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Impact of climatic anomalies and reservoir induced seismicity on earthquake generation using Federated Learning

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Abstract

In this article, impact of climatic anomalies and artificial hydraulic loading on earthquake generation has been studied using federated learning (FL) technique and a model for the prediction of earthquake has been proposed. Federated Learning being one of the most recent techniques of machine learning (ML) guarantees that the proposed model possesses the intrinsic ability to handle all concerns related to data involving data privacy, data availability, data security, and network latency glitches involved in earthquake prediction by restricting data transmission to the network during different stages of model training. The main objective of this study is to determine the impact of artificial stresses and climatic anomalies on increase and decrease in regional seismicity. Experimental verification of proposed model has been carried out within 100 km radial area from 34.708° N, 72.5478° E in Western Himalayan region. Regional data of atmospheric temperature, air pressure, rainfall, water level of reservoir and seismicity has been collected on hourly bases from 1985 till 2022. In this research, four client stations at different points within the selected area have been established to train local models by calculating time lag correlation between multiple data parameters. These local models are transmitted to central server where global model is trained for generating earthquake alert with ten days lead time alarming a specific client that reported high correlation among all selected parameters about expected earthquake.

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1 Introduction

Earthquakes are one of the most hazardous natural disasters. Many researchers and organizations have been working for earthquake prediction but till now no one can successfully predict when this natural disaster would occur. Many computational algorithms for earthquake prediction have been proposed in the literature based on multiple percussive signals defined in the literature that would probably occur before an earthquake [1]. Researchers have also applied statistical methods to predict earthquakes in different regions [2],[3]. It has been observed that before an earthquake the seismic region goes through a preparatory period, during which the tectonic stresses cause electromagnetic emissions and heat transferred from the solid-earth to the atmosphere producing climatic anomalies [4]. Many natural processes have been recognized as precursors or warning signals before devastating earthquakes [5] including atmospheric temperature anomalies [6], atmospheric pressure anomalies [7], air ionization [8] and anomalies in rate of rainfall [9] within the selected region. Although, many studies have been conducted to determine the relationship between earthquake precursors but most of the researchers have worked to find out relationship of any single precursor on earthquake generation [10].

Rainfall, temperature, and pressure being essential atmospheric parameters, have been focused by a large number of studies in the last decade to elaborate their direct or indirect impact on earthquake generation [11]. Recent studies on climate change argue that increase in atmospheric temperature and air pressure along with decreasing rate of rainfall during the past decade, have demonstrated a significant relationship with earthquake generation [12]. Similarly, other researchers anticipated significant anomalies in rainfall and extremes in temperature may be significant in an earthquake generation [13]. Varying patterns of rainfall and temperature may be considered as environmental driving forces that affects the generation of major seismic events [14].

1.1 Hypothesis

- Ho = There is no significant relationship between climatic precursors and the occurrence of major earthquakes.
- H1 = There is a significant relationship between climatic precursors and the occurrence of major earthquakes.

1.2 Research Objectives

- RO1. To provide a generalized framework for earthquake prediction that can process large scale datasets from any seismic zone of the world.
- RO2. To improve the accuracy in earthquake prediction process by implementing both traditional and state-of-the-art AI methods.
- RO3. To present a framework for earthquake prediction that remains equally effective for centralized as well as distributed processing of dataset.

1.3 Research Questions

1: How AI methods could be applied to develop a generalized framework for earthquake prediction that can process large scale dataset from any seismic zone of the world?RQ2: How accuracy in earthquake prediction be improved by the application different AI methods on same dataset ? RQ3: How can the proposed framework support centralized as well as distributed data processing for earthquake prediction?

1.4 Research Contribution

- RC1: The proposed a framework that is capable enough to generate earthquake predictions by processing datasets from any seismic zone of the world using different AI methods.
- RC2: Three different datasets have been processed using traditional as well as state-of-the-art AI methods and significant increase in accuracy of earthquake prediction has been obtained.

1.5 Challenges and Mitigation

There are many challenges faced while applying federated learning strategy. Some are listed below:

- 1. Earthquake and climatic data can come from diverse sources, such as seismographic networks, weather stations, and satellite observations. These datasets may vary in format, quality, and spatial-temporal resolution, making it challenging to integrate them effectively for analysis.
- 2. FL involves training models across multiple decentralized data sources without sharing raw

data. However, seismic and climatic data often contain sensitive information, and ensuring privacy and security while training models across distributed nodes can be complex.

- 3. FL requires communication between the central server coordinating the model training and the participating nodes. The large volume of seismic and climatic data may result in high communication overhead, leading to latency issues and increased resource consumption.

The present comprehensive research investigates the relationship between hourly records of atmospheric pressure, air temperature, average rainfall and impact of artificial hydraulic load on earthquake generation by analyzing dataset containing records of area selected in Western Himalayan zone from 1980 to 2022, for the first time in literature. Dataset has been analyzed through computational tool (MATLAB) to find out the impact of mutual relationship in above mentioned precursors on an earthquake occurrence. On each client time-lagged correlation test has also been performed to determine possible connections between earthquake events , climatic anomalies and artificial hydraulic loading on daily and monthly time scales through cross-correlation method. The novelty of this work is a comprehensive analysis of the above-mentioned variables and their mutual correlations over the selected time period, processing three huge datasets (climatic dataset, reservoir level dataset and seismic dataset) with numerous records from Western Himalayan zone and application of FL technique for prediction of earthquake within the selected area.

This research has been organized into following sections: Section 1 presents introduction to the problem of earthquake generation due to atmospheric anomalies and artificial hydraulic load. Section 2 narrates the related work conducted in this domain. Section 3 presents the material & methods used to conduct this research. Experimental verification has been performed in Section 4. Data Analysis has been presented in section 5. Section 6 demonstrates results and discussion about the impact of selected anomalies on earthquake generation. Section 7 concludes the research.

2 Related Work

Natural hazards threaten lives and livelihoods and result in billions of dollars in damage every year. Occurrence of an earthquake are one of the most difficult natural phenomena that is very hard to predict. Many researchers have been working for earthquake prediction but no fruitful result have been obtained yet [15]. In the current research, impact of climatic anomalies and artificial stresses or regional seismicity has been studied as presented below:

2.1 Climatic Anomalies

Many researchers have struggled to determine any possible relationship of climatic anomalies on earthquake generation and investigated its significance. [16] analyzed the process of increase in rate of rainfall, its impact on land sliding and its contribution in causing earthquake events. [17] studied the land sliding hazard associated with heaving rainfall becoming a significant cause of earthquake hazard. [18] studied the pattern , mechanism and impact of induced seismicity in generation of earthquakes. [19] presented network-based simulation of regional seismicity using seismological methods. [20] assessed reservoir induced seismicity using artificial neural network and GIS. [21] studied the relationship of atmospheric temperature and rainfall with onset of earthquakes.[22] applied statistical analysis to demonstrate the relationship of atmospheric temperature on earthquake occurrence. [23] , [24] applied recurrent neural network technique to investigate the relationship of increasing global temperature on earthquake generation. [25] and [26] investigated to determine the impact of air pressure and increase in volume of ground water on regional seismicity increase.

2.2 Induced Seismicity

In literature, researcher have applied different methods to investigate about upcoming earthquake. [27] studied reservoir induced seismicity and parameters that are controlling an increase and decrease in regional seismicity. [28] performed Spatio-temporal examination of ground motion due to seismicity induced by artificial reservoir in Italy. [29] studied phenomena of induced seismicity and its effects on sub surface. [30] focused on focal mechanisms and studied the characteristics of stress field caused by reservoir induced seismicity. [31] applied ensembling approach to characterize induced seismicity. [32] presented a framework to model surface deformation and forecast induced seismicity for reservoir operations. [33] - [40], reviewed challenges offered by reservoir induced seismicity. [41] studied regional seismicity of reservoir area using digital seismometric observations. [42] studied induced seismicity caused by mines, fluid injection, reservoirs and oil extractions. [43] reviewed two types of reservoir- induced seismicity and its impact on earthquake generation in surrounding areas.[44] studied the modeling pattern of reservoir induced seismicity causing stressing and nucleation effects.

2.3 Computational Approaches

Computational methods have been applied by different researchers to study the phenomena of earthquake generation and for its prediction. Machine learning (ML) has emerged as very promising domain that offers multiple methods that can be applied on datasets for prediction of outcomes [45]. Researchers have processed earthquake datasets of different regions using ML methods . [46] automated the construction of earthquake catalog for multiple reservoirs in China using ML. [47] proposed ML based method to control risk of induced seismicity in unconventional reservoirs. [48] applied ML algorithms to classify seismic driven reservoirs.[49] employed ML and IoT for generation of early warnings before and occurrence of an earthquake. [50] applied deep learning methods to study induced seismicity impact caused by artificial loading by man-made objects. [51] examined hydrological impact of reservoirs on earthquake generation using deep learning methods.

2.4 Federated Learning

Regional seismic data collection involves data privacy, data availability and data communication concerns imposed by data protection legislation [52],[53] . To mitigate these challenges the concept of FL has been proposed [54]. FL alleviates the privacy concerns by allowing the users to collaboratively train a shared model while keeping personal data safe on edge devices [55].

FL is an ML technique that can facilitate the earthquake prediction process by training local data models onsite and ensure data privacy at local stations. FL also applies multiple data security protocols on local data models before transmitting them to the network [56]. Basically, FL is a client-server architecture that transmits local data model generated at the local station to the server machine for training global model. This feature protects the network from getting overloaded resolving latency along with other security and privacy issues [57]. Application of FL technique for earthquake prediction is also cost effective by transmitting updates only to the central server machine as compared to transmitting huge data to the server.

Model proposed in this research is responsible to determine correlation among fluctuation in atmospheric pressure, inclining and declining of air temperature, increase and decrease in rate of regional rainfall and the impact of filling and evacuation period of water reservoir on increase and decrease in seismicity of the selected region.

3 Material and Method

In this article, a FL based model for earthquake prediction has been proposed. In the proposed model many rules, functions that are defined according to the expert judgments and mathematical formulas are applied on local stations for extracting significant parameters from local datasets. Different ML techniques have been used to train local data models by processing local datasets onsite. Local data models have been transmitted through network to the FL server where global data model is trained by aggregating local models using SeismicFed algorithm. Then, meta classifier has been trained on global data model to generate earthquake predictions with more accuracy.

Four stations located in the selected area have been considered as clients shown in figure 1. Historical time series data containing records about atmospheric temperature, air pressure, precipitation rate and seismicity of these four stations have been obtained from online repository [58]. Reservoir is also located in the selected zone and data about filling and evacuation of the reservoir has been obtained from regional seismic center. Figure 1 presents the proposed methodology of this research.

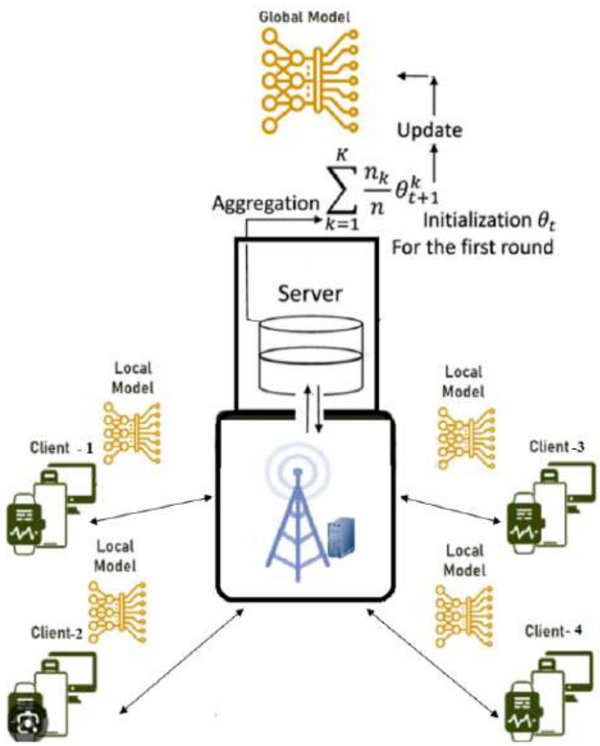
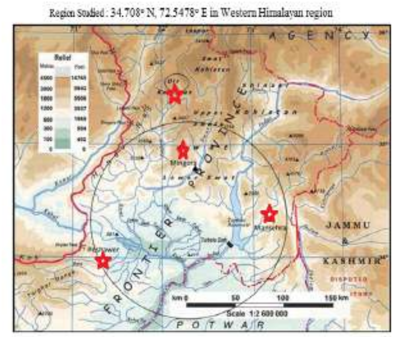


Figure 1. Proposed Methodology

These clients are responsible to calculated time-lagged correlation by pair-wise processing of regional atmospheric temperature, air pressure , rainfall and reservoir level against regional seismicity. To implement FL technique in its full essence, initially each client receives a centralized model from central server in first training round. After that each client updates that model received from central server, adds the correlation values obtained during local processing and transmits towards central server. Central server collects all local updates and calculates their average using federated averaging algorithm (Seismic-Fed) presented in figure 2.

Central server is also responsible to apply set of multivariate rules to analyze that aggregated correlation value of global model is within the predefined threshold otherwise earthquake alert is generated.



Client Name	Client-1	Client-2	Client-3	Client-4
Area covered	Mansehra	Peshawar	Mingora	Dir
Parameters Collected to train each model				
Atmospheric Temperature	√	√	√	√
Air pressure	√	√	√	√
Rainfall	√	√	√	√
Seismicity	√	√	√	√
Reservoir level	√	√	√	√

Federated Averaging Algorithm (SeismicFed)

```
ServerUpdation module
ω0 = 0
for R = 1,2,...do // R training rounds
m =max(Z, k) // Z: active clients, k: parameters trained
St = m
for g ∈ St do // g is an active participant
ω(t+1)^k ← ClientUpdatation(k, ωt)
end_for
// privacy determination
ω(t+1)^k = Σ_t^{k=1} (nk/N) (ωt+1)^k
end_for
end_procedure
module Client Updation (k, ω)
for i = 1 to ε ...do // handling local epoches
  for batch b ∈ β do
    ωt = ωk-Δ(ω)
  end_for
end_for
return ωk // client updates are returned to the server
end_module
```

Figure 2. Region studied and Seismic Fed algorithm

Updated global model is again disseminated to clients so that every client may add its updates which are sent back to the central server for completing the cyclic activity. This process of federated training goes on and global model generates earthquake alerts to the clients only when it observes that the correlation values are crossing thresholds.

Federated Learning (FL) has been practiced at every stage in the proposed model. In each round, all intrinsic parameters of FL technique have been collected such as batch size (β) of training dataset used in each round during the learning process, data learning rate (α), the required training rounds ('r'), threshold criteria (γ), and the time ('t') needed to complete each training round. Two-fold FL has been applied in the proposed earthquake prediction model. Initially it starts with on-device training of local data models at local stations, and then in next fold it involves the training of a global data model on central server. Global model is completely based on the local data models received from local data stations during learning process. During FL workflows, client devices receive the initial model '0,' at time t = 0; that indicates reception of all primary parameters necessary for local model training, have been received from central server. Clients add their updates to the initial model received from central server based on locally calculated weight matrix '1' at their respective local stations. Clients then transmit back an updated version of the initial data model, denoted as

ω_1 = updated_model(in, out, γ, r, α)

where 'in' and 'out' are input and output variables, respectively. The server collects updated models from all connected clients and stores them in a cloud storage. Central server calculates the weighted average using the SeismicFed algorithm. This calculation is presented as follows:

connected clients = N,
participating devices = Z,
Data points participated = n,
communication delay = λh
$\omega_{1n} = \frac{n \times Z}{N}$ (updated model)
global(T) = Local(T) + λh (Total time of each round)

After calculating updated weights, SeismicFed algorithm is applied to compute the federated average of all weighted updates received from connected clients. The updated model, 'k,' is generated by central server and transmitted back to all connected clients. Here, 'k' refers to the set of parameters utilized by the clients in 'St' during their local model training. This training process continues until threshold () is achieved. Finally, the central server again calculates weighted average using SeismicFed algorithm and trains the global data model accordingly to trigger earthquake alarms towards specific clients where parametric values are crossing the safety limits.

4 Experimental Verification

This section presents the experimental verification of proposed FL based model for earthquake prediction.

4.1 Area Studied

A region between 100 km radial area from 34.708 N, 72.5478 E in Western Himalayan region has been studied. Pakistan has suffered many destructive earthquakes due to its location in one of the seismically most active regions of the world. Its high seismic activity is due to its geographical location in the IndusSanpo-sutur zone, where the Eurasian and Asian plates interact [59] . The geology and seismology of Pakistan are also affected by many first-order plate tectonic processes, including subduction zones, ongoing large-scale transform faulting, crustal compression, and extension [60]. Climatic data for the Himalayan region are scarce and the region overall has far too few weather stations because of the difficulties presented by extreme variations in altitude and aspect. The data that are available indicate that there is a moderate warming trend and that temperature increases are more pronounced at higher than at lower elevations. The data on precipitation are even scarcer and do not show any statistically significant trend. In view of the paucity of observational data, global climate models are down-scaled to the region to help predict trends.

4.2 Data Preparation

The main aim of this study was to investigate in a reliable way the possible relationship between climatic indicators (atmospheric temperature, air pressure and precipitation), artificial stresses and subsequent earthquakes in 100 km radial area of Western Himalayan range. For this purpose, an extended period from 1980 to 2022 was analysed using month-by-month time series. Initially dataset as presented in Table 1 contained records on hourly base, during analysis daily, monthly and yearly values have been calculated.

4.3 Data Collection Process

Dataset for this research has been collected using different means. Seismic data has been collected from Seismic center, Tarbela dam, Pakistan; International seismic center, United Kingdom (ISC,UK) and United States Geological Survey (USGS). Reservoir data has been taken from Dam safety organization (DSO), Lahore, Pakistan. Atmospheric temperature and air pressure data has been obtained from Open weather International data selling company. Rainfall data has been obtained from Asian development bank. Data specifications presenting time period (start and end date) , number of observations, data providing source and data division that has been considered for FL based model training and testing are presented in

Table 1. Training set is from the year 1980 to 2018, whereas testing set is from 2019 to 2022.

Table 1. Dataset Information

Dataset	Time Period	No. of observations	Source
Temperature Data	1979 - 2021	3504000	Open Weather Ltd.
Pressure Data	1979 - 2021	3504000	Open Weather Ltd.
Rainfall Data	1969 - 2002	2978400	IEEE Report 2011, Asian Development Bank
	2002 - 2010	788400	
	2011 - 2021	3504000	
Seismicity Data	1974 - 2021	4029600	Seismic Center, Tarbela Dam, Pakistan
	1965 - 2010	550783	
	2011 - 2021	450264	
Reservoir Data	1974 - 2021	403200	Dam Safety organization, Pakistan

4.4 Data Preprocessing

Data pre-processing involves various stages in which different measures including data cleaning, data integration, data transformation and data reduction have been taken to clean datasets and make it appropriate for training the proposed federated learning model.

4.4.1 Data quality assessment cleaning

Data cleaning, also known as data cleansing or data scrubbing, is the process of identifying and correcting errors, inconsistencies, and inaccuracies in datasets. The goal of data cleaning is to improve the quality and reliability of data by addressing issues that can affect its accuracy and usefulness for analysis, reporting, and decision-making. This process is a crucial step in data preparation, ensuring that the data is fit for purpose and can yield meaningful insights.

4.4.2 Data Integration

Data integration refers to the process of combining and unifying data from different sources into a single, coherent view. During data integration, different data files of our dataset have been combined from multiple source folders into a single consistent file and mapping data from different source folders into single common format while reconciling inconsistencies. Data integration has been performed to ensure data easy accessibility and facilitate analysis of dataset that has been composed of multiple files to ensure complete and in depth understanding of dataset.

4.4.3 Data Transformation

Data transformation is the process of converting raw data from its original format into a more suitable or structured format for analysis, reporting, and other data-related tasks. In data transformation step, measures have been taken to aggregate multiple data files into a single .csv file. Dataset for this research has been obtained as four compressed folders each of size 2 GB (while zipped). Each folder contained 88 separate binary (.bin) files of 5 GB size. In total 200,000 records have been aggregated during data transformation. Dataset compressed folders have been downloaded in 32 GPU core for normalization. All files are appended tail to tail for the formulation of single (.csv) data file. Feature extraction and then feature selection is also performed in data transformation.

4.4.4 Data Reduction

Data reduction is the process of reducing the volume but producing the same or similar analytical results when working with large datasets. Data reduction has been performed for capacity optimization to reduce data to its simplest possible form for improving efficiency. Data complexity is also controlled while retaining its inbuilt characteristics by summarization during data reduction step. Numerosity reduction has been applied to reduce huge amount of irrelevant and duplicate data values and only restoring important information.

4.4.5 Data Validation

Data validation is typically performed during data preprocessing. It's an essential step to ensure that the data is accurate, complete, and consistent before it's used for analysis or training machine learning models. Data validation involves checking for errors, outliers, missing values, and inconsistencies within the dataset.

4.5 Experimental Setup

In this research, client-server based experimental setup has been formed. Four points declared as clients that have been connected to one cloud-based server. Client data collection centers have been established at the locations outlined in Figure 2. Each client is equipped with an earthquake forecasting module responsible for computing time-lagged correlations among various data parameters. The proposed earthquake prediction model has been implemented using Python on the TensorFlow Federated platform.

4.5.1 Client Station details

Technological Specification of experimental setup include operating system (Ubuntu 22.04 LTS), GPU (RTX 1650 4GB), System Ram (8GB), Python version (3.11.5), Tensorflow version (2.12.1), Cuda Version (12.0) Cudnn Version (8.8), Cuda Toolkit (11.8), Nvidia Drivers Version (525.147.05).

4.5.2 Data Processing model

All data parameters have been paired with regional seismicity and Time-lagged correlation has been calculated by each client to determine correlation of each data parameter with regional seismicity. Results from each client have been sent to central server which decides about the most correlated climatic precursor with regional seismicity. The central model also predicts that at which point seismicity of the selected region is increasing to the optimum level and an earthquake may encounter in near future (within 10 Days).

4.5.3 Local computation at client

Each client station is responsible to calculate pair wise Time-Lagged correlation. Following correlation values have been calculated in Time lag (0-5) among the pairs identified from climatic dataset, reservoir level dataset and seismicity dataset on each client as presented below:

Each client transmits its updates to the central server after calculating correlation among all data parameters against regional seismicity. Central server all correlations at each time lag year. These average correlation values are presented in Table 2. In the proposed federated earthquake forecasting model, cloud-based central server generates an initial model, which is then transmitted to all clients. Each client station is responsible to calculate pairwise time-lagged

Table 2. Correlation Analysis

Pair #	Identified Pairs	Time Lag (Years), Avg. Correlation (CORRE), Interpretation
1	Air Temperature and Seismicity	Lag 0 years, CORRE: 0.3585, Moderate positive correlation. This suggests that in the same year, as "Temperature" increases, there is a moderate tendency for "Earthquakes recorded" to increase as well.
		Lag 1 year, CORRE: 0.6181, Strong positive correlation. This suggests that when "Temperature" increases one year prior, there is a strong tendency for "Earthquakes recorded" .
		Lag 2 years, CORRE: 0.6388, Strong positive correlation. The relationship between the two variables strengthens with this longer time lag.
		Lag 3 years, CORRE: 0.6484, Positive correlation. This suggests a more pronounced connection between these variables with a 3-year lag.
		Lag 4 years, CORRE: 0.6957, Very strong positive correlation. The relationship is becoming highly significant with this extended time lag.
		Lag 5 years, CORRE: 0.5669, Strong positive correlation. This suggests a lasting and relatively strong connection between these variables with a 5-year lag.
2	Air pressure and Seismicity	Lag 0 years, CORRE: 0.08424, Weak positive correlation. This suggests that in the same year, as "Pressure" increases, there is a slight tendency for "Earthquakes recorded" to increase as well.
		Lag 1 year, CORRE: 0.43734, Moderate positive correlation. This suggests that when "Pressure" increases one year prior, there is a moderate tendency for "Earthquakes recorded" to increase in the current year.
		Lag 2 years, CORRE: 0.46579, Slightly stronger positive correlation. The relationship between the two variables strengthens with this longer time lag.
		Lag 3 years, CORRE: 0.47713, Positive correlation. This suggests a more pronounced connection between these variables with a 3-year lag.
		Lag 4 years, CORRE: 0.51380, Stronger positive correlation. The relationship is becoming more significant with this extended time lag.
		Lag 5 years, CORRE: 0.50535, Strong positive correlation. This suggests a lasting and relatively strong connection between these variables with a 5-year lag.
3	Rainfall and Seismicity	Lag 0 years, CORRE: 0.2348, Weak positive correlation. This suggests that in the same year, as "Rainfall" increases, there is a slight tendency for "Earthquakes recorded" to increase as well.
		Lag 1 year, CORRE: 0.3554, Moderate positive correlation. This suggests that when "Rainfall" increases one year prior, there is a moderate tendency for "Earthquakes recorded" to increase in the current year.
		Lag 2 years, CORRE: 0.4651, Relatively strong positive correlation. The relationship between the two variables strengthens with this longer time lag.
		Lag 3 years, CORRE: 0.3808, Positive correlation. While still positive, it is somewhat weaker compared to the 2-year lag.
		Lag 4 years, CORRE: 0.4011, Moderate positive correlation. The relationship is not as strong as at a 2-year lag but stronger than at a 3-year lag.
		Lag 5 years, CORRE: 0.4852, Relatively strong positive correlation. This suggests a lasting and relatively strong connection between these variables with a 5-year lag.
4	Reservoir level and Seismicity	Lag 0 years, CORRE: 0.0384, Very weak positive correlation. This suggests that in the same year, as the "Avg. reservoir level" increases, there is only a slight tendency for "Earthquakes recorded" to increase as well.
		Lag 1 year, CORRE: 0.1856, Moderate positive correlation. This suggests that when the "Avg. reservoir level" increases one year prior, there is a moderate tendency for "Earthquakes recorded" to increase in the current year.
		Lag 2 years, CORRE: 0.2082, Moderate positive correlation. The relationship between the two variables strengthens with this longer time lag.
		Lag 3 years, CORRE: 0.3467, Stronger positive correlation. This suggests a more pronounced connection between these variables with a 3-year lag.
		Lag 4 years, CORRE: 0.4202, Relatively strong positive correlation. The relationship is becoming highly significant with this extended time lag.
		Lag 5 years, CORRE: 0.2799, Moderate positive correlation. This suggests a lasting but somewhat weaker connection between these variables with a 5-year lag.

correlations between climatic data and seismicity data, as well as between reservoir data and seismicity data as presented in Table 2. These correlations are used to update the model received from the central server. Subsequently, the updated models from all clients are sent back to the cloud server. Here, the federated averaging algorithm (SeismicFed) is applied to calculate the average of all the received models, resulting in an updated model. This updated model is then transmitted back to all the clients, enabling them to predict earthquake occurrences with a lead time of ten days. In the experimental setup, each client is responsible for on-site data collection, including hydraulic, climatic, and seismic data. Edge devices are utilized for data preprocessing, which includes tasks such as data normalization to handle missing, corrupt, or incomplete records. Additionally, clients import the necessary TensorFlow Federated (TFF) libraries to generate or update their local data models.

For experimentation purposes, the data was divided into an 80 percent training set and a 20 percent testing set. Each client is responsible for defining the architecture of their local data model, including parameters such as batch size (), learning rate (), and the number of training rounds (r). In the experimental setup, four local data models are trained or updated, and their weights are transmitted to the central server.

The central server employs a federated averaging algorithm known as SeismicFed to obtain the average of the local updates sent from the clients. These results are used to update the state of the global data model through a TensorFlow Federated (TFF) script. The FL variables go through various states during the process of training the global data model, as presented in Table 3.

Table 3. State of FL variables in global model training process

Label	Flag Tag
Central server	Job Name
Task Number	0 to 4
Host server	0
Host Client	Client

To execute FL with a single central server and four clients, the training script is executed five times, once on each node. Dictionary parameters from the central server and client keys are used to initialize clusters defined in the dataset using ‘tf.train.ClusterSpec()’. For each iteration, the training script begins execution on the central server and enters a "listen and wait" state to complete read/write operations within the specified time frame. The script becomes blocked when the waiting time expires, and the initialization of server-side FL parameters, along with the training process on client hosts, commences.

All clients, labeled from Client-1 to Client-4, collaboratively train a batch on-site and update the weight matrix for each client to ensure an isolated training process. Based on the configuration of all clients, weighted model updates are transmitted to the central server. Here, the SeismicFed is applied to calculate the weighted average of all updates received from clients. The newly trained model is then shared with all clients by the central server before further batch training. TFF acts as a moderator and ensures synchronization among multiple clients using a "replica device setter object."

The central server repeatedly performs the model updating process and instructs the clients to pull the new version of the model. This process continues until a threshold defined by the model engineer is reached, indicating that all identified parameters have attained their maximum values and the earthquake risk is high. After successfully training the global data model, it is transmitted to each client for data analysis.

5 Analysis

In this section, datasets have been analysed with the intent to formulate a rule base for earthquake prediction task. Multiple parameters of regional dataset have been analysed to determine the increasing or decreasing trend in regional seismicity with respect to atmospheric temperature, atmospheric pressure, regional rainfall and reservoir water level. Dataset have been collected from 34.708 N, 72.5478 E within the 100 km radial area covering different cities of

Pakistan including Peshawar, Haripur and Der.
Dataset have been analysed to determine the regional tendency to generate significant earthquake with 10 days lead time. Hourly temperature, air pressureand and total precipitation data were obtained from the Open Weather International data centre and then processed to get daily, monthly, yearly values.

5.1 Trends in Yearly Seismicity

Seismicity refers to the measure of the frequency of earthquakes in a region. Yearly seismicity pattern from 1980 to 2014 has been analysed in the Figure 3.

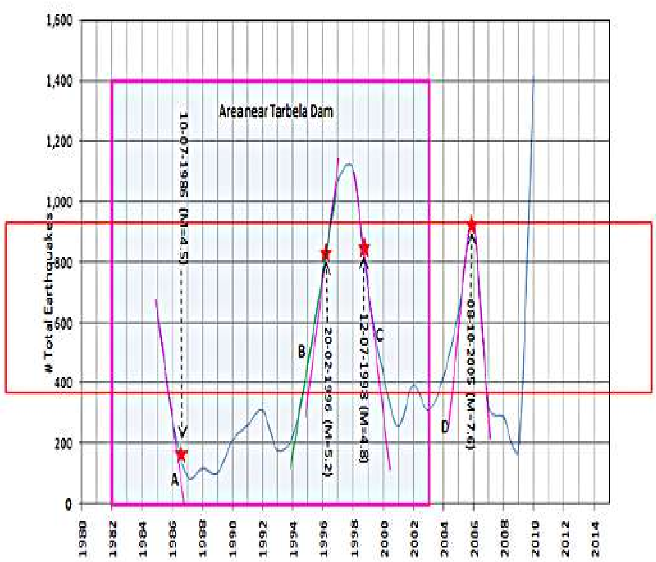


Figure 3. Yearly Seismicity Pattern

Gradient line has been drawn to present the steepness in the annual seismicity. It has been observed that the prominent earthquakes (as presented by A, B, C and D) happened at the maximum gradient presenting increasing or decreasing trends in annual seismicity. Point A, B, C and D from Table 4 present significant earthquakes that have encountered in the region during this time.

It has been observed from the regional seismic dataset that 343 and 347 foreshocks have been recorded before main shocks 'A' and 'B'. These phenomena increased the regional seismicity up to 55

Table 4. State of FL variables in global model training process

Earthquake	Magnitude	Foreshocks	Seismicity increase
A	4.5	343	55
B	5.2	345	57
C	4.8	436	22.2
D	7.6	533	76

percent than usual as presented in figure 3. Before the main shock 'C' 436 foreshocks have been recorded presenting 22.2 percent increase in the regional seismicity. In the same way, 533 foreshocks have been recorded before main shock 'D' that increased the regional seismicity to 76 percent. This increasing trend in regional seismicity that cause the steepness in the gradient vector can be considered as a precursor or an early warning that a gigantic earthquake is about to come. It also indicates that the selected area is highly sensitive and vulnerable to catastrophic earthquakes.
After exploring seismic dataset in more details, it has been observed that there is a common feature of minor increase in yearly seismicity before the prominent or major raise in the yearly seismicity as indicated by the gradient vectors presented in figure 4. The oval shaped regions indicate that every major earthquake had been preceded by a small peak presenting increase in regional seismicity. It can be observed from the figure 4 that regional seismicity increased gently with 7.7 micro earthquakes per year (G1) for the period of 4.5 years and then an earthquake with magnitude 4.6 has encountered in 1986 as represented by 'A' in the figure 4.
Similar situation has been observed before the major earthquake encountered in 2005 with magnitude 7.6 represented by 'B' in the Figure 4. A gentle increase in regional seismicity with 7.7 micro earthquakes per year (G2) has been observed for fifteen years before event 'B'. Similarly, before event 'C' regional seismicity increase showing 7.1 micro earthquakes per year (G3) has been observed for five years in Figure 4. Hence, it can be perceived from Figure 3 and 4 that larger the gradient in seismicity pattern , the larger earthquake event could be expected.

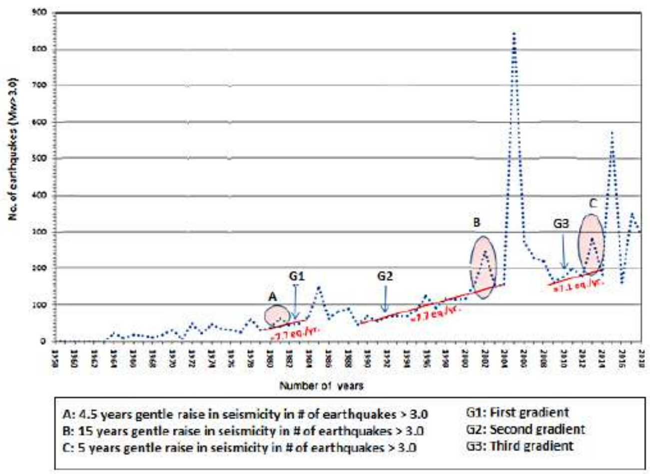


Figure 4. Trends in seismicity

5.1.1 The impact of Atmospheric Pressure on Regional Seismicity

The impact of atmospheric pressure on the increasing or decreasing trend of regional seismicity has been presented in Figure 5 (Year 2000-2004), Figure 6 (Year 2005-2009), Figure 7 (Year 2010-2014), Figure 8(Year 2015-2018) respectively. In these figures, earthquakes that have encountered in the region are presented with dotted arrows. Thin arrows present single event while thick arrows present clusters of the events. It has been observed from these figures that very few events have encountered when atmospheric pressure was at its maximum or minimum value. Most of the earthquake events (including Kashmir earthquake) have encountered at inclining or declining period of the atmospheric pressure. Hence, it can be perceived that inclining or declining period of atmospheric pressure also have a connection with the probability of an earthquake occurrence. In the Figure 9, it can be observed that Kashmir earthquake occurred less than one month before achieving the maximum pressures in the region. On October 08, 2005 when Kashmir earthquake encountered, the atmospheric pressure in earthquake-epicentral area was 1001.84 mb during the month of June 2005 that rose to 1015.62 mb till October 2005. There was pressure fluctuation of 13.78 mb (1378 pascal) from minimum to maximum of that period while with respect to standard atmospheric pressure at sea level. It was 2.62 mb higher. This stress-difference might be one of the reasons of triggering of this earthquake. Naturally, such additional pressure may not be sufficient to generate an earthquake of magnitude 7.6 on its own and there must be a major role of tectonic stresses as well. Since, research area is in a region where the Indian tectonic plate is subducting under the Eurasian mega plate, the region was already under huge tectonic stress. So, even a trivial stress change in atmospheric pressure may become an earthquake triggering reason.

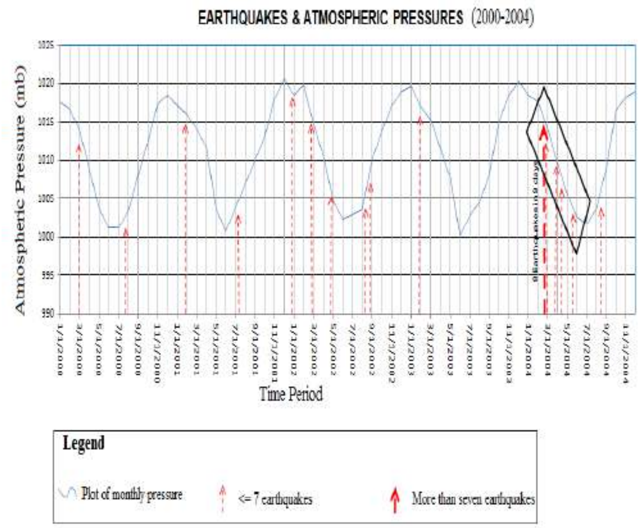


Figure 5. Impact of pressure on regional seismicity (2000-2004)

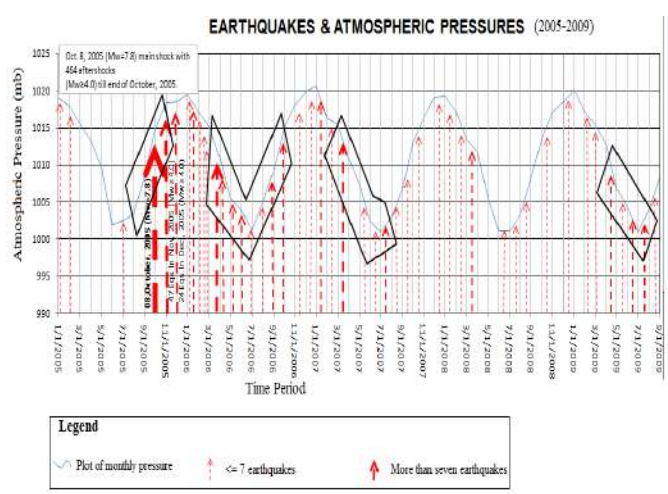


Figure 6. Impact of pressure on regional seismicity (2005-2009)

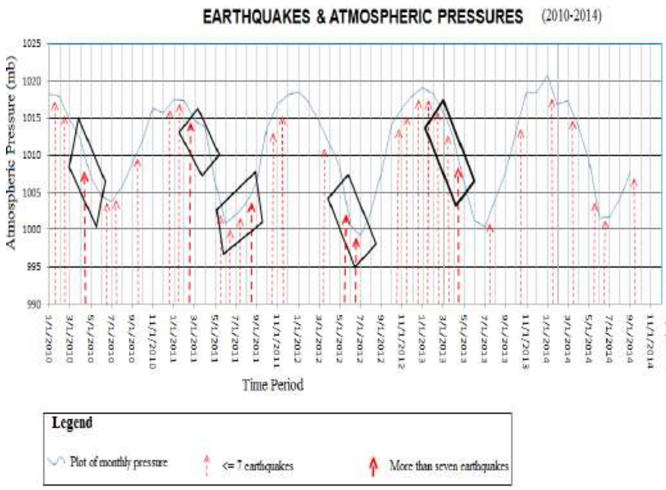


Figure 7. Impact of pressure on regional seismicity (2010-2014)

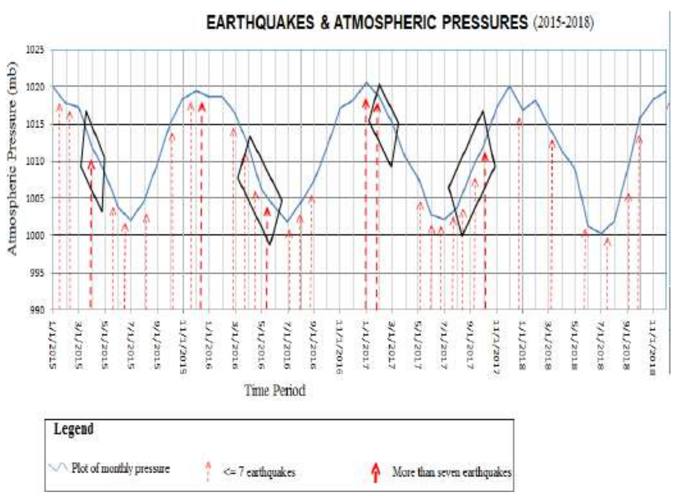


Figure 8. Impact of pressure on regional seismicity (2014-2018)

Some similar examples based upon "13 major earthquakes" occurred during the autumn and winter when atmospheric pressure was high were quoted by Hadfield. Hadfield's research region was located where the Philippine plate is moving under the Eurasian (Japanese) plate. Tectonically, Pakistan being in the subduction area between the Indian tectonic Plate and that of the Eurasian Plate. Outake [7] narrated that average monthly atmospheric pressure in Hadfield region is around 10 millibars higher between August and February than during the rest of the year. The extra force on the Eurasian (Japanese) plate is equivalent to placing 100-kilogram weights on each square meter. This pushes down the Eurasian plate, but the extra air pressure has no effect on the Philippine plate, which lies underneath. The researcher expressed that such change in atmospheric pressure might not be enough to cause an earthquake on its own. But if the stress around the fault was already at near breaking point, even trivial increase in atmospheric pressure could be enough to trigger an earthquake. Similar are the views of Rikitake, another Japan's leading seismologists agreeing that atmospheric changes could be enough to trigger a quake under some conditions. However, such observation is only useful for cases when the state of stress between the plates is critical.

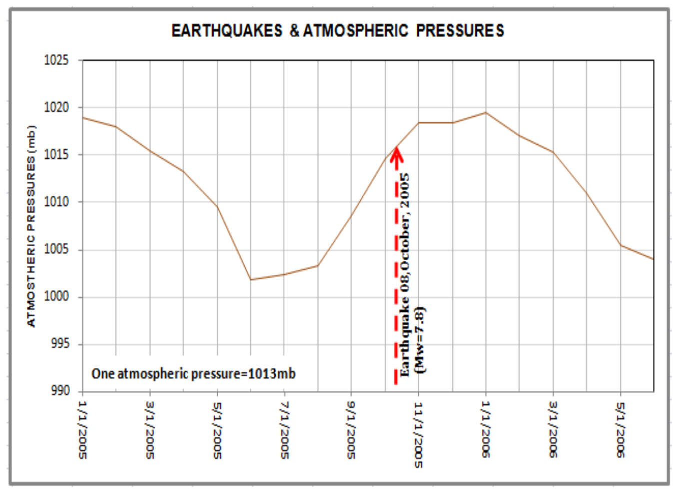


Figure 9. Atmospheric pressure onset of earthquake event of Oct 08,2005

5.1.2 The impact of Atmospheric Temperature on Regional Seismicity

The impact of temperature on regional seismicity has been presented in Figures below. Average temperature from the selected region has been recorded in Kelvins. Vertical arrowhead shows clustering of earthquakes. Thickness or vertical arrowheads show the cluster size. Figure 10 presents average temperature during the year 2000 to 2004. Many single earthquakes have been recorded but during 2004 cluster of earthquakes encountered during three months from January till March. Atmospheric temperature was in its inclining phase at that time. Similar phenomena have been observed in year 2005 when Kashmir earthquake has encountered, the atmospheric temperature was neither maximum nor minimum but was in its declining phase as presented in the Figure 11 (Year 2005-2009).

It can be noted from Figure 12 that during the year 2010 to 2014 majority of earthquake events have encountered in inclining or declining phase of atmospheric temperature. None of the earthquake or very few earthquakes have encountered on maximum temperature or at minimum temperature. Figure 13 (Year 2015-2018) shows the seismicity with respect to monthly average temperature within 100 km radius from 34.708 to 72.5478 reference point. It has been observed that seismicity increases during the inclining and declining periods of temperature in last 18 years.

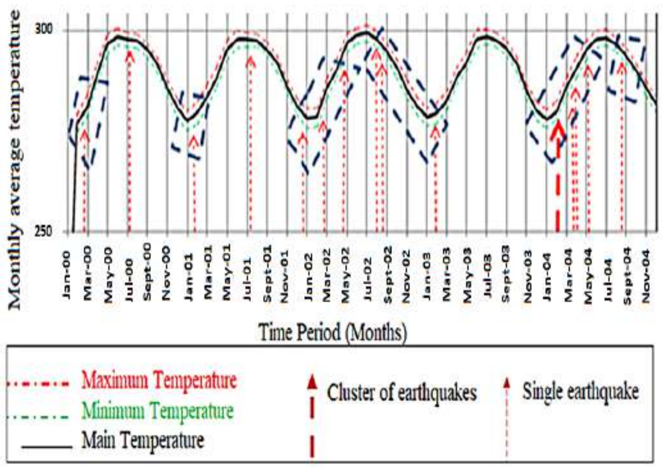


Figure 10. Impact of Temperature on regional seismicity (2000-2004)

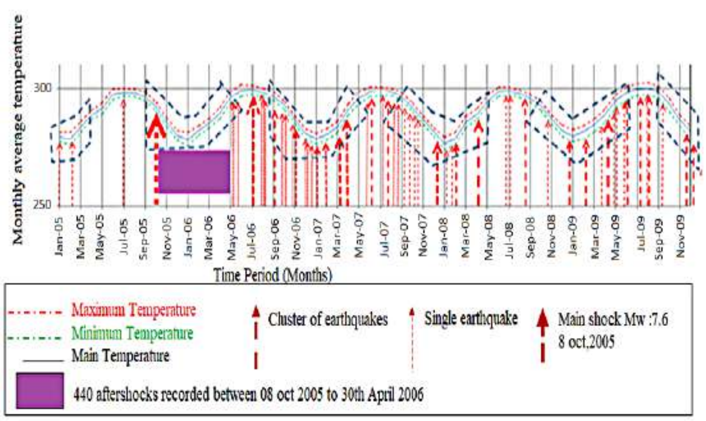


Figure 11. Impact of Temperature on regional seismicity (2005-2009

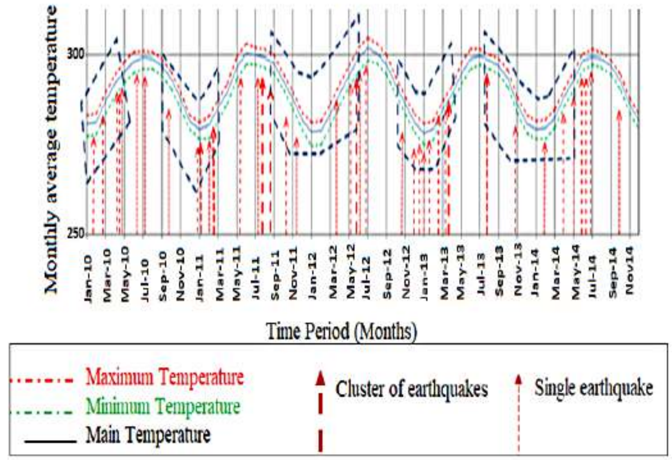


Figure 12. Impact of Temperature on regional seismicity (2010-2014)

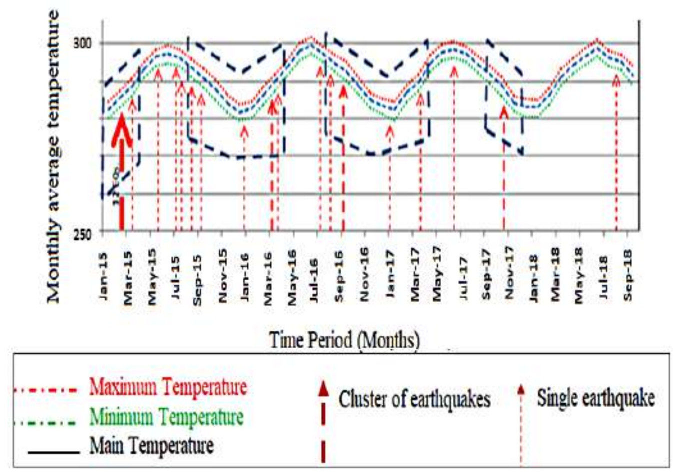


Figure 13. Impact of Temperature on regional seismicity (2015-2018)

Figure 14 specifically focuses on the Kashmir earthquake encountered in Pakistan on Oct 08, 2005. It has been observed that it occurred about one month after initiation of decline in atmospheric temperatures in the region. It can be perceived that there is more probability of a major earthquake event during inclining or declining period of atmospheric temperature. It possesses some meaningful pre-warning value before the occurrence of some significant earthquake. It might not have a severe impact alone but may become significant when combined with other precursors.

5.1.3 The impact of Induced Seismicity

The region under observation also has a 400 feet long reservoir with 134004 cusec feet water storage capacity. Hydraulic load also has direct impact on increase in regional seismicity. Figure 15 presents the pattern of periodic storage and restoration of seismic energy at Tarbela dam. In Figure 15 energy storage and release periods have been shown in multiple zones. Zone ‘a’ presents the seismic energy storage period from 1974 till 1979. Then energy released level restoration phase started that leaded to an earthquake in 1985. After that energy again started accumulating that caused an earthquake of magnitude 4.8 in 1988 with epicentre just 1.98 km away from Tarbela dam. Then again energy started accumulating and finally released in 1996 by an earthquake having magnitude 5.2 .

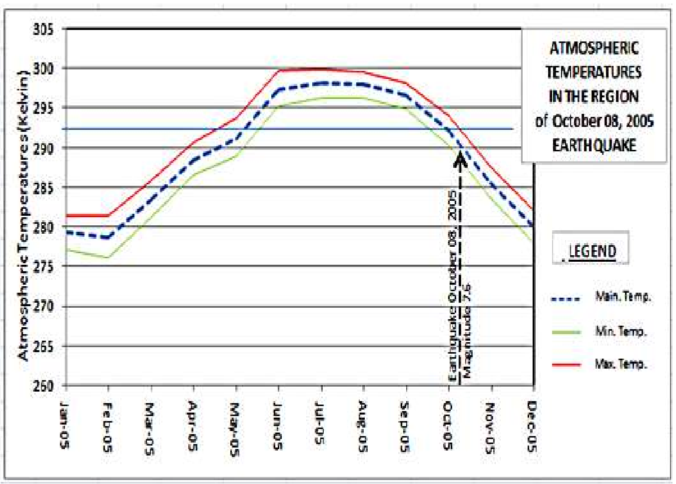


Figure 14. Atmospheric temperatures before Kashmir earthquake

Tarbela is the largest dam in Pakistan and has been located in the area being observed in this research. Its construction has placed a huge structural load on that ground. Huge additional hydraulic load was applied by filling of water in its reservoir. A proportion of such load must remain constant and adds up to the afore mentioned one. Due to all such activity, stress level within the reservoir floor as well as near about area has changed. The operational part of hydraulic load fluctuates periodically due to seasonal filling and depletion of the reservoir. A part of all such artificially developed stresses remains releasing in the shape of small earthquakes (micro-seismicity), while the remaining part goes on accumulating and adding up the pre-existing stress-level till it does not remain compromising. This 1-1 correspondence has been presented in Figure 16.

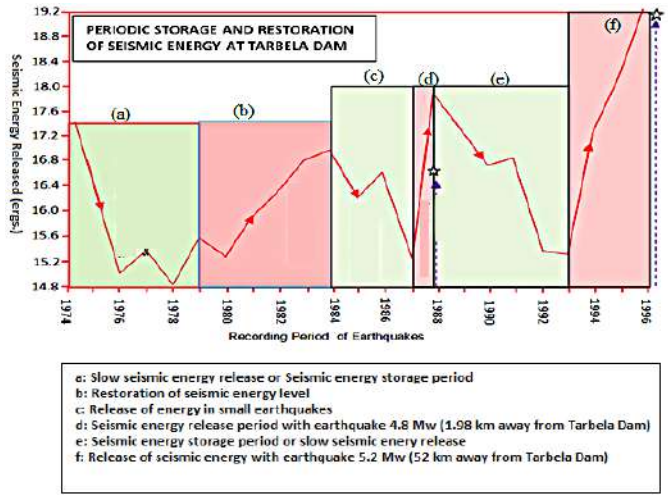


Figure 15. Periodic seismic energy level below Tarbela dam

5.1.4 Impact of Rainfall on Regional Seismicity

Amount of rainfall is another natural phenomenon that have a major share in weakening of earth’s interior. The Figure 17 presents the comparison on annual rainfall with yearly seismicity pattern. It can be observed from the highlighted zones ‘a’, ‘b’, ‘c’, ‘d’, and ‘e’ that increasing or decreasing trends of rainfall are also relevant to increase or decrease in the number of earthquakes occurred in the region.

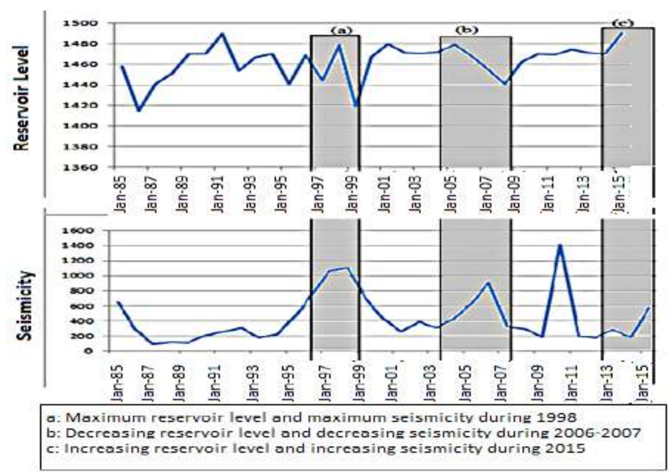


Figure 16. Comparison of Reservoir level and regional seismicity

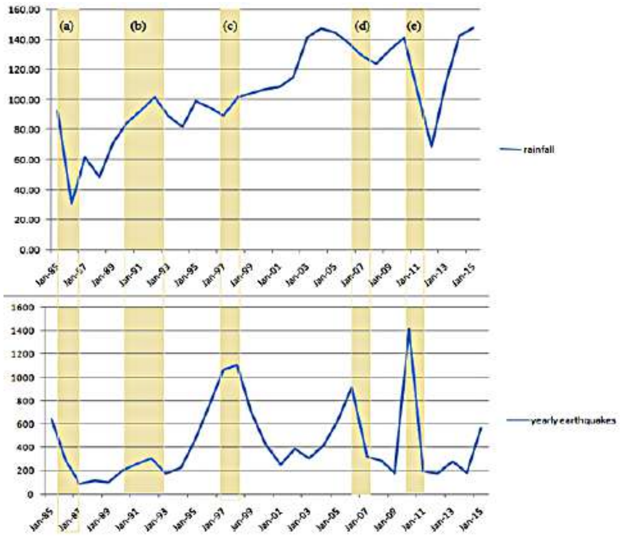


Figure 17. Comparison of yearly earthquakes with annua lrainfall

6 Results and Discussion

After completion of detailed data analysis of all significant aspects of dataset, it has been observed that energy released, maximum magnitude, time elapsed, atmospheric temperature, atmospherics pressure, pressure built due to reservoir water, and its water level are jointly working in increasing regional seismicity. These closely working parameters can have major impact on earthquake prediction process in this region. For detailed observation, we have analysed the relationship among these co-working parameters through a mathematical simulating tool. From seismic dataset, the relationship of energy released with time elapsed has been shown by the surface graph presented in Figure 15. It shows that if the energy released is low and elapsed time is higher than expected magnitude would also have high value. Initially, the parameters from the climate data, including temperature, rainfall, pressure, and humidity level have been considered. The basic relationship between mean atmospheric temperature, air pressure and seismicity have been determined in Figure 18. It can be observed from Figure 19 that when earthquake 'a' has encountered, regional temperature remained consistent for some time then it started decreasing, but regional atmospheric pressure was having an inclining trend. With the onset of earthquake 'b', the regional atmospheric temperature and pressure were declining but regional seismicity was inclining. In event 'c', atmospheric temperature has been decreasing but atmospheric pressure has been increasing. In event 'd', there is a slight increasing trend in atmospheric pressure while atmospheric temperature is decreasing. Similar trend has been observed in event 'e', atmospheric pressure has been increasing and regional atmospheric temperature has been decreasing. It can be perceived that most of the earthquakes have encountered when atmospheric temperature was declining, and atmospheric pressure was inclining.

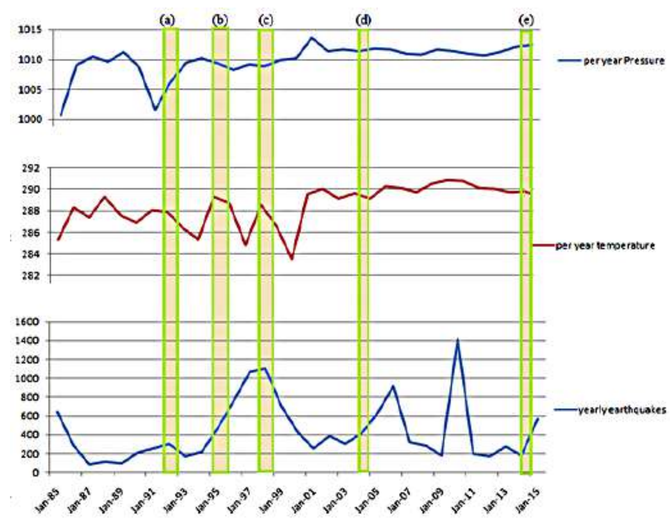


Figure 19. Climate parameters in relation with regional seismicity

This observation can be partially significant when combined with the impact of other natural forces in earthquake prediction process. Line Graph presented in the Figure 19 shows an increase or decrease in the regional atmospheric temperature and atmospheric pressure before the onset of earthquake events in the year 1992 (Shaded zone 'a'), 1995(Shaded zone 'b'), 1998 (Shaded zone 'c'), 2005 (Shaded zone 'd') and 2015 (Shaded zone 'e').

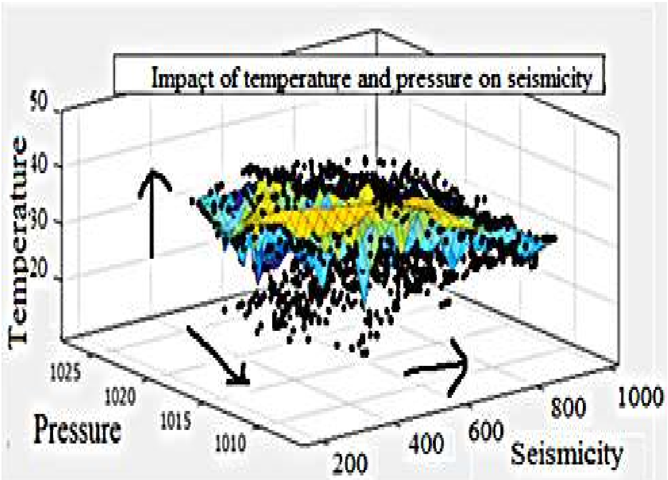


Figure 18. Impact of climate parameters on regional seismicity

Reservoir data have also been analysed in this research as earthquakes are also caused by reservoir induced seismicity. Reservoir data have been collected at different phases, including filling the reservoir to its maximum level, evacuating reservoir to its minimum level, in static position while maintaining its water level and in flowing state maintaining its water level. The amount of sediment inflow and outflow has been calculated and Figure 20 presents the analysis of multiple parameters of reservoir data. The change in underground pressure due to the water load may also cause earthquakes. The water level of the reservoir may also change due to sedimentation. More sediment inflow as compared to its outflow also results in an increased water level.

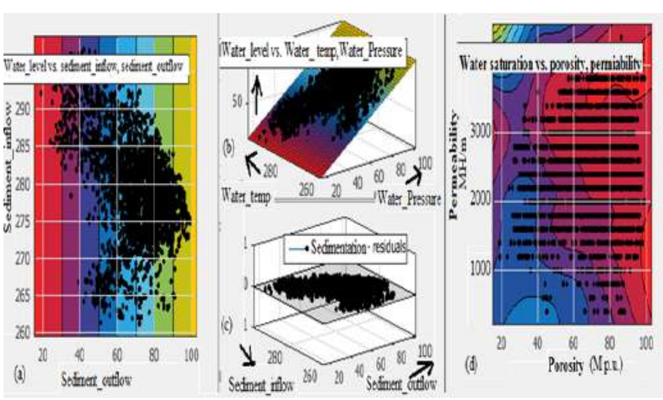


Figure 20. Climate parameters in relation with regional seismicity

7 Conclusions

In this research, multiple climate parameters including atmospheric temperature, air pressure and precipitation rates, were obtained from daily and monthly time series from different datasets for a long-term period of 1980 and 2022, equal to 43 years using federated learning. Four different client stations have been established in the study area where local models were trained using time-lagged correlation. These local models were transmitted to the central server where global model is trained by aggregation of local models. Global model generated alerts to the regions where all observed parameter have values above than predetermined threshold with 10 days lead time. A detailed analysis was performed to evaluate the hypothesis that for a region which is already under stress of huge hydraulic load, regional seismicity may have a relation with increasing and decreasing period of atmospheric temperature, air pressure and regional precipitation rate before major earthquake events. Average temperature and precipitation time series were obtained taking daily and monthly means based on area wise averaged and analysed data for the selected study area in Western Himalayas. earthquake time series were constructed based on the frequency of earthquakes with a magnitude of M 3.0. The results reveal a positive relation between inclining and declining period of atmospheric temperature, air pressure, increased precipitation rate and during filling and evacuation period of water reservoir located in the studied region.

Author Contributions

Rabia Tehseen: Conceptualization, Methodology, Software **Uzma Omer**: Data curation, Writing- Original draft preparation. **Rabia Tehseen**: Visualization, Investigation. **Maham Mehr**: Supervision.: **Rubab Javaid**: Software, Validation. **Madiha Yousaf and Ayesha Zaheer**: Writing- Reviewing and Editing

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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