Problem statement

predicting the house price in USA.To create a model to help him estimate of what the house would sell for.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df=pd.read_csv("bottle")
```

```
C:\ProgramData\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3165: DtypeWarning: Columns (47,
73) have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

To display top 10 rows

In [3]:

```
df.head(10)
```

Out[3]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R_PHAEO	R_PRES	R_SAMP	DIC1	DIC
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.50	33.440	NaN	25.649	NaN	...	NaN	0	NaN	NaN	Na
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.46	33.440	NaN	25.656	NaN	...	NaN	8	NaN	NaN	Na
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	10.46	33.437	NaN	25.654	NaN	...	NaN	10	NaN	NaN	Na
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.45	33.420	NaN	25.643	NaN	...	NaN	19	NaN	NaN	Na
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	10.45	33.421	NaN	25.643	NaN	...	NaN	20	NaN	NaN	Na
5	1	6	054.0 056.0	19-4903CR-HY-060-0930-05400560-0030A-7	30	10.45	33.431	NaN	25.651	NaN	...	NaN	30	NaN	NaN	Na

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R_PHAEO	R_PRES	R_SAMP	DIC1	DIC
6	1	7	054.0 056.0	19-4903CR-HY-060-0930-05400560-0039A-3	39	10.45	33.440	NaN	25.658	NaN	...	NaN	39	NaN	NaN	Na
7	1	8	054.0 056.0	19-4903CR-HY-060-0930-05400560-0050A-7	50	10.24	33.424	NaN	25.682	NaN	...	NaN	50	NaN	NaN	Na
8	1	9	054.0 056.0	19-4903CR-HY-060-0930-05400560-0058A-3	58	10.06	33.420	NaN	25.710	NaN	...	NaN	58	NaN	NaN	Na
9	1	10	054.0 056.0	19-4903CR-HY-060-0930-05400560-0075A-7	75	9.86	33.494	NaN	25.801	NaN	...	NaN	75	NaN	NaN	Na

10 rows × 74 columns

Data Cleaning And Pre-Processing

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 864863 entries, 0 to 864862
Data columns (total 74 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   Cst_Cnt              864863 non-null  int64  
 1   Btl_Cnt              864863 non-null  int64  
 2   Sta_ID               864863 non-null  object 
 3   Depth_ID             864863 non-null  object 
 4   Depthm               864863 non-null  int64  
 5   T_degC               853900 non-null  float64
 6   Salnty               817509 non-null  float64
 7   O2ml_L               696201 non-null  float64
 8   STheta               812174 non-null  float64
 9   O2Sat                661274 non-null  float64
 10  Oxy_µmol/Kg          661268 non-null  float64
 11  BtlNum               118667 non-null  float64
 12  RecInd               864863 non-null  int64  
 13  T_prec               853900 non-null  float64
 14  T_qual               23127 non-null   float64
 15  S_prec               817509 non-null  float64
 16  S_qual               74914 non-null   float64
 17  P_qual               673755 non-null  float64
 18  O_qual               184676 non-null  float64
 19  SThtaq               65823 non-null   float64
 20  O2Satq               217797 non-null  float64
 21  ChlorA               225272 non-null  float64
 22  Chlqua               639166 non-null  float64
 23  Phaeop               225271 non-null  float64
 24  Phaqua               639170 non-null  float64
 25  PO4uM                413317 non-null  float64
 26  PO4q                 451786 non-null  float64
 27  SiO3uM               354091 non-null  float64
 28  SiO3qu               510866 non-null  float64
 29  NO2uM                337576 non-null  float64
 30  NO2q                 529474 non-null  float64
 31  NO3uM                337403 non-null  float64
 32  NO3q                 529933 non-null  float64
 33  NH3uM                64962 non-null   float64
 34  NH3q                 808299 non-null  float64
 35  C14As1               14432 non-null   float64
 36  C14A1p               12760 non-null   float64
 37  C14A1q               848605 non-null  float64
```

```
 38  C14As2             14414 non-null   float64
 39  C14A2p             12742 non-null   float64
 40  C14A2q             848623 non-null  float64
 41  DarkAs             22649 non-null   float64
 42  DarkAp             20457 non-null   float64
 43  DarkAq             840440 non-null  float64
 44  MeanAs             22650 non-null   float64
 45  MeanAp             20457 non-null   float64
 46  MeanAq             840439 non-null  float64
 47  IncTim             14437 non-null   object
 48  LightP             18651 non-null   float64
 49  R_Depth            864863 non-null  float64
 50  R_TEMP             853900 non-null  float64
 51  R_POTEMP           818816 non-null  float64
 52  R_SALINITY         817509 non-null  float64
 53  R_SIGMA            812007 non-null  float64
 54  R_SVA              812092 non-null  float64
 55  R_DYNHT            818206 non-null  float64
 56  R_O2               696201 non-null  float64
 57  R_O2Sat            666448 non-null  float64
 58  R_SIO3             354099 non-null  float64
 59  R_PO4              413325 non-null  float64
 60  R_NO3              337411 non-null  float64
 61  R_NO2              337584 non-null  float64
 62  R_NH4              64982 non-null   float64
 63  R_CHLA             225276 non-null  float64
 64  R_PHAEO            225275 non-null  float64
 65  R_PRES             864863 non-null  int64
 66  R_SAMP             122006 non-null  float64
 67  DIC1               1999 non-null    float64
 68  DIC2               224 non-null     float64
 69  TA1                2084 non-null    float64
 70  TA2                234 non-null     float64
 71  pH2                10 non-null      float64
 72  pH1                84 non-null      float64
 73  DIC Quality Comment  55 non-null      object
dtypes: float64(65), int64(5), object(4)
memory usage: 488.3+ MB
```

In [5]:

```python
# Display the statistical summary
df.describe()
```

Out[5]:

	Cst_Cnt	Btl_Cnt	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	Oxy_
count	864863.000000	864863.000000	864863.000000	853900.000000	817509.000000	696201.000000	812174.000000	661274.000000	66126
mean	17138.790958	432432.000000	226.831951	10.799677	33.840350	3.392468	25.819394	57.103779	14
std	10240.949817	249664.587267	316.050259	4.243825	0.461843	2.073256	1.167787	37.094137	9
min	1.000000	1.000000	0.000000	1.440000	28.431000	-0.010000	20.934000	-0.100000	-
25%	8269.000000	216216.500000	46.000000	7.680000	33.488000	1.360000	24.965000	21.100000	6
50%	16848.000000	432432.000000	125.000000	10.060000	33.863000	3.440000	25.996000	54.400000	15
75%	26557.000000	648647.500000	300.000000	13.880000	34.196900	5.500000	26.646000	97.600000	24
max	34404.000000	864863.000000	5351.000000	31.140000	37.034000	11.130000	250.784000	214.100000	48

8 rows × 70 columns

In [6]:

```python
# To display the col headings
df.columns
```

Out[6]:

```
Index(['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depth_ID', 'Depthm', 'T_degC',
       'Salnty', 'O2ml_L', 'STheta', 'O2Sat', 'Oxy_µmol/Kg', 'BtlNum',
       'RecInd', 'T_prec', 'T_qual', 'S_prec', 'S_qual', 'P_qual', 'O_qual',
       'SThtaq', 'O2Satq', 'ChlorA', 'Chlqua', 'Phaeop', 'Phaqua', 'PO4uM',
       'PO4q', 'SiO3uM', 'SiO3qu', 'NO2uM', 'NO2q', 'NO3uM', 'NO3q', 'NH3uM',
       'NH3q', 'C14As1', 'C14A1p', 'C14A1q', 'C14As2', 'C14A2p', 'C14A2q',
       'DarkAs', 'DarkAp', 'DarkAq', 'MeanAs', 'MeanAp', 'MeanAq', 'IncTim',
       'LightP', 'R_Depth', 'R_TEMP', 'R_POTEMP', 'R_SALINITY', 'R_SIGMA',
       'R_SVA', 'R_DYNHT', 'R_O2', 'R_O2Sat', 'R_SIO3', 'R_PO4', 'R_NO3',
       'R_NO2', 'R_NH4', 'R_CHLA', 'R_PHAEO', 'R_PRES', 'R_SAMP', 'DIC1',
       'DIC2', 'TA1', 'TA2', 'pH2', 'pH1', 'DIC Quality Comment'],
      dtype='object')
```

In [7]:

```python
cols=df.dropna(axis=1)
```

In [8]:
```
cols.columns
```

Out[8]:
```
Index(['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depth_ID', 'Depthm', 'RecInd',
       'R_Depth', 'R_PRES'],
      dtype='object')
```

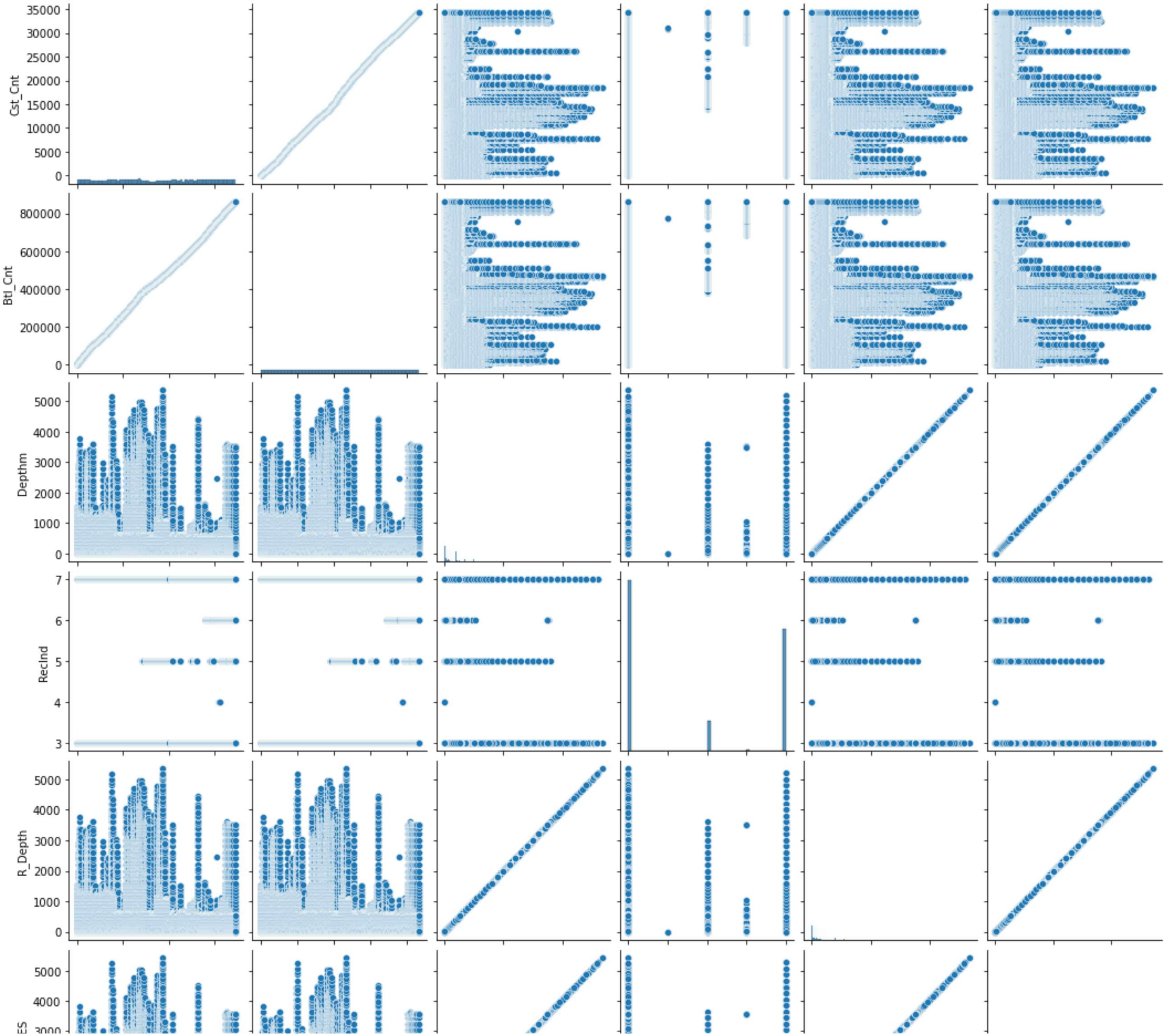
EDA and Visualization

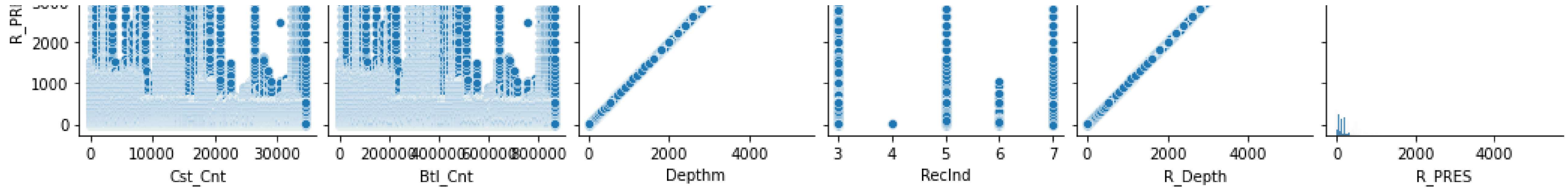
In [9]:

```
sns.pairplot(cols)
```

Out[9]:

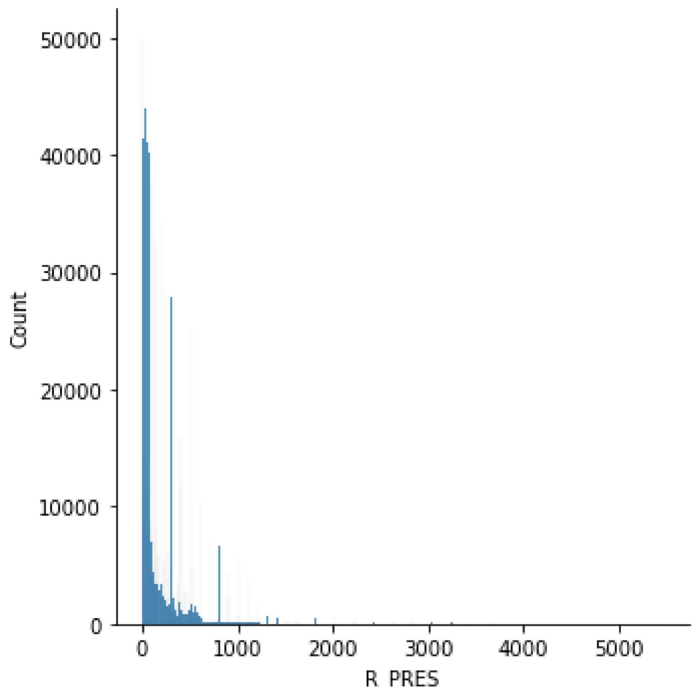
```
<seaborn.axisgrid.PairGrid at 0x2201b5544f0>
```


Cst_Cnt
35000
30000
25000
20000
15000
10000
5000
0
Btl_Cnt
800000
600000
400000
200000
0
Depthm
5000
4000
3000
2000
1000
0
RecInd
7
6
5
4
3
R_Depth
5000
4000
3000
2000
1000
0
5000
4000
3000



In [10]:
```
1 sns.displot(df['R_PRES'])
```

Out[10]: <seaborn.axisgrid.FacetGrid at 0x2201b554670>



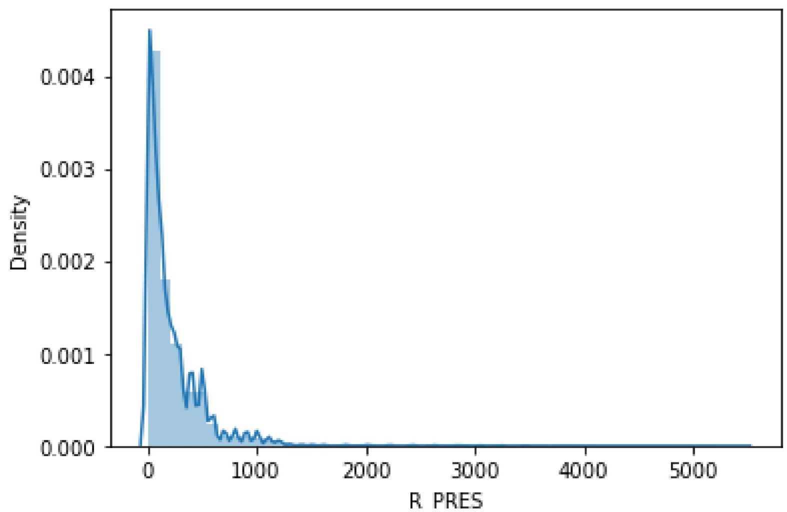
In [11]:

```python
# We use displot in older version we get distplot use displot
sns.distplot(df['R_PRES'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a dep
recated function and will be removed in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[11]:

```
<AxesSubplot:xlabel='R_PRES', ylabel='Density'>
```



In [12]:

```
df1=cols[['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depthm', 'RecInd', 'R_PRES']]
df1
```

Out[12]:

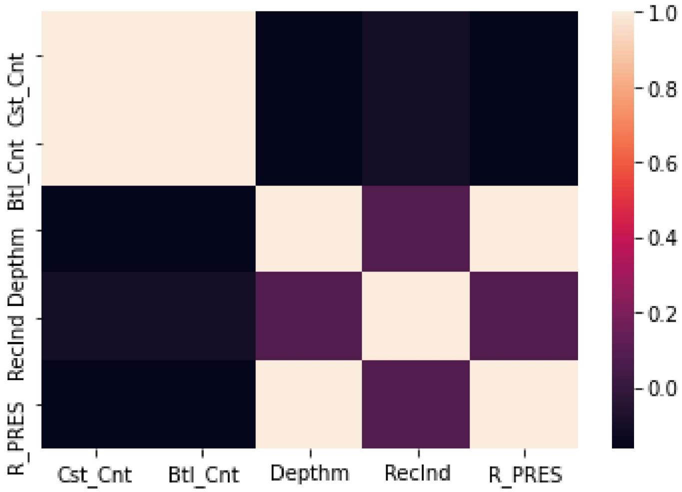
	Cst_Cnt	Btl_Cnt	Sta_ID	Depthm	RecInd	R_PRES
0	1	1	054.0 056.0	0	3	0
1	1	2	054.0 056.0	8	3	8
2	1	3	054.0 056.0	10	7	10
3	1	4	054.0 056.0	19	3	19
4	1	5	054.0 056.0	20	7	20
...	...	...	...	...	...	...
864858	34404	864859	093.4 026.4	0	7	0
864859	34404	864860	093.4 026.4	2	3	2
864860	34404	864861	093.4 026.4	5	3	5
864861	34404	864862	093.4 026.4	10	3	10
864862	34404	864863	093.4 026.4	15	3	15

864863 rows × 6 columns

In [13]:

```
sns.heatmap(df1.corr())
```

Out[13]: <AxesSubplot:>



To train the model - MODEL BUILD

Going to train linear regression model;We split our data into 2 variables x and y where x is independent var(input) and y is dependent on x(output), we could ignore address col as it is not required for our model

In [14]:

```
x=df1[['Cst_Cnt', 'RecInd', 'Depthm',
        'R_PRES']]
y=df1[['Depthm']]
```

To split the dataset into test data

In [15]:

```
# importing lib for splitting test data
from sklearn.model_selection import train_test_split
```

In [16]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3)
```

In [17]:

```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[17]:

```
LinearRegression()
```

In [18]:

```
print(lr.intercept_)
```

```
[-3.97903932e-13]
```

In [19]:

```
print(lr.score(x_test,y_test))
```

```
1.0
```

In [20]:

```
coeff=pd.DataFrame(lr.coef_)
coeff
```

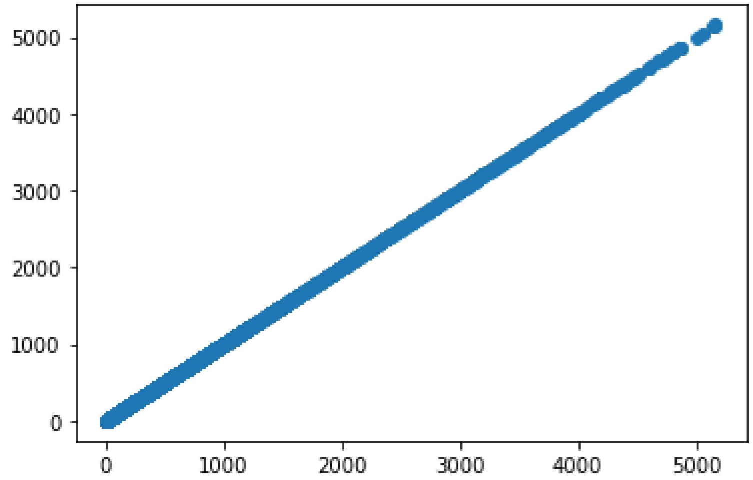
Out[20]:

	0	1	2	3
0	-4.790455e-18	-2.086311e-15	1.0	3.596789e-16

In [21]:

```
pred = lr.predict(x_test)
plt.scatter(y_test,pred)
```

Out[21]: `<matplotlib.collections.PathCollection at 0x22049fbc700>`



In [22]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [23]:

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[23]: `Ridge(alpha=10)`

In [24]:

```
rr.score(x_test,y_test)
```

Out[24]: `0.9999999999999976`

In [25]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[25]: `Lasso(alpha=10)`

In [26]:

```
la.score(x_test,y_test)
```

Out[26]: `0.9999999898844992`

ELASTICNET

In [27]:
```python
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```
Out[27]:
```
ElasticNet()
```

In [28]:
```python
print(en.coef_)
```
```
[ 9.54623262e-08 -0.00000000e+00  9.99925944e-01  6.88589296e-05]
```

In [29]:
```python
print(en.intercept_)
```
```
[-0.00056341]
```

In [30]:
```python
prediction=en.predict(x_test)
prediction
```
Out[30]:
```
array([1.88000519e+02, 1.00015563e+01, 1.00000185e+02, ...,
       7.29909478e-04, 1.17999504e+02, 1.09994261e+01])
```

In [31]:
```python
print(en.score(x_test,y_test))
```
```
0.9999999999660899
```

EVALUATION METRICS

In [32]:
```python
from sklearn import metrics
```

In [33]:
```python
print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
```
```
Mean Absolute Error: 0.001294558105316059
```

In [34]:

```
print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
Mean Squared Error: 3.401356044107772e-06
```

In [35]:

```
print("Root Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
Root Mean Squared Error: 3.401356044107772e-06
```