reg_year_r_2011

January 31, 2024

0.1 Importing

[ ]:
```
import xarray as xr
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.ensemble import BaggingRegressor
from sklearn.tree import ExtraTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn import preprocessing

from sklearn.metrics import mean_squared_error as mse

import os
```

0.2 Datasets Preparation (Training)

[ ]:
```
def datasets_preparation ():

    # Dataset and date
    ds_name = ('/results2/SalishSea/nowcast-green.202111/' + i + '/
 ↪SalishSea_1d_' + '20' + str(i[5:7]) + str(dict_month[i[2:5]])+str(i[0:2]) +␣
 ↪'_' + '20' + str(i[5:7]) + str(dict_month[i[2:5]]) + str(i[0:2]) + '_grid_T.
 ↪nc')

    ds_bio_name = ('/results2/SalishSea/nowcast-green.202111/' + i + '/
 ↪SalishSea_1d_'  + '20' + str(i[5:7]) + str(dict_month[i[2:5]])+str(i[0:2]) +␣
 ↪'_' + '20' + str(i[5:7]) + str(dict_month[i[2:5]]) + str(i[0:2]) + '_biol_T.
 ↪nc')

    ds = xr.open_dataset (ds_name)
    ds_bio = xr. open_dataset (ds_bio_name)

    temp_i1 = (ds.votemper.where(mask==1)[0,0:15] * ds.e3t.where(mask==1)
```

```
            [0,0:15]).sum('deptht', skipna = True, min_count = 15) / mesh.
↪gdepw_0[0,15]
    temp_i2 = (ds.votemper.where(mask==1)[0,15:27] * ds.e3t.where(mask==1)
            [0,15:27]).sum('deptht', skipna = True, min_count = 12) / (mesh.
↪gdepw_0[0,27] - mesh.gdepw_0[0,14])
    saline_i1 = (ds.vosaline.where(mask==1)[0,0:15] * ds.e3t.where(mask==1)
                [0,0:15]).sum('deptht', skipna = True, min_count = 15) /␣
↪mesh.gdepw_0[0,15]
    saline_i2 = (ds.vosaline.where(mask==1)[0,15:27] * ds.e3t.where(mask==1)
                [0,15:27]).sum('deptht', skipna = True, min_count = 12) /␣
↪(mesh.gdepw_0[0,27] - mesh.gdepw_0[0,14])

    diat_i = (ds_bio.diatoms.where(mask==1)[0,0:27] * ds.e3t.where(mask==1)
            [0,0:27]).sum('deptht', skipna = True, min_count = 27) / mesh.
↪gdepw_0[0,27]
    flag_i = (ds_bio.flagellates.where(mask==1)[0,0:27] * ds.e3t.where(mask==1)
            [0,0:27]).sum('deptht', skipna = True, min_count = 27) / mesh.
↪gdepw_0[0,27]

    return (temp_i1, temp_i2, saline_i1, saline_i2, diat_i, flag_i)
```

0.3 Regressor

[ ]:
```
def regressor (inputs, targets, variable_name):

    inputs = inputs.transpose()

    # Regressor
    scale = preprocessing.StandardScaler()
    inputs2 = scale.fit_transform(inputs)
    X_train, X_test, y_train, y_test = train_test_split(inputs2, targets)

    extra_tree = ExtraTreeRegressor(criterion='poisson')
    regr = BaggingRegressor(extra_tree, n_estimators=10, max_features=4).
↪fit(X_train, y_train)

    outputs_test = regr.predict(X_test)

    m = scatter_plot(y_test, outputs_test, variable_name + ' (Testing dataset)')
    r = np.round(np.corrcoef(y_test, outputs_test)[0][1],3)
    rms = np.round(mse(y_test, outputs_test),4)


    return (r, rms, m, regr)
```

1 Printing

[ ]:
```
def printing (targets, outputs, m):

    print ('The amount of data points is', outputs.size)
    print ('The slope of the best fitting line is ', np.round(m,3))
    print ('The correlation coefficient is:', np.round(np.corrcoef(targets,␣
 ↪outputs)[0][1],3))
    print (' The mean square error is:', np.round(mse(targets,outputs),5))
```

1.1 Scatter Plot

[ ]:
```
def scatter_plot(targets, outputs, variable_name):

    # compute slope m and intercept b
    m, b = np.polyfit(targets, outputs, deg=1)

    printing (targets, outputs, m)

    fig, ax = plt.subplots()

    plt.scatter(targets,outputs, alpha = 0.2, s = 10)
    plt.xlabel('targets')
    plt.ylabel('outputs')

    lims = [
        np.min([ax.get_xlim(), ax.get_ylim()]),  # min of both axes
        np.max([ax.get_xlim(), ax.get_ylim()]),  # max of both axes
    ]

    # plot fitted y = m*x + b
    plt.axline(xy1=(0, b), slope=m, color='r')

    ax.set_aspect('equal')
    ax.set_xlim(lims)
    ax.set_ylim(lims)

    ax.plot(lims, lims,linestyle = '--',color = 'k')

    fig.suptitle(str(year) + ', ' + variable_name)

    plt.show()

    return (m)
```

1.2 Plotting

[ ]:
```
def plotting (variable, name):

    plt.plot(years,variable, marker = '.', linestyle = '')
    plt.legend(['diatom','flagellate'])
    plt.xlabel('Years')
    plt.ylabel(name)
    plt.show()
```

1.3 Regressor 2

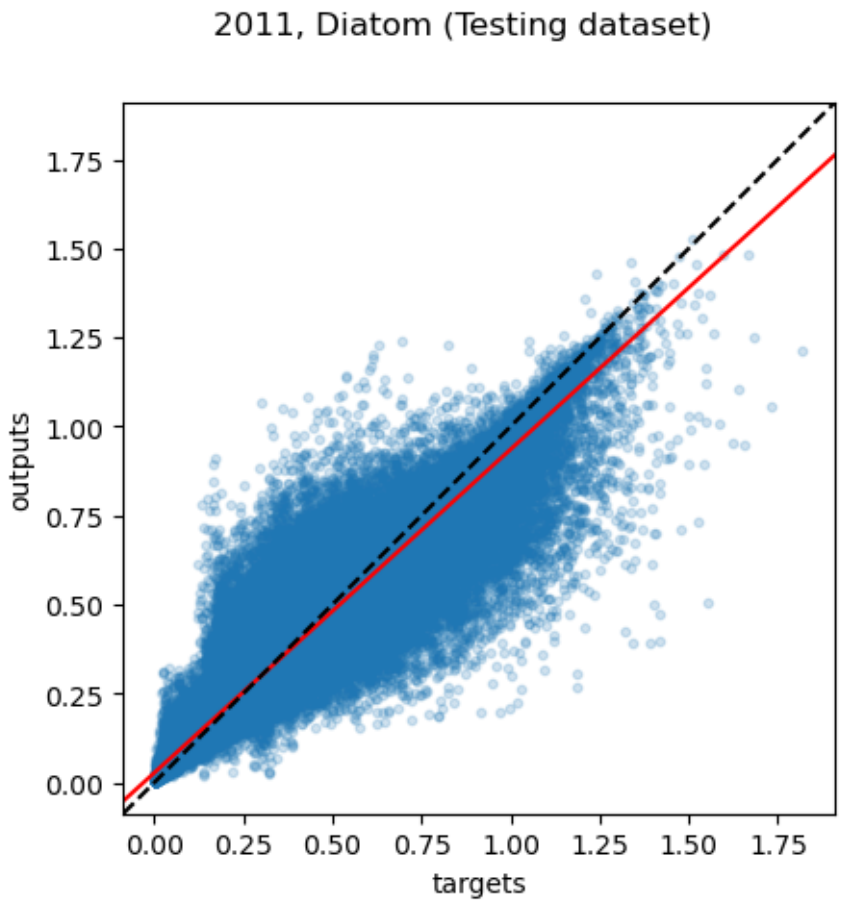
[ ]:
```
def regressor2 (inputs, targets, variable_name):

    inputs = inputs.transpose()

    # Regressor
    scale = preprocessing.StandardScaler()
    inputs2 = scale.fit_transform(inputs)

    outputs_test = regr.predict(inputs2)

    m = scatter_plot(targets, outputs_test, variable_name + ' (Testing␣
 ↪dataset)')
    r = np.round(np.corrcoef(targets, outputs_test)[0][1],3)
    rms = np.round(mse(targets, outputs_test),4)

    return (r, rms, m)
```

1.4 Training of 2007

[ ]:
```
dict_month = {'jan': '01',
          'feb': '02',
          'mar': '03',
          'apr': '04',
          'may': '05',
          'jun': '06',
          'jul': '07',
          'aug': '08',
          'sep': '09',
          'oct': '10',
          'nov': '11',
          'dec': '12'}
```

```
path = os.listdir('/results2/SalishSea/nowcast-green.202111/')

# Open the mesh mask
mesh = xr.open_dataset('/home/sallen/MEOPAR/grid/mesh_mask202108.nc')
mask = mesh.tmask.to_numpy()

year = 2014

year_str = str(year)[2:4]

folders = [x for x in path if ((x[2:5]=='mar' or x[2:5]=='apr' or (x[2:
 ↪5]=='feb' and x[0:2] > '14')) and (x[5:7]==year_str))]
indx_dates=(np.argsort(pd.to_datetime(folders, format="%d%b%y")))
folders = [folders[i] for i in indx_dates]

drivers_all = np.array([[],[],[],[]])
diat_all = np.array([])

print ('Gathering days for year ' + str(year))

for i in folders:

    temp_i1, temp_i2, saline_i1, saline_i2, flag_i = datasets_preparation()

    drivers = np.stack([np.ravel(temp_i1), np.ravel(temp_i2), np.
 ↪ravel(saline_i1), np.ravel(saline_i2)])
    indx = np.where(~np.isnan(drivers).any(axis=0))
    drivers = drivers[:,indx[0]]
    drivers_all = np.concatenate((drivers_all,drivers),axis=1)

    flag = np.ravel(flag_i)
    flag = [indx[0]]
    diat_all = np.concatenate((diat_all,diat))

print ('Done gathering, building the prediction model')
print ('\n')

r, rms, m, regr = regressor(drivers_all, diat_all, 'Diatom')
```

```
Gathering days for year 2011
Done gathering, building the prediction model


The amount of data points is 871482
The slope of the best fitting line is  0.908
The correlation coefficient is: 0.958
 The mean square error is: 0.00199
```

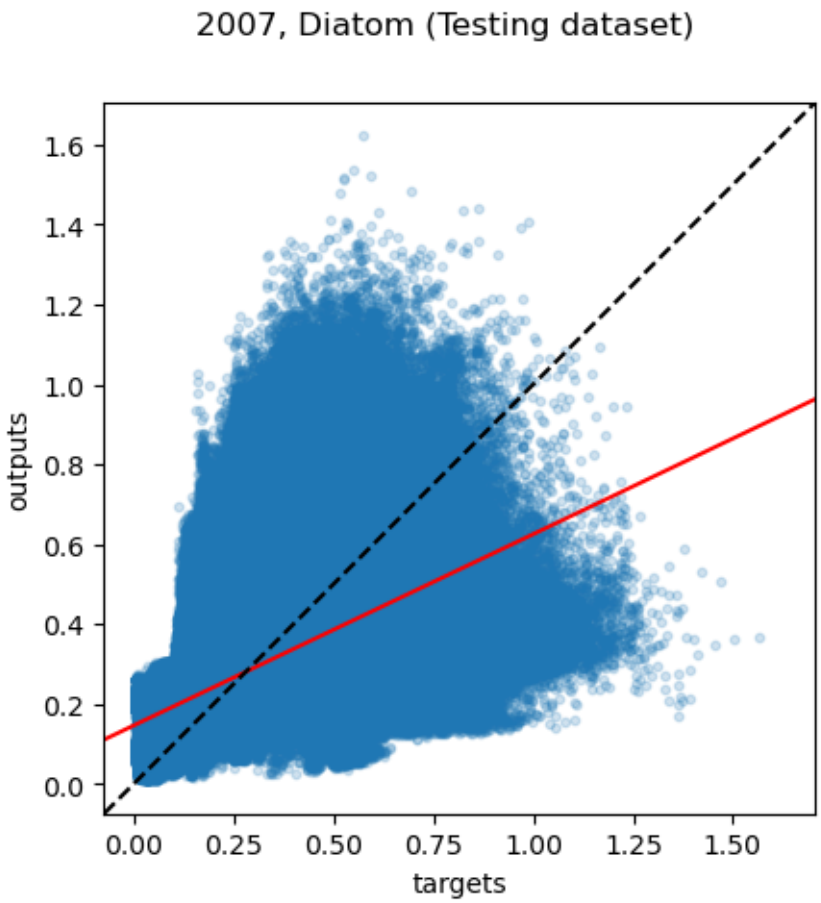


1.5 Other Years

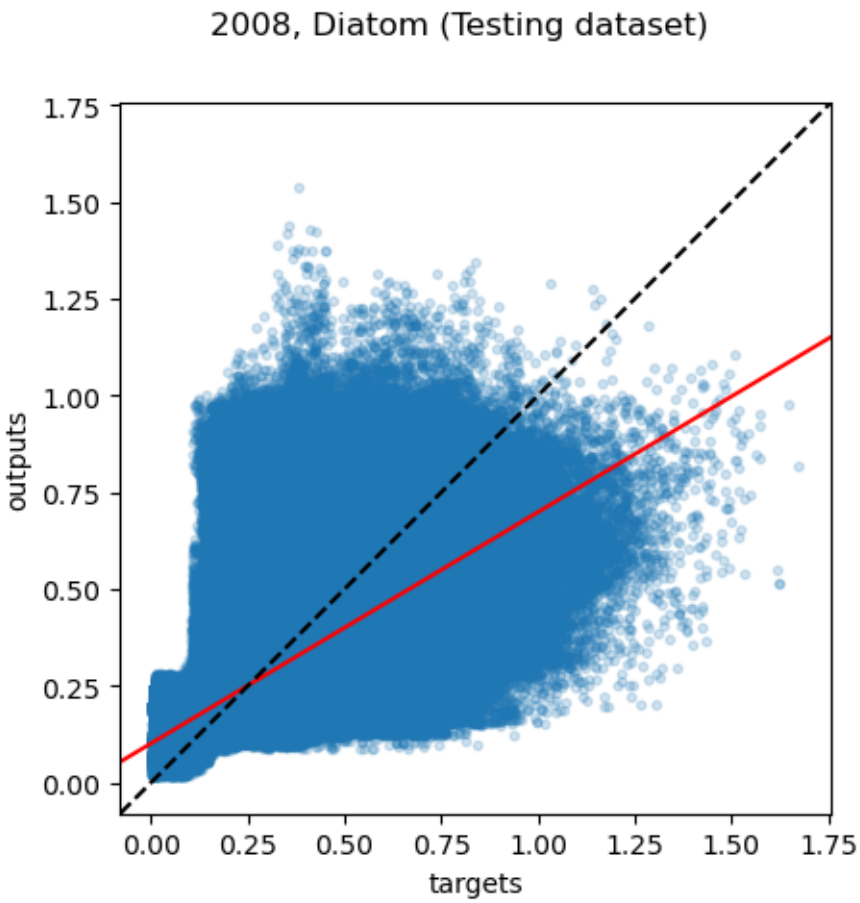
[ ]:
```
years = range (2007,2024)

r_all = []
rms_all = []
slope_all = []

for year in range (2007,2024):

    year_str = str(year)[2:4]

    folders = [x for x in path if ((x[2:5]=='mar' or x[2:5]=='apr' or (x[2:
↪5]=='feb' and x[0:2] > '14')) and (x[5:7]==year_str))]
    indx_dates=(np.argsort(pd.to_datetime(folders, format="%d%b%y")))
    folders = [folders[i] for i in indx_dates]
```

```
    drivers_all = np.array([[],[],[],[]])
    diat_all = np.array([])

    print ('Gathering days for year ' + str(year))
    for i in folders:

        temp_i1, temp_i2, saline_i1, saline_i2, diat_i, flag_i =␣
 ↪datasets_preparation()

        drivers = np.stack([np.ravel(temp_i1), np.ravel(temp_i2), np.
 ↪ravel(saline_i1), np.ravel(saline_i2)])
        indx = np.where(~np.isnan(drivers).any(axis=0))
        drivers = drivers[:,indx[0]]
        drivers_all = np.concatenate((drivers_all,drivers),axis=1)

        diat = np.ravel(diat_i)
        diat = diat[indx[0]]
        diat_all = np.concatenate((diat_all,diat))

    r, rms, m = regressor2(drivers_all, diat_all, 'Diatom')
    r_all.append(r)
    rms_all.append(rms)
    slope_all.append(m)

plotting(np.transpose(r_all), 'Correlation Coefficient')
plotting(np.transpose(rms_all), 'Mean Square Error')
plotting (np.transpose(slope_all), 'Slope of the best fitting line')
```

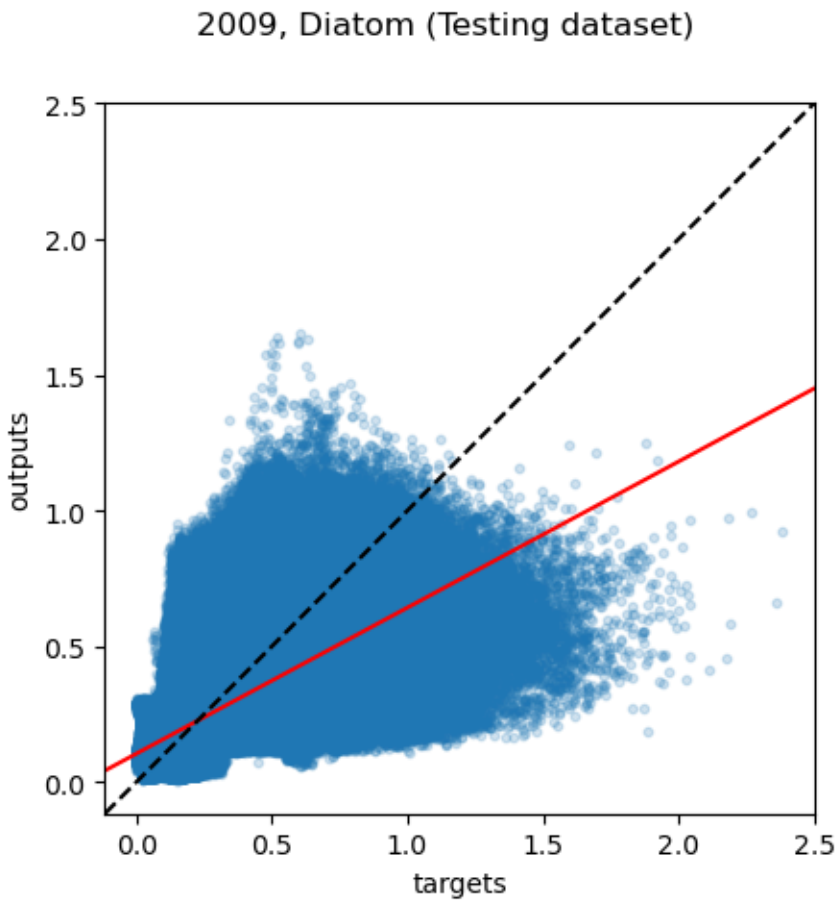
```
Gathering days for year 2007
The amount of data points is 3485925
The slope of the best fitting line is  0.479
The correlation coefficient is: 0.511
 The mean square error is: 0.02418
```



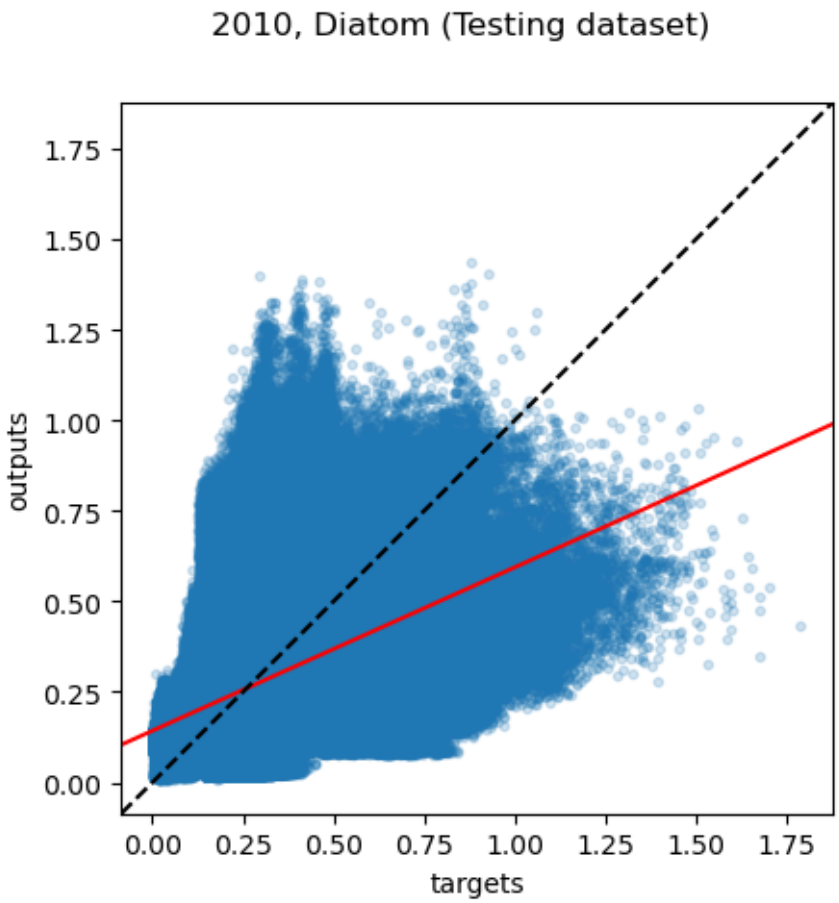

```
Gathering days for year 2008
The amount of data points is 3532404
The slope of the best fitting line is  0.598
The correlation coefficient is: 0.577
 The mean square error is: 0.01982
```



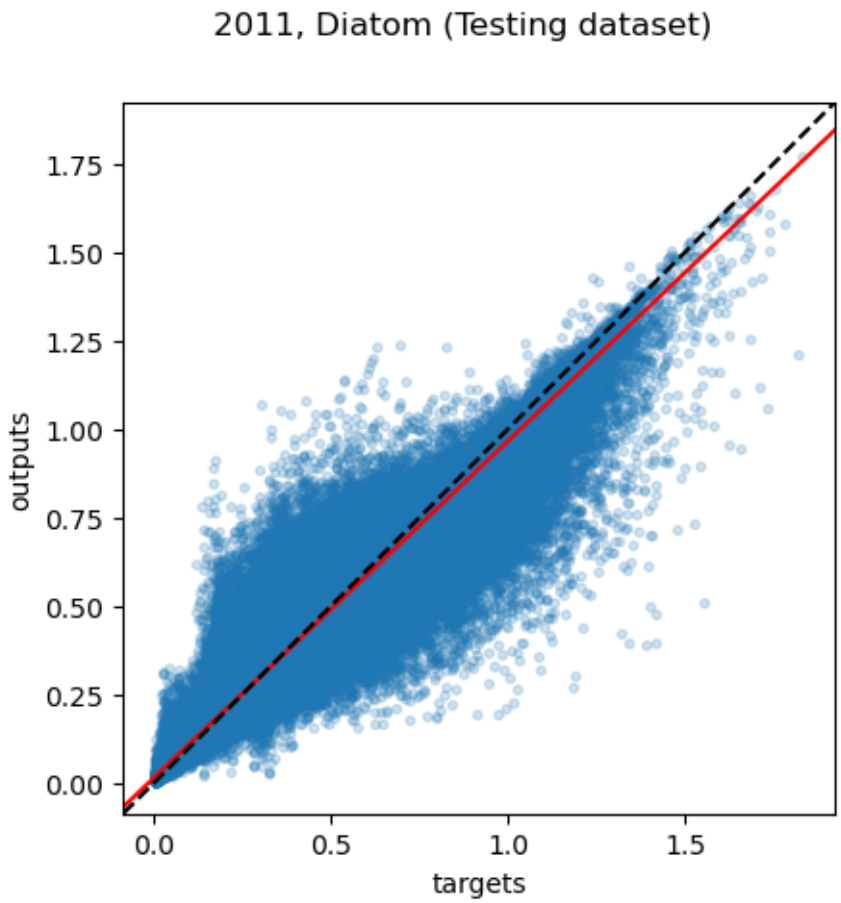

```
Gathering days for year 2009
The amount of data points is 3485925
The slope of the best fitting line is  0.538
The correlation coefficient is: 0.671
 The mean square error is: 0.0251
```



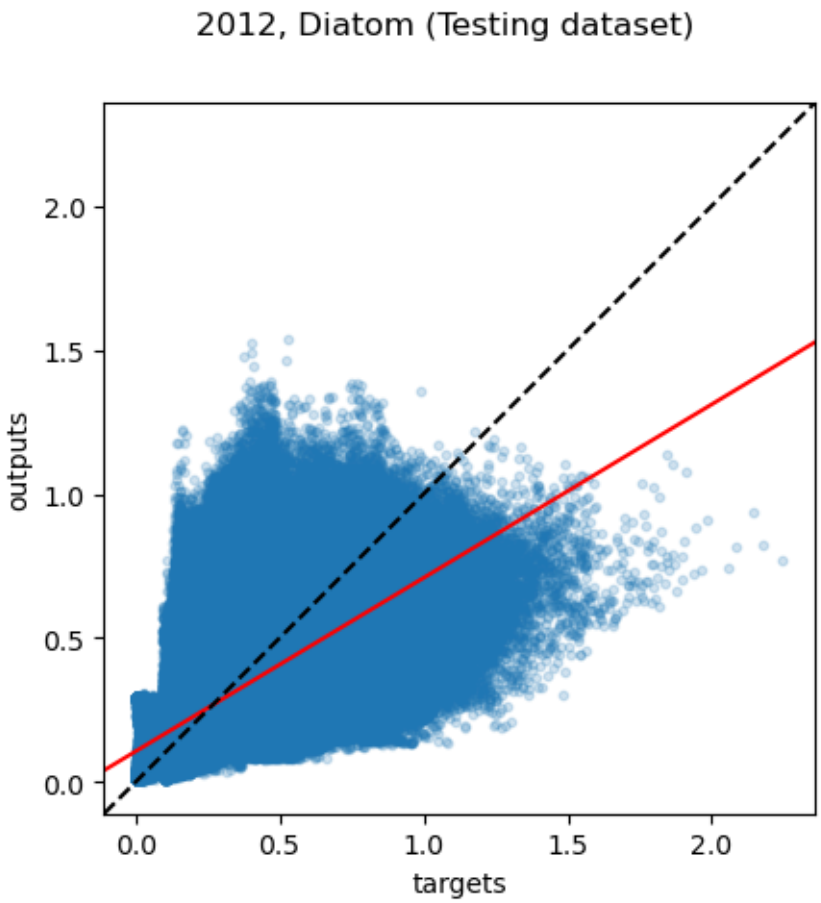

```
Gathering days for year 2010
The amount of data points is 3485925
The slope of the best fitting line is  0.451
The correlation coefficient is: 0.468
 The mean square error is: 0.02277
```



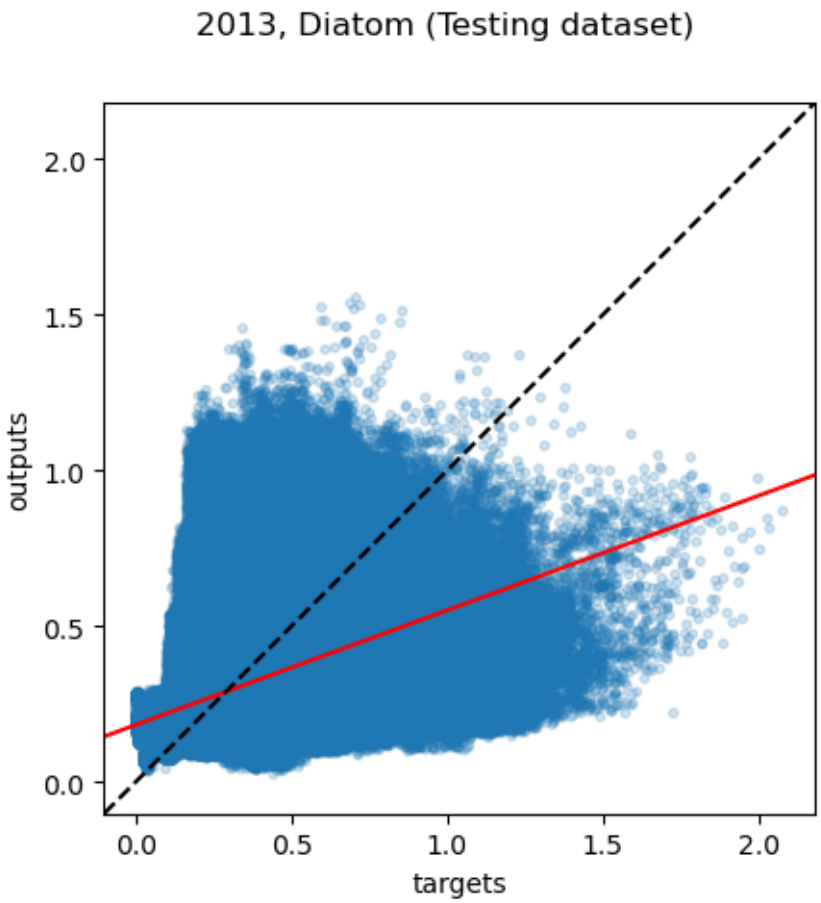

```
Gathering days for year 2011
The amount of data points is 3485925
The slope of the best fitting line is  0.952
The correlation coefficient is: 0.984
 The mean square error is: 0.00078
```



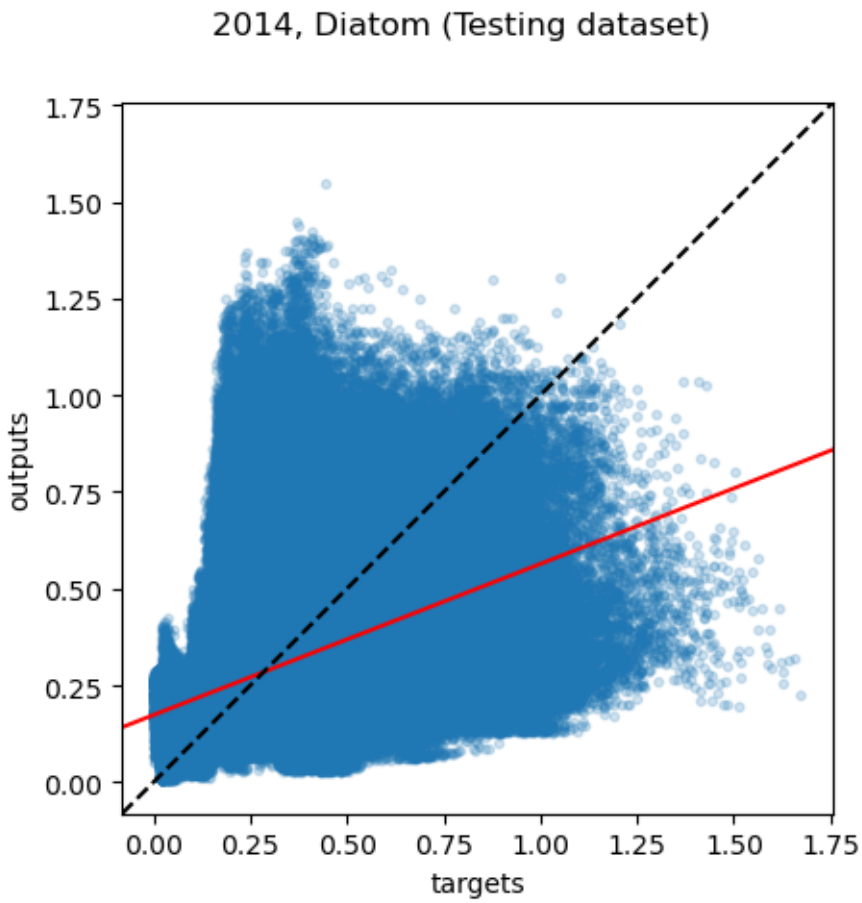

```
Gathering days for year 2012
The amount of data points is 3532404
The slope of the best fitting line is  0.602
The correlation coefficient is: 0.625
 The mean square error is: 0.01825
```



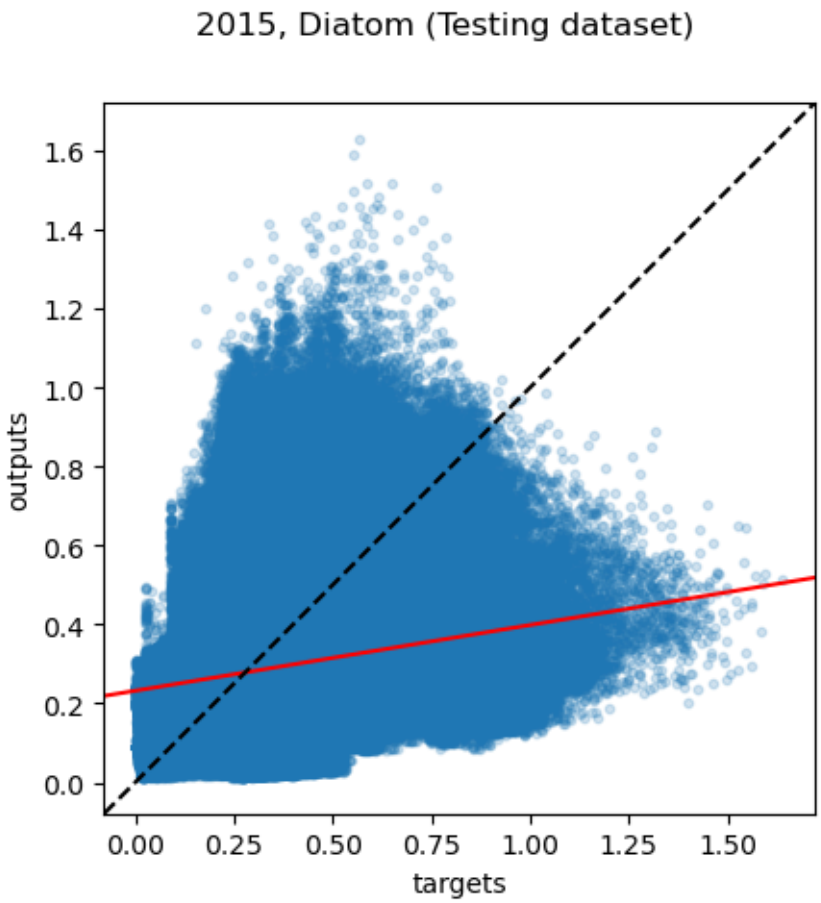

```
Gathering days for year 2013
The amount of data points is 3485925
The slope of the best fitting line is  0.368
The correlation coefficient is: 0.429
 The mean square error is: 0.03215
```



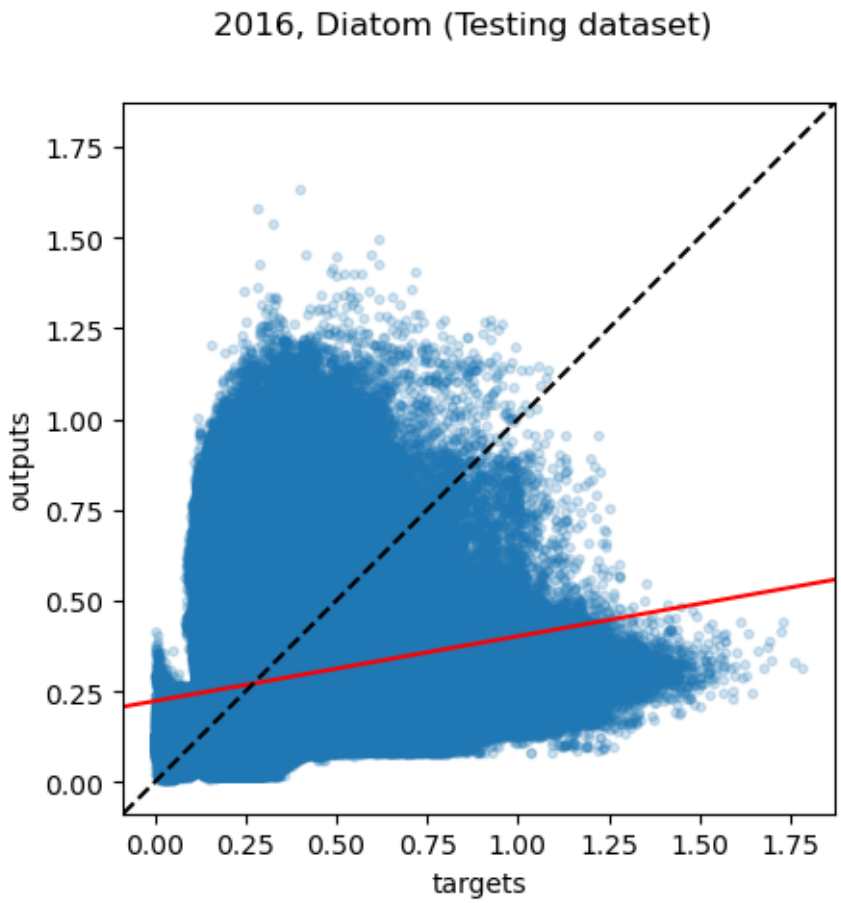

```
Gathering days for year 2014
The amount of data points is 3485925
The slope of the best fitting line is  0.391
The correlation coefficient is: 0.378
 The mean square error is: 0.0276
```



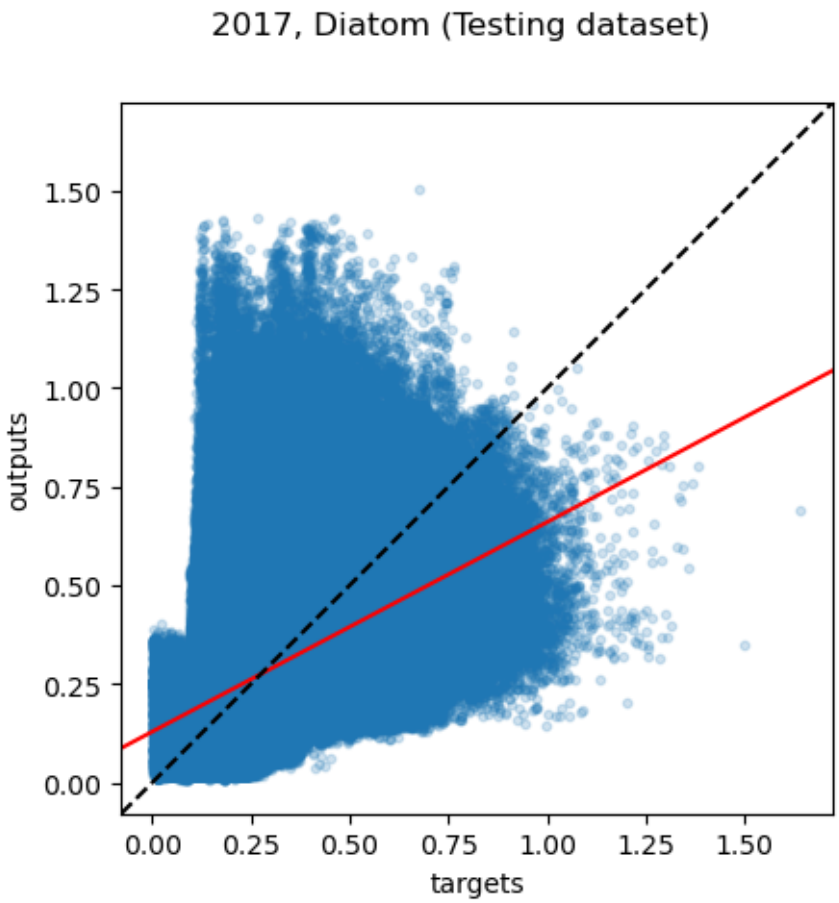

```
Gathering days for year 2015
The amount of data points is 3485925
The slope of the best fitting line is  0.166
The correlation coefficient is: 0.187
 The mean square error is: 0.03726
```



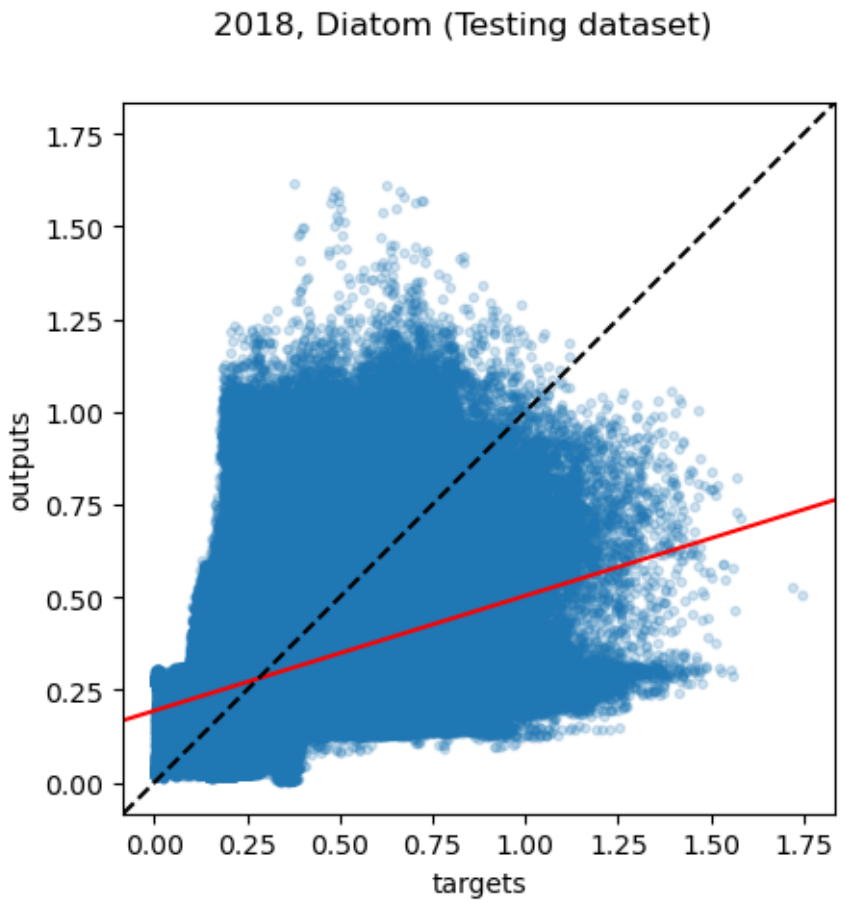

```
Gathering days for year 2016
The amount of data points is 3532404
The slope of the best fitting line is  0.179
The correlation coefficient is: 0.19
 The mean square error is: 0.04594
```



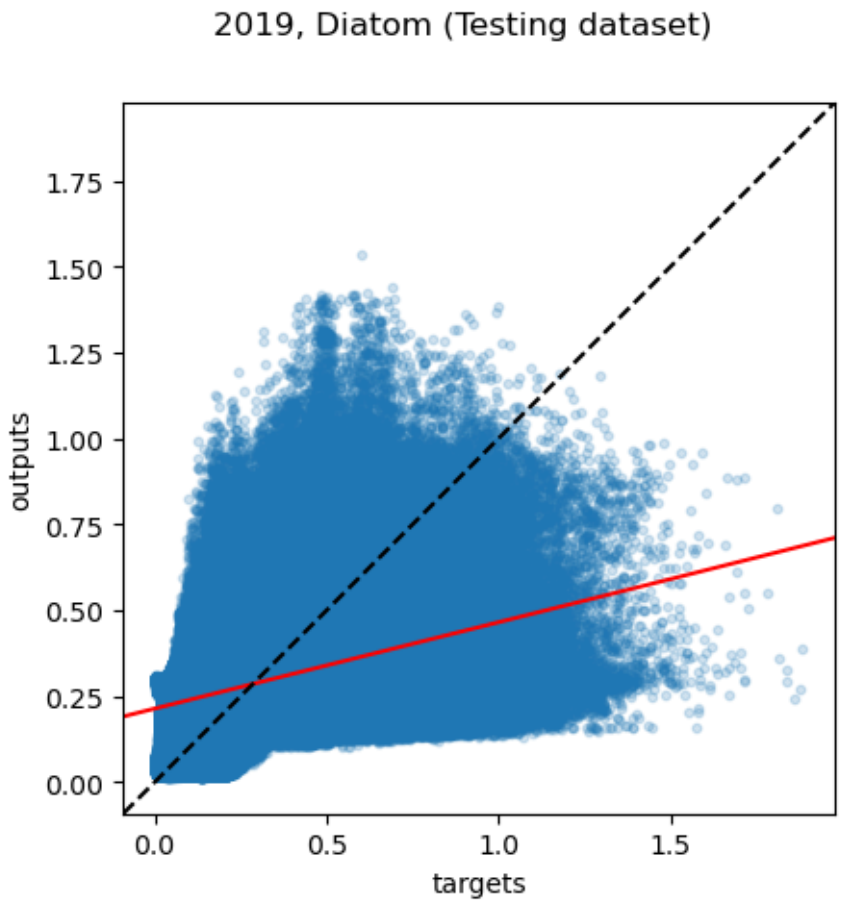

```
Gathering days for year 2017
The amount of data points is 3485925
The slope of the best fitting line is  0.531
The correlation coefficient is: 0.473
 The mean square error is: 0.02206
```



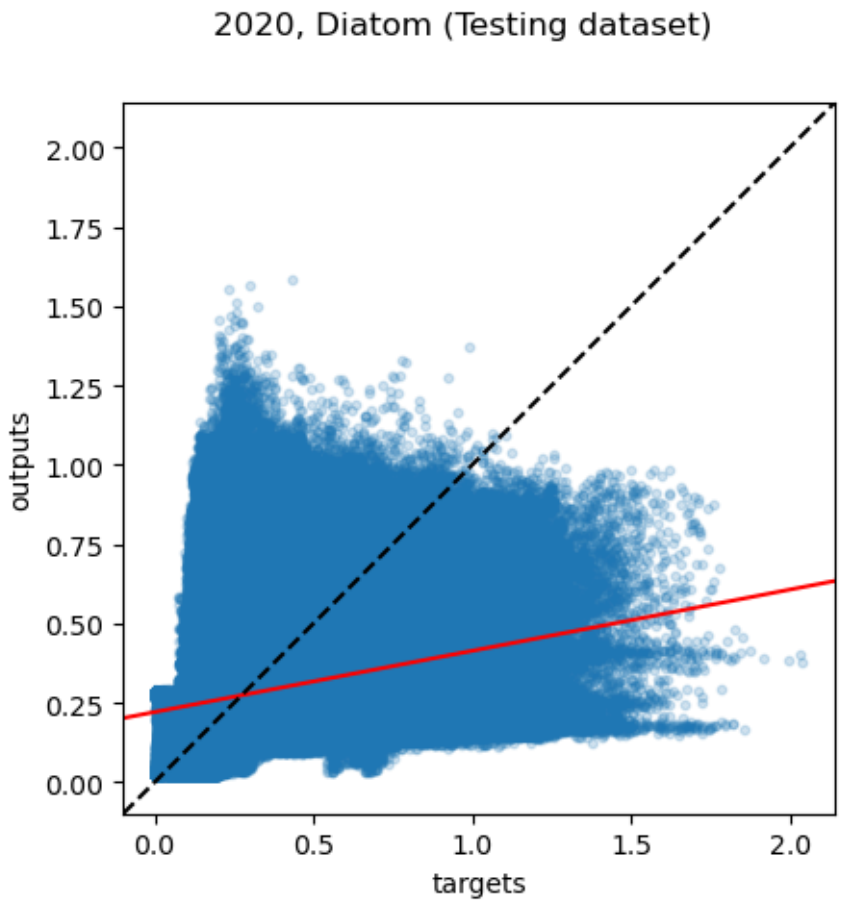

```
Gathering days for year 2018
The amount of data points is 3485925
The slope of the best fitting line is  0.31
The correlation coefficient is: 0.332
 The mean square error is: 0.03298
```



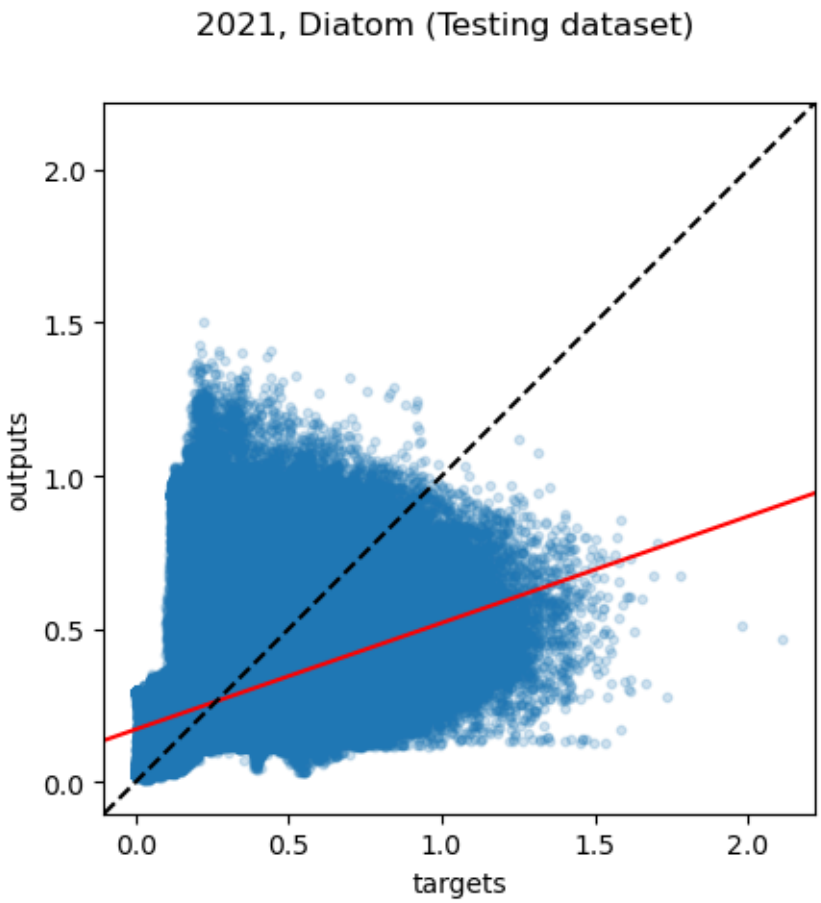

```
Gathering days for year 2019
The amount of data points is 3485925
The slope of the best fitting line is  0.251
The correlation coefficient is: 0.297
 The mean square error is: 0.04029
```



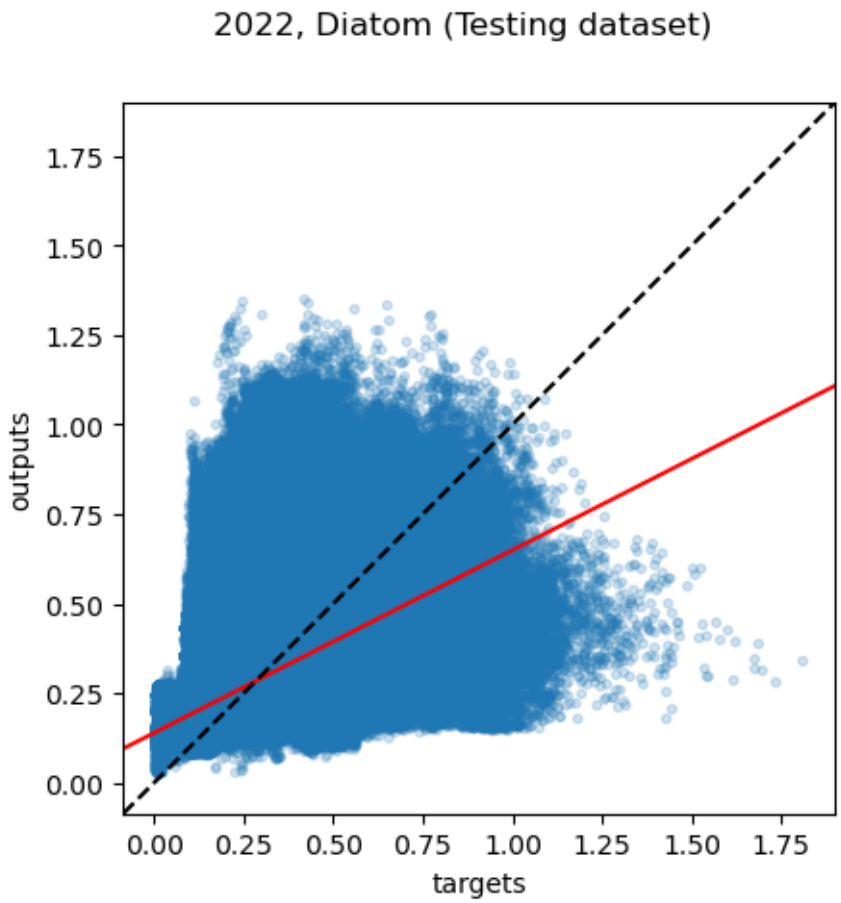

```
Gathering days for year 2020
The amount of data points is 3532404
The slope of the best fitting line is  0.193
The correlation coefficient is: 0.243
 The mean square error is: 0.05684
```



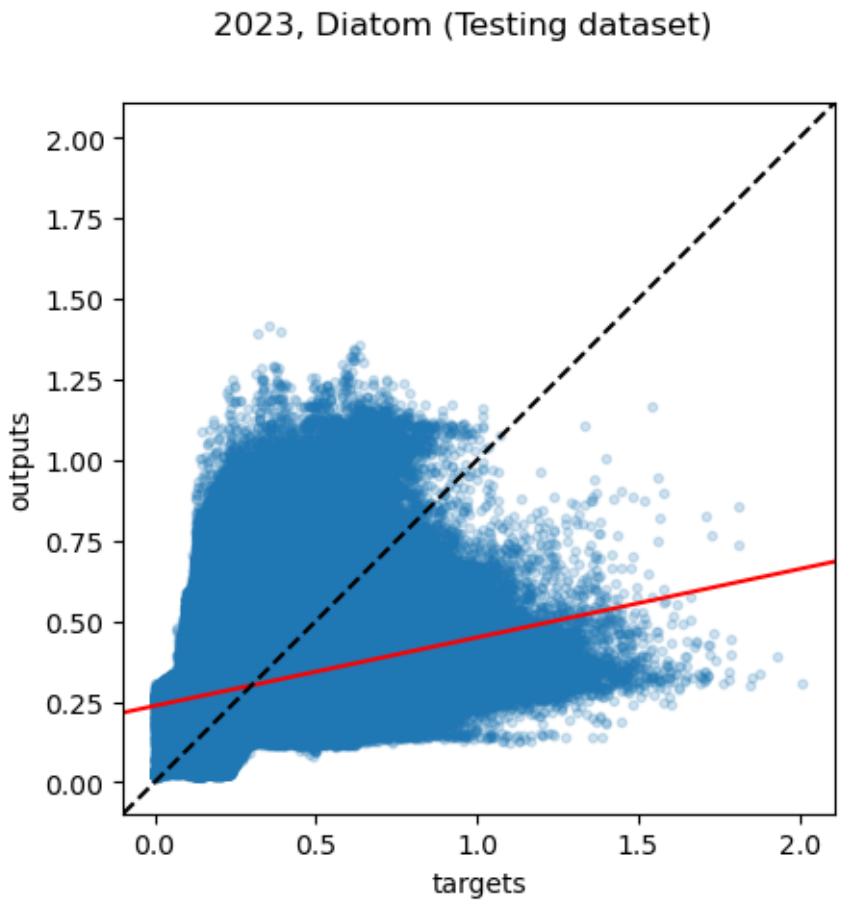

```
Gathering days for year 2021
The amount of data points is 3485925
The slope of the best fitting line is  0.348
The correlation coefficient is: 0.401
 The mean square error is: 0.03619
```

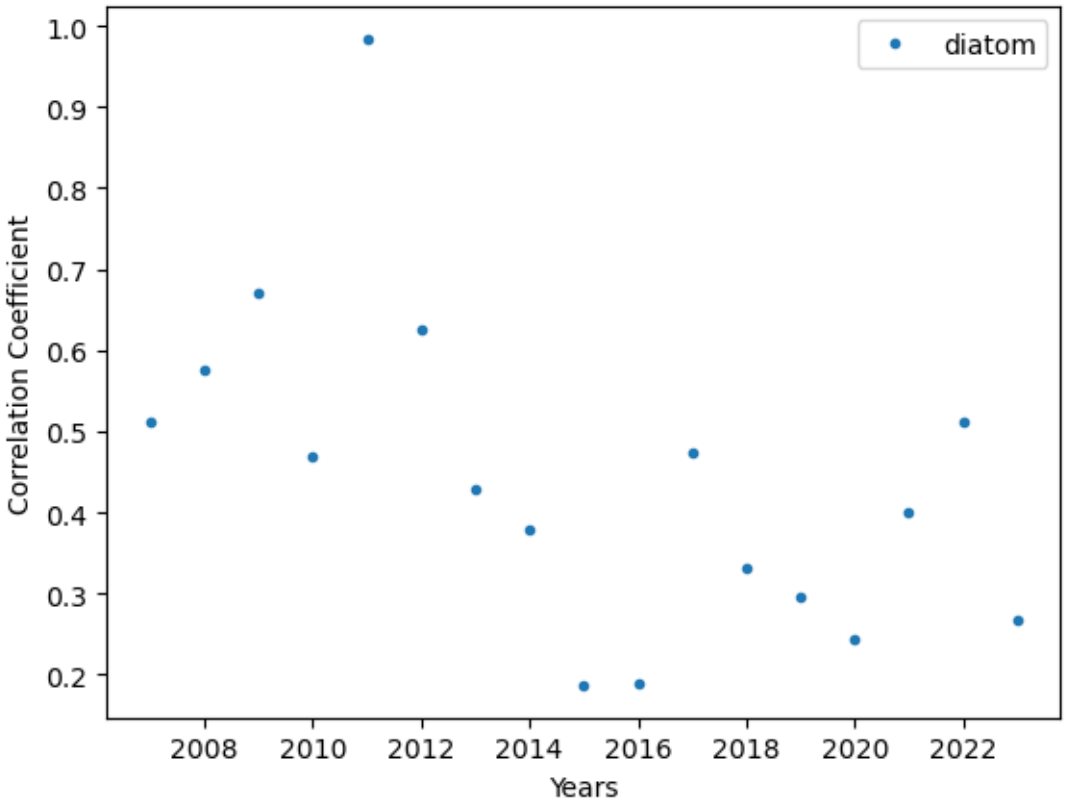


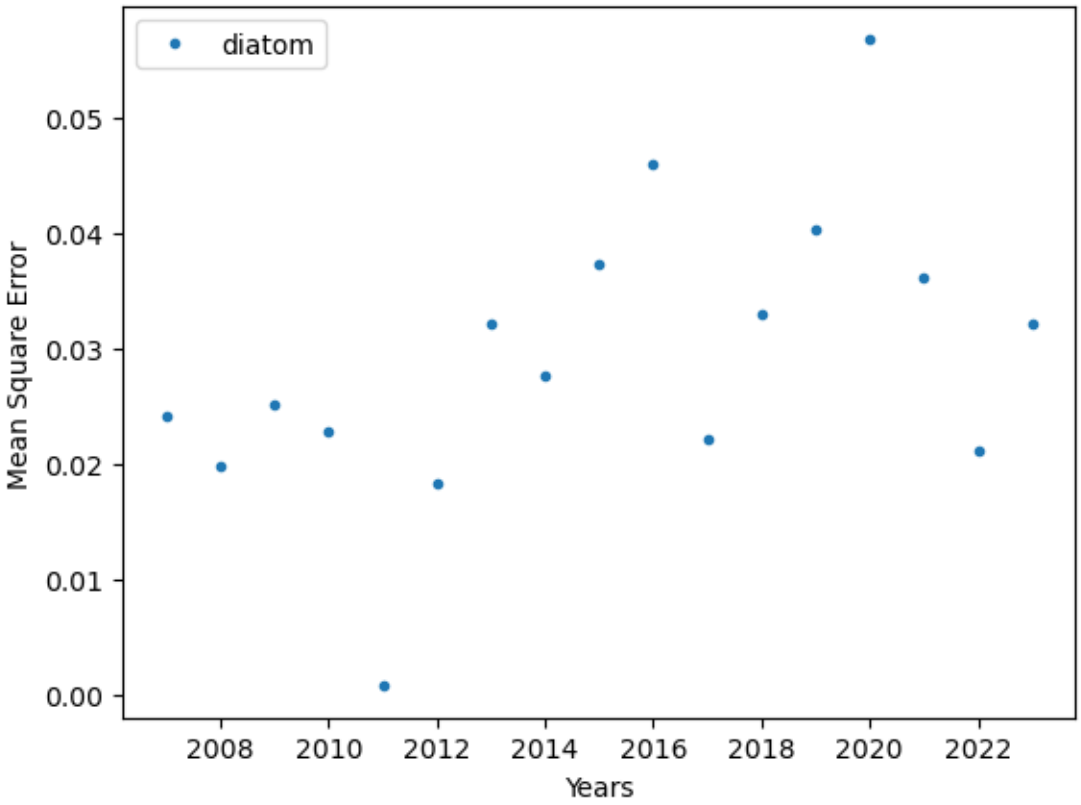

```
Gathering days for year 2022
The amount of data points is 3485925
The slope of the best fitting line is  0.51
The correlation coefficient is: 0.512
 The mean square error is: 0.02118
```

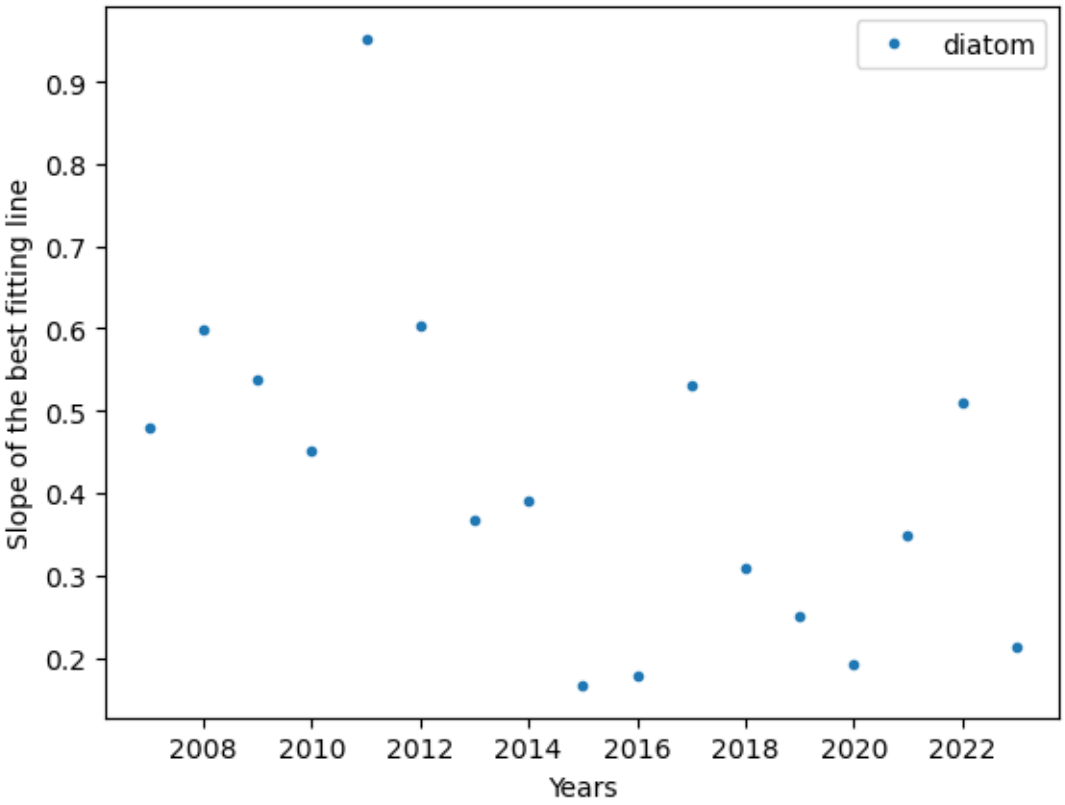



```
Gathering days for year 2023
The amount of data points is 3485925
The slope of the best fitting line is  0.212
The correlation coefficient is: 0.268
 The mean square error is: 0.0322
```


2023, Diatom (Testing dataset)
outputs
targets
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
1.5
2.0


diatom
Correlation Coefficient
Years
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
2008
2010
2012
2014
2016
2018
2020
2022


diatom
0.05
0.04
0.03
0.02
0.01
0.00
Mean Square Error
2008
2010
2012
2014
2016
2018
2020
2022
Years


diatom
Slope of the best fitting line
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
2008
2010
2012
2014
2016
2018
2020
2022
Years