Loading Libraries

In [1]:
```
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn import model_selection
from sklearn import linear_model
import os
import datetime as dt
import matplotlib.pyplot as plt
```

Gathering Live Data

- Collecting live data from USGS.gov (United States Geological Survey)
- Using Aws services like Amazon EventBridge, Lambda to collect live-data periodically at midnight(cron-job).
- Using S3 to store data in json format and converting it into .csv file.
- Merging Historical data with live Data and creating the final dataset.

In [2]:
```
# Historical Data from USGS
df1=pd.read_csv('h1.csv')
df2=pd.read_csv('h2.csv')
df3=pd.read_csv('h3.csv')
df4=pd.read_csv('h4.csv')
df5=pd.read_csv('h5.csv')
df6=pd.read_csv('h6.csv')
df7=pd.read_csv('h7.csv')
df8=pd.read_csv('h8.csv')
df9=pd.read_csv('h9.csv')
df10=pd.read_csv('h10.csv')
df11=pd.read_csv('h11.csv')
df=pd.concat([df1,df2,df3,df4,df5,df6,df7,df8,df9,df10,df11])
df.shape
```

Out[2]:
```
(119841, 22)
```

In [3]:
```
df.drop_duplicates(subset=['time'])
df
```

Out[3]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin
0	2022-10-31T17:18:03.640Z	33.684000	-116.754833	14.63	1.04	ml	38.0	45.00	0.043400
1	2022-10-31T17:12:25.837Z	53.968000	-166.513900	13.10	0.90	ml	NaN	NaN	NaN
2	2022-10-31T17:08:26.522Z	51.722400	-178.535600	6.70	1.30	ml	NaN	NaN	NaN
3	2022-10-31T17:02:37.070Z	37.302667	-121.671667	6.79	0.92	md	16.0	46.00	0.043620
4	2022-10-31T17:02:26.899Z	34.499833	-97.276000	0.00	1.18	ml	42.0	120.00	0.086383
...	...	...	...	...	...	...	...	...	...
7636	2022-01-01T00:08:48.730Z	34.051167	-117.213833	14.00	1.61	ml	55.0	50.00	0.070070
7637	2022-01-01T00:05:51.536Z	40.148400	-119.636000	5.20	1.40	ml	9.0	179.27	0.077000
7638	2022-01-01T00:04:07.650Z	33.319000	-116.849833	10.58	1.00	ml	30.0	41.00	0.036150
7639	2022-01-01T00:02:24.512Z	-17.026900	-174.214200	60.87	4.60	mb	NaN	85.00	3.886000
7640	2022-01-01T00:01:06.780Z	35.982667	-120.537500	1.41	0.51	md	13.0	91.00	0.019050

119841 rows × 22 columns

In [4]:
```
df.to_csv('historical_data_eq2022.csv',index=False)
```

In [5]:

```
# Downloading data from aws3
import boto3
s3= boto3.client('s3')
bucket_name='eq-data-csv-to-json-cron-job'
fileName = 'eq_data_csv_to_json_format.json'
fName='C:/Users/ratup/Desktop/ASP/DataSets/USGSgov/eq_json_format_data.json'
s3.download_file(Bucket=bucket_name,Key=fileName,Filename=fName)

df=pd.read_json(fName)
s=df.to_csv('all_month.csv',index=None)
```

In [6]:

```
df0=pd.read_csv('historical_data_eq2022.csv')
df1=pd.read_csv('all_month.csv')
```

In [7]:
```
df=pd.concat([df1,df0])
df.to_csv('final_dataset.csv',index=False)
df=pd.read_csv('final_dataset.csv')
df
```

Out[7]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmi
0	2022-12-01T05:52:55.249Z	63.528900	-147.656400	17.70	1.30	ml	NaN	NaN	Na
1	2022-12-01T05:51:24.102Z	61.999300	-147.671600	37.00	1.30	ml	NaN	NaN	Na
2	2022-12-01T05:42:28.760Z	38.834999	-122.816834	1.68	0.92	md	11.0	72.00	0.0127
3	2022-12-01T05:28:57.530Z	32.501833	-116.831833	11.87	1.57	ml	19.0	180.00	0.1150
4	2022-12-01T05:27:21.260Z	19.155834	-155.467163	31.98	2.15	md	41.0	167.00	Na
...	...	...	...	...	...	...	...	...	.
130189	2022-01-01T00:08:48.730Z	34.051167	-117.213833	14.00	1.61	ml	55.0	50.00	0.0700
130190	2022-01-01T00:05:51.536Z	40.148400	-119.636000	5.20	1.40	ml	9.0	179.27	0.0770
130191	2022-01-01T00:04:07.650Z	33.319000	-116.849833	10.58	1.00	ml	30.0	41.00	0.0361
130192	2022-01-01T00:02:24.512Z	-17.026900	-174.214200	60.87	4.60	mb	NaN	85.00	3.8860
130193	2022-01-01T00:01:06.780Z	35.982667	-120.537500	1.41	0.51	md	13.0	91.00	0.0190

130194 rows × 22 columns

Features in the dataset

- time ---- Time when the event occurred. Times are reported in milliseconds since the epoch.
- latitude ---- Decimals degrees latitude. Negative values for southern latitudes.
- longitutde ----Decimals degrees longitude. Negative values for western longitudes.
- depth ---- Depth of the event in kilometers.

- mag ---- Magnitude of event occurred.
- magType ---- The method or algorithm used to calculate the preferreds magnitude.
- nst ---- The total number ofseismic stations used to determine earthquake locations.
- gap ---- The largest azimuthal gap between azimuthally adjacent stations (in degrees).
- dmin ---- Horizontal distance from the epicenter to the nearest station (in degrees).
- rms ---- The root-mean-square (RMS) travel time residual, in sec, using all weights.
- net ---- The ID of data source contributor for event occured.
- id ---- A unique identifier for the event.
- types ---- A comma-seperated list of product types associated to this event.
- place ---- named geographic region near to the event.
- type ---- Type of seismic event.
- locationSource ---- The network that originally authored the reported the location of this event.
- magSource ---- Network that orginally authored the reported magnitude for this event.
- horizontalError ---- Uncertainty of reported location of the event in kilometers.
- depthError---- The depth erroe, three princcipal errora on a vertical line.
- magError ---- Uncertainty of reported magnitude of the event.
- magNst ---- The total number of seismic stations to calculate the magnitude of earthquake.
- status ---- Indicates whether the event has been reviewed by a human.

In [8]:

```
df.head()
```

Out[8]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms
0	2022-12-01T05:52:55.249Z	63.528900	-147.656400	17.70	1.30	ml	NaN	NaN	NaN	0.33
1	2022-12-01T05:51:24.102Z	61.999300	-147.671600	37.00	1.30	ml	NaN	NaN	NaN	0.73
2	2022-12-01T05:42:28.760Z	38.834999	-122.816834	1.68	0.92	md	11.0	72.0	0.01273	0.01
3	2022-12-01T05:28:57.530Z	32.501833	-116.831833	11.87	1.57	ml	19.0	180.0	0.11500	0.26
4	2022-12-01T05:27:21.260Z	19.155834	-155.467163	31.98	2.15	md	41.0	167.0	NaN	0.11

5 rows × 22 columns

In [9]:

```
df.shape
```

Out[9]: (130194, 22)

In [10]:
```
df.describe()
```

Out[10]:

	latitude	longitude	depth	mag	nst	ga
count	130194.000000	130194.000000	130194.000000	130192.000000	86105.000000	93016.00000
mean	39.108100	-110.854981	27.412120	1.748165	23.777307	120.1000
std	21.041793	74.497891	57.681147	1.205964	21.928043	65.3398
min	-69.773900	-179.999700	-3.740000	-1.600000	0.000000	10.0000
25%	33.493500	-151.928250	4.530000	0.930000	10.000000	70.0000
50%	38.821333	-122.760333	10.000000	1.410000	17.000000	104.0000
75%	55.494525	-115.606708	26.085500	2.130000	30.000000	157.0000
max	86.647700	179.998100	664.700000	7.600000	492.000000	359.0000

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 130194 entries, 0 to 130193
Data columns (total 22 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   time             130194 non-null  object 
 1   latitude         130194 non-null  float64
 2   longitude        130194 non-null  float64
 3   depth            130194 non-null  float64
 4   mag              130192 non-null  float64
 5   magType          130192 non-null  object 
 6   nst              86105 non-null   float64
 7   gap              93016 non-null   float64
 8   dmin             77221 non-null   float64
 9   rms              130194 non-null  float64
 10  net              130194 non-null  object 
 11  id               130194 non-null  object 
 12  updated          130194 non-null  object 
 13  place            128924 non-null  object 
 14  type             130194 non-null  object 
 15  horizontalError  83558 non-null   float64
 16  depthError       130194 non-null  float64
 17  magError         88683 non-null   float64
 18  magNst           92892 non-null   float64
 19  status           130194 non-null  object 
 20  locationSource   130194 non-null  object 
 21  magSource        130194 non-null  object 
dtypes: float64(12), object(10)
memory usage: 21.9+ MB
```

Finding out the features which are list important and having many null values.So, that we can select best features for feature engineering and data wrangling.

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
time                   0
latitude               0
longitude              0
depth                  0
mag                    2
magType                2
nst                44089
gap                37178
dmin               52973
rms                    0
net                    0
id                     0
updated                0
place               1270
type                   0
horizontalError    46636
depthError             0
magError           41511
magNst             37302
status                 0
locationSource         0
magSource              0
dtype: int64
```

Visualize latitude and longitude features from dataframe to see where the points fall from the feature set.

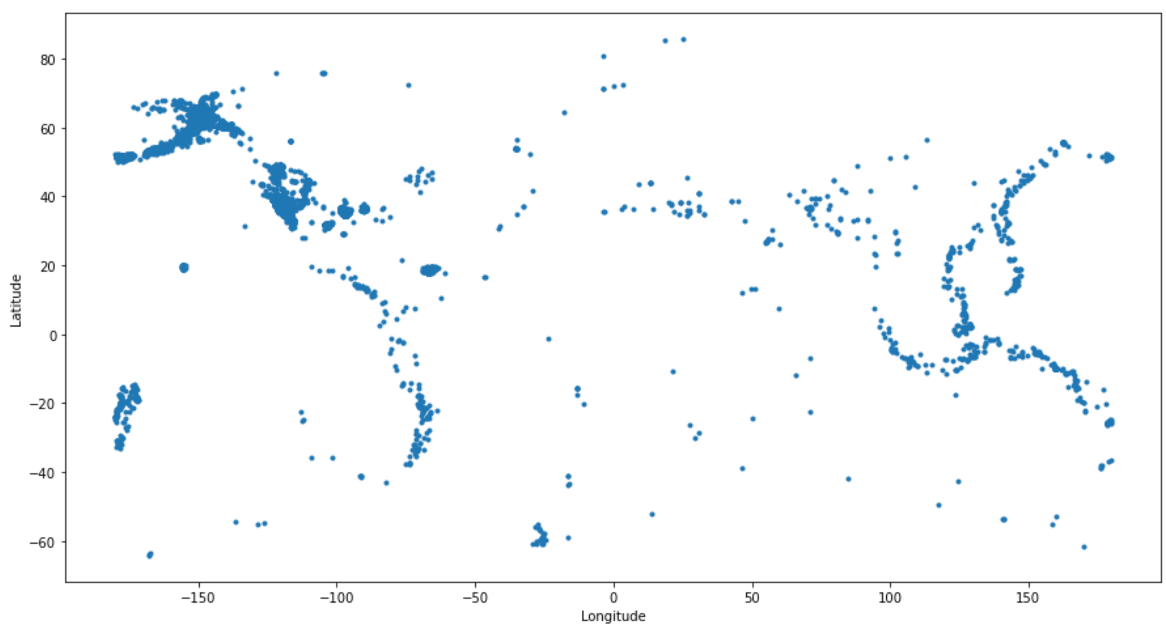
In [13]:

```
rounding_factor = 10
fig, ax = plt.subplots(figsize=(15,8))

# latitude and longitude of earthquake site of top 10500 samples.
plt.plot(np.round(df['longitude'].head(10500),rounding_factor),
         np.round(df['latitude'].head(10500),rounding_factor),
         linestyle='none', marker='.')

plt.suptitle('Earthquakes from ' + str(np.min(df['time']))[:20] + ' to ' + st
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

Earthquakes from 2022-01-01T00:01:06. to 2022-12-01T05:52:55.



Extracting Date from time column.

In [14]:
```python
df = df.sort_values('time', ascending=True)

#Date extraction
df['date'] = df['time'].str[0:10]
df.head()
```

Out[14]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmi
130193	2022-01-01T00:01:06.780Z	35.982667	-120.537500	1.41	0.51	md	13.0	91.00	0.0190
130192	2022-01-01T00:02:24.512Z	-17.026900	-174.214200	60.87	4.60	mb	NaN	85.00	3.8860
130191	2022-01-01T00:04:07.650Z	33.319000	-116.849833	10.58	1.00	ml	30.0	41.00	0.0361
130190	2022-01-01T00:05:51.536Z	40.148400	-119.636000	5.20	1.40	ml	9.0	179.27	0.0770
130189	2022-01-01T00:08:48.730Z	34.051167	-117.213833	14.00	1.61	ml	55.0	50.00	0.0700

5 rows × 23 columns

Data cleaning for seperating 'place' column.Hence only consider city by seperating string by ','.

In [15]:
```python
# only keep the columns needed
df = df[['date','time' ,'latitude', 'longitude', 'depth', 'mag', 'place']]
# df['date'] = df['time'].str.split(', ', expand=True)
newdf = df['place'].str.split(', ', expand=True)
```

In [16]:
```
newdf.head()
```

Out[16]:

	0	1	2	3	4
130193	13km NW of Parkfield	CA	None	None	None
130192	126 km SSW of Hihifo	Tonga	None	None	None
130191	4km SSE of Palomar Observatory	CA	None	None	None
130190	22 km N of Sutcliffe	Nevada	None	None	None
130189	3km W of Redlands	CA	None	None	None

In [17]:
```
df['place'] = newdf[1]
df = df[['date','latitude', 'longitude', 'depth', 'mag', 'place']]
```

In [18]:
```
df.head()
```

Out[18]:

	date	latitude	longitude	depth	mag	place
130193	2022-01-01	35.982667	-120.537500	1.41	0.51	CA
130192	2022-01-01	-17.026900	-174.214200	60.87	4.60	Tonga
130191	2022-01-01	33.319000	-116.849833	10.58	1.00	CA
130190	2022-01-01	40.148400	-119.636000	5.20	1.40	Nevada
130189	2022-01-01	34.051167	-117.213833	14.00	1.61	CA

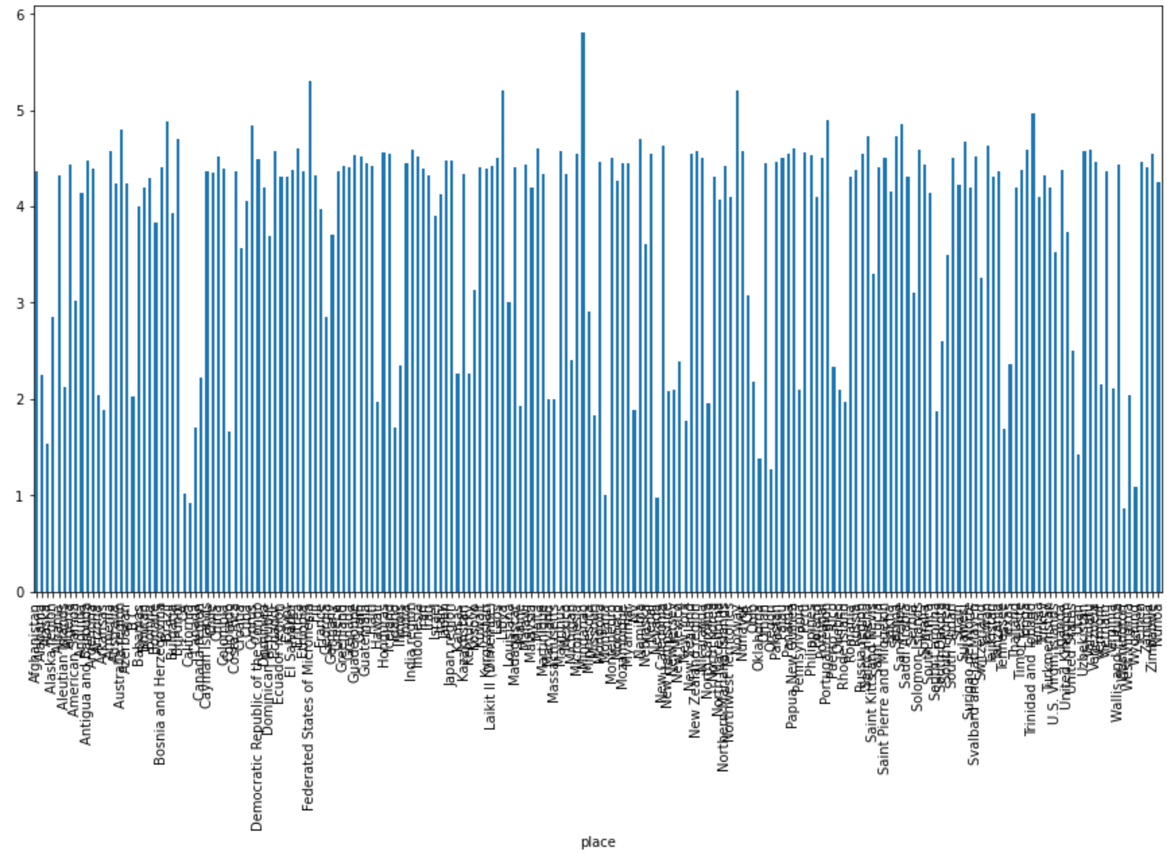
In [19]:
```
print('total locations:',len(set(df['place'])))
```

```
total locations: 200
```

Bar plot of mean magnitude vs place, as we can see from the graph, only few countries are considered as epicenter of dangerous since they have magnitude more than 2.8

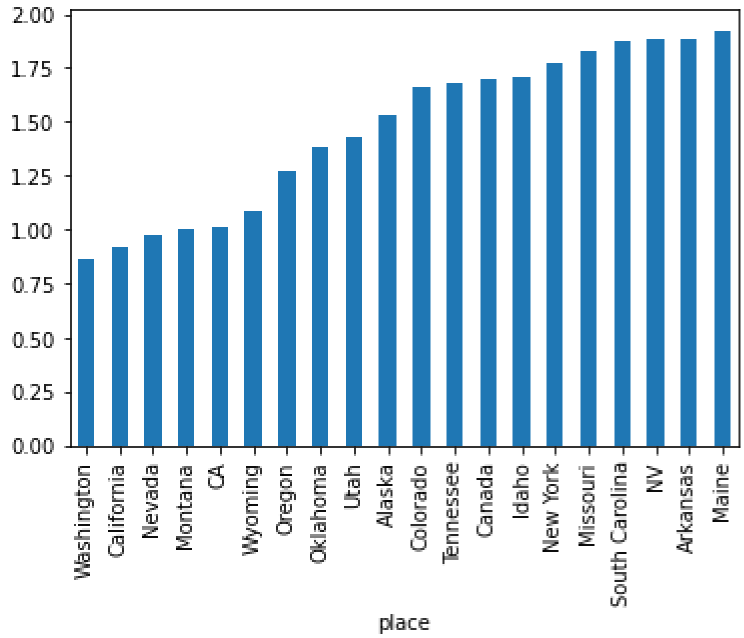
In [20]:

```python
df.groupby(['place'])['mag'].mean().plot(kind='bar',figsize=(15,8));
```



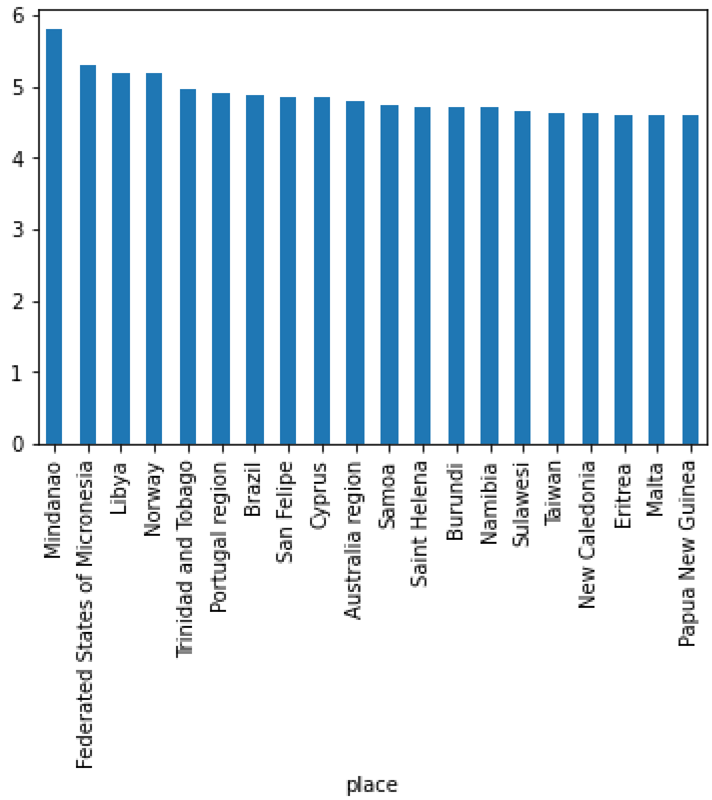
In [21]:

```
df.groupby(['place'])['mag'].mean().nsmallest(20).plot(kind='bar');
```



In [22]:

```
df.groupby(['place'])['mag'].mean().nlargest(20).plot(kind='bar');
```



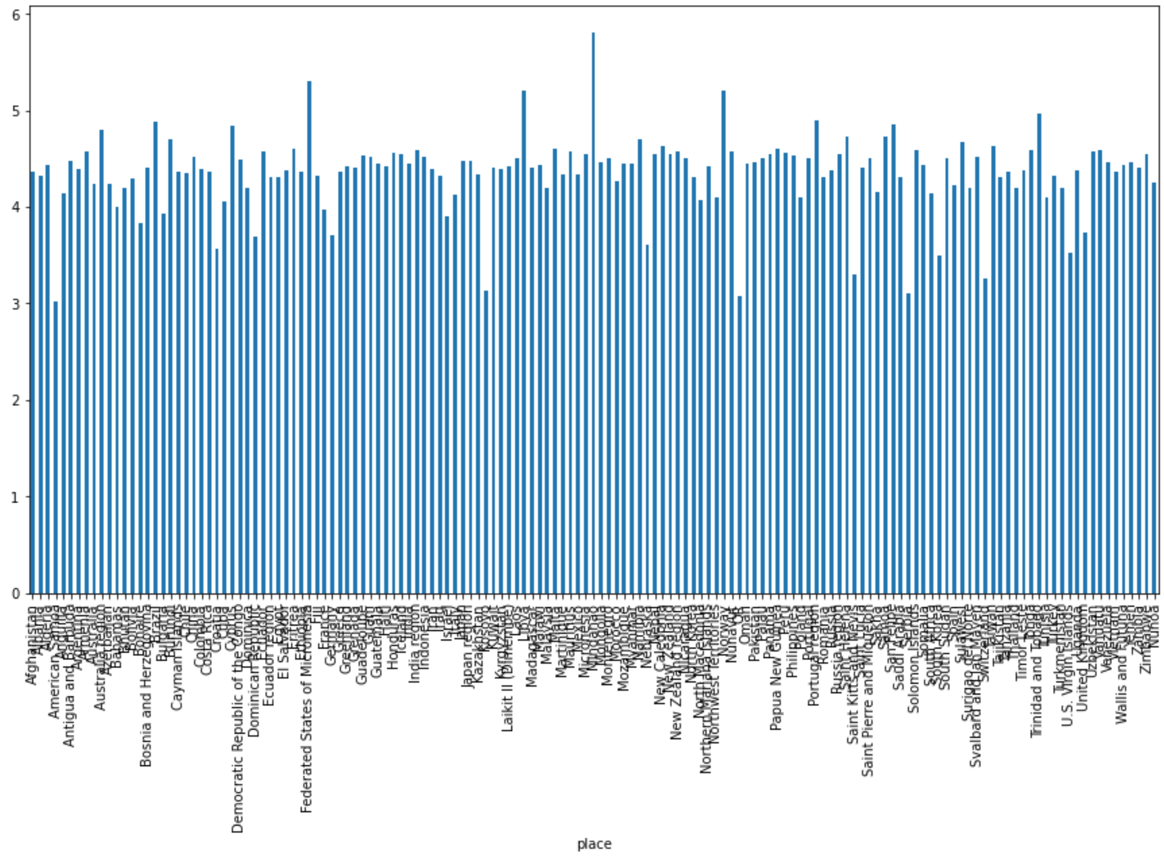
Lets consider 3 as threshold for how high the earthquake has hit and lets visualize countries with more than 3 magnitude.

In [23]:

```
more_dangerous_places=df.groupby('place')['mag'].mean()
more_dangerous_places=more_dangerous_places[more_dangerous_places>3]
```

In [24]:

```
more_dangerous_places.plot(kind='bar',figsize= (15,8));
```



In [25]:

```
# calculate mean latitude and longitude for simplified locations

df_coords = df[['place','latitude', 'longitude']]
df_coords = df_coords.groupby(['place'], as_index=False).mean()
df_coords = df_coords[['place','latitude', 'longitude']]
```

In [26]:

```
df_coords.head()
```

Out[26]:

	place	latitude	longitude
0	Afghanistan	36.269245	70.586485
1	Alabama	34.417250	-86.234500
2	Alaska	59.242208	-151.928201
3	Alaska region	58.501700	-169.335100
4	Albania	41.074600	20.016543

Merge the two dataframes of mean latitude and longitude locations calculated above with dataframe only considering ['date','depth','mag','place'] as columns out of total features

In [27]:

```
df = df[['date','depth', 'mag', 'place']]
df = pd.merge(left=df, right=df_coords, how='inner', on=['place'])
df.head()

print('total locations:',len(set(df['place'])))
```

```
total locations: 198
```

In [28]:
```
print(set(df['place']))
```

```
{'Japan', 'Saint Lucia', 'Tanzania', 'Spain', 'Panama', 'B.C.', 'South Kore
a', 'South Dakota', 'Puerto Rico', 'Norway', 'Oman', 'Guatemala', 'Italy',
'Taiwan', 'New Zealand', 'Egypt', 'Pakistan', 'Tennessee', 'Svalbard and Ja
n Mayen', 'Cayman Islands', 'Kosovo', 'Bolivia', 'Namibia', 'South Africa',
'Laikit II (Dimembe)', 'Solomon Islands', 'Zimbabwe', 'Wyoming', 'Ethiopi
a', 'Algeria', 'Maine', 'Bahamas', 'Tunisia', 'New Hampshire', 'New York',
'Uzbekistan', 'Turkmenistan', 'Montana', 'Kyrgyzstan', 'Vietnam', 'Russia r
egion', 'Saudi Arabia', 'Wallis and Futuna', 'Israel', 'Saint Kitts and Nev
is', 'Canada', 'United States', 'Turkey', 'Georgia', 'Surigao del Norte',
'Ecuador', 'Papua New Guinea', 'Australia', 'Alaska region', 'West Virgini
a', 'Nunavut', 'North Macedonia', 'New Jersey', 'Greenland', 'Colombia', 'I
ran', 'Libya', 'Guadeloupe', 'Cuba', 'Romania', 'Massachusetts', 'France',
'Micronesia', 'Democratic Republic of the Congo', 'Michigan', 'Minnesota',
'Samoa', 'Hawaii', 'El Salvador', 'Idaho', 'Dominican Republic', 'Trinidad
and Tobago', 'Saint Helena', 'Louisiana', 'Venezuela', 'Mauritius', 'Orego
n', 'New Caledonia', 'Yemen', 'Cyprus', 'Armenia', 'Arizona', 'Indonesia',
'Mozambique', 'Peru', 'China', 'Costa Rica', 'Eritrea', 'Palau', 'Australia
region', 'Mongolia', 'India', 'New Mexico', 'Azerbaijan', 'Kansas', 'Domini
ca', 'Switzerland', 'Vanuatu', 'Bosnia and Herzegovina', 'San Felipe', 'Bhu
tan', 'Martinique', 'Croatia', 'Nebraska', 'Tajikistan', 'Washington', 'Arg
entina', 'Japan region', 'New Zealand region', 'Anguilla', 'Zambia', 'Nepa
l', 'Russia', 'Utah', 'Nevada', 'Oklahoma', 'Tonga', 'American Samoa', 'Por
tugal', 'Alabama', 'Antigua and Barbuda', 'Northwest Territories', 'Mindana
o', 'Uganda', 'Iraq', 'Malaysia', 'NV', 'Honduras', 'Mexico', 'Vermont', 'V
irginia', 'Rhode Island', 'Arkansas', 'Morocco', 'Grenada', 'Pennsylvania',
'South Carolina', 'South Sudan', 'Bonaire', 'Philippines', 'Colorado', 'Afg
hanistan', 'Germany', 'Sulawesi', 'Ohio', 'Aleutian Islands', 'Kentucky',
'California', 'Haiti', 'Laos', 'Kazakhstan', 'Poland', 'Missouri', 'Illinoi
s', 'Nicaragua', 'U.S. Virgin Islands', 'Federated States of Micronesia',
'Texas', 'Alaska', 'Sakha', 'Greece', 'Portugal region', 'Brazil', 'Thailan
d', 'North Korea', 'Maryland', 'United Kingdom', 'Malawi', 'Timor Leste',
'Madagascar', 'Somalia', 'Chile', 'North Carolina', 'Canada region', 'Icela
nd', 'Malta', 'OR', 'India region', 'Northern Mariana Islands', 'Myanmar',
'Ecuador region', 'Fiji', 'Montenegro', 'Saint Pierre and Miquelon', 'Quebe
c', 'Albania', 'Serbia', 'Burundi', 'CA', 'Bulgaria', 'Kuwait', 'Guam', 'Ñu
ñoa'}
```

In [29]:
```
df.head()
```

Out[29]:

	date	depth	mag	place	latitude	longitude
0	2022-01-01	1.41	0.51	CA	36.571914	-119.880454
1	2022-01-01	10.58	1.00	CA	36.571914	-119.880454
2	2022-01-01	14.00	1.61	CA	36.571914	-119.880454
3	2022-01-01	1.71	1.09	CA	36.571914	-119.880454
4	2022-01-01	19.08	2.88	CA	36.571914	-119.880454

Feature Engineering and Data Wrangling

- Set rolling window size for future prediction based on past values with fixed window size in past.
- I have created 6 new features based on rolling window size on average depth and average magnitude.
- A final outcome 'mag_outcome' has been defined as target values and the output is considered as shifted values from set rolling window of past days e.g:'7'

In [30]:

```
eq_tmp = df.copy()

#rolling window size
DAYS_OUT_TO_PREDICT = 7

# loop through each zone and apply MA
eq_data = []
eq_data_last_days_out = []

for place in list(set(eq_tmp['place'])):
    temp_df = eq_tmp[eq_tmp['place'] == place].copy()

    #avg. depth of 22 days rolling period and so on..
    temp_df['depth_avg_22'] = temp_df['depth'].rolling(window=22,center=False
    temp_df['depth_avg_15'] = temp_df['depth'].rolling(window=15,center=False
    temp_df['depth_avg_7'] = temp_df['depth'].rolling(window=7,center=False).
    temp_df['mag_avg_22'] = temp_df['mag'].rolling(window=22,center=False).me
    temp_df['mag_avg_15'] = temp_df['mag'].rolling(window=15,center=False).me
    temp_df['mag_avg_7'] = temp_df['mag'].rolling(window=7,center=False).mear
    temp_df.loc[:, 'mag_outcome'] = temp_df.loc[:, 'mag_avg_7'].shift(DAYS_OU

    #days to predict value on earth quake data this is not yet seen or witnes

    eq_data_last_days_out.append(temp_df.tail(DAYS_OUT_TO_PREDICT))

    eq_data.append(temp_df)
```

In [31]:

```
# concat all location-based dataframes into master dataframe
eq_all = pd.concat(eq_data)
```

In [32]:

```python
eq_all.head()
```

Out[32]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	depth
103030	2022-01-01	10.00	4.6	Japan	33.299778	135.513876	NaN	NaN	
103031	2022-01-01	10.00	4.8	Japan	33.299778	135.513876	NaN	NaN	
103032	2022-01-01	98.80	4.4	Japan	33.299778	135.513876	NaN	NaN	
103033	2022-01-01	49.35	4.3	Japan	33.299778	135.513876	NaN	NaN	
103034	2022-01-02	61.80	4.3	Japan	33.299778	135.513876	NaN	NaN	

In [33]:

```python
# remove any NaN fields
eq_all = eq_all[np.isfinite(eq_all['depth_avg_22'])]
eq_all = eq_all[np.isfinite(eq_all['mag_avg_22'])]
eq_all = eq_all[np.isfinite(eq_all['mag_outcome'])]
```

In [34]:

```python
eq_all.head()
```

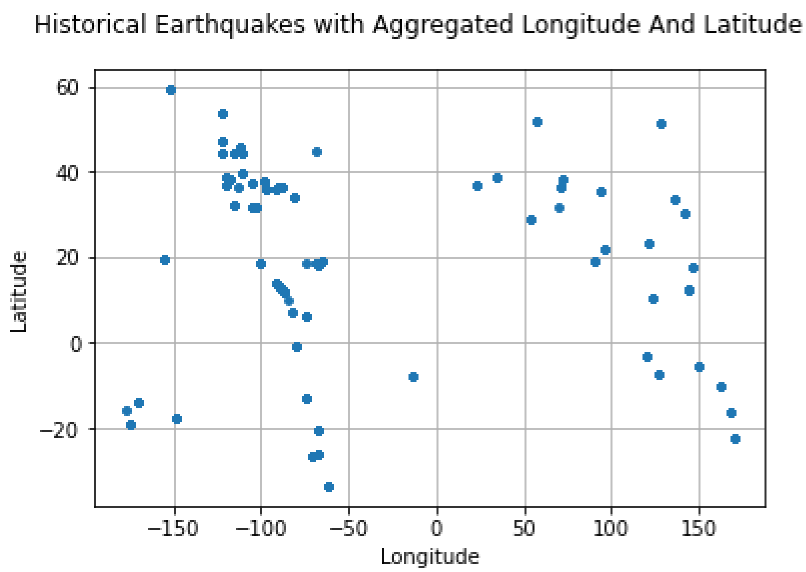
Out[34]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	dept
103051	2022-01-10	339.33	4.2	Japan	33.299778	135.513876	69.870000	85.812667	8
103052	2022-01-10	84.74	4.3	Japan	33.299778	135.513876	73.267273	87.372000	8
103053	2022-01-11	46.28	4.4	Japan	33.299778	135.513876	74.916364	86.615333	8
103054	2022-01-11	34.49	4.6	Japan	33.299778	135.513876	71.993182	87.402667	8
103055	2022-01-11	380.35	4.2	Japan	33.299778	135.513876	87.038636	111.248000	13

Location after feature engineering

In [35]:

```
plt.plot(eq_all['longitude'],
         eq_all['latitude'],
         linestyle='none', marker='.')
plt.suptitle('Historical Earthquakes with Aggregated Longitude And Latitude')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.grid()
plt.show()
```



In [36]:

```
# keep our live data for predictions
eq_data_last_days_out = pd.concat(eq_data_last_days_out)


eq_data_last_days_out = eq_data_last_days_out[np.isfinite(eq_data_last_days_c
predict_unknown=eq_data_last_days_out
```

In [37]:
```
# here 'mag_outcome' has NaN because these are future outcome event to be pre
predict_unknown
```

Out[37]:

	date	depth	mag	place	latitude	longitude	depth_avg_22	depth_avg_15	dep
103930	2022-11-27	49.711	4.6	Japan	33.299778	135.513876	83.077636	89.482467	1:
103931	2022-11-29	10.000	5.0	Japan	33.299778	135.513876	83.077636	89.482467	1'
103932	2022-11-29	55.283	4.4	Japan	33.299778	135.513876	84.939636	92.501333	{
103933	2022-11-30	53.289	5.0	Japan	33.299778	135.513876	85.541909	95.401533	(
103934	2022-11-30	10.000	4.6	Japan	33.299778	135.513876	69.749136	91.681733	{
...	...	...	...	...	...	...	...	...	
111356	2022-11-04	114.016	4.3	Guam	12.533887	144.307219	101.198455	102.098533	1'
111357	2022-11-05	40.012	4.5	Guam	12.533887	144.307219	102.562636	103.221400	1(
111358	2022-11-05	94.093	3.9	Guam	12.533887	144.307219	106.385045	108.827600	1'
111359	2022-11-09	127.518	4.3	Guam	12.533887	144.307219	106.393136	103.416000	1'
111360	2022-11-16	153.053	4.4	Guam	12.533887	144.307219	106.789727	104.648533	1:

511 rows × 13 columns

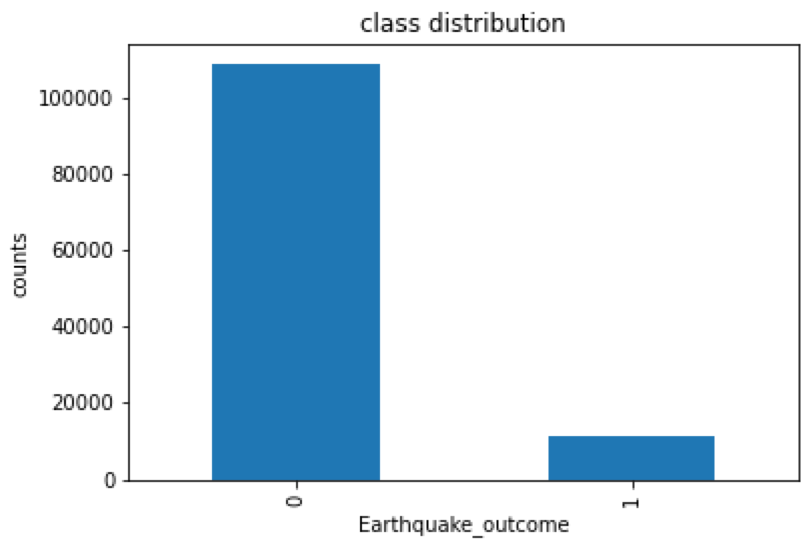
Considered magnitude above 2.5 as dangerous hence prediction outcome as '1'else '0'

In [38]:
```
eq_all['mag_outcome'] = np.where(eq_all['mag_outcome'] > 2.5, 1,0)
print(eq_all['mag_outcome'].describe())
eq_all['mag_outcome'].value_counts()
```

```
count    119495.000000
mean          0.092397
std           0.289587
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max           1.000000
Name: mag_outcome, dtype: float64
```

Out[38]:
```
0    108454
1     11041
Name: mag_outcome, dtype: int64
```

In [39]:
```
eq_all['mag_outcome'].value_counts().plot(kind='bar',)
plt.xlabel('Earthquake_outcome')
plt.ylabel('counts')
plt.title('class distribution');
```



Save the data of fixed rolling window and live unknown prediction data in sql database using sql engine

In [40]:
```
from sqlalchemy import create_engine
engine = create_engine('sqlite:///Earthquakedata.db')
eq_all.to_sql('Earthquake_features', engine, index=False,if_exists='replace')
```

In [41]:
```
engine = create_engine('sqlite:///Earthquakedata_predict.db')
predict_unknown.to_sql('Earthquake_predict', engine, index=False,if_exists='r
```