ESKİŞEHİR TECHNICAL UNIVERSITY

FACULTY OF ENGINEERING

REGIONAL EARTHQUAKE FORECASTING FOR TÜRKİYE USING THE PAST EARTHQUAKE DATA AND DIFFERENT FORECASTING MODELS

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by

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ABSTRACT

The aim of this project is to forecast earthquakes in Türkiye using various forecasting models based on deep learning. Specifically, long short-term memory (LSTM) networks are used for the forecasting task. The models are trained using the magnitude, latitude, longitude, depth, and date parameters, as well as their statistical features, of the past earthquakes in Türkiye. The data is retrieved from Kandilli Observatory and Earthquake Research Institute of Boğaziçi University. The models are developed for both the entire country and particular regions of the country. The earthquake data is split into training and test parts. While the training data is used to train the models, the test data is used to evaluate them. The experimental analysis reveals that the models can forecast magnitudes and locations of future earthquakes with a root mean square error (RMSE) as low as 0.14.

This project is supported by TÜBİTAK 2209-A Research Project Support Programme for Undergraduate Students.

Keywords: Artificial intelligence, deep learning, LSTM network, earthquake forecasting, earth sciences, disaster management.

ÖZET

Bu projenin amacı, derin öğrenme tabanlı çeşitli tahmin modellerini kullanarak Türkiye'deki depremlerin tahmin edilmesidir. Tahmin modeli olarak uzun kısa süreli bellek (LSTM) ağları kullanılmıştır. Modelleri eğitmek için Türkiye'deki deprem verilerinin deprem büyüklüğü, enlem, boylam, derinlik ve tarih parametreleri ile bu parametreleri kullanarak elde edilmiş istatistikler veriler kullanılmıştır. Veriler, Boğaziçi Üniversitesi Kandilli Rasathanesi ve Deprem Araştırma Enstitüsünden alınmıştır. Modeller hem ülke geneli hem de ülkenin belirli bölgeleri için geliştirilmiştir. Deprem verileri, eğitim ve test bölümlerine ayrılmıştır. Modelleri eğitmek için eğitim verileri kullanılırken, bunları değerlendirmek için test verileri kullanılmıştır. Deneysel çalışmalar, kullanılan modellerin gelecekteki depremlerin büyüklüklerini ve yerlerini en düşük 0.14 Kök Ortalama Kare Hatası (RMSE) ile tahmin edebileceğini ortaya koymaktadır.

Bu proje, TÜBİTAK 2209-A Üniversite Öğrencileri Araştırma Projeleri Destekleme Programı tarafından desteklenmektedir.

Anahtar Kelimeler: Yapay zeka, derin öğrenme, LSTM ağ, deprem tahmini, yer bilimleri, afet yönetimi.

ACKNOWLEDGEMENT

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ABBREVIATIONS

LSTM	Long Short-Term Memory
Seq2Seq	Sequence-to-Sequence
RNN	Recurrent Neural Network
RSME	Root-Mean-Square Error
GRU	Gated Recurrent Unit
FNN	Feedback Neural Network
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
VAR	Vector Autoregression
ARIMA	Autoregressive Integrated Moving Average

1. INTRODUCTION

Türkiye is located on the Alpine-Himalayan seismic belt, which is one of the most active seismic belts in the world. 43% of the country's surface area is located in areas with an expected acceleration value greater than 0.40 g, which is defined as the first-degree seismic belt. The earthquakes that have developed in Türkiye from past to present have caused great damage by causing loss of life and property.

To avoid the devastating effects of earthquakes in the world, machine learning methods are frequently used in earthquake forecasting studies in many countries located in the earthquake zone. In our research project, we aim to estimate the earthquake magnitudes that may occur in the future and which region may be affected by this earthquake by using earthquake data in Türkiye and different forecasting models.

Earthquake magnitude estimation was made by using the Back Propagation Neural Networks model and developing this model with the Particle Swarm Optimization algorithm based on the earthquake data that took place in China before [1]. Earthquake magnitude estimations have been tried to be made using Artificial Neural Networks, M5P, Support Vector Machine, and Naive Bayes models on earthquake data in Pakistan [2]. In this study [2], the accuracy rates of Artificial Neural Network results stand out. Earthquake magnitude estimation has been tried to be made by using Pattern Recognition Neural Network, Renewed Neural Network, Random Forest, and Linear Programming Support models over the earthquake data that occurred in the Iberian Peninsula [3]. Later, in this study [3], the results were tried to be improved with machine learning algorithms. Our goal is to repeat the models used in studies like these over the earthquake data in Türkiye and to compare the results of the models. After this comparison, choosing a model that stands out with its prediction performance and improving that model to give better results. Making this study specific to Türkiye, using Türkiye earthquake data and at the same time creating a model taking into account Türkiye's geographical structure. In order to minimize the damages caused by earthquake danger, it was aimed to make earthquake predictions. In order to make this estimation, earthquake data of the last hundred years of Türkiye were used. With the data obtained, the earthquake; A deep learning model has been developed that can give size, time, and location information.

2. DATA

2.1. Data Set

In obtaining earthquake data, Boğaziçi University Kandilli Observatory BDTIM earthquake inquiry system [4] was used. The dataset that is in the type of time series, covers earthquakes between the year 1900 and 2021 30 March. 53.554 earthquake data with a magnitude greater than 3. The data set includes date, earthquake magnitude, latitude (lat), longitude (lon), and depth information.

Table 2.1. Sample Earthquake Data for Türkiye

Datetime	*lat*	*lon*	*depth*	*magnitude*
1/2/2021 5:03	38.9748	26.0442	8.1	4.1
1/2/2021 5:46	38.9535	26.0643	13.7	4.9
1/2/2021 5:47	38.9773	26.0743	5	4.9
1/2/2021 6:00	38.9557	26.0568	11	4.6
1/2/2021 6:34	38.9638	26.0427	6.7	4
1/2/2021 8:35	38.9607	26.0202	13.7	5.2
1/2/2021 13:10	38.9488	26.061	10	4.7
1/2/2021 20:46	38.9765	26.044	13.5	4.7
2/2/2021 0:02	39.0985	36.0918	5	4.7
2/2/2021 6:35	39.0342	41.7668	5	4
6/2/2021 16:09	38.9412	26.0557	9.2	4.2
6/2/2021 18:22	38.9428	26.0568	8.7	4.1
7/2/2021 22:01	39.1055	36.08	5	4.2
9/2/2021 7:30	37.7672	26.4	7.5	4.2
9/2/2021 15:51	38.6082	31.6613	4.8	4.5
9/2/2021 15:53	38.5958	31.6502	5.4	4.2
10/2/2021 5:06	36.76	41.2448	3.4	4
12/2/2021 3:37	41.3603	33.5418	1.7	4.6
13/2/2021 11:29	39.9817	44.5312	11.2	4.6
14/2/2021 21:08	38.1803	30.042	5	4
17/2/2021 10:02	39.4425	40.2757	5	4.2
22/2/2021 22:42	39.691	37.3128	5	4
25/2/2021 9:48	39.2965	41.1382	5.2	4.3
8/3/2021 9:09	40.149	35.1063	5	4
9/3/2021 8:20	39.0337	40.534	1.6	4.2
12/3/2021 5:57	39.758	43.6788	5	4.2
15/3/2021 1:55	37.1548	28.7873	6.4	4.1
20/3/2021 5:51	39.83	39.0897	3.4	4.3

Sample of earthquake data is listed in Table 2.1. The distribution of earthquakes according to earthquake magnitude is shown in Figures 1 and 2.

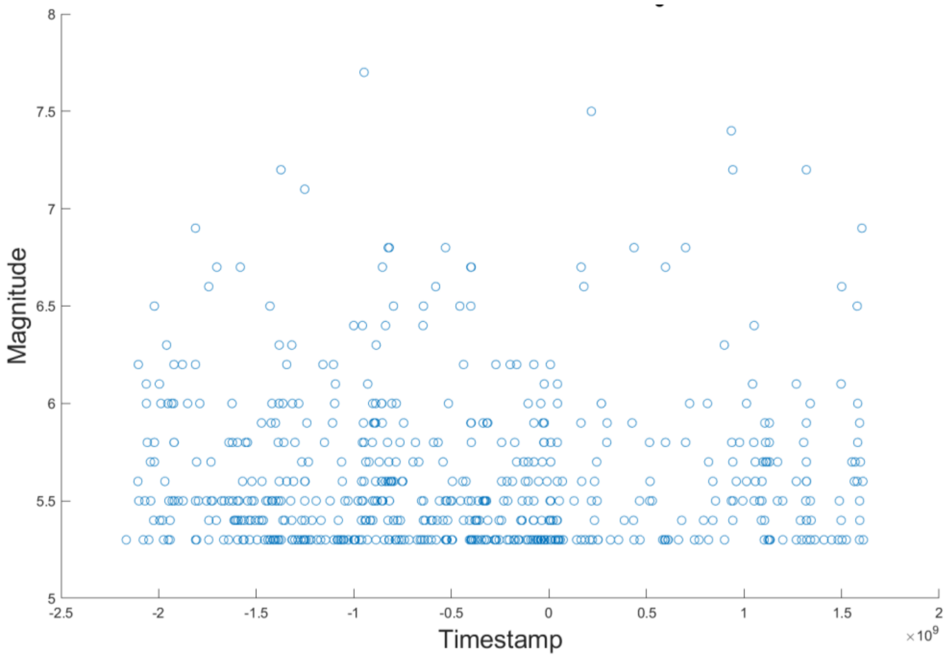

Figure 1. Earthquake distribution by magnitude, magnitudes are greater than 5.3

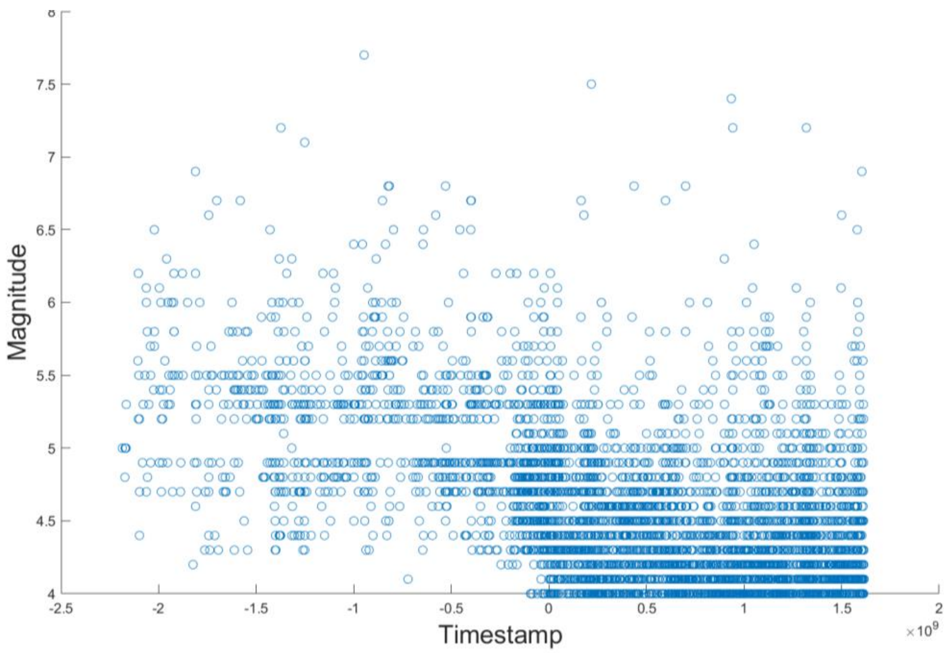

Figure 2. Earthquake distribution by magnitude, magnitudes are greater than 4

2.2. Statistical Features

The selected model utilizes statistical features extracted from various parameters of previous earthquakes. Specifically, for each earthquake, 35 distinct features are extracted using minimum, maximum, mean, median, variance, skewness, and kurtosis of Magnitude, Latitude, Longitude, Depth, Date-Time values belonging to the previous 30 earthquakes as listed in Table 2.2.

Table 2.2. Statistical Features Derived From Earthquake Data Parameters

Feature No	***Feature Description***
1 – 7	[Min, Max, Mean, Median, Variance, Skewness, Kurtosis] of MAGNITUDE
8 – 14	[Min, Max, Mean, Median, Variance, Skewness, Kurtosis] of LATITUDE
15 – 21	[Min, Max, Mean, Median, Variance, Skewness, Kurtosis] of LONGITUDE
22 – 28	[Min, Max, Mean, Median, Variance, Skewness, Kurtosis] of DEPTH
29 – 35	[Min, Max, Mean, Median, Variance, Skewness, Kurtosis] of DATETIME

While training the model, these 35 different statistical data and historical data as features are used. So, 37 features are extracted with 30 backward earthquake magnitudes and 7 statistical data calculated for earthquake magnitudes. In total, 185 features are extracted for an earthquake.

3. FORECASTING MODELS

As a result of the observations, the most suitable model for the data type was determined as Sequence-to-Sequence LSTM. GARCH, VAR ARIMA, etc. It has been observed with various experiments that the models are not efficient enough. Seq2Seq is a type of Encoder-Decoder model using RNN. Seq2Seq modeling is about training the models that can convert sequences from one domain to sequences of another domain. It can be used as a model for machine interaction and machine translation.

3.1 RNN

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable-length sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition, or speech recognition.

The term “recurrent neural network” is used indiscriminately to refer to two broad classes of networks with a similar general structure, where one is finite impulse and the other is infinite impulse. Both classes of networks exhibit temporal dynamic behavior. A finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced with a strictly feedforward neural network, while an infinite impulse recurrent network is a directed cyclic graph that cannot be unrolled.

Both finite impulse and infinite impulse recurrent networks can have additional stored states, and the storage can be under direct control by the neural network. The storage can also be replaced by another network or graph if that incorporates time delays or has feedback loops. Such controlled states are referred to as gated state or gated memory and are part of long short-term memory networks (LSTMs) and gated recurrent units. This is also called Feedback Neural Network (FNN).

3.2 LSTM

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can not only process single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unsegmented, connected handwriting recognition, speech recognition, and anomaly detection in network traffic or IDSs (intrusion detection systems). A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. LSTM networks are well-suited to classifying, processing, and making predictions based on time series data since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the vanishing gradient problem that can be encountered when training traditional RNNs. Relative insensitivity to gap length is an advantage of LSTM over RNNs, hidden Markov models, and other sequence learning methods in numerous applications.

3.3 Seq2Seq

To train a neural network to input the sequence x and output the translation as sequence y we’re going to use an encoder and decoder network. The encoder network can be built as an RNN (and this could be a GRU or LSTM cells) where we feed in the input one word at a time. And after ingesting the input sequence, the RNN then offers a vector that represents the input sentence.

4. EXPERIMENTAL WORK

Matlab language was used with statics and machine learning toolbox(version 12.1), deep learning toolbox(version 14.2) and parallel computing toolbox(version 7.4) for experimatal work and pyhon language was used to organize the dataset.

While training the model, different combinations of 185 different extracted features were tested. For example, earthquake magnitude and location estimates were made using only magnitude attributes or using earthquake magnitude and depth attributes.

By making changes in the number of backward data, we changed the number of features and made different forecasts.

By filtering the dataset, it was made more stable and earthquake-related forecasts were made. For example, only earthquake data with earthquake magnitude greater than 4 or greater than 5 were used when training the model.

The model was made more stable by assigning different values to variables such as batch size and epoch size in the algorithm used while training the model.

Table 2.3. All Features for Training

Features and variables	***Values***
Statistical features	Magnitude features Magnitude and depth features Magnitude, depth, timestamp features …
Backward size	20, **30**, 50, 100
Magnitude	Greater than 3, **4, 4.4, 5, 5.3**
Batch size	10, 20, 50, **100** and size of data
Number of Epochs	200, 500, **1000**
Initial learning rate	0.1, **0.01**, 0.05, 0.001

Experimental studies are under two main headings. The effect of Türkiye-wide data on the model and the effect of regional (1-15) data on the model. The features and amount of data used in the predictions affect the prediction performance. After applying multiple combinations, the predictions with the lowest RSME values were selected.

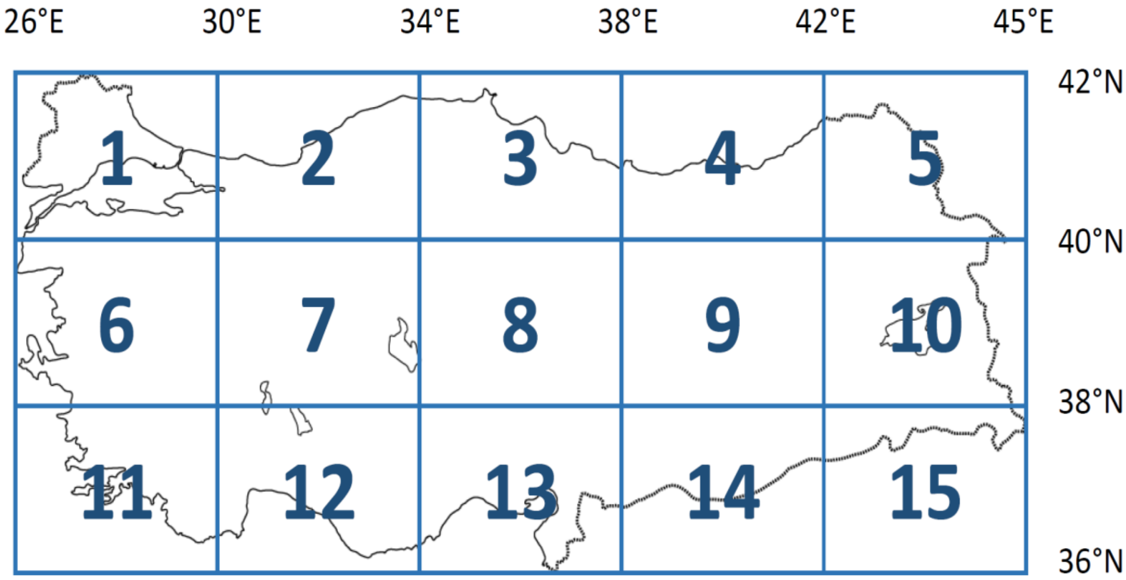

Figure 3. A map of Türkiye divided into 15 regions based on latitude and longitude

In order to forecast the location of the earthquake and improve the results about forecasting magnitude obtained throughout Turkey, Turkey was divided into 15 different regions as in Figure 1.

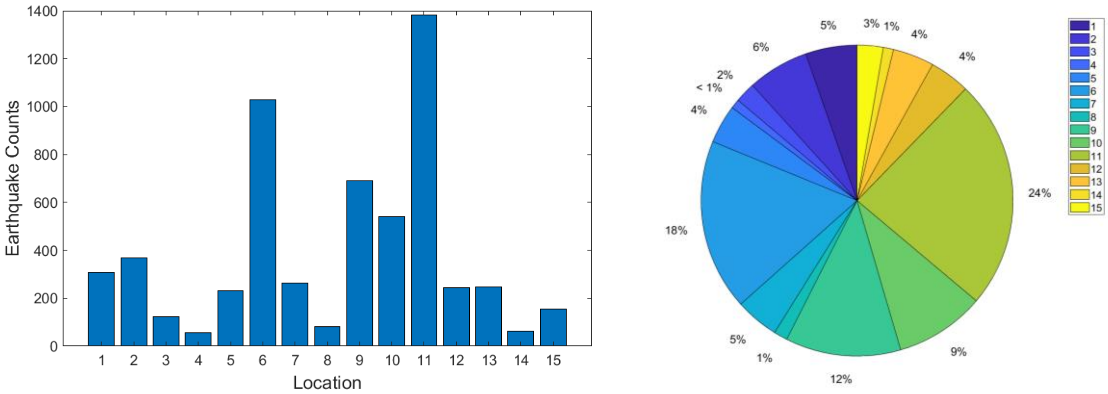

Figure 4. Distribution of earthquakes by region, magnitudes are greater than 4

There are 5,784 earthquake data with earthquake magnitude greater than 4 and the distribution of earthquakes is as in Figure 2. Region 11 is the one where earthquakes occur the most with 24%.

4.1 Results for Türkiye

4.1.1 Magnitude Forecasting

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in Turkey. There are 3.128 earthquake data, 3.113 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.39.

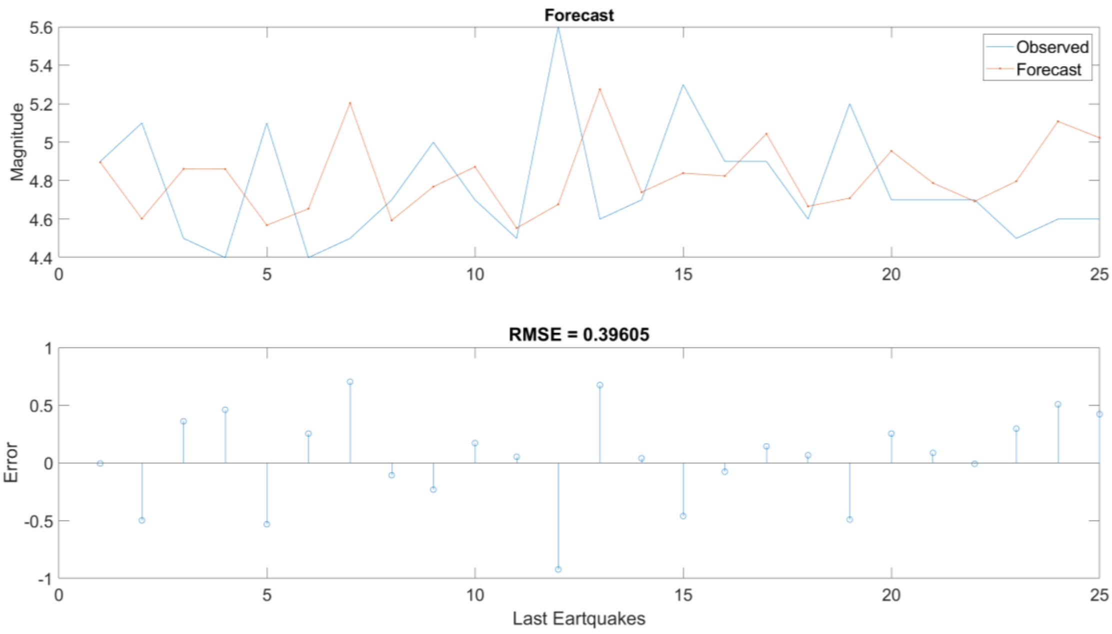

Figure 5. Magnitude forecasting, magnitude is greater than 4.4

Dataset: Earthquakes with earthquake magnitude greater than 5 in Turkey. There are 970 earthquake data, 945 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 500. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.44

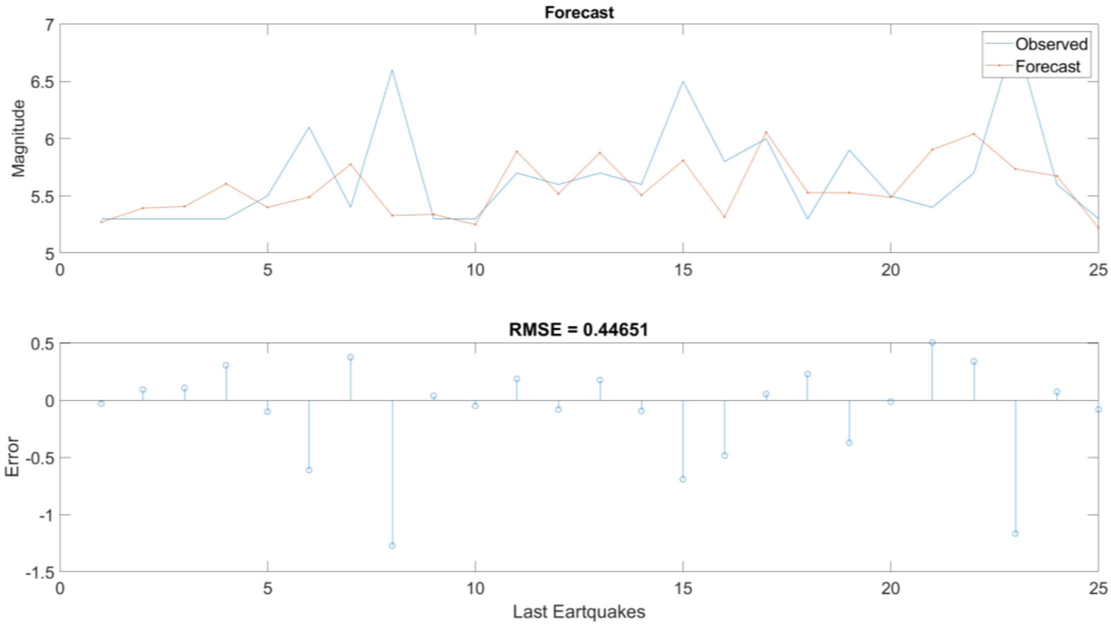

Figure 6. Magnitude forecasting, magnitude is greater than 5

4.1.2 Location Forecasting

Dataset: Earthquakes with earthquake magnitude greater than 5 in Turkey. There are 970 earthquake data, 945 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, latitude, longitude and timestamp are used to extract features.

Algorithm variables: Epoch size is 500. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 1.83.

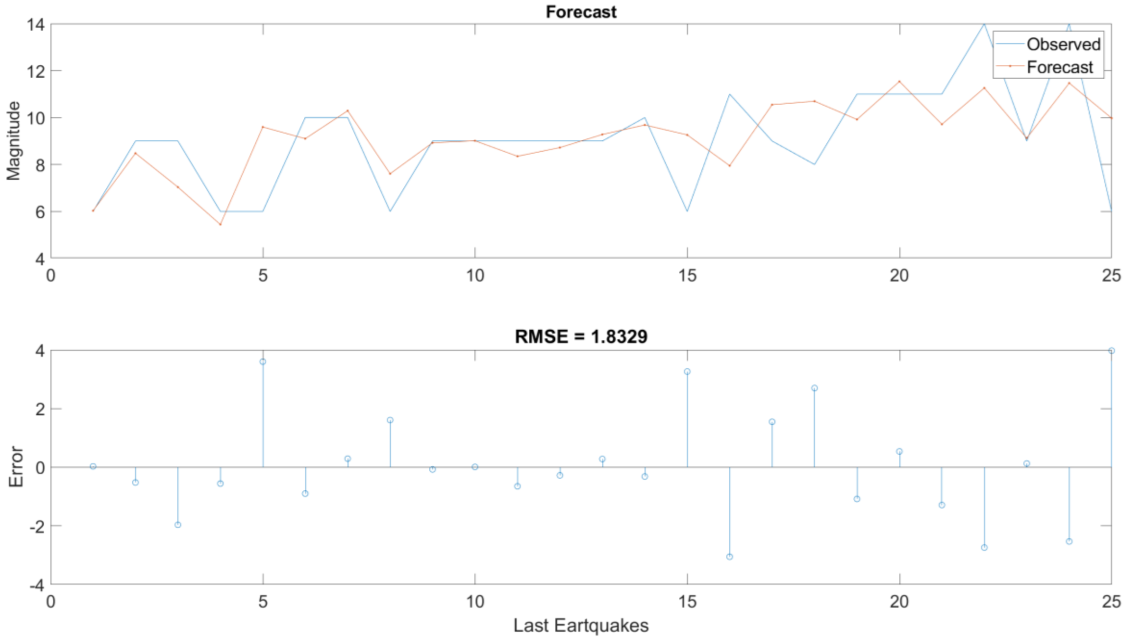

Figure 7. Location forecasting, magnitude is greater than 5

4.1.3 Magnitude and Location Forecasting

Dataset: Earthquakes with earthquake magnitude greater than 5 in Turkey. There are 970 earthquake data, 945 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, latitude, longitude and timestamp are used to extract features.

Algorithm variables: Epoch size is 500. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes and locations of future earthquakes with an RMSE of magnitude 0.50 and location RMSE of location 2.06.

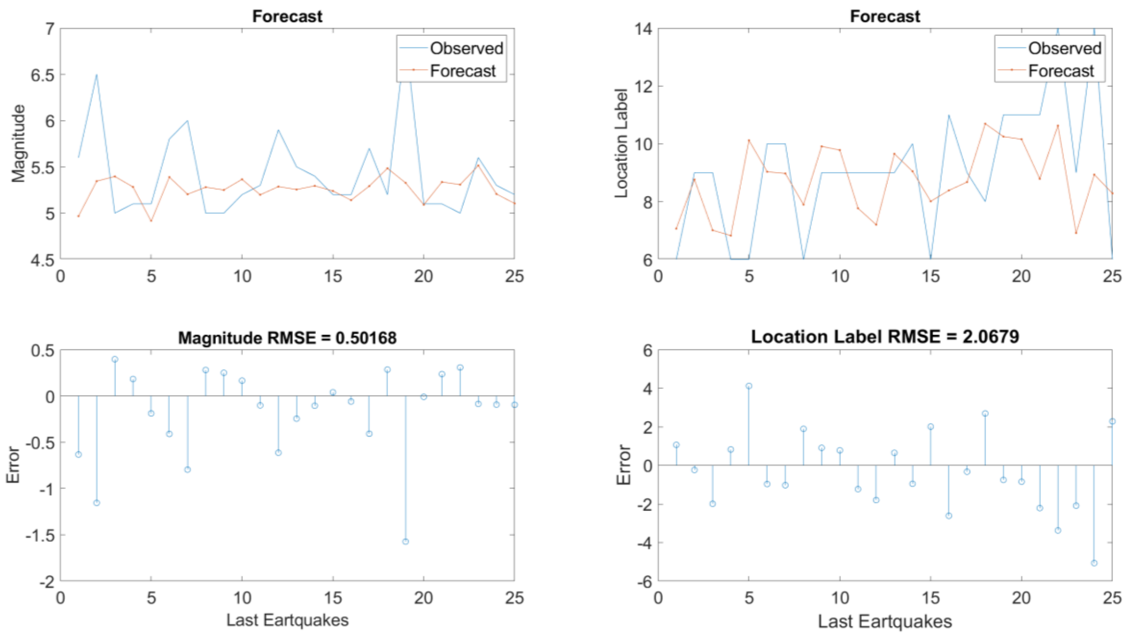

Figure 8. Magnitude and Location forecasting, magnitude is greater than 5

4.2 Results for Regions

Due to insufficient data, earthquake magnitude forecasts were not made for regions 4, 8 and 14.

4.2.1 Region 1

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 1. There are 309 earthquake data, 284 data are used for training and 25 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.38.

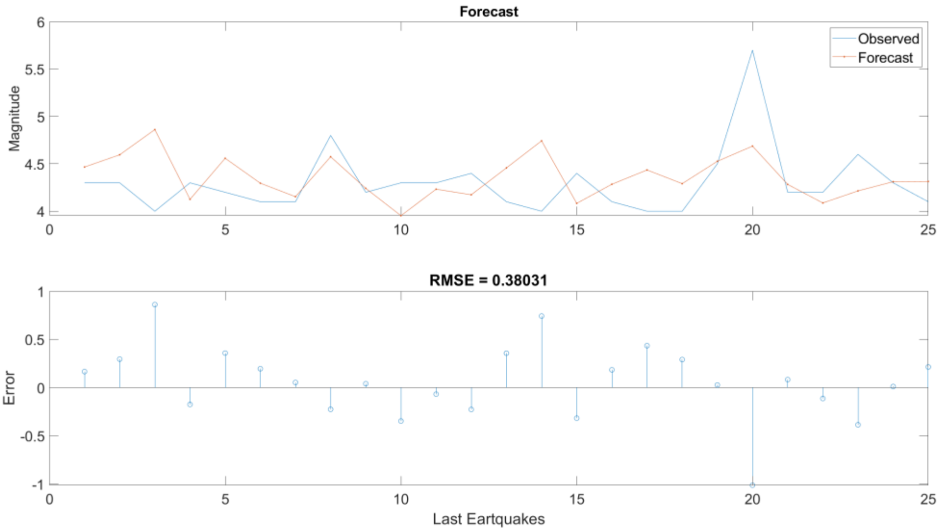

Figure 9. Magnitude forecasting for region 1, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 1. There are 163 earthquake data, 153 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.41.

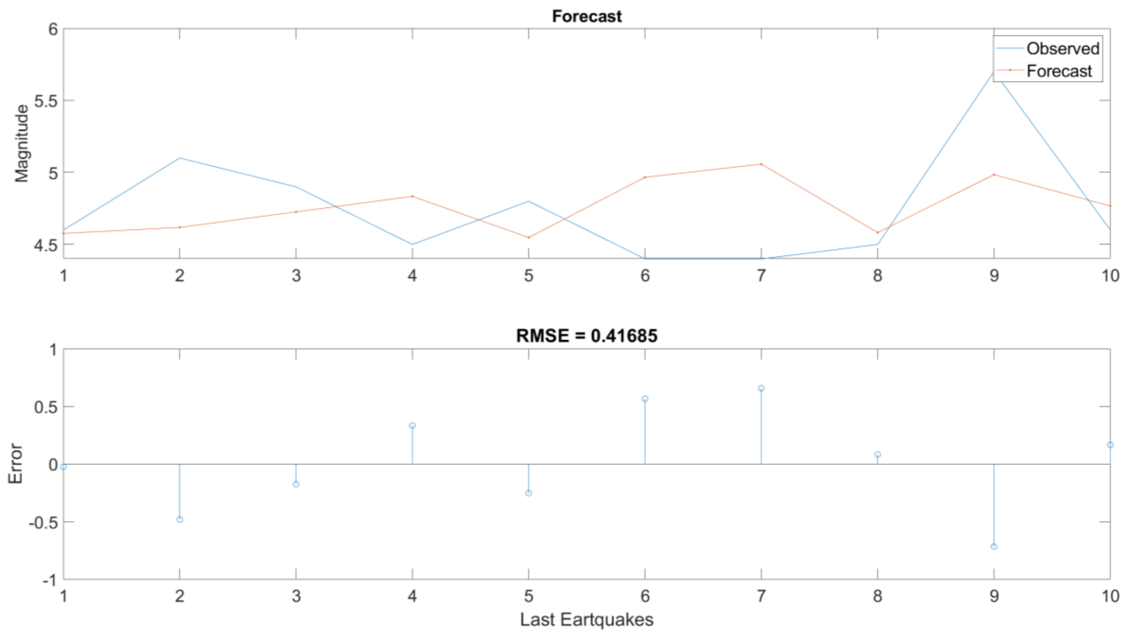

Figure 10. Magnitude forecasting for region 1, magnitude is greater than 4.4

4.2.2 Region 2

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 2. There are 224 earthquake data, 199 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.29.

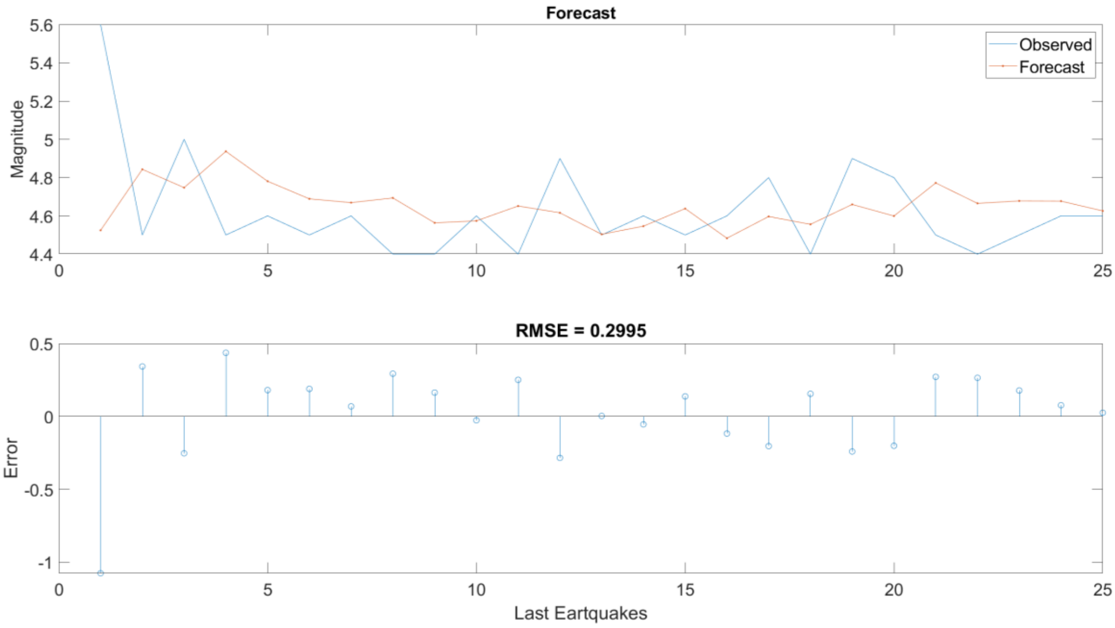

Figure 11. Magnitude forecasting for region 2, magnitude is greater than 4.4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 2. There are 224 earthquake data, 199 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.31.

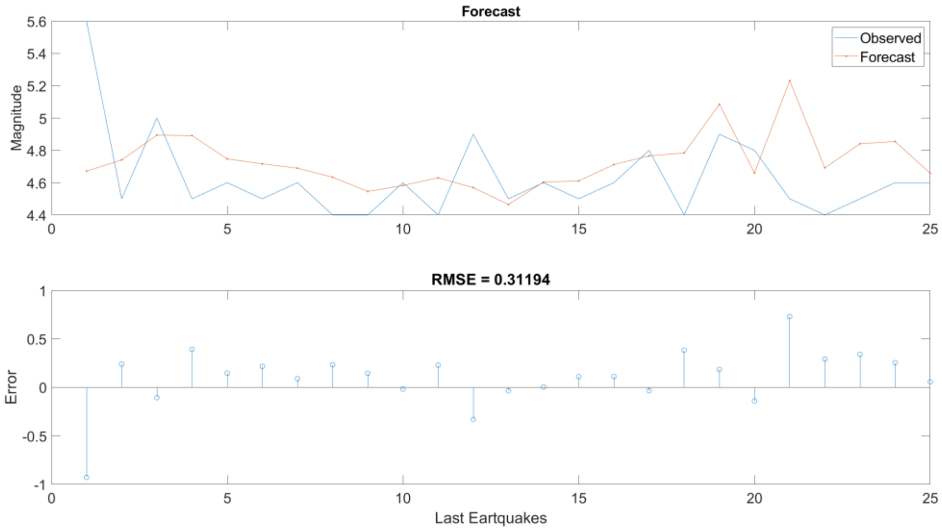

Figure 12. Magnitude forecasting for region 2, magnitude is greater than 4.4

4.2.3 Region 3

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 3. There are 123 earthquake data, 113 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.18.

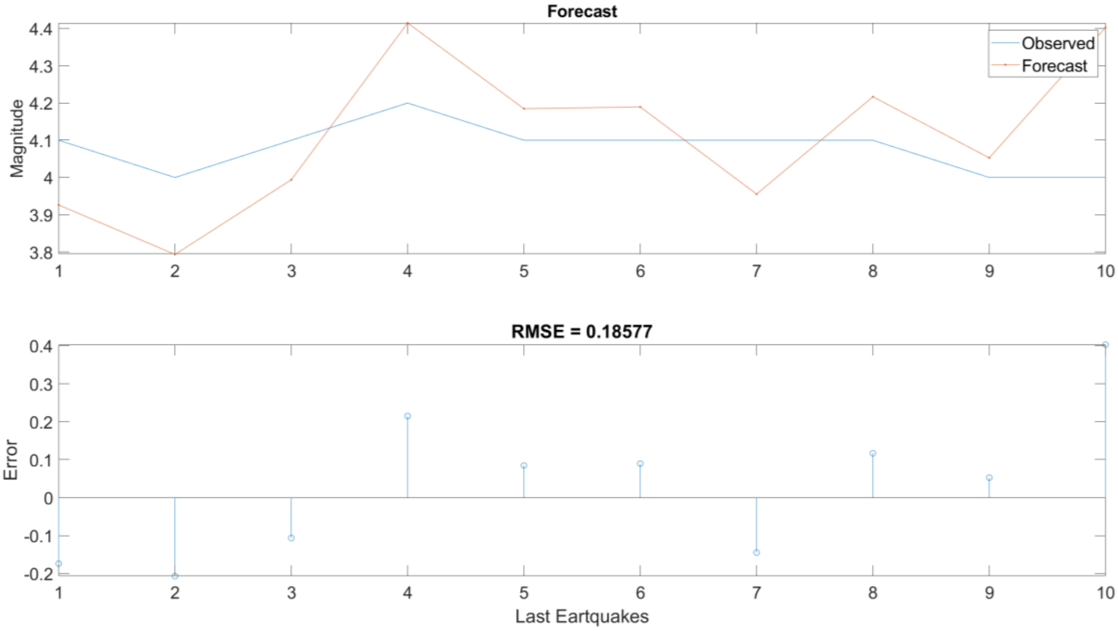

Figure 13. Magnitude forecasting for region 3, magnitude is greater than 4

4.2.4 Region 5

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 5. There are 232 earthquake data, 207 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.30.

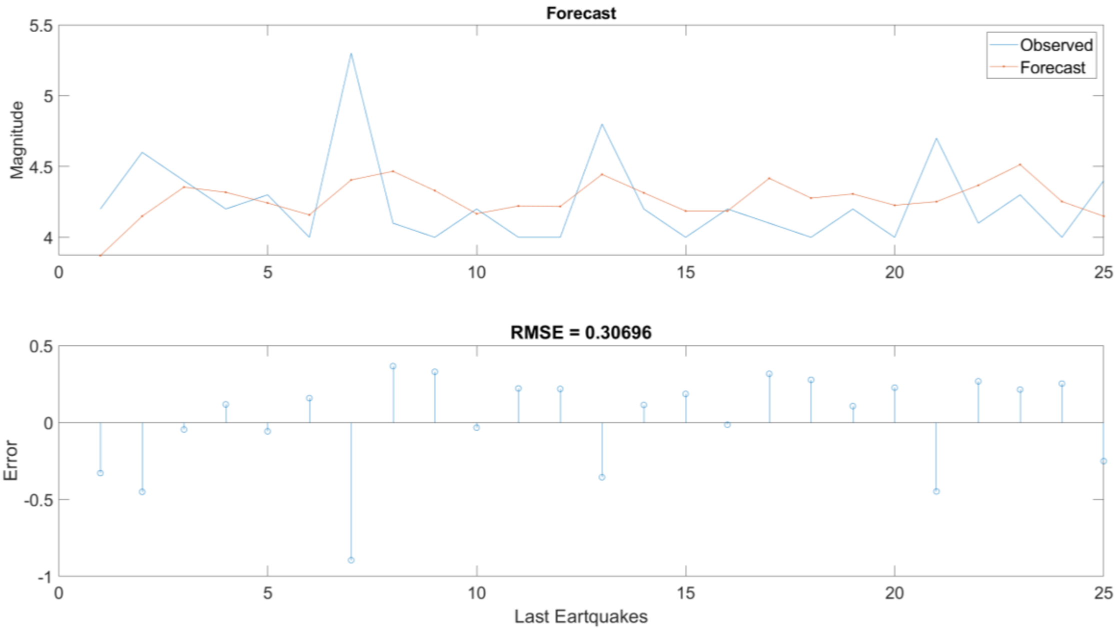

Figure 14. Magnitude forecasting for region 5, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 5. There are 178 earthquake data, 168 data are used for training and 10 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.47.

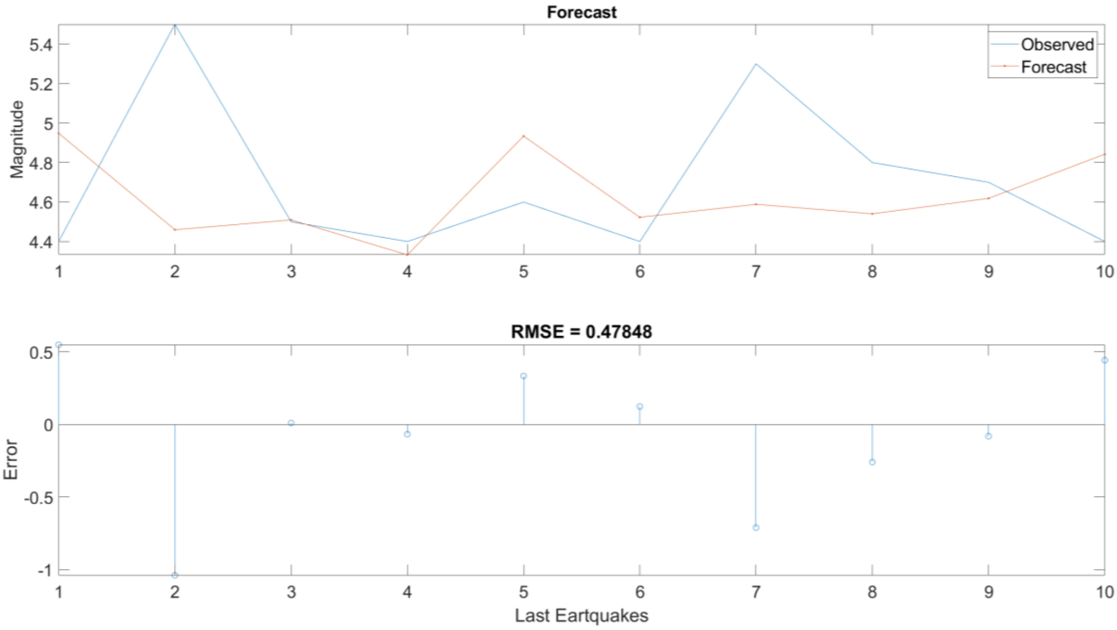

Figure 15. Magnitude forecasting for region 5, magnitude is greater than 4.4

4.2.5 Region 6

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 6. There are 529 earthquake data, 504 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.39.

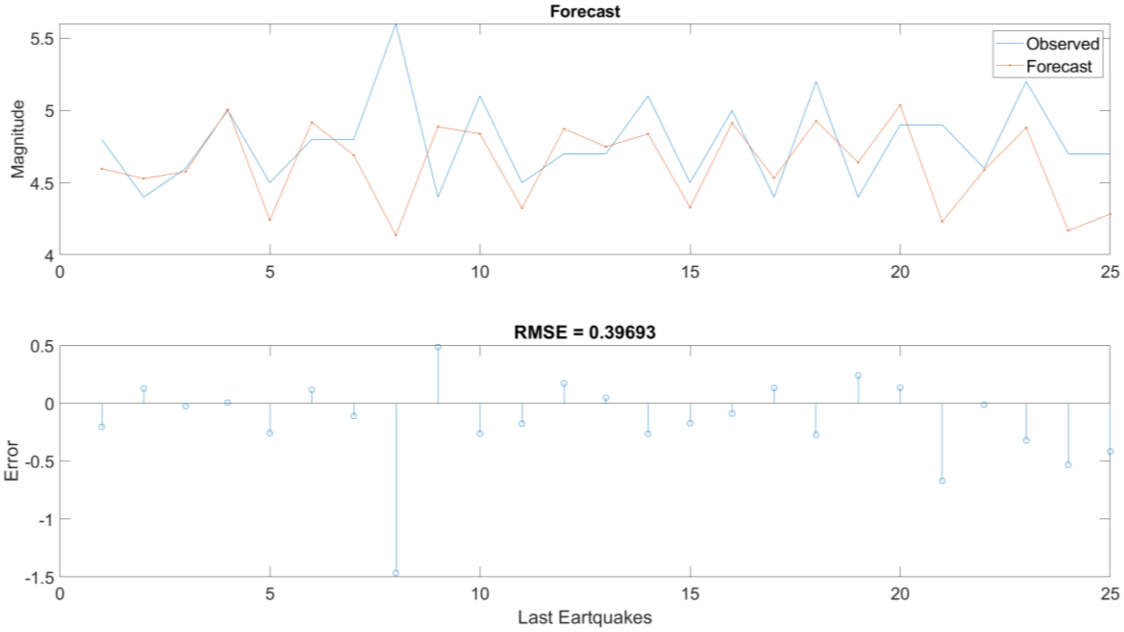

Figure 16. Magnitude forecasting for region 6, magnitude is greater than 4.4

Dataset: Earthquakes with earthquake magnitude greater than 5.3 in region 6. There are 102 earthquake data, 92 data are used for training and 10 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.26.

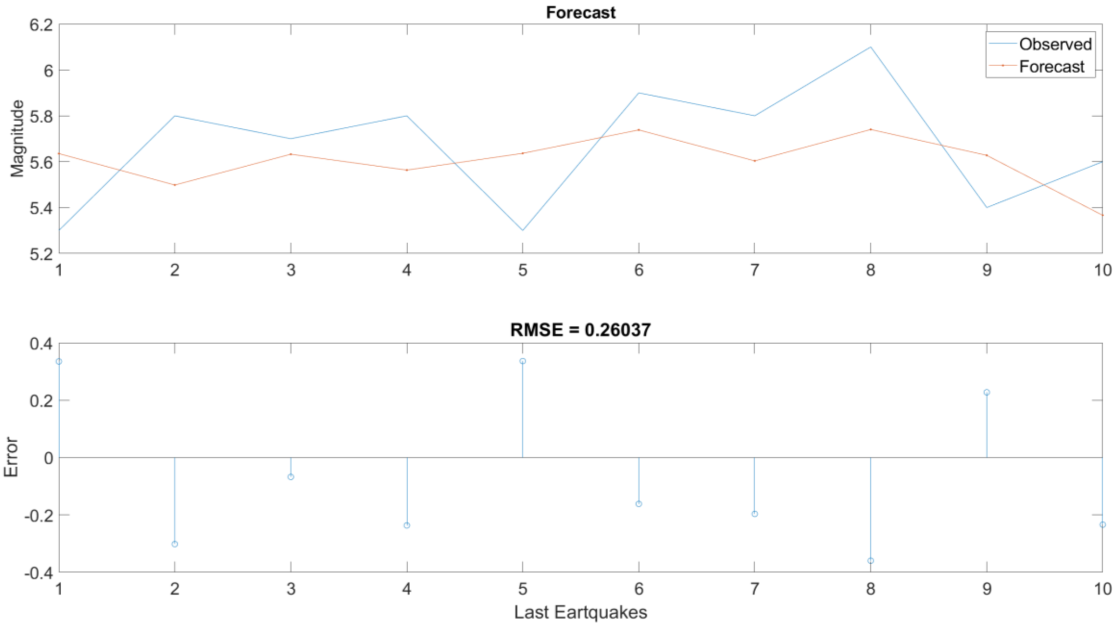

Figure 17. Magnitude forecasting for region 6, magnitude is greater than 5.3

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 6. There are 1029 earthquake data, 1004 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.49.

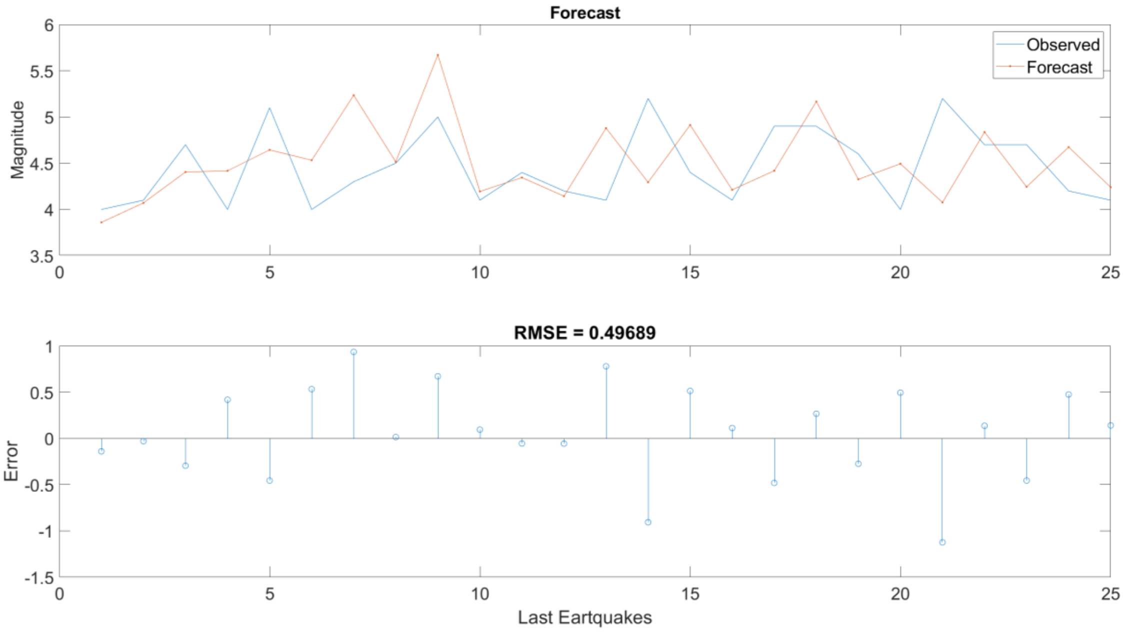

Figure 18. Magnitude forecasting for region 6, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 5 in region 6. There are 168 earthquake data, 158 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.37.

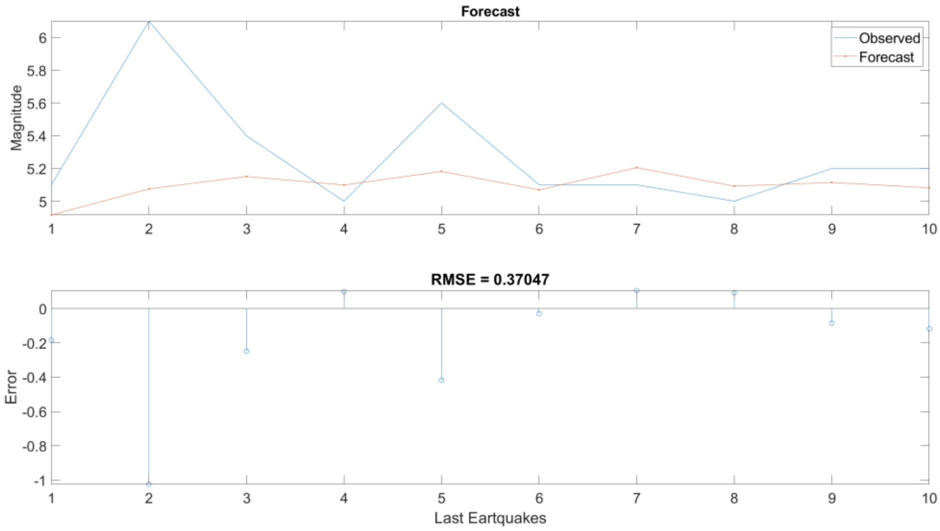

Figure 19. Magnitude forecasting for region 6, magnitude is greater than 5

Dataset: Earthquakes with earthquake magnitude greater than 5 in region 6. There are 168 earthquake data, 158 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.44.

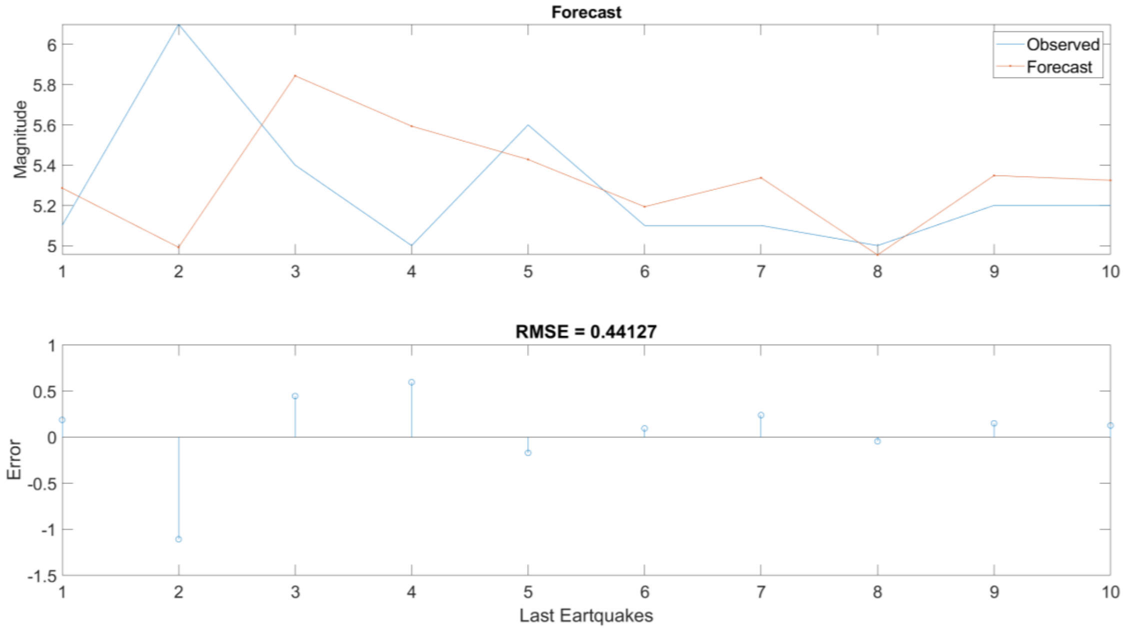

Figure 20. Magnitude forecasting for region 6, magnitude is greater than 5

4.2.6 Region 7

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 7. There are 262 earthquake data, 237 data are used for training and 25 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.44.

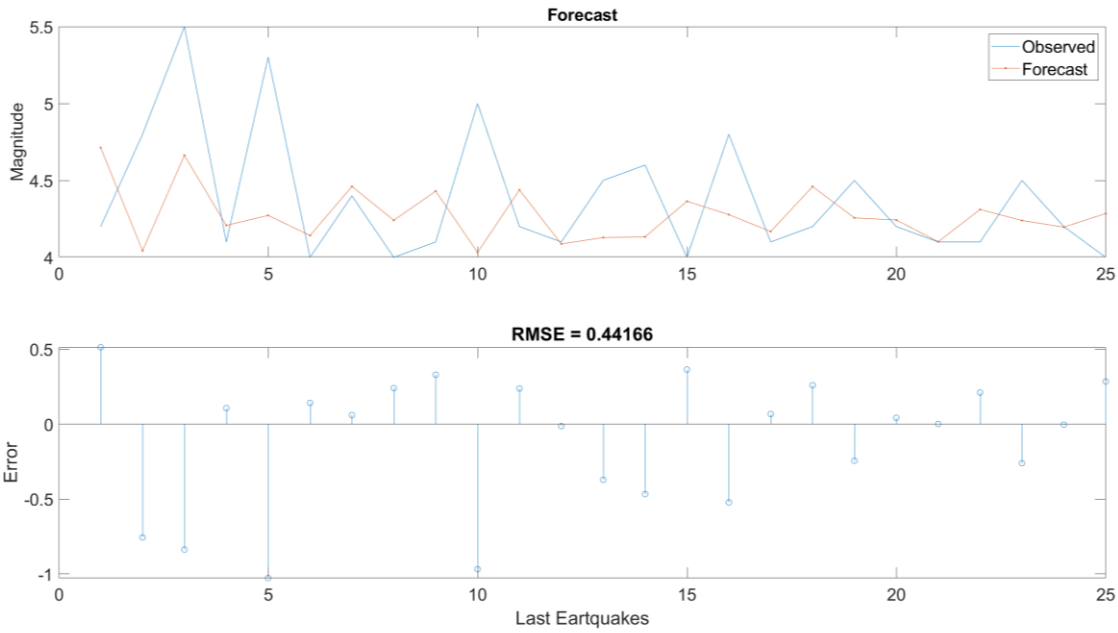

Figure 21. Magnitude forecasting for region 7, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 7. There are 146 earthquake data, 136 data are used for training and 10 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.31.

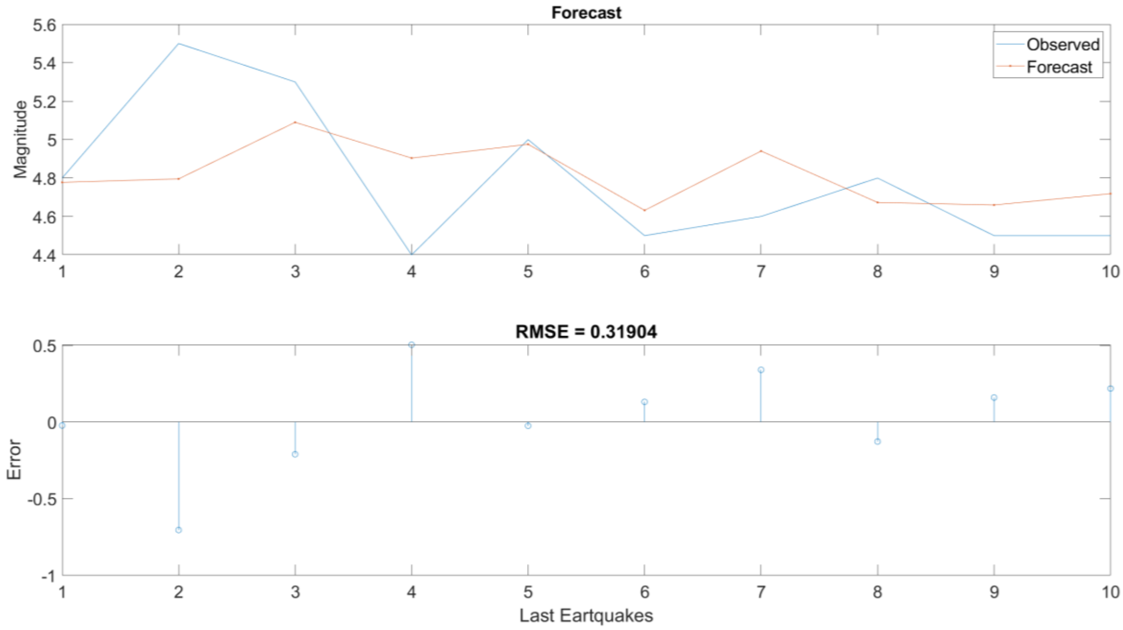

Figure 22. Magnitude forecasting for region 7, magnitude is greater than 4.4

4.2.7 Region 9

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 9. There are 692 earthquake data, 667 data are used for training and 25 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.46.

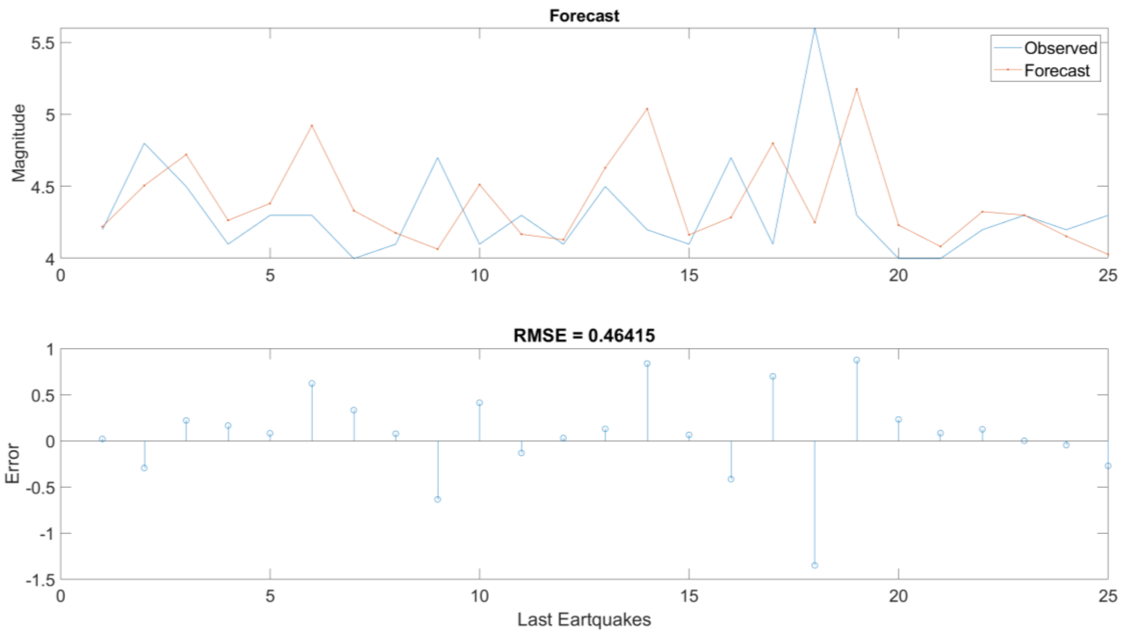

Figure 23. Magnitude forecasting for region 9, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 9. There are 372 earthquake data, 347 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.42.

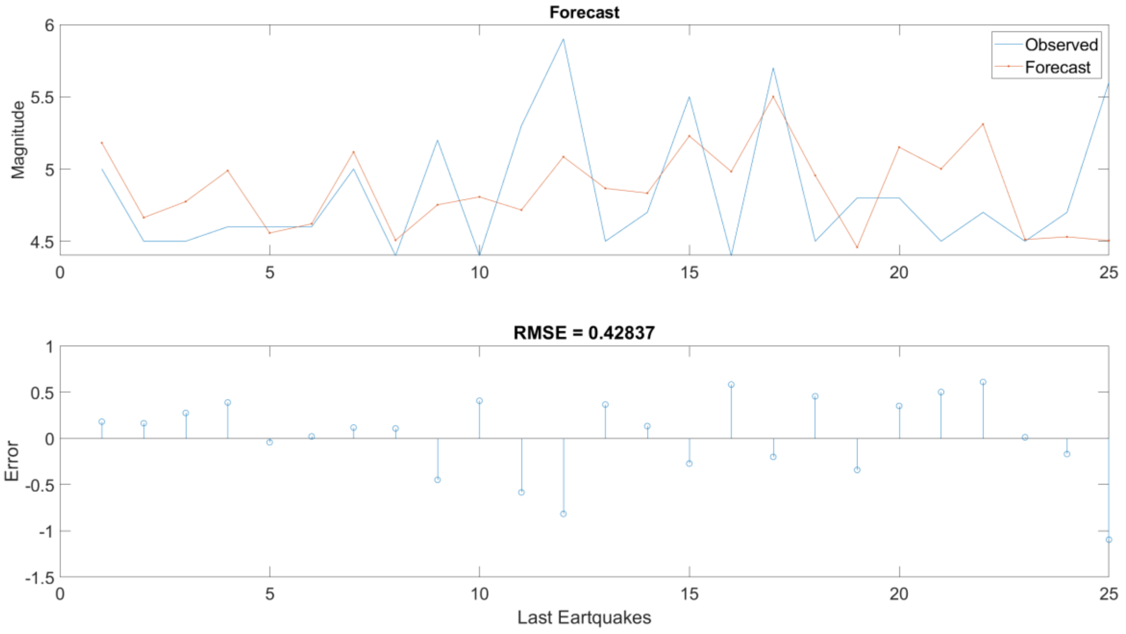

Figure 24. Magnitude forecasting for region 9, magnitude is greater than 4.4

4.2.8 Region 10

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 10. There are 540 earthquake data, 515 data are used for training and 25 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.41.

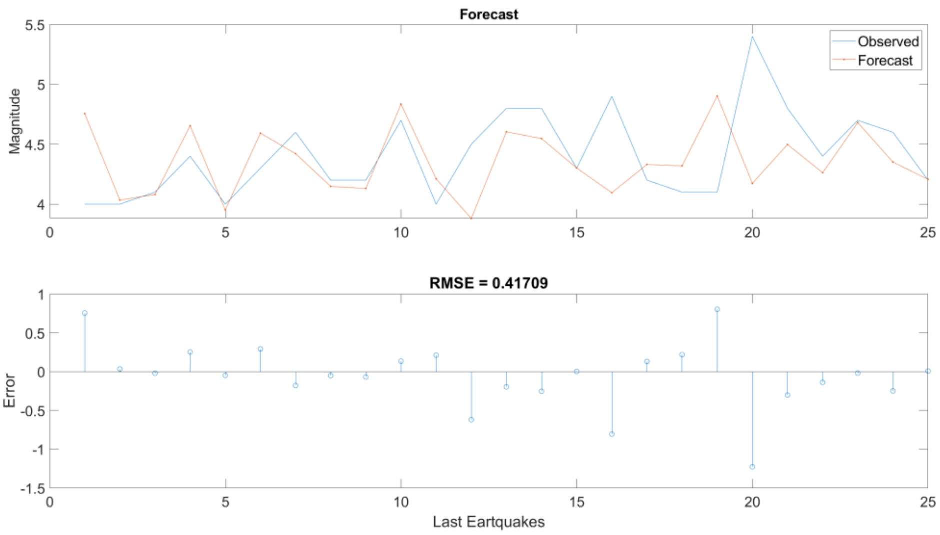

Figure 25. Magnitude forecasting for region 10, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 10. There are 284 earthquake data, 259 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.34.

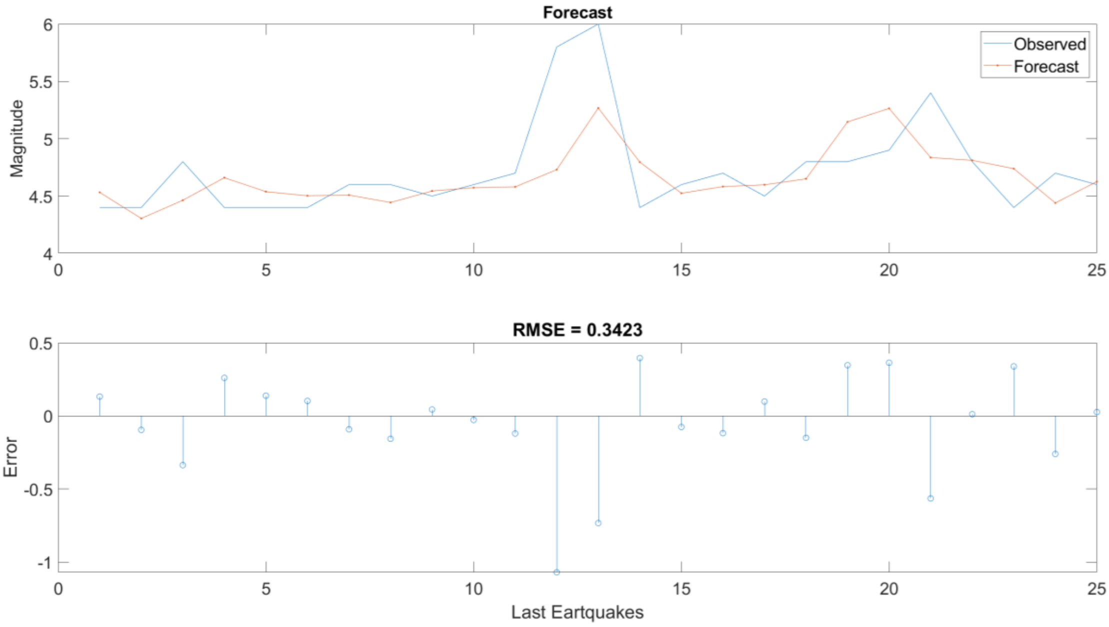

Figure 26. Magnitude forecasting for region 10, magnitude is greater than 4.4

4.2.9 Region 11

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 11. There are 1383 earthquake data, 1358 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.32.

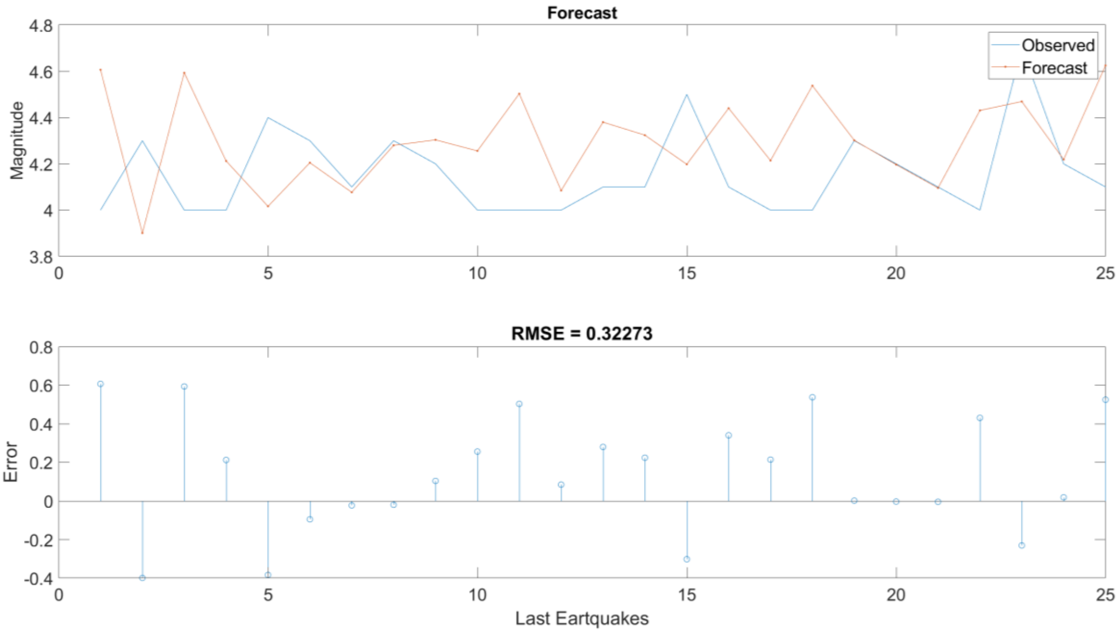

Figure 27. Magnitude forecasting for region 11, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 11. There are 722 earthquake data, 897 data are used for training and 25 data are used for the test.

Features: Backward 20 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.51.

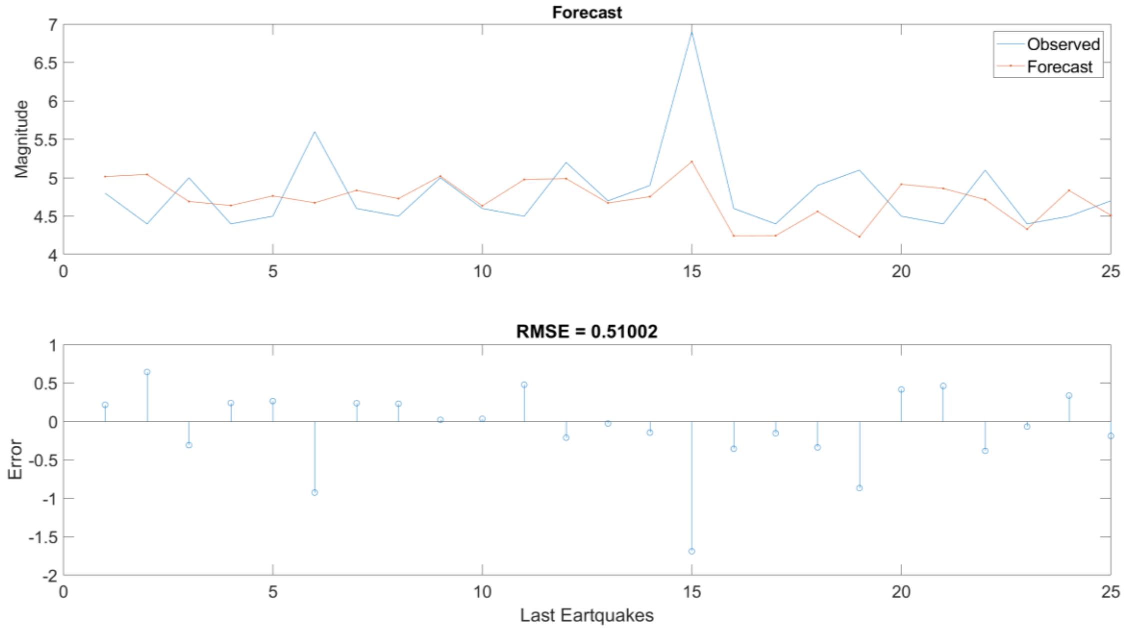

Figure 28. Magnitude forecasting for region 11, magnitude is greater than 4.4

4.2.10 Region 12

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 12. There are 243 earthquake data, 218 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.46.

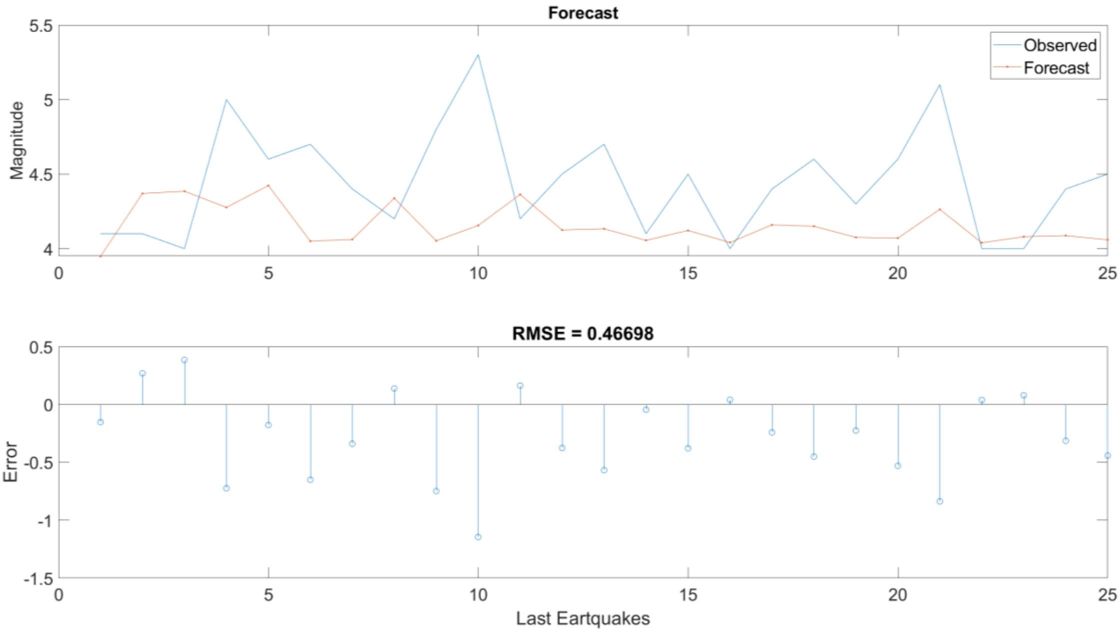

Figure 29. Magnitude forecasting for region 12, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 12. There are 144 earthquake data, 134 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.30.

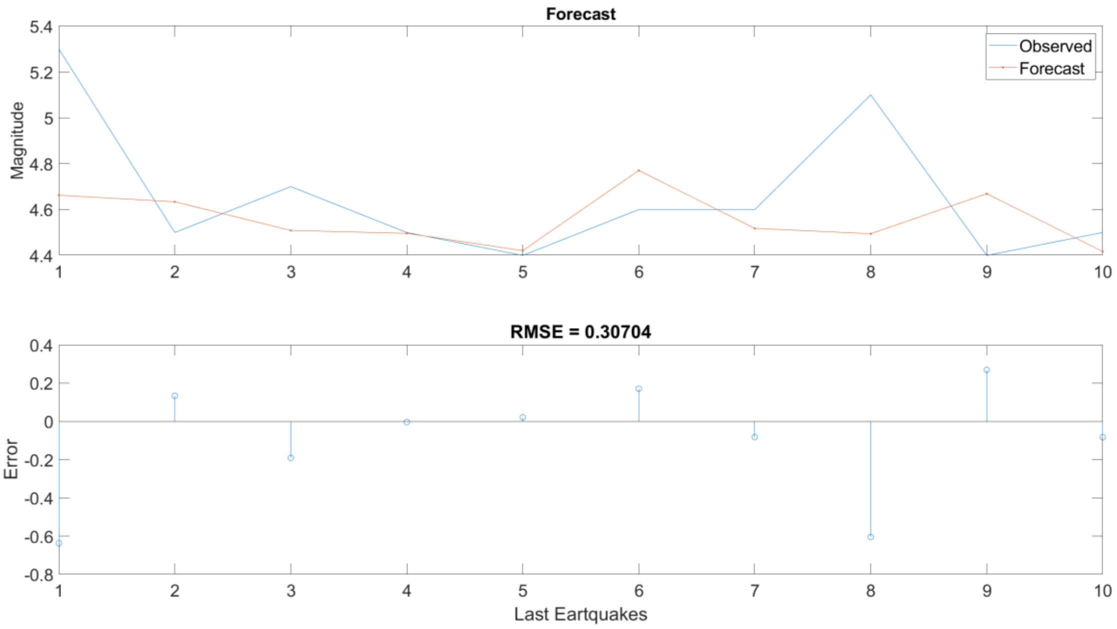

Figure 30. Magnitude forecasting for region 12, magnitude is greater than 4

4.2.11 Region 13

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 13. There are 248 earthquake data, 223 data are used for training and 25 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.31.

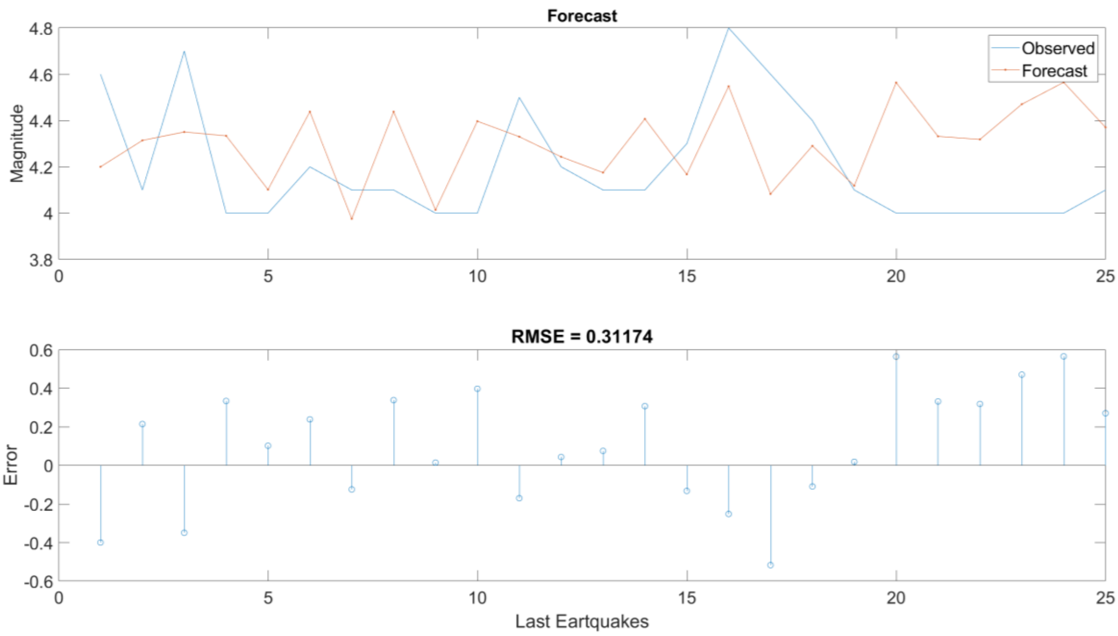

Figure 31. Magnitude forecasting for region 13, magnitude is greater than 4

Dataset: Earthquakes with earthquake magnitude greater than 4.4 in region 13. There are 126 earthquake data, 116 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.14.

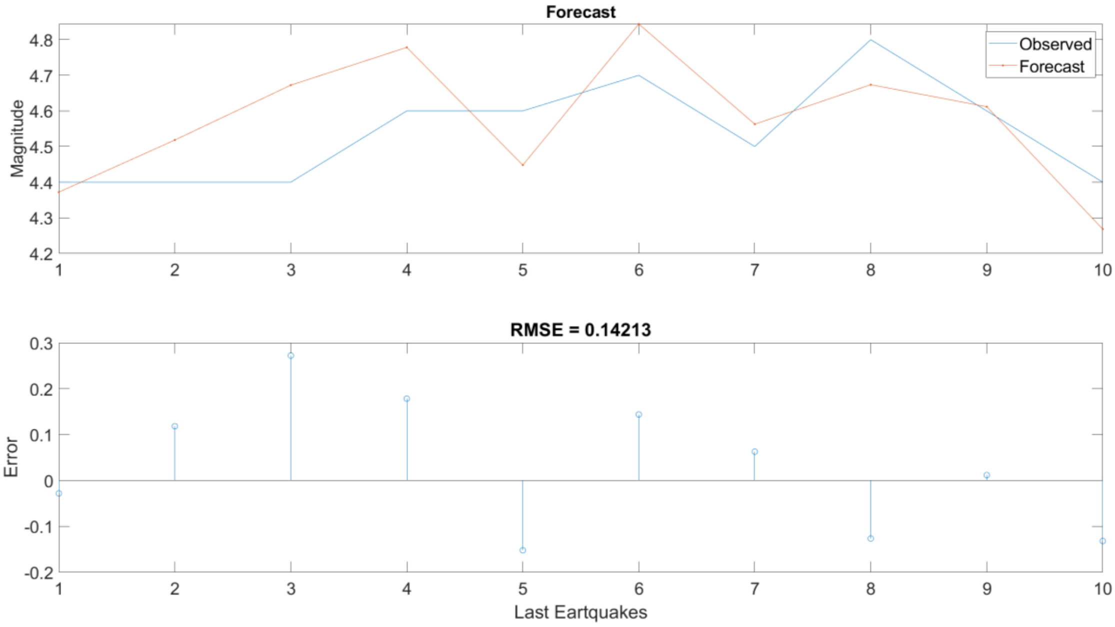

Figure 32. Magnitude forecasting for region 13, magnitude is greater than 4.4

4.2.12 Region 15

Dataset: Earthquakes with earthquake magnitude greater than 4 in region 15. There are 156 earthquake data, 146 data are used for training and 10 data are used for the test.

Features: Backward 30 earthquake data are used. Magnitude, depth, and timestamp are used to extract features.

Algorithm variables: Epoch size is 1000. The number of hidden units is 200. The batch size is 100. The learning rate is 0.01.

In this experiment, the model can forecast magnitudes of future earthquakes with an RMSE of 0.22.

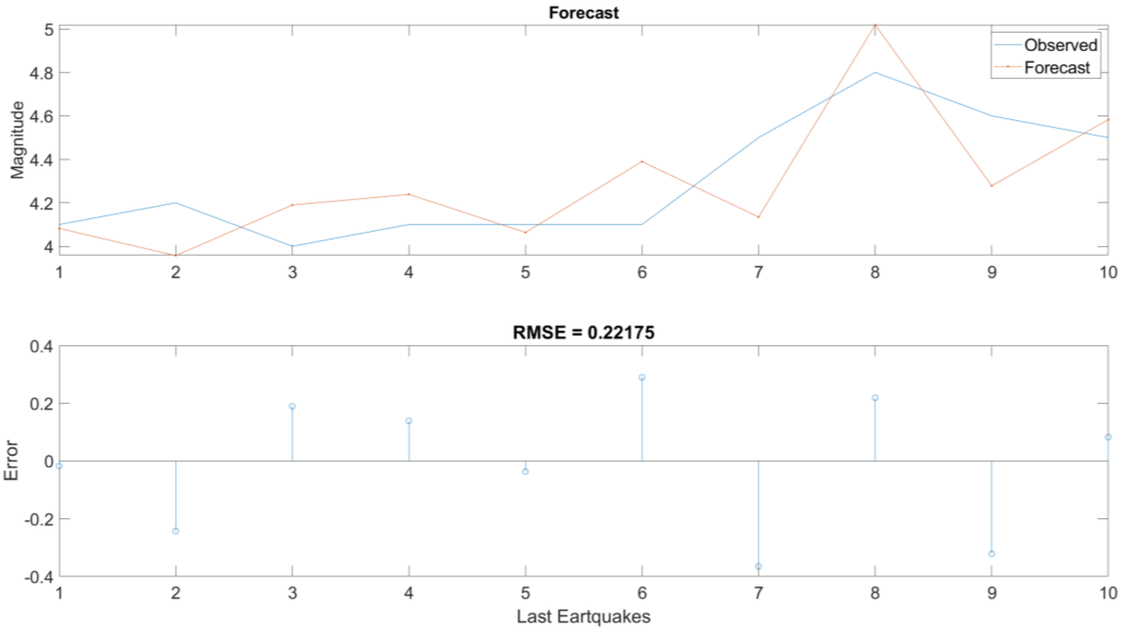

Figure 33. Magnitude forecasting for region 15, magnitude is greater than 4

5. CONCLUSIONS

In these studies, we forecast the magnitude and location of the earthquake. Based on the results we have obtained, we have demonstrated that the more limited area is studied to make earthquake forecasts, the better results can be achieved. Better results can be obtained by choosing different models according to the activity of the fault lines in the region. The experimental analysis reveals that the models can forecast magnitudes of future earthquakes with a root mean square error (RMSE) as low as 0.14 and the models can forecast the location of future earthquakes with a root mean square error (RMSE) as low as 1.83.

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