.027454	1.80E-02	0.011858	0.04926
4.01E-02	2.04E-02	0.00851	4.71E-02	2.13E-05	0.042803
0.023198	0.016031	0.027855	0.063203	1.17E-06	0.059631
1.30E-03	0.000937	1.75E-02	0.033038	2.07E-10	0.05058
0.034859	0.198727	0.158928	0.103237	0.008372	0.206305
0.040819	0.058383	8.70E-02	0.078226	0.004067	0.111811
1.13E-02	0.036359	6.13E-02	0.091297	0.002465	0.103551
0.016393	0.005109	1.10E-02	1.28E-02	1.19E-08	0.039705
0.015185	0.017842	1.63E-02	6.22E-03	6.92E-08	0.042869
0.00118	0.006365	0.013729	1.75E-04	8.05E-05	2.20E-02
3.54E-03	0.012826	0.013559	1.43E-04	0.000799	0.034603
0.010104	3.25E-02	2.86E-02	1.85E-03	0.000555	0.058956
1.42E-08	0.005469	0.013135	3.44E-05	1.03E-10	0.032918
2.36E-06	0.005888	0.013399	2.36E-03	4.64E-07	0.042805
9.21E-08	0.004944	0.013442	0.001959	7.24E-10	3.06E-02
5.64E-06	0.004373	1.25E-02	3.89E-03	3.48E-08	0.044736
0.000342	0.006874	0.033447	0.068651	1.39E-05	4.55E-02

0.134344	0.298447	1.55E-01	0.375411	0.068589	0.311109
1.72E-02	0.030551	0.055232	0.099485	0.001096	0.088286
0.007597	0.004857	0.005204	4.05E-03	4.38E-07	0.032609
0.008794	0.01863	1.24E-02	2.61E-03	5.27E-08	0.045937
0.001453	0.006865	0.015853	2.07E-04	3.83E-05	0.021539
4.49E-03	0.014874	0.014751	1.77E-04	0.000129	0.034614
0.000204	0.013215	1.20E-02	9.49E-05	2.31E-08	0.042398
3.28E-04	0.013595	0.017353	6.29E-04	7.55E-06	6.83E-02
4.34E-05	0.056711	0.027641	1.90E-02	0.001176	0.047433
0.03917	7.53E-03	0.004769	0.058922	1.69E-06	0.043708
2.92E-03	0.00363	0.023416	0.026043	6E-09	0.070643
0.063621	0.238845	1.41E-01	0.154554	0.262506	0.20201
0.084215	0.14423	1.48E-01	0.162093	0.050563	0.156488
1.07E-02	0.005842	0.013373	0.023284	1.4E-05	0.038043
0.011518	0.009654	0.011981	6.94E-03	2.59E-08	0.040961
0.002924	0.010829	1.24E-02	4.42E-04	7.57E-07	0.029311
0.000918	0.009291	0.015409	1.79E-04	2.44E-06	0.022593
0.000629	0.010675	0.016405	1.04E-04	3E-06	2.11E-02
3.46E-05	0.006113	1.11E-02	1.07E-04	6.43E-08	0.051019
1.71E-05	6.96E-03	0.012126	2.07E-04	2.17E-10	5.61E-02
7.59E-06	0.037316	0.020834	5.54E-03	0.000229	0.046301
0.015563	9.44E-03	0.007536	6.28E-02	0.000127	0.045078
5.88E-03	0.001353	0.009917	0.022497	9.73E-10	0.03821
0.074759	0.140956	1.86E-01	0.105692	0.139216	0.181734
0.127862	0.334678	0.128651	0.338417	0.080395	0.296421
2.51E-02	0.014855	3.03E-02	0.045899	3.49E-06	0.052228
0.01774	0.008104	1.26E-02	1.93E-02	0.004828	0.034574
0.002625	0.016289	1.31E-02	1.09E-03	1.04E-06	0.034708
0.00309	0.016881	0.020081	6.18E-04	1.35E-05	0.034544
0.000998	0.012256	0.014649	9.18E-05	1.71E-06	2.38E-02
5.41E-05	0.009587	0.012386	1.12E-04	2.35E-09	0.0534
0.078879	5.61E-02	0.037157	7.35E-02	0.173176	4.56E-02
4.21E-03	0.02179	0.005724	7.35E-03	4.55E-06	4.76E-02
3.82E-05	8.42E-03	0.008051	0.033247	2.77E-10	0.032823
2.37E-07	2.03E-03	8.54E-03	0.015414	1.31E-12	3.16E-02
0.165046	0.001285	5.45E-03	0.249145	0.000129	0.085479
0.145484	0.130921	0.060004	0.469596	0.496063	0.37231
0.10932	0.382567	0.152477	0.33288	0.226888	0.296051
0.027078	0.006905	1.76E-02	0.0329	5E-08	0.041021
0.008772	0.017113	0.019128	7.96E-03	0.170234	0.035681
0.00094	0.005916	0.014049	1.61E-04	4.18E-05	2.10E-02
1.48E-03	0.009117	0.012268	6.48E-05	0.000291	0.022856
1.69E-04	7.10E-03	0.013252	1.62E-04	2.54E-07	0.051705
1.44E-05	0.025848	0.027881	2.82E-03	0.003038	4.68E-02

0.05163	0.003663	0.013314	1.22E-01	0.01109	0.054049
2.62E-05	3.63E-02	0.011994	0.024916	3.9E-10	2.52E-02
0.154103	0.291078	0.116535	0.207185	0.019856	0.293853
0.037408	0.42876	1.88E-01	0.241576	1.63E-06	0.322524
0.119594	0.174395	1.68E-01	0.230547	0.009866	0.204449
0.108828	0.326383	0.152329	0.365072	0.040069	0.252848
0.005105	0.020933	7.33E-02	0.047884	9.79E-05	0.054568
0.005197	0.008389	0.012314	6.15E-03	0.127708	0.03471
0.000944	0.006356	1.35E-02	1.63E-04	4.76E-05	0.021471
0.000866	0.01054	0.018587	1.50E-04	2.85E-05	2.14E-02
6.84E-07	0.00679	0.008809	3.49E-05	3.86E-08	4.17E-02
5.74E-07	3.69E-02	8.76E-03	1.17E-03	5.51E-11	2.34E-02
0.007047	1.09E-02	0.005043	3.35E-02	1.68E-07	0.040454
1.67E-02	0.003174	0.014155	0.057714	1.95E-08	0.044027
0.041703	0.050097	0.086253	0.124525	1.34E-06	0.149992
3.23E-02	0.013812	0.026367	0.206154	1.1E-07	1.25E-01
0.008483	0.08459	4.17E-02	0.22407	4.47E-09	0.244153
0.169474	0.050788	6.81E-02	0.602225	0.002499	0.284756
1.01E-03	0.014327	3.81E-02	0.023136	5.89E-05	7.42E-02
0.002123	0.020413	0.020662	3.72E-03	0.658984	0.087084
0.000637	0.011218	0.015524	2.01E-04	9.27E-06	2.49E-02
0.004094	0.015027	0.019713	1.90E-04	0.000106	2.51E-02
1.84E-05	1.05E-02	0.017151	3.13E-04	4.53E-07	0.050121
4.19E-07	8.03E-02	0.005603	2.06E-02	8.64E-07	1.60E-02
3.90E-08	0.004655	0.015557	0.000753	2.51E-09	2.73E-02
3.84E-07	0.008749	0.020096	0.006665	3.6E-10	3.05E-02
0.186786	0.002516	0.008721	0.388729	2E-06	0.184938
0.105634	0.16988	4.87E-02	0.383635	6.38E-07	0.302821
0.035723	0.082787	0.148037	0.211809	1.17E-06	0.217231
0.078042	0.103614	0.235073	0.211192	0.002783	0.171802
0.33306	0.01628	1.10E-01	0.745527	0.011949	0.227995
0.085414	0.032695	0.043069	0.12948	7.43E-04	0.057843
0.001504	0.008857	0.02536	1.32E-03	0.979621	0.035094
0.000847	0.010084	0.030552	2.94E-04	0.346277	0.027325
4.40E-04	0.009487	9.81E-03	2.84E-05	0.000994	0.040376
0.581236	0.067321	0.063738	1.72E-02	0.992436	0.059294
0.848664	0.233222	0.028967	4.27E-02	0.992365	0.036775
7.76E-03	0.002697	0.017838	0.030293	2.61E-09	0.042162
0.515101	0.218779	0.155791	0.467702	0.220331	0.387575
0.104795	0.106285	0.068528	0.148414	0.175418	0.11573

ffb1	ffb2	ff3	ff4	ff5	ff6
0.004047	4.34E-03	0.006783	4.37E-02	1.34E-04	0.000129
0.000213	0.018034	0.012493	0.049131	9.04E-03	0.09419

0.974757	0.165428	1.73E-01	2.64E-01	2.75E-01	1.74E-01
0.000442	0.133084	0.103547	1.60E-01	8.22E-02	0.175382
0.01319	0.005412	0.001773	3.94E-02	0.006532	0.010941
0.00823	0.000475	0.003981	2.76E-02	0.003981	0.007008
0.004772	1.13E-04	0.005741	2.03E-02	6.28E-03	0.005058
0.008054	6.88E-05	0.008126	0.01459	5.67E-03	0.007334
0.001687	6.64E-05	0.004922	0.010775	6.60E-04	0.001506
0.013856	3.60E-03	1.53E-02	0.010806	1.63E-05	6.69E-03
0.011789	6.22E-03	0.007736	0.013755	1.55E-05	0.002955
9.82E-05	6.91E-03	9.05E-03	3.52E-02	8.39E-06	3.64E-06
0.009161	5.76E-03	0.005391	4.44E-02	1.31E-03	0.004563
0.036522	1.00E-02	1.03E-02	3.95E-02	1.24E-02	1.98E-02
0.009729	0.007052	0.002833	0.042597	3.68E-03	0.011592
0	0.008447	0.011265	6.39E-02	9.63E-03	0.021004
0.017579	0.002425	0.002956	4.62E-02	4.56E-03	0.577344
0.021117	0.000851	0.005594	0.055996	0.004646	0.014263
0.00278	1.06E-04	0.004529	0.010318	3.84E-03	0.002415
0.002059	5.23E-05	0.005082	0.008879	2.05E-03	0.002912
0.00882	1.62E-04	0.011248	0.021038	1.03E-03	0.006307
0.015671	2.21E-03	0.025554	0.021561	3.55E-04	0.0175
0.015078	4.94E-03	0.007475	3.41E-02	2.15E-04	0.009712
0.027369	9.75E-03	0.0175	5.58E-02	5.45E-04	0.012568
0.000277	5.97E-03	3.87E-03	4.53E-02	4.63E-04	6.44E-04
5.37E-09	0.012449	5.67E-03	5.17E-02	3.82E-03	8.35E-04
0.42491	0.346647	0.297489	3.63E-01	4.81E-01	0.532016
0.001011	0.309931	0.23783	0.272767	3.00E-01	0.017261
1.07E-05	0.221719	0.098961	2.21E-01	0.026883	0.006352
0.006954	0.008524	0.004111	0.039253	4.61E-03	0.009559
0.002587	1.81E-04	0.004206	0.013483	2.96E-03	0.00217
0.001875	6.79E-05	0.004909	0.008955	3.59E-03	0.001597
0.001985	7.22E-05	0.004875	0.010401	9.21E-04	0.001281
0.012278	1.85E-03	0.023234	2.32E-02	1.95E-04	0.006534
0.013245	5.44E-03	0.008454	0.008129	1.80E-05	0.000318
0.000174	8.10E-03	4.52E-03	3.11E-02	1.46E-05	4.63E-06
0.008008	6.25E-03	0.012829	0.02382	5.58E-04	5.81E-05
1.11E-07	0.011264	5.75E-03	5.92E-02	2.97E-03	5.24E-03
0.027677	0.460363	0.336523	0.340575	5.57E-01	0.089944
9.11E-07	0.126462	0.118327	2.15E-01	3.77E-02	0.037152
0.006337	0.004764	0.002172	0.025755	0.002157	0.004555
0.017636	0.000626	0.003029	0.026969	0.007395	0.009843
0.004794	1.32E-04	0.005909	2.31E-02	6.15E-03	0.005393
0.001528	5.70E-05	0.004968	0.008271	3.30E-03	0.001426
0.001335	8.95E-05	0.005185	0.013023	4.31E-04	0.000756
0.019925	1.82E-03	0.018558	0.009543	7.33E-05	0.087078

0.019789	0.004968	0.019626	5.65E-02	6.66E-04	0.032082
9.08E-08	0.010313	0.008671	8.52E-02	7.07E-04	0.015299
6.93E-06	7.13E-03	0.002736	3.83E-02	3.64E-04	0.003631
0.834403	0.176791	0.196829	1.95E-01	1.13E-01	0.004302
0.000329	0.06251	0.052619	1.69E-01	1.53E-02	0.22384
0.594913	0.02391	0.022202	8.05E-02	6.46E-03	0.002168
0.009294	0.001958	0.001712	0.036753	0.004931	0.00797
0.01306	0.000365	0.004871	0.029539	5.17E-03	0.014913
0.001622	7.81E-05	0.005061	6.83E-03	6.07E-03	0.001468
0.004413	7.30E-05	0.006291	0.01633	4.68E-03	0.005353
0.01651	1.02E-04	1.41E-02	0.015121	0.002171	2.81E-02
0.002125	5.17E-04	0.005911	0.01549	6.30E-05	7.88E-05
0.011942	8.93E-03	0.008199	2.23E-02	3.29E-05	0.013103
3.04E-05	8.86E-03	8.68E-03	0.029093	1.42E-05	2.53E-07
0.007224	7.36E-03	0.006992	3.44E-02	2.29E-05	0.012041
0	1.37E-02	0.015416	0.018997	4.09E-04	4.29E-06
0.254688	0.430644	0.329778	0.361426	6.43E-01	0.224619
0.016073	0.024911	0.023373	1.02E-01	5.39E-03	0.002388
0.00501	0.001645	0.0023	0.022333	0.002321	0.007003
0.010644	2.30E-04	0.005667	0.023487	0.003079	0.012089
0.002381	5.63E-05	0.005917	6.90E-03	5.86E-03	0.001927
0.005782	7.04E-05	0.008005	0.018053	5.11E-03	0.006753
0.003257	5.57E-05	0.00565	0.010874	7.41E-04	0.004206
0.0119	3.37E-04	1.84E-02	0.017041	3.10E-04	4.39E-03
0.011307	6.30E-03	0.016727	0.008716	3.31E-05	0.000216
0.013705	0.009161	0.018544	6.74E-02	6.47E-04	0.006365
0.000368	0.010363	7.28E-03	4.50E-02	3.69E-03	1.72E-02
0.898787	0.197583	0.162374	0.197148	3.27E-01	0.286006
0.001546	0.149982	0.118133	0.173453	9.66E-02	0.098424
0.002986	0.012174	0.004989	4.89E-02	1.54E-03	0.00297
0.00929	0.000973	0.003042	0.035413	4.03E-03	0.008114
0.004497	9.81E-05	0.006799	0.013727	4.25E-03	0.004093
0.002358	3.57E-05	0.00673	6.51E-03	3.84E-03	0.003073
0.001844	2.59E-05	0.00646	6.40E-03	2.92E-03	0.003094
0.005681	1.17E-04	0.007743	0.015315	5.99E-04	0.003947
0.009661	3.80E-04	1.86E-02	0.022313	4.49E-04	3.47E-03
0.013512	8.84E-03	0.01317	0.010503	1.15E-05	0.002784
0.028403	9.38E-03	0.036457	5.19E-02	4.94E-04	0.074137
0.002617	5.50E-03	0.004623	4.70E-02	5.64E-04	0.000183
0.795901	0.129497	0.127328	2.48E-01	7.61E-02	0.860904
0.003828	0.438303	0.333036	3.72E-01	4.23E-01	0.009008
0.010752	0.019151	0.006842	6.47E-02	9.38E-03	0.009873
0.01214	0.001757	0.002378	0.028452	0.004263	0.006954
0.005789	1.08E-04	0.005797	0.011166	3.59E-03	0.006696

0.00763	3.89E-05	0.009881	0.008773	3.49E-03	0.005874
0.002342	3.15E-05	0.00605	0.0078	2.03E-03	0.00291
0.005006	8.14E-05	0.007166	0.013589	5.19E-04	0.004185
0.024179	0.003343	0.020753	0.071763	0.00037	0.284748
0.009724	2.34E-03	0.003703	2.72E-02	1.87E-04	0.004671
4.05E-08	7.53E-03	2.66E-03	4.87E-02	2.45E-04	9.49E-07
5.9E-06	6.03E-03	0.002163	4.68E-02	3.88E-05	8.8E-06
0.015716	0.023644	1.70E-02	0.072722	2.19E-03	3.57E-05
0.756006	0.275575	0.177076	4.80E-01	2.35E-01	0.837657
0.009167	0.429024	0.335646	0.398626	4.21E-01	0.010538
0.011101	0.007536	0.002599	0.049439	0.006775	0.011864
0.011014	0.000349	0.003512	0.014982	0.005982	0.005822
0.001445	7.19E-05	0.00535	0.006429	5.83E-03	0.001529
0.001569	4.38E-05	0.00546	0.008933	2.80E-03	0.002025
0.008537	1.54E-04	0.011916	0.020601	1.16E-03	0.004646
0.013199	2.56E-03	1.39E-02	0.006332	7.07E-06	4.40E-03
2.65E-08	0.01398	0.047748	3.69E-02	1.36E-03	0.099397
1.61E-07	1.23E-02	7.40E-03	2.81E-02	1.58E-04	4.30E-07
0.07584	0.137645	0.141155	2.54E-01	3.39E-02	0.000155
0.079188	0.21499	0.045184	0.137126	1.03E-03	0.992021
0.130932	0.240766	0.173953	2.08E-01	3.05E-01	0.011508
0.152727	0.377182	0.268516	0.341317	3.13E-01	0.008319
9.31E-05	0.008648	0.008633	5.62E-02	0.005408	6.66E-05
0.007649	0.000691	0.003174	0.013531	0.004798	0.005144
0.001417	7.62E-05	0.005061	0.006547	6.00E-03	0.00151
0.002314	2.79E-05	0.006446	6.14E-03	3.77E-03	0.00278
0.001572	8.77E-05	0.004949	0.010642	3.98E-04	0.001278
0.016233	3.82E-03	0.030322	0.013568	9.14E-05	0.001745
0.016258	5.46E-03	0.013621	4.38E-02	4.64E-04	0.012738
1.9E-12	0.008641	4.28E-03	6.71E-02	4.27E-04	2.74E-04
4.69E-09	0.059247	0.02416	1.71E-01	1.67E-03	0.974108
0.381669	0.015166	0.004413	4.33E-02	5.55E-03	6E-09
0.991424	0.110607	0.04673	1.14E-01	1.40E-03	0.002696
0.919029	0.35628	0.190558	0.349384	0.625787	0.018311
5.34E-15	0.005028	0.008781	6.16E-02	0.004763	5.55E-08
0.00298	2.73E-04	0.003057	0.009931	0.010235	0.000412
0.001845	4.09E-05	0.005471	6.26E-03	4.51E-03	0.00339
0.005704	3.81E-05	0.008499	0.009418	5.72E-03	0.004488
0.011564	2.78E-04	0.01568	0.01297	1.19E-03	0.012957
0.011557	5.87E-03	0.004303	0.01287	0.000514	2.45E-06
4.84E-05	9.74E-03	8.90E-03	0.024695	1.69E-05	2.02E-07
3.98E-05	7.60E-03	5.45E-03	3.29E-02	2.86E-05	8.69E-07
0.046149	0.040838	0.011039	0.13245	3.91E-04	0.000247
0.000614	0.078245	7.15E-02	0.140819	6.47E-04	2.14E-02

0.906237	0.217023	0.027254	1.08E-01	1.88E-02	0.970396
0.052002	0.194078	0.096644	0.170301	1.79E-01	0.009971
0.052692	0.447683	0.10021	0.397788	0.1132	0.329973
0.00E+00	0.006355	0.011471	0.077936	0.010322	0.001491
0.002928	1.32E-04	0.00426	5.21E-03	0.014092	0.002699
0.001479	4.06E-05	0.007118	4.13E-03	9.18E-03	0.002591
0.00145	7.79E-05	0.005744	0.021135	1.15E-03	0.00299
0.021661	8.32E-06	1.14E-02	0.003416	0.005378	2.75E-01
0.02492	1.52E-05	2.21E-02	0.003928	0.012768	4.08E-01
0.00396	0.007706	0.004615	0.049959	0.002384	0.002135
0.193861	0.290088	0.200115	0.328919	0.230033	0.143347
0.222464	0.117746	0.082873	0.122503	0.126581	0.198418

enn1	enn2	enn3	enn4	enn5	enn6
1.84E-06	2.50E-03	4.12E-03	0.001414	0.014331	0.000325
0.002075	0.011814	0.039382	0.001666	0.021679	9.05E-03
0.985601	0.152819	1.87E-01	0.197687	1.93E-01	0.355841
2.93E-03	0.107655	1.63E-01	1.15E-01	8.04E-02	3.41E-02
1.35E-02	3.23E-03	2.81E-02	0.000874	1.34E-02	8.18E-06
8.04E-03	0.001923	6.18E-03	0.001568	0.019373	5.17E-07
0.004857	0.003551	2.97E-03	5.02E-03	1.69E-02	2.81E-07
0.007759	4.25E-03	2.60E-03	5.51E-03	1.81E-02	1.61E-07
1.82E-03	4.10E-03	2.16E-03	6.48E-03	0.006792	1.47E-05
1.32E-02	2.41E-02	2.61E-03	6.27E-03	0.018454	0.000243
9.74E-05	1.65E-02	2.96E-03	1.59E-03	0.023029	0.000368
3.45E-03	1.18E-03	1.92E-03	0.000841	0.029746	0.000111
4.61E-03	0.012178	1.01E-02	0.002932	0.018565	0.002046
2.16E-03	0.003732	0.023844	0.001707	1.38E-02	0.010317
0.010915	0.008778	2.02E-02	1.90E-03	1.08E-02	0.002076
1.90E-02	1.69E-02	2.44E-02	0.004509	2.46E-02	0.000496
1.80E-02	0.00994	1.39E-02	0.001987	1.38E-02	1.80E-05
2.17E-02	0.008037	1.08E-02	2.19E-03	2.15E-02	2.88E-06
2.98E-03	2.26E-03	3.30E-03	0.002849	0.012614	7E-07
2.15E-03	0.003448	2.70E-03	4.56E-03	1.11E-02	1.23E-06
8.34E-03	5.31E-03	2.26E-03	7.41E-03	0.014162	3.32E-06
1.52E-02	6.07E-03	2.31E-03	1.15E-02	0.02223	0.000253
2.02E-02	5.35E-03	3.87E-03	2.40E-03	0.014721	0.000533
1.78E-03	3.35E-03	5.86E-03	2.09E-03	0.012883	0.000341
1.05E-02	4.30E-03	9.89E-03	1.05E-03	1.51E-02	0.000793
0.001032	2.76E-03	1.93E-02	0.001086	0.018542	0.00108
8.33E-01	0.274312	1.94E-01	0.31671	2.36E-01	0.414089
1.20E-01	0.164629	1.91E-01	0.254731	0.155385	3.15E-01
8.83E-01	0.100336	1.92E-01	0.087529	1.21E-01	0.045914
7.01E-03	0.002535	2.50E-02	1.32E-03	0.014935	1.15E-05

2.86E-03	1.98E-03	3.75E-03	2.42E-03	1.10E-02	1.86E-06
2.09E-03	2.97E-03	2.73E-03	4.22E-03	0.010407	5.88E-07
2.23E-03	3.71E-03	2.19E-03	5.67E-03	0.006445	1.01E-05
1.15E-02	8.16E-03	2.26E-03	8.48E-03	2.20E-02	0.000259
2.22E-03	7.29E-03	3.50E-03	9.85E-04	0.015982	0.000274
1.42E-03	6.88E-03	2.36E-03	7.14E-05	0.024021	0.000302
2.05E-02	2.31E-03	4.77E-03	2.10E-03	0.010939	0.000318
0.00047	1.54E-02	0.026079	0.002511	2.41E-02	0.003994
0.243844	0.137205	2.19E-01	3.85E-01	2.49E-01	0.229494
1.09E-01	1.21E-01	1.65E-01	0.058098	9.74E-02	0.013725
6.82E-03	0.003959	1.90E-02	7.36E-04	1.09E-02	1.71E-05
1.75E-02	4.04E-03	1.08E-02	0.000745	2.27E-02	3.53E-06
4.84E-03	0.003438	3.21E-03	5.00E-03	1.90E-02	2.76E-07
1.73E-03	3.30E-03	2.57E-03	4.59E-03	0.009202	6.68E-07
1.55E-03	3.41E-03	2.03E-03	7.85E-03	0.005506	3.37E-05
2.00E-02	2.09E-02	3.58E-03	0.017693	1.65E-02	1.1E-05
7.86E-03	0.018057	7.74E-03	1.94E-02	0.021633	0.000868
3.39E-02	1.48E-02	2.09E-02	3.19E-03	0.036264	0.004284
5.86E-07	4.45E-03	1.84E-02	0.000449	0.016114	9.49E-04
0.000724	0.108297	1.66E-01	1.17E-01	7.58E-02	0.094128
1.83E-04	5.04E-02	1.26E-01	0.065365	0.043176	0.011538
9.39E-03	0.009928	6.30E-02	0.007163	3.66E-02	3.05E-03
9.53E-03	0.001694	1.19E-02	0.001036	0.009042	4.54E-06
0.01265	0.00281	5.44E-03	1.73E-03	0.022828	2.46E-07
1.76E-03	1.94E-03	3.26E-03	0.003251	1.53E-02	2.58E-07
4.36E-03	0.005106	2.50E-03	6.95E-03	0.016083	2.8E-07
1.57E-02	7.84E-03	3.04E-03	7.26E-03	0.026417	7.32E-08
2.24E-03	5.64E-03	1.75E-03	2.35E-03	1.18E-02	0.000133
1.15E-02	1.05E-02	2.68E-03	7.01E-04	0.026601	0.000409
1.92E-03	2.64E-03	2.14E-03	2.25E-04	0.025296	0.000124
6.12E-06	7.00E-03	3.57E-03	3.48E-04	0.022442	0.000403
0.020591	1.39E-03	5.30E-03	0.001091	0.013937	2.42E-04
0.248598	0.141402	2.16E-01	0.36443	2.22E-01	0.203902
1.27E-02	0.014396	7.81E-02	9.93E-03	3.78E-02	0.002244
5.26E-03	2.40E-03	9.62E-03	8.90E-04	0.009315	8.12E-06
1.01E-02	3.35E-03	4.35E-03	2.34E-03	0.023598	3.59E-07
2.40E-03	2.00E-03	3.19E-03	0.003923	1.99E-02	1.97E-07
5.45E-03	0.005703	2.52E-03	7.64E-03	0.020551	2.16E-07
3.22E-03	5.17E-03	2.29E-03	5.96E-03	0.009325	5.24E-06
1.09E-02	1.71E-02	2.60E-03	7.79E-03	1.77E-02	5.61E-06
1.53E-02	4.60E-03	3.85E-03	0.001731	1.87E-02	0.000307
7.22E-06	0.005503	1.02E-02	0.006688	0.021309	0.001007
3.75E-03	0.011079	2.44E-02	0.002132	0.022492	0.005012
2.05E-02	0.205652	1.60E-01	0.232546	0.125035	2.62E-01

3.80E-03	0.141397	1.65E-01	0.121957	9.99E-02	0.046165
5.46E-03	0.006718	3.48E-02	0.002601	9.47E-03	0.00024
9.23E-03	0.001877	8.40E-03	1.37E-03	1.36E-02	1.51E-06
4.23E-03	2.54E-03	3.61E-03	4.25E-03	2.77E-02	2.38E-07
2.24E-03	2.44E-03	3.07E-03	0.004594	2.10E-02	2.2E-07
1.80E-03	0.00314	2.72E-03	5.01E-03	0.014777	2.93E-07
5.52E-03	4.89E-03	2.06E-03	7.37E-03	0.009902	1.18E-05
8.87E-03	7.40E-03	2.15E-03	8.72E-03	0.016024	2.79E-05
7.94E-06	8.11E-03	3.03E-03	1.15E-03	0.026749	0.000293
2.45E-02	5.41E-03	5.09E-03	7.24E-03	0.016247	0.000342
1.10E-06	9.08E-03	1.01E-02	1.56E-03	0.018738	0.001321
0.220093	1.61E-01	1.73E-01	0.157647	1.08E-01	0.101604
1.22E-01	0.184822	2.14E-01	0.271774	2.40E-01	0.086248
1.05E-02	0.005758	5.38E-02	4.07E-03	2.07E-02	1.51E-04
1.18E-02	3.38E-03	1.35E-02	6.69E-04	0.019804	1.93E-06
5.46E-03	2.48E-03	4.09E-03	2.37E-03	2.65E-02	2.91E-07
0.007065	2.76E-03	3.11E-03	4.32E-03	0.025142	1.35E-07
2.32E-03	3.89E-03	2.53E-03	5.60E-03	0.012657	4.32E-07
4.72E-03	6.50E-03	2.21E-03	0.006871	0.010523	8.32E-06
2.64E-02	0.006679	6.10E-03	8.60E-02	0.028081	1.37E-05
9.12E-03	1.83E-02	6.40E-03	1.55E-03	0.018483	0.000287
4.61E-03	7.78E-04	5.43E-03	5.31E-04	0.010314	0.000164
5.55E-07	4.05E-04	4.70E-03	4.88E-04	0.009635	9.94E-05
0.001925	2.88E-03	0.042963	0.000266	3.35E-02	4.26E-03
0.695725	0.062978	2.38E-01	1.86E-01	3.82E-01	0.112235
3.80E-01	2.39E-01	2.07E-01	0.267032	2.49E-01	1.44E-01
1.12E-02	0.003227	2.76E-02	1.51E-03	0.01495	1.65E-05
1.05E-02	2.39E-03	7.06E-03	8.59E-04	2.86E-02	4.36E-07
0.001501	1.91E-03	3.33E-03	3.71E-03	0.018383	2.3E-07
1.59E-03	4.14E-03	2.58E-03	6.67E-03	1.38E-02	3.68E-07
8.10E-03	5.86E-03	2.07E-03	8.36E-03	0.012598	3.45E-06
1.27E-02	2.82E-02	2.59E-03	6.18E-03	0.013549	0.000115
2.48E-02	5.16E-03	7.34E-03	0.020841	1.87E-02	0.000686
7.80E-05	0.00155	5.08E-03	8.21E-04	0.010108	0.000186
6.70E-04	0.235737	0.16756	1.08E-01	0.207959	0.241053
2.71E-06	3.35E-02	0.201205	5.85E-02	1.30E-01	0.17432
0.990198	1.49E-01	1.64E-01	2.23E-01	9.20E-02	0.152193
1.70E-02	2.16E-01	2.01E-01	0.233827	1.86E-01	9.86E-02
1.64E-02	0.008436	3.88E-02	2.27E-03	2.37E-02	2.09E-05
7.33E-03	2.35E-03	8.06E-03	0.000689	2.50E-02	6.36E-07
1.53E-03	0.001939	3.29E-03	3.29E-03	0.015561	2.69E-07
2.34E-03	2.69E-03	2.76E-03	4.21E-03	1.40E-02	2.35E-07
1.68E-03	4.72E-03	2.00E-03	6.63E-03	0.006354	2.97E-05
4.04E-08	3.29E-03	1.92E-03	1.19E-02	2.66E-02	0.001242

2.11E-05	3.55E-03	5.36E-03	4.17E-03	0.012987	0.000492
6.85E-03	3.71E-03	1.53E-02	8.71E-04	0.024362	0.001002
4.92E-06	3.28E-02	0.074498	8.15E-03	0.071211	0.012998
0.056765	1.62E-03	0.074526	0.0003	0.038101	0.000778
0.091743	0.019264	1.59E-01	0.023684	3.60E-02	2.97E-03
7.87E-03	0.050268	2.44E-01	0.277467	0.162674	4.84E-02
7.63E-09	0.003444	2.97E-02	0.003609	0.016664	4.15E-05
2.80E-03	0.002454	5.48E-03	0.000804	4.01E-02	5.23E-07
0.001882	0.002621	3.10E-03	3.34E-03	0.015309	3.52E-07
5.47E-03	3.90E-03	2.54E-03	6.07E-03	0.018907	1.58E-07
1.16E-02	5.41E-03	1.89E-03	7.70E-03	0.008596	1.32E-05
6.91E-03	6.59E-04	1.83E-03	0.003246	9.81E-03	0.000246
1.55E-03	0.003953	1.83E-03	8.35E-05	2.67E-02	9.77E-05
3.25E-06	0.000754	2.92E-03	3.46E-04	0.01405	7.54E-05
9.92E-01	1.70E-03	0.083647	1.51E-04	0.046506	0.058243
0.992457	7.59E-03	0.221967	1.55E-02	0.107799	1.88E-01
0.99186	3.60E-02	0.173098	0.062333	0.043402	1.43E-02
0.081411	0.06882	1.80E-01	0.220559	0.061444	0.09693
3.59E-03	0.057035	2.84E-01	1.33E-01	0.143467	0.025101
1.24E-03	6.84E-03	0.053817	1.18E-03	0.029237	0.000384
0.003026	1.29E-03	4.42E-03	1.15E-03	0.023895	1.64E-07
0.001462	1.76E-03	3.28E-03	0.00298	0.021466	1.32E-07
0.001485	0.008941	2.08E-03	1.48E-02	0.010242	1.72E-06
0.022111	8.52E-03	4.59E-03	0.008096	3.46E-02	1.31E-06
0.02705	0.018643	5.74E-03	1.97E-02	3.36E-02	8.42E-06
0.001168	1.39E-02	1.74E-02	0.001873	0.020483	0.003231
0.281649	0.139584	0.377333	0.241963	0.328079	0.222026
0.224372	0.061516	0.084549	0.08662	0.074159	0.074495