EARTHQUAKE PREDICTION MODEL USING MACHINE LEARNING

Name : Santhosh N
College code: 8106
deparmant : CSE -III year

Abstract :

Earthquake prediction is a cruciat area of research in seismotogy and geophysics. In this project, we aim to develop a data-driven earthquake prediction model using Python and a Kaggte dataset containing historical earthquake data. The primary goal is to analyse patterns and build a machine learning model that can provide probabilistic earthquake predictions. Additionally, we will visualize earthquake occurrences on a world map to gain insights into their spatial distribution.

Modules:

Python libraries:

The following Python modules are needed to build an earthquake prediction model using the Kaggle earthquake dataset and visualize the results on a world map:

1. numpy - for scientific computing
2. pandas - for data manipulation and analysis
3. matplotlib - for data visuaiizat\on2
4. folium - for interactive map visualization
5. sCikit-learn - for machine learning

IMPORTING PYTHON LIBRARIES:

```
import numpy as np
import pandas as pd
import matplotIib.pypIot as plt
import folium
from skIearn.model selection import train test split
from skiearn.ensembIe import RandomForestRegressar
```

Metnods:

1. **Data Acquisition and Preprocessing:**

Download the Kaggle dataset and obtain the required day from it. Pre-process the dataset, inc(uding data cleaning, handling missing values, and converting data types.

```
# Load the earthquake dataset

        df = pd.read_csv('earthquake-database.csv')
```

2. **Exploratory Data Analysis (EDA):**

Perform statistical **analysis** to understand the distribution of earthquake magnitudes, depths, and locations. Visualize earthquake data with histograms, scatter plots, and time serias ptote.

3. **Feature Engineering:**

Extract relevant features from the dataset, such as earthquake location coordinates. time, magnitude, depth, and possibly external factors like geological data, weather, or tectonic plate information.

```
# Prepare the data
#Remove outliers
df = df[(df['Magnitude'] > 5) & (df['Oepth'] > 0)s
```

the data from tha csv file where magnitude is greater than 5 and depth is greater than 0.

4. **Data Splitting:**

Split the dataset into training and teMing subsets to evaluate model performance.

# **Split the data into training and testing sets**

```
X train, X_test, y train, y_test = train_test_sptit(df[['Latitude, 'Longitude']],
df{'f•\agnitude'}, test_size=0.25)
```

5. f4ode\ **Selection and Training:**

Choose appropriate machine learning models for earthquake prediction (e.g., regression, classification, time aeries forecasting). Train and fine-tune the selected models using the training data.

```
# Train tha maehine learning model

model = RandomForestRegressor()
model.fit(X_train, y_train)
```

WHY RANDOM FOREST REGRESSION MODEL:

A random forest regression model is easy to identify the struGtural safety status of buildings damaged by the earthquake is probabilistic. An earthquake’s Latitude, longitude. magnitude, and depth may be predicted using tha random forest algorithm.

A random forest with muftioutput technique is employed, with variables being each station’s recorded value and geographic position.

B. **Model Evaluation:**

Evaluate the model's performance using appropriate metrics i.e., Mean Absolute Error.

# **Evaluate the model on the testing set**

```
y red = model.predict(X test)
    print('Model accuracy:', np.mean(y_pred == y test))
```

7. Visualization with World I•Iap:

Use library Folium to create a world map. Plot earthquake data on the world map using latitude and longitude information. Customize markers to represent earthquake attributes such as magnitude. depth, and date.

fi Visualize the resutta on a wortd map

```
wortd_map = fotium.Map()
```

Fotium :

Folium makes it easy to visualize data that's been manipulated in python on an interactive leaflet map. It enables both the binding of data to a map for choropteth visualizations as passing as a HTML visualization as markers on the map.

B. Plotting the data.

```
# Plot the training data
for i in range(len(X_train)):
folium.CircIeMarker(
location= [X_train.iloC[i, 0], X_train.iIoc[i, 1j],
 popup= str (X train.iloc[L 0]) + ', ' + str(X_train.iloc|i, 1]),
coIor='bIue',
fiII_coIor='bIue',
fiII_opacity=0.5
).add_to(worId_map)

# Plot the testing data
for i in range(Ien(X_test)):
foIium.CircIeMarker(
location= [X_test.iIoc[i, 0], X_test.hoc[i, 1]],
     popup= str (X_test.iIoc[i, 0]) + ',' + str(X_test.iloc[i, 1]),
coIor='red',
fiII_coIor='red',
fiII_opacity=0.5
).add_to(worId_map)

world_map.save('earthquake rediction_map.html')
```

In [1]:

```
import pandas as pd
```

In [2]:

```
import numpy aa np
```

In [3]:

```
import matplotlib.pyplot aa pit
```

In [6]:

```
!pip ínstall folium
```

```
Collecting folium
```

```
osiDg cached folium-0.l4.0-py2.py3-none-aOy.whl (102 kB)
Collecting branca>=0,6.0 (from folium)
Psing cached branca-0.6.0-py3-none-any.whl (24 kB)
Requirement already satisfied: jinja2>=2.9 in
c:\user6\sriOi\,conda\lib\site-packages (from folium) (3.1.2}
Requirement already satisfied: numpy in c:\users\srini\.conda\lib\site-packages
{from folium) (1,24.3)
Requirement already satisfied: requests in c:\users\srini\.conda\lib\site-
packages (from folium) (2.31.0)
Requirement already satisfied: Markupsate•=2.D in c:\users\srini\.conda\lib\sire-
packages ([rom jinja2>=2.9- folium) (2.1.1) Requirement already satisfied:
charset-normalizer‹4,>=2 in c:\users\srini\,conda\lib\site-packages (from
requests->folium) (2.0.4) Requirement already satisfied: idna<4,>=2.5 in
c:\users\srini\.conda\lib\site-packages (from requests->folium) (3.4)
Requirement already satisfied: urllib3<2,>=l.2l.l in
c:\users\srini\.conda\lib\site-packages {from requests->fOlium) (1.26.16)
Requirement already satisfied: certifi>=2017,4.17 im
c:\users\sriDi\.conda\lib\site-packages    (from    requests->folium)    (2023.7.22)
Installing collected packages: braoca, folium

Successfully insea12ed branea- 0 . 6 . 0 £olium - 0 . 14 . 0
```

In |7]:

```
import lolium
```

In [8].

```
from sklearn.model selection import traiD test_split
```

In [9].

```
from sk1earn.ensemble import RandomForestRegressor
```

```
df pd.read_csv(r'/Dsers/srini/OneDrive/Documents/database.csv')
print(df)
```

```
              Date  Time Latitude Longitude                  Type Oeptfl \
0       01/02/1965      13:44:18 19.2460 145.6160 Earthquake 121.60
1       01/04/1965  11:29:49 1.8630 127.3520             Earthquake 80.00
2       01/05/196s         18.05.5B -a0.6790 -172.9780 Earthquake         20.00
3       01/08/196s         18.49:42 -59.0760 -22.5570 Earthquake          15.00
4       01/09/196s  Earth Je 13:32:50   11.9380   126.4270                15.0D

234 07  12/28/2016  0B:22:12  38.3917   -118.a941  Earthquake  12.30
234 0B  12/28/2016  09:l3:47  38.3777   -118.8957  Earthquake  B.B0
234 09  12/28/2016  l2:18:51  36.9179 140.4262     Earthquake  10.00
23410   12/29/2016  22:30:19  -9.02BE3    1I8.6629 Earthquake  79.00
234 11  12/30/2016  20:08:28  y.3973      141.4T02 Earthquake  11,94

        Depth Error Depth seismic Stations Nagnitude Magnitude Type      .   \
0            NaN                      NaN      6.0          MW
1            NaN                      NaN      5.8          MW  ...
2            NaN                      NaN      6.2          M
3            NaN                      NaN      B.8          W
4            NaN                      NaN      5.B          MW
                                                              W
234 07       1.2                     40.0      5 C          ML  ...
```

```
23408            2.0                      33.0       5.5           ML  ...
23409            1.8                       NaN       5.9          MWW
23410            1.8                       NaN       6.3          MWW
23411            2.2                       NaN       5.5           MB  ...

       Magnitude Seismic Stations Azimutbal Gap Horizontal Distance \
0      maN NaN NaN
1      NaN NaN NaN
2                          NaN         NaN            NaN
3                          san         NaN            NaN
4                          NaN         NaN            NaN

234 0V                    1.8   0     42.47           0,120
234 08                    18.0        48.58           0.129
234 09                     NaN        91.00           0.992
23410                      NaN        26.00           3.553
23411                     428.0       9?.00           0.681

       Horizontal Error Root Mean Square                  ID Source \
0      NaN NaN                              ISCGEM860706 ISCGEM
1                NaN              NaN       ISCGEN860737 ISCGEM
2                NaN              NaN       ISCGEM860762  ISCGEM
3                NaN              NaN       ISCGEM860856  ISCGEM
4                Ra 1'4           RAM       ISCGEM860890 ISCGEM

23407            NaN          O.189B      Nm00570710     NN
23408            NaN          0.2187      Nm00570744     NN
234 0            4.8          1.5200      DS10007NAR     US
9    23          6.0          1,4300      US10007NL0     US
410              4.5          0.9100      USl0007NTD     US
23411
                 Location Source Nagnitude Source status
0                           ISCGEM ISCGEM Automatic
1                           ISC€EM ISCGEM Automatic
2                           ISC€EM ISCGEM Automatic
3                ISCGEM          ISCOEM Automatic
4                ISCGEM          ISCGEM Automatic

23407            NN                   Reviewed
23408            NN              NN   Reviewed
234 09           US              US   Reviewed
2341 0           US              DS   Reviewed
23411            US              DS   Reviewed
```

```
(23412 rows x 21 columns)
```

In |35]:

```
df = df[(df['Magnitude') > 5) & (df['Depth') > 0))
```

In |36]:

```
print(df)
```

```
                                  Date Time Latitude Loogitude Type Depth \
U        Dl/02/1965 13:44:18 19.2460 145.6160 Earthquake 131.60
1        01/04/1965 II: 29 : 49 I . 863D 127 . 3520 Earthquake 80.00
2        01/05/1965 GB : 05 : 58 -2Q . 579D - 173.3720 Earthquake Z0.00
3        0 / 0 8 /1 9 d 5 18:49- 42 -59.0750 -22. 5510 Earthquake 15.00
4        D1/09/1965 12 : 3Z 50 11 . 938 0 126. 4270 Earthquake 15.00

23407 12/29/2016        0B: 22:12     28.3917          -118.894I   Earthquake      12.30
2 3 4 DR    I2 / 2 8 /2 0 l 6 12   D9 : I3 ' 47   38.    3777     -1I8. 8957   Earthquake       8.80
2 3 4 0 9   / 2 B / 2 01 6 12        12 : *8 : 51   36.    9179     140. 4262   Earthquake      10.00
2 3 41 D    /2 9 / 2 0 l 6 12 /    22 : 30 : I9   -9.    0283      118.6639  Earthquake      79.00
2 3 4 11    3 D / 2 0 l 6           2D : 08 : 28   37 . 2973        141. 4103   Earthquake      11.94

         Depth Error Depth Seismic Stations Magnitude Magnitude Type                 \
0                NaN                         NaN         6.0              MW
1                NaN                         NaN         5.8              MW
2                NaN                         NaN         6.2              MW
```

```
3          NaN              NaN     5.8         MW  ...
4          NaN              NaN    5.8          MW  ...

234 07     1.2             40.0    5.6          ML  ...
23 4 08    2.0             33.0     5.5         ML
2 34 0 9   1.8             NaN      8.9        Mww
2 34 10    1.8             NaN     6.3         Mww
23 411     2.2              NaN    5.5          MB

        Magnitude Seismic Stations Azimuthal Gap Horizontal Distance \

1     NaN               NaN         NaN
2     NaN NaN                                      NaN
3                            NaN NaN               NaN
4                            NaN NaN               NaN

234 07                 8.0          42.47        0.12 0
23 4 08               18.0          48.58        0 . 129
23 4 09                NaN          9i.00        0.992
23410                  NaN          26.00        3.5b3
23411                 428.0         97.00        0.68i

      Borizootal Error Root Mean Square LD Source \
0     Ra 1'4 RAM ISCGEM860706 ISCGEM
1     NaN NaN ISCGFMB60737 ISCGEN
2     NaN NaN ISCGEMB6O762 ISCGEM
3     NaN NaN ISCGEMB6O856 ISCGEM
4     NaN NaN ISCGEMB60890 ISCGEM

234 07          NaN        0.1898    NN00570710     NN
234 0B          NaN        0.Zi87    NN00570744     NN
234 09          4.8        1.5200    DSI0007NAF     US
23 41 0         6.0        1.4300    DSI0007NL      DS
234 11          4.5        0.9i00    0              oS
                                     oSI0007mT
        Location Source Magnitude source S0tatus
0                    ISCGEM ISCGEM Automatic
1                    ISCGEM ISCGEM Automatic
2                    ISCGEM ISCGEM Automatic
3                    ISCGEM ISCGEM Automatic
4                    ISCGEN ISCGEM Automatic

234 07          NN             m    Reviewed
```

```
Z3408      NN     NN   Rev ie we d
23409      US     US   Reviewed
 23410     US     US   Reviewed
 22411     US     US   Reviewed

[23239 rows x 21 columns)
```

In {37]:

```
X train, X test, y train, y test = train test split(df[[' atitude', 'Longitude']],
df['Magnitude'], test size=0.25)
```

In (38]:

```
model = RandomFOrestRegressor()
model.fitlX_train, y train)
```

Out(38]:

```
RandomForestRegressor()
                 In a Jupyter environment, please rerun this cell to show the HTML representation or trust the
     e 0
On GitHub, the HTML representation is unable to render, please try loading this page with
nbviewer.org.

  RandomForestRegressor

    RandomForestRegressor( )
```

In |39]:

```
ypred = model.predict(X test)
print('Model accuracy: ', np.mean(ypred == y test))
```

```
Model accuracy: 0.0D0172Il70395869l9lZ
```

In [40]:

```
world_map = folium.Map()
```

In |41]:

```
print(world_map)
```

```
<folium.folium.Map Object at 0x0000026DBB0A4850>
```

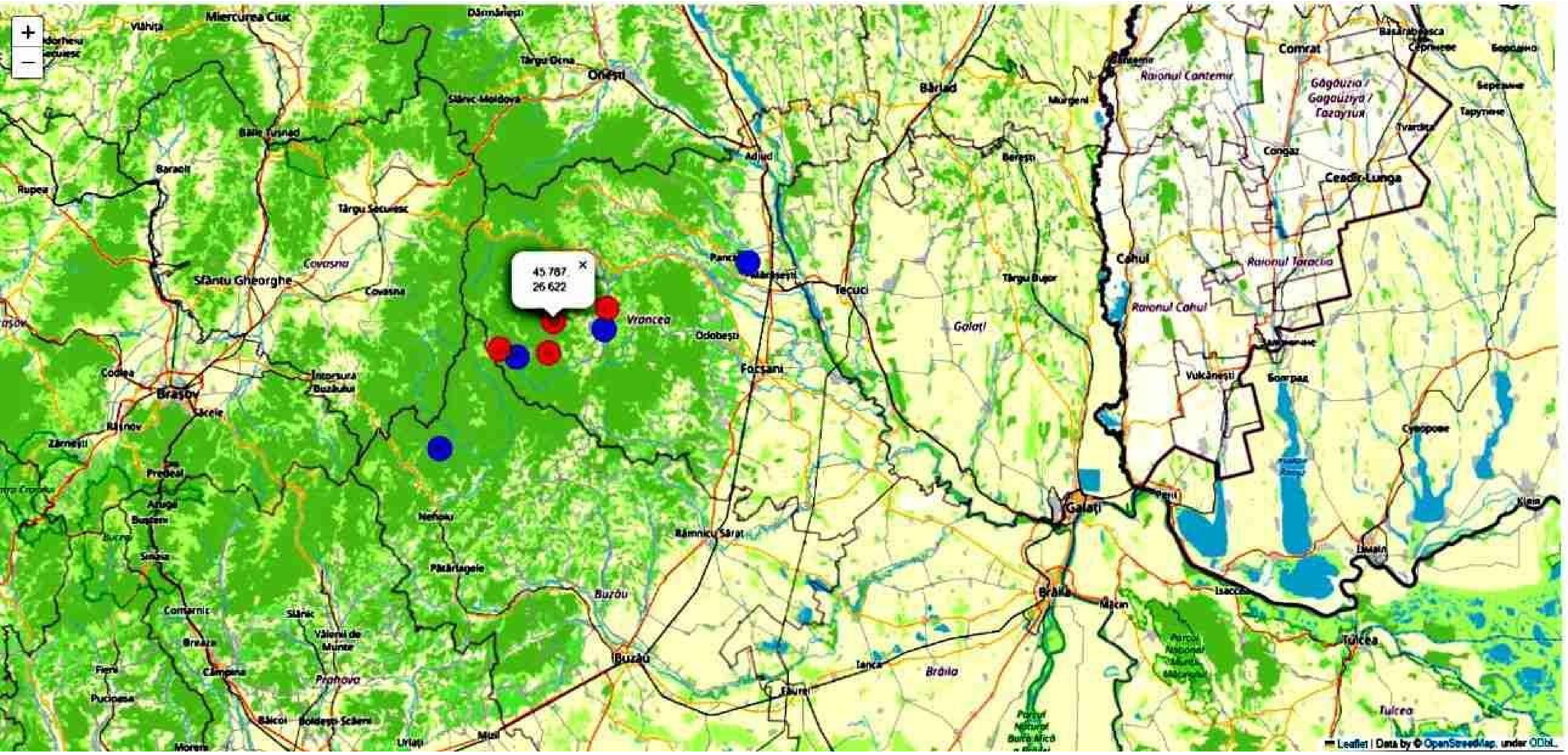
In {42]:

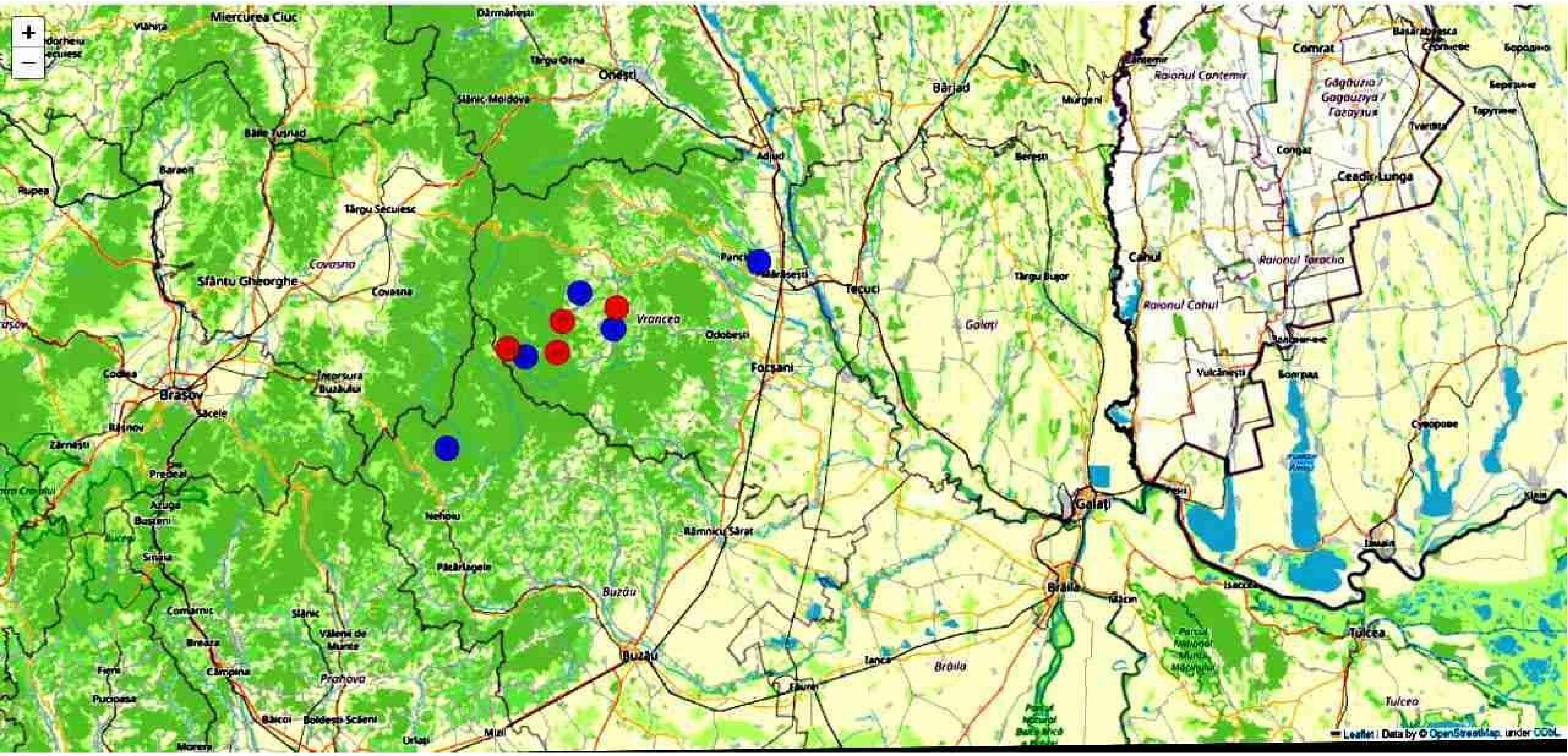
```
for i in raoge(len(X traio)) :
folium.CircleMarkerl
location= (X train.iloc[i, D), X train.iloc[i, 1)),
                                                popup= str (X_train.iloc[i, 0)) + ', ' + str(X train.iloc(i, lj),
color='biue',
fill color='blue',
fill_opacity=D.5
       ).add to(world map)
```

In (43]:

```
for i in range(len(X test)) :
       folium.CircleMarker(
       location= (X test.iloc(i, 0), X_test.iloc(i, 1)),
                                      popup= str (X_test.iloc[i, 0)) + ', ' + str(X test.iloc(i, 1)),
               color='red',
               fill           color='red',
               fill_opacity=D.5
       ).add to(world map)

world map.save('earthquake_prediction map.html')
```


45.787
26.622
Vrancea
Focșani
Galați
Brăila
Buzău
Brașov
Leaflet | Data by © OpenStreetMap, under ODbL.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Miercurea Ciuc
Dărmănești
Târgu Ocna
Onești
Slănic-Moldova
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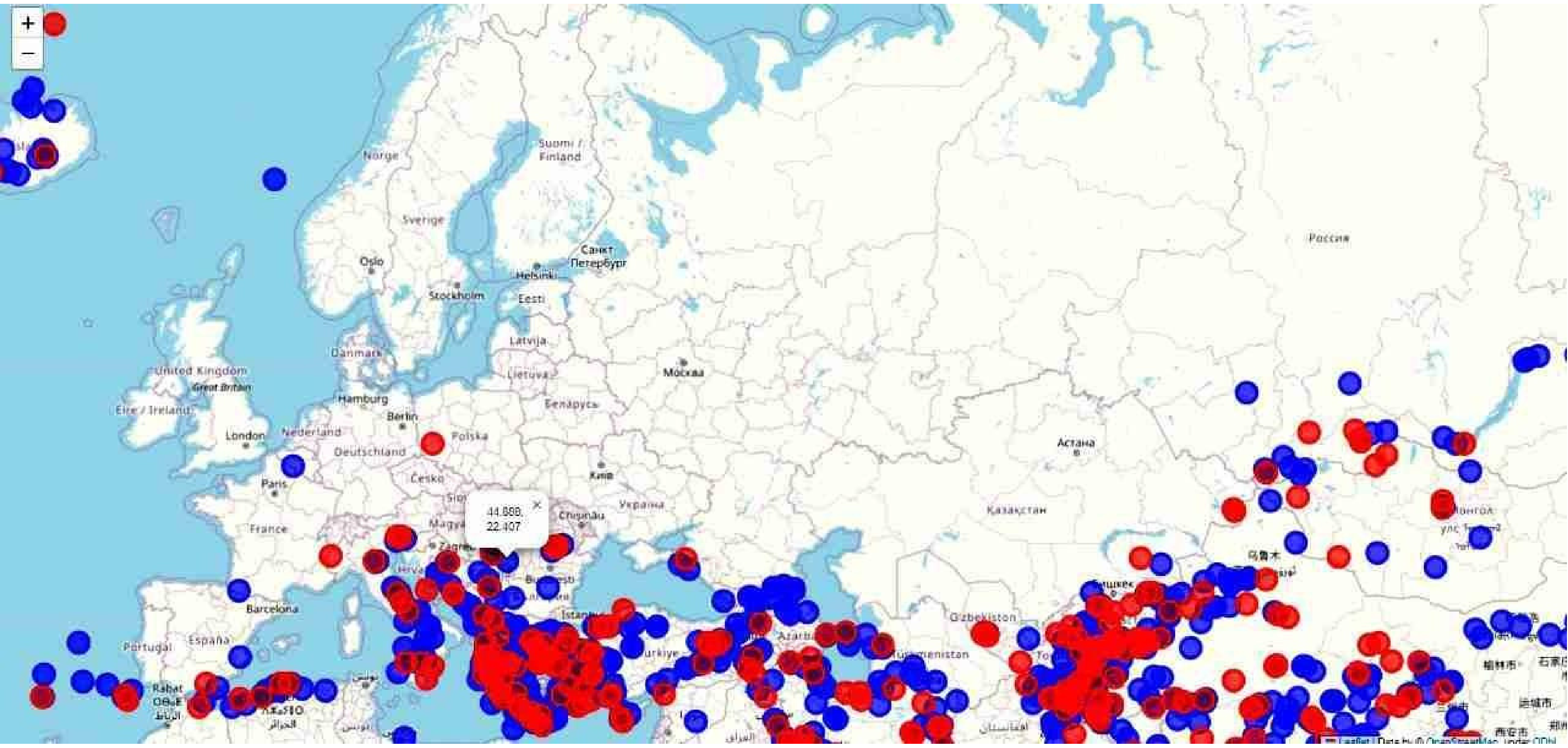
Baraolt
Rupea
Târgu Secuiesc
Sfântu Gheorghe
Covasna
Covasna
Vrancea
Odobești
Panciu
Mărășești
Adjud
Tecuci
Focșani
Bârlad
Murgeni
Berești
Târgu Bujor
Galați
Cahul
Raionul Cahul
Raionul Cantemir
Comrat
Găgăuzia / Gagauziya / Гагаузия
Congaz
Ceadîr-Lunga
Raionul Taraclia
Vulcănești
Codlea
Brașov
Săcele
Întorsura Buzăului
Râșnov
Zărnești
Predeal
Azuga
Bușteni
Sinaia
Comarnic
Breaza
Câmpina
Nehoiu
Pătârlagele
Buzău
Buzău
Râmnicu Sărat
Slănic
Vălenii de Munte
Prahova
Băicoi
Boldești-Scăeni
Urlați
Mizil
Făurei
Ianca
Brăila
Brăila
Măcin
Isaccea
Tulcea
Tulcea
Galați
Reni
Izmail
Parcul Natural Munții Măcinului
Leaflet | Data by © OpenStreetMap, under ODbL


44.888,
22.407
Norge
Suomi / Finland
Sverige
Oslo
Stockholm
Helsinki
Санкт Петербург
Eesti
Latvija
Lietuva
Danmark
United Kingdom
Great Britain
Éire / Ireland
London
Hamburg
Berlin
Nederland
Deutschland
Polska
Беларусь
Москва
Česko
Київ
Україна
Paris
France
Chișinău
Barcelona
España
Portugal
Rabat
Türkiye
Россия
Астана
Казахстан
Uzbekiston
Türkmenistan
Бишкек
Монгол
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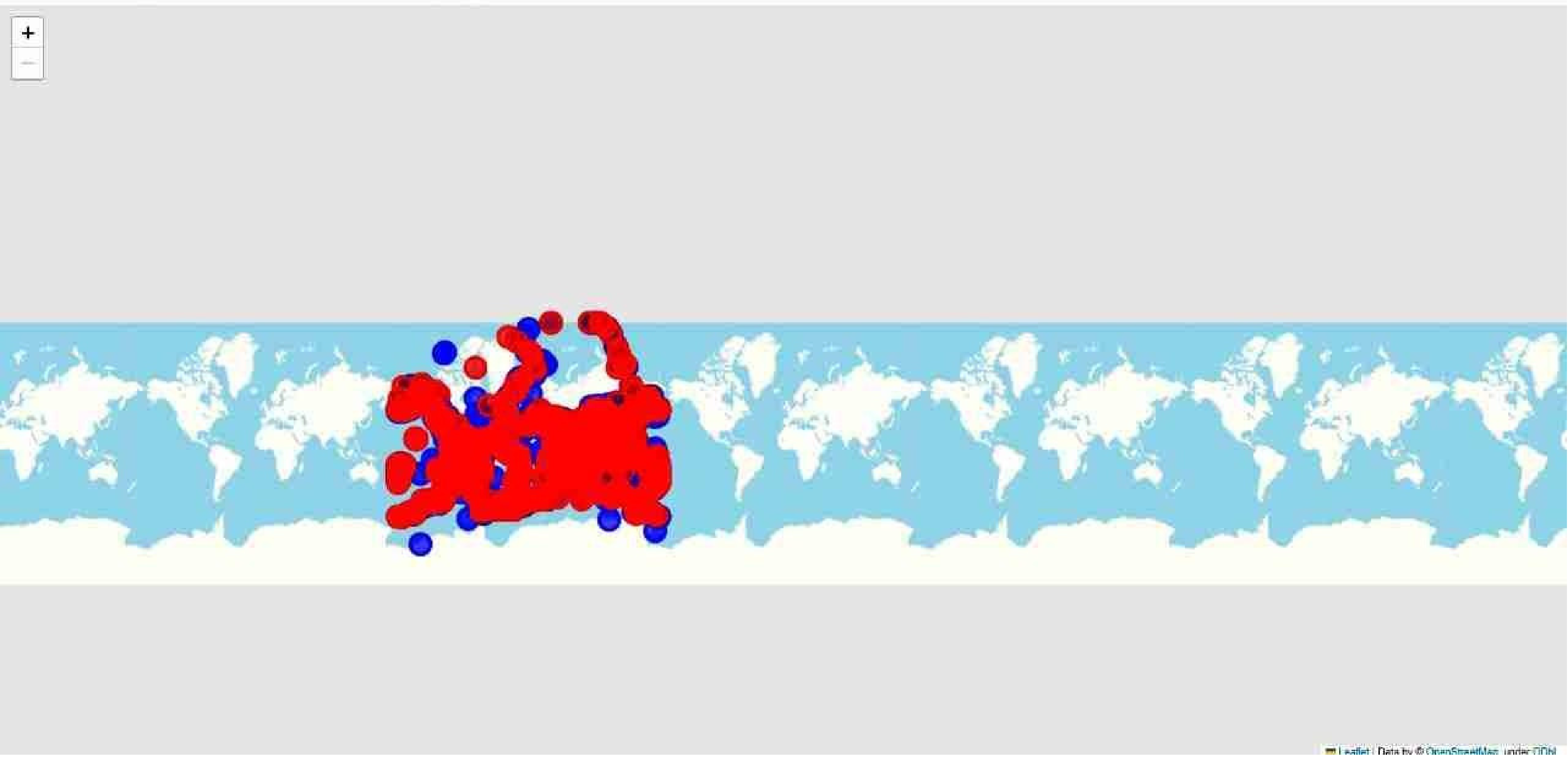
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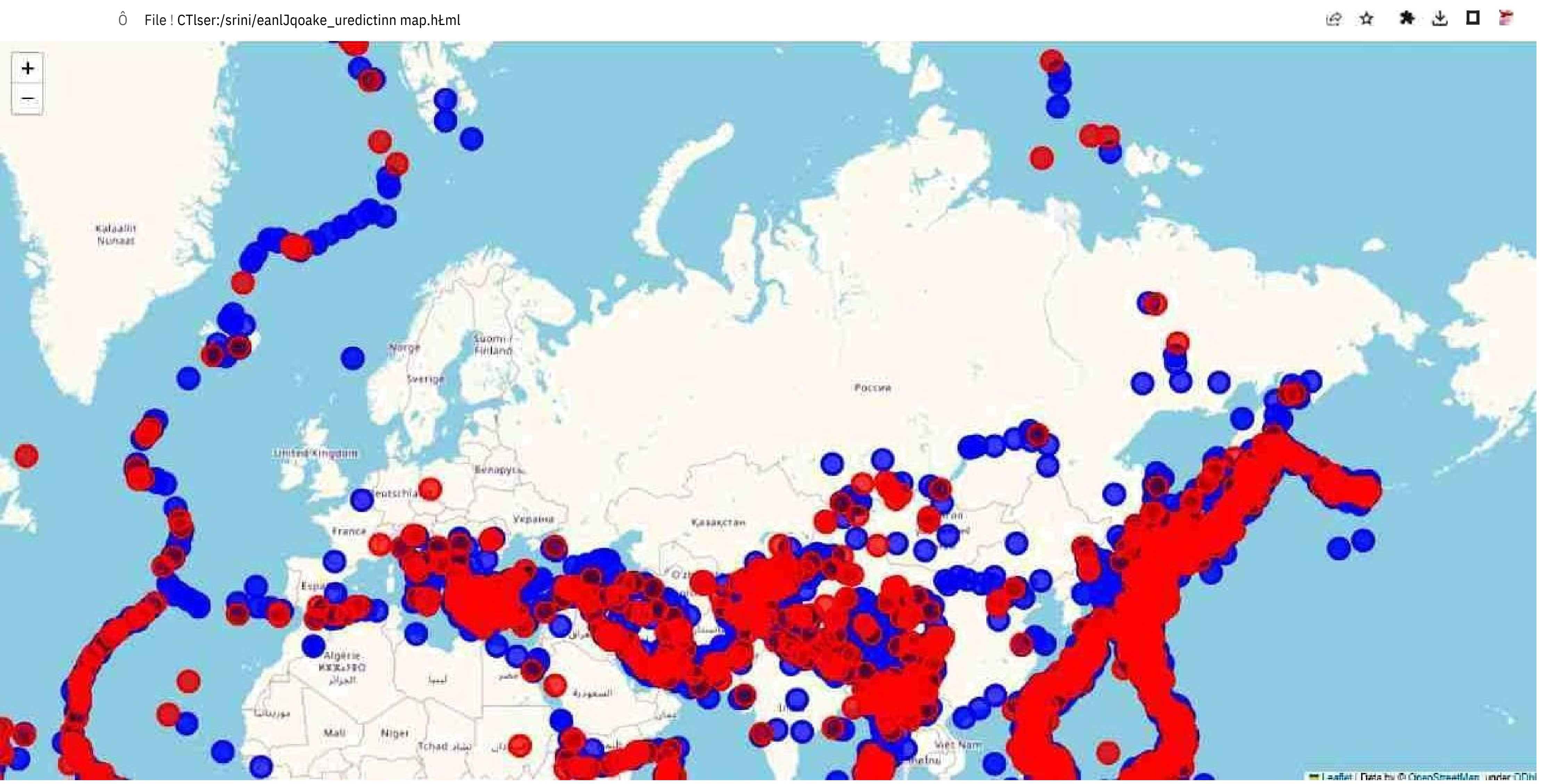
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