reg_year_r_2011-2021

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)
```

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)
```

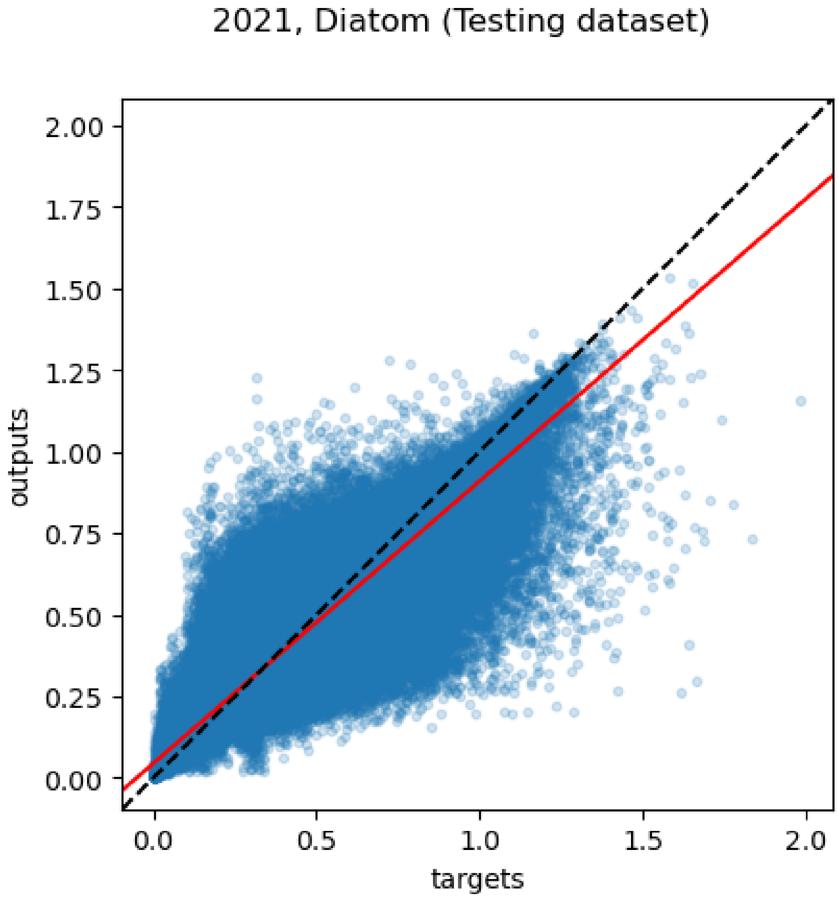
1.4 Training of 2007

[ ]:
```
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'}
```

```python
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()

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

for year in (2011, 2021):

    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]

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

    for i in folders:

        temp_i1, temp_i2, saline_i1, saline_i2, diat_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))

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

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

```
Gathering days for year 2011
Gathering days for year 2021
Done gathering, building the prediction model


The amount of data points is 1742963
The slope of the best fitting line is  0.865
The correlation coefficient is: 0.935
```

```
The mean square error is: 0.00358
```

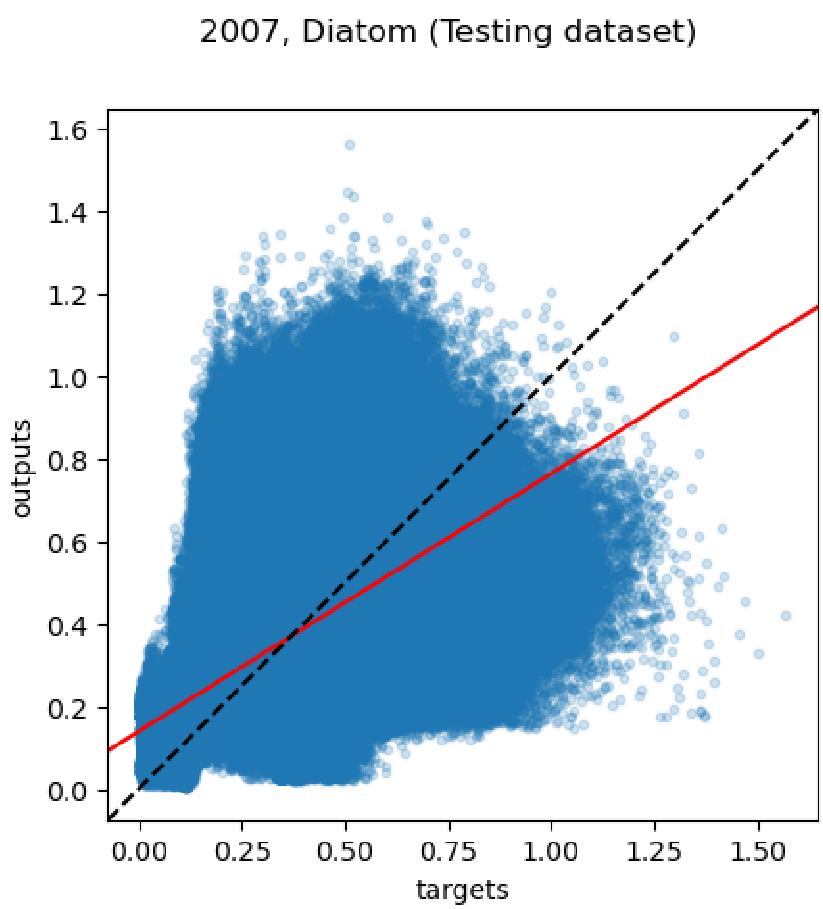


1.5 Other Years

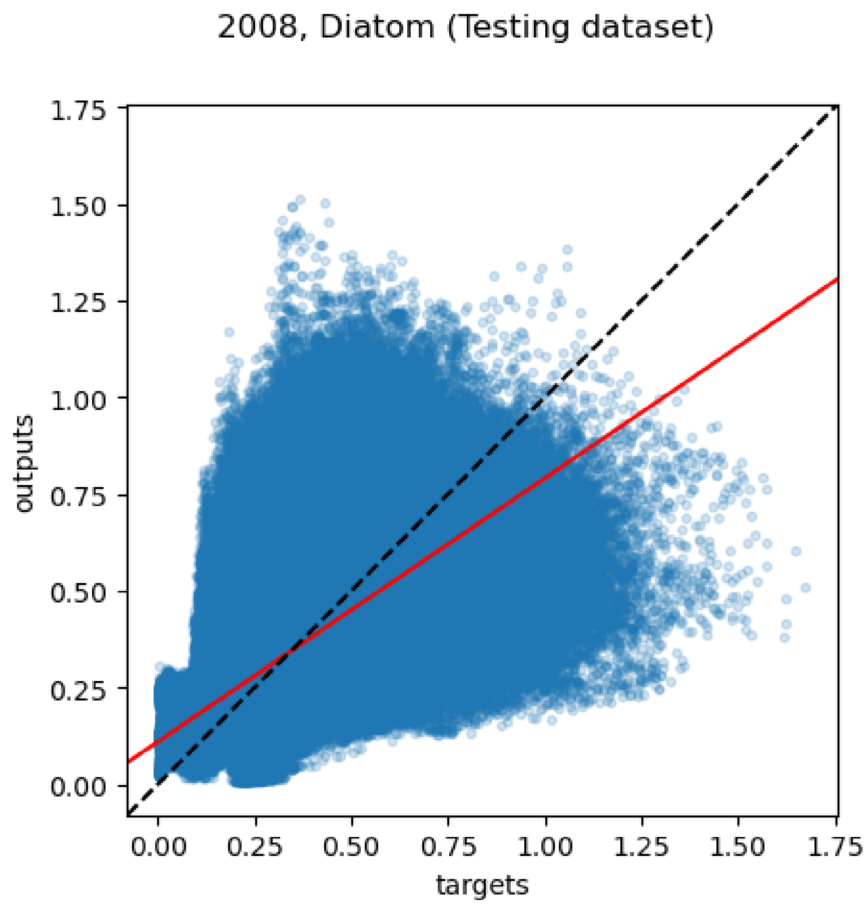
```
[ ]: years = range (2007,2024)

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 = 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')
```

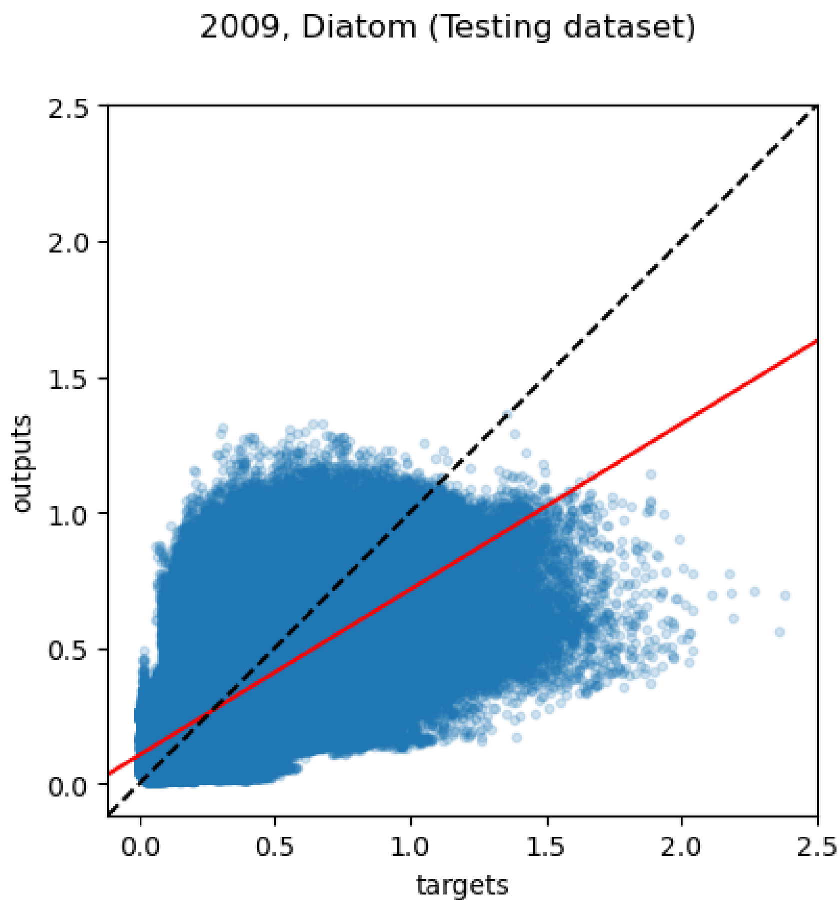
```
Gathering days for year 2007
The amount of data points is 3485925
The slope of the best fitting line is  0.624
The correlation coefficient is: 0.586
 The mean square error is: 0.02363
```



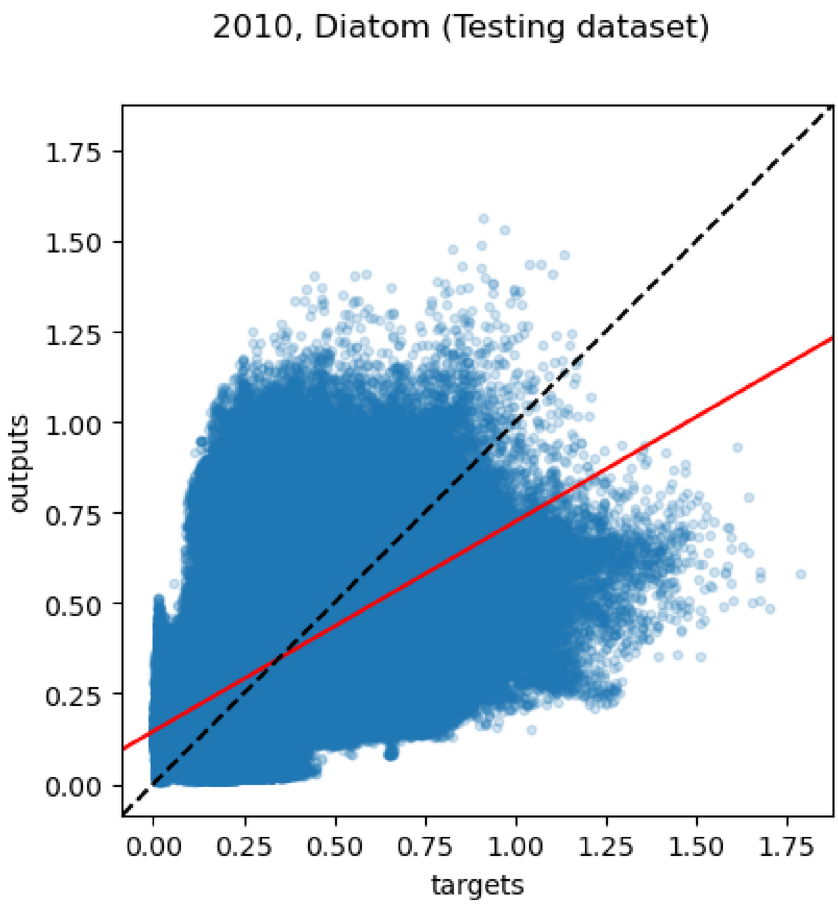

```
Gathering days for year 2008
The amount of data points is 3532404
The slope of the best fitting line is  0.681
The correlation coefficient is: 0.63
 The mean square error is: 0.01696
```



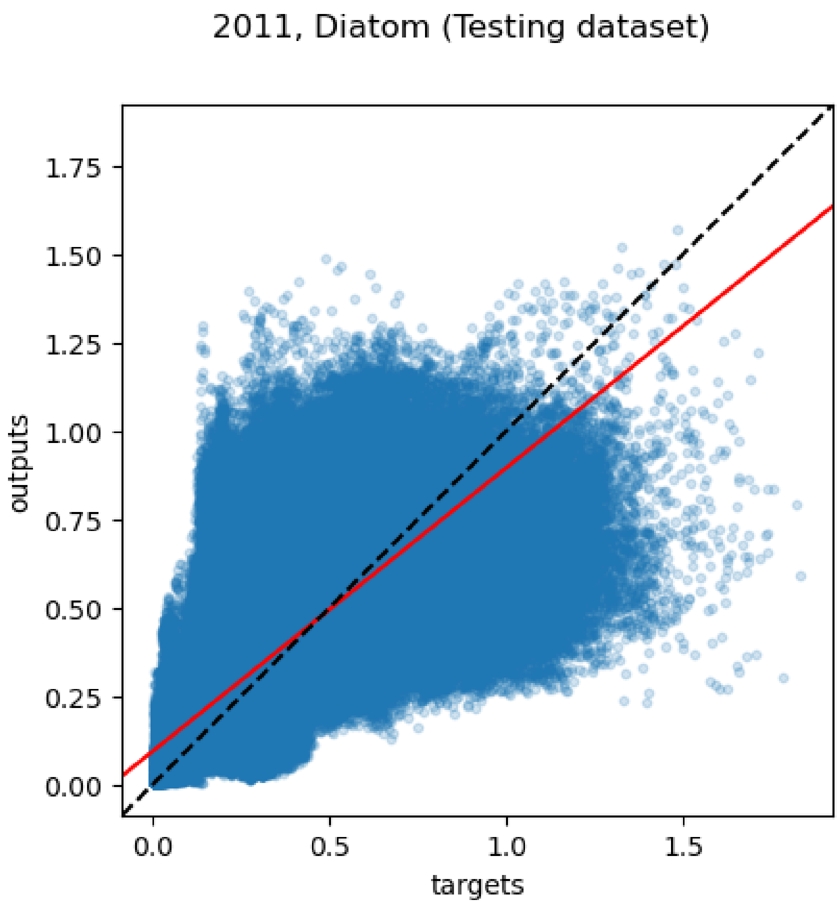

```
Gathering days for year 2009
The amount of data points is 3485925
The slope of the best fitting line is  0.611
The correlation coefficient is: 0.697
 The mean square error is: 0.02199
```



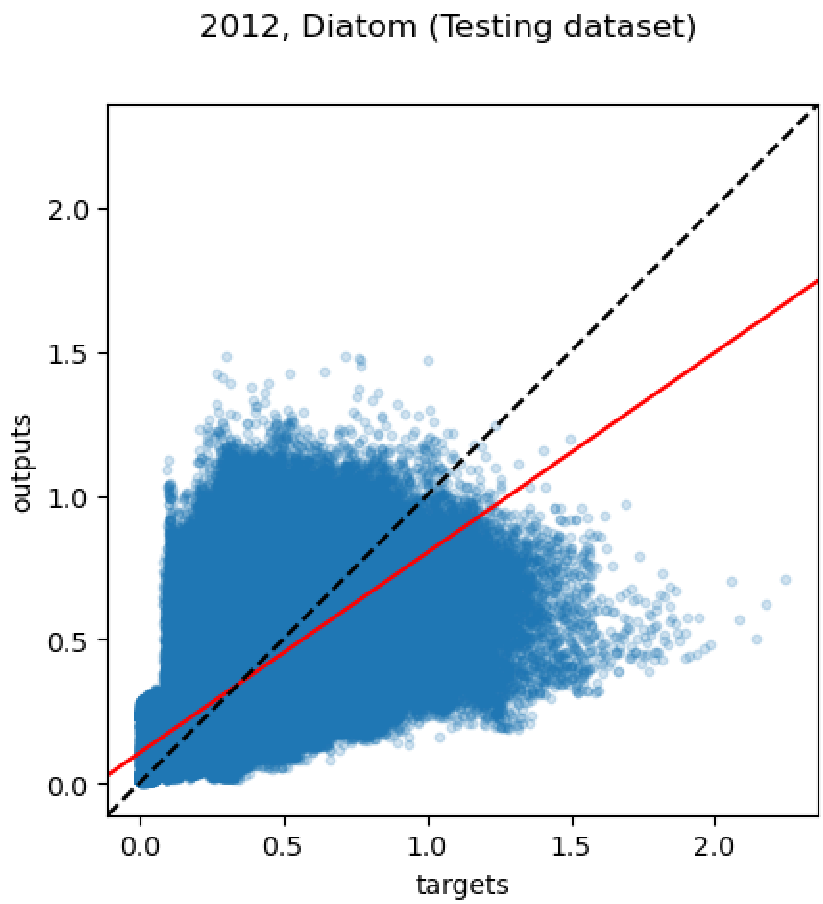

```
Gathering days for year 2010
The amount of data points is 3485925
The slope of the best fitting line is  0.579
The correlation coefficient is: 0.498
 The mean square error is: 0.02554
```




```
Gathering days for year 2011
The amount of data points is 3485925
The slope of the best fitting line is  0.802
The correlation coefficient is: 0.753
 The mean square error is: 0.01408
```

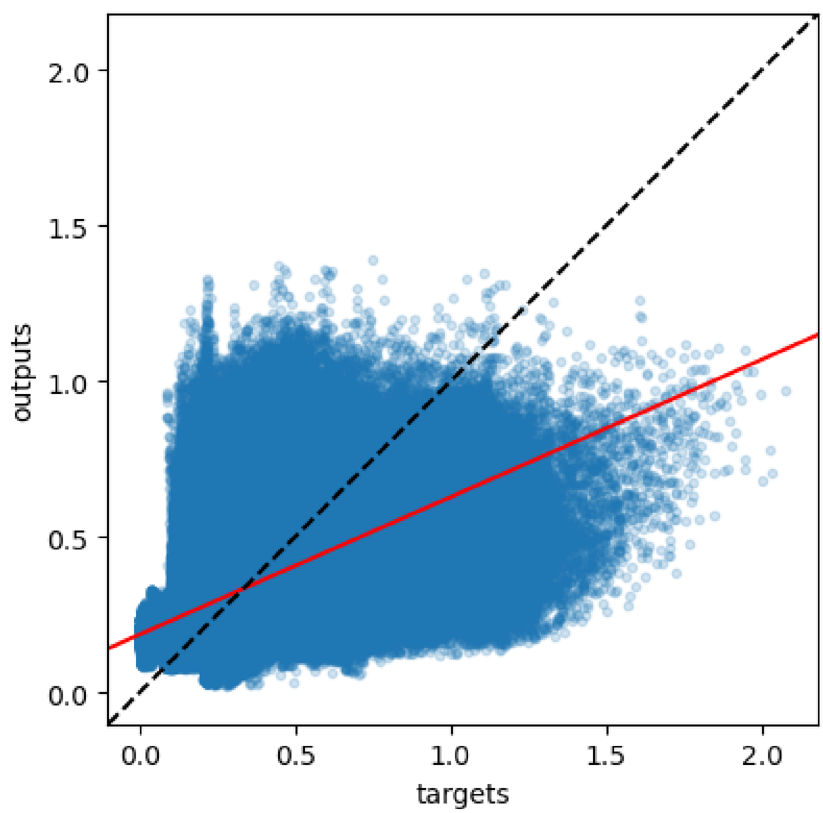



```
Gathering days for year 2012
The amount of data points is 3532404
The slope of the best fitting line is  0.696
The correlation coefficient is: 0.661
 The mean square error is: 0.0179
```

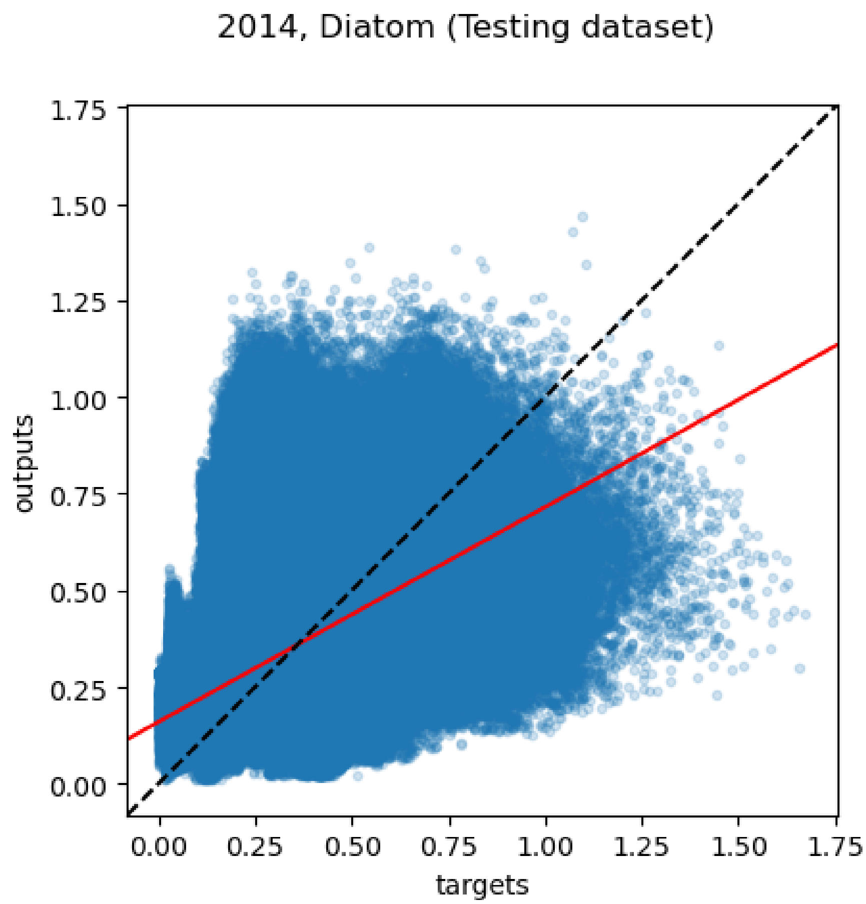



```
Gathering days for year 2013
The amount of data points is 3485925
The slope of the best fitting line is  0.442
The correlation coefficient is: 0.495
 The mean square error is: 0.02898
```

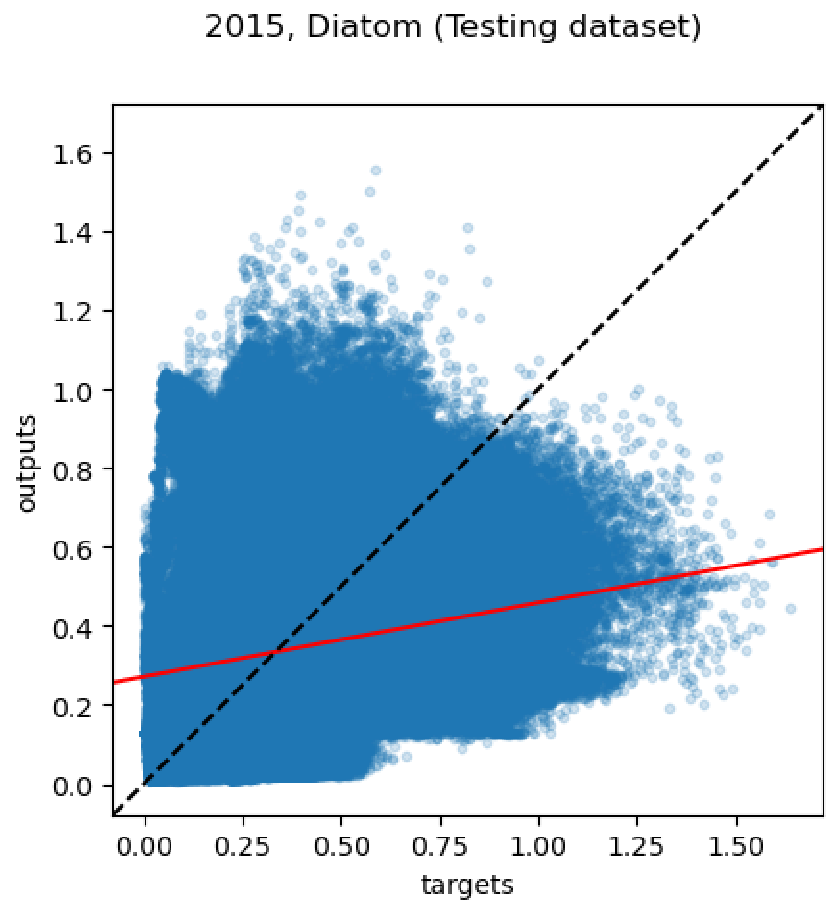
2013, Diatom (Testing dataset)



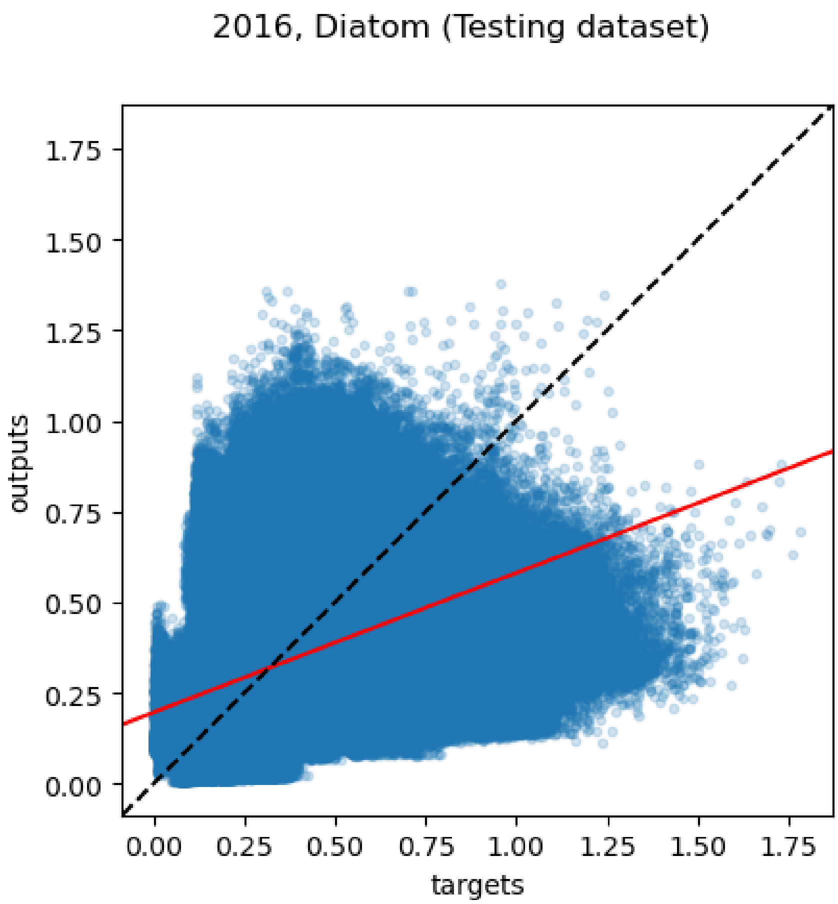

```
Gathering days for year 2014
The amount of data points is 3485925
The slope of the best fitting line is  0.555
The correlation coefficient is: 0.461
 The mean square error is: 0.02842
```




```
Gathering days for year 2015
The amount of data points is 3485925
The slope of the best fitting line is  0.187
The correlation coefficient is: 0.172
 The mean square error is: 0.04211
```

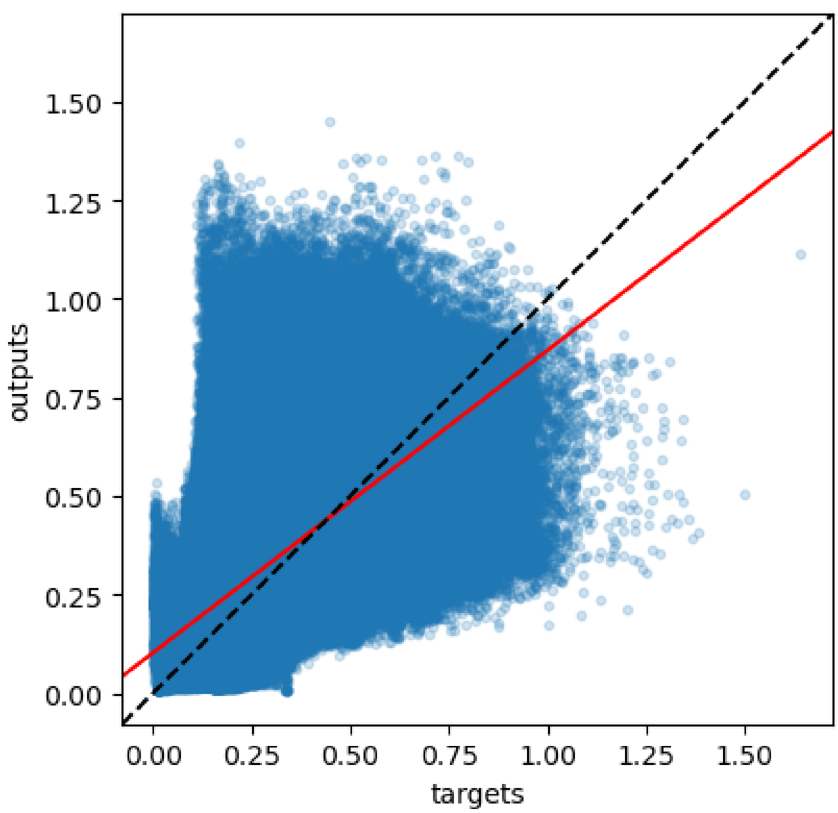



```
Gathering days for year 2016
The amount of data points is 3532404
The slope of the best fitting line is  0.385
The correlation coefficient is: 0.366
 The mean square error is: 0.0381
```

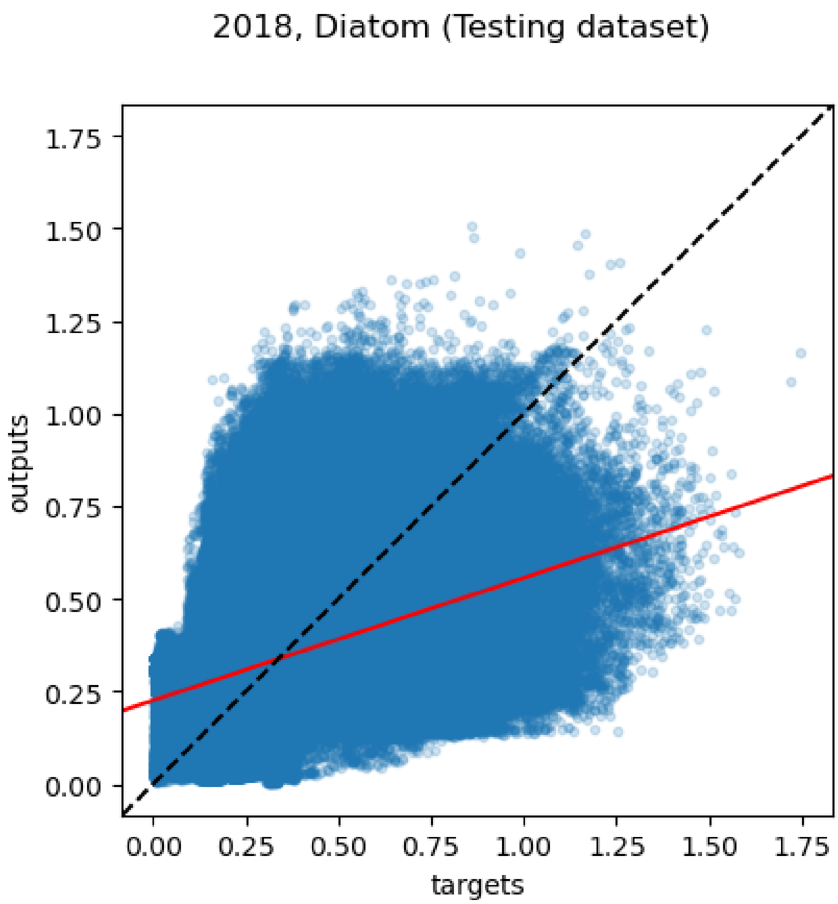



```
Gathering days for year 2017
The amount of data points is 3485925
The slope of the best fitting line is  0.767
The correlation coefficient is: 0.58
 The mean square error is: 0.02292
```

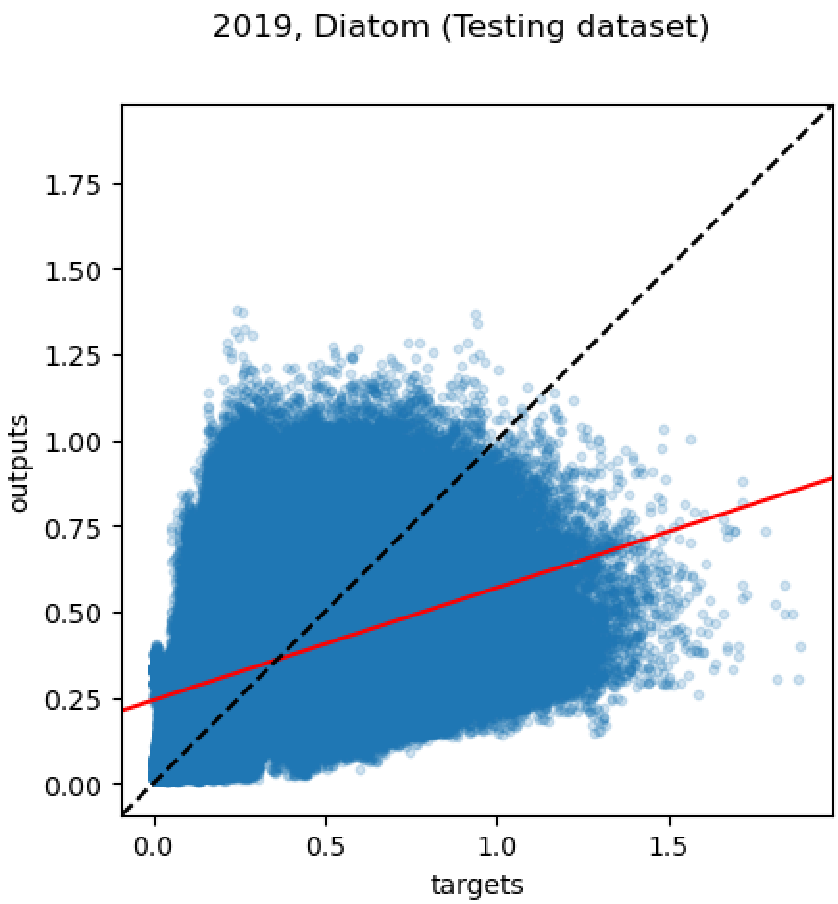
2017, Diatom (Testing dataset)



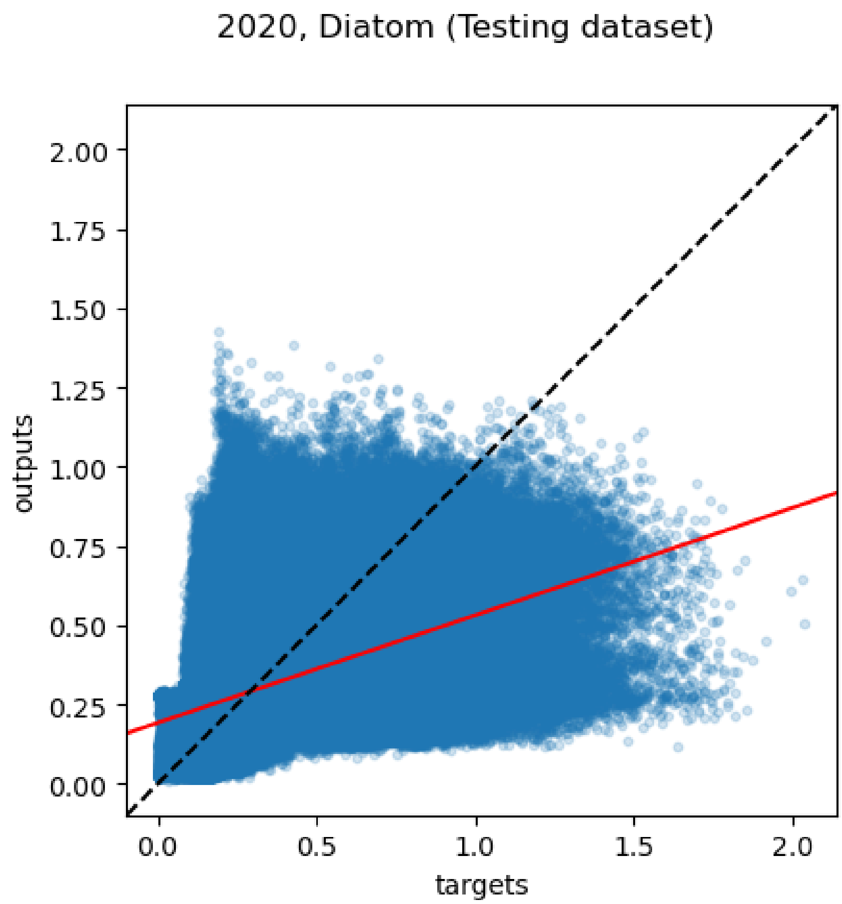

```
Gathering days for year 2018
The amount of data points is 3485925
The slope of the best fitting line is  0.331
The correlation coefficient is: 0.318
 The mean square error is: 0.03486
```



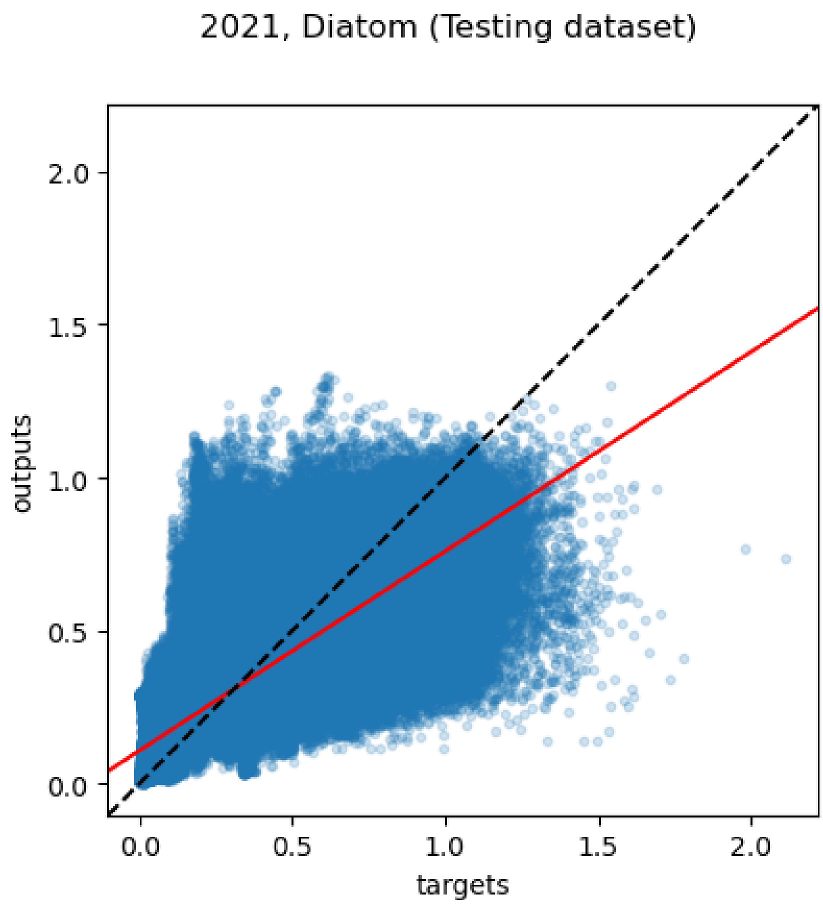

```
Gathering days for year 2019
The amount of data points is 3485925
The slope of the best fitting line is  0.327
The correlation coefficient is: 0.319
 The mean square error is: 0.04264
```



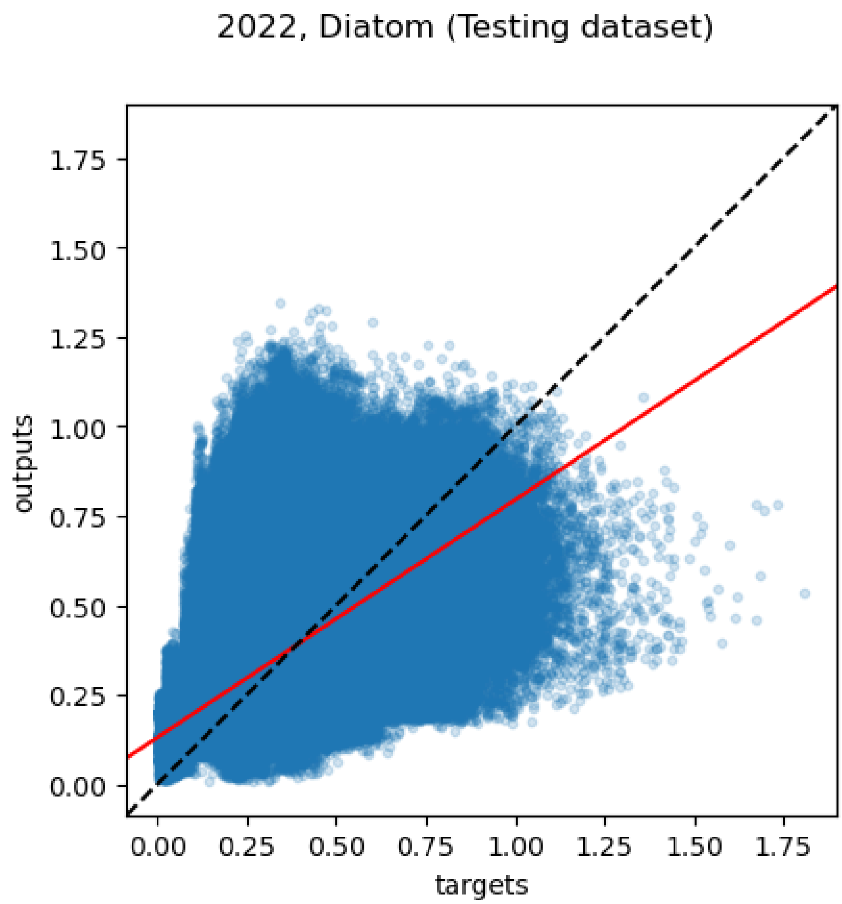

```
Gathering days for year 2020
The amount of data points is 3532404
The slope of the best fitting line is  0.339
The correlation coefficient is: 0.469
 The mean square error is: 0.03714
```



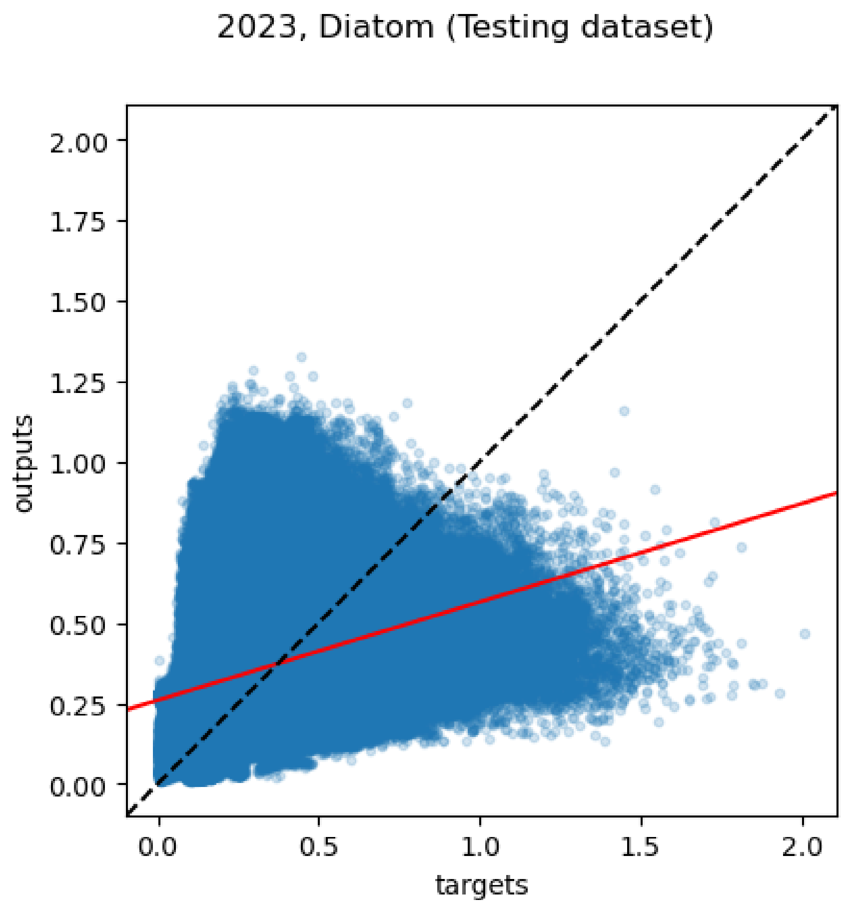

```
Gathering days for year 2021
The amount of data points is 3485925
The slope of the best fitting line is  0.652
The correlation coefficient is: 0.775
 The mean square error is: 0.0127
```



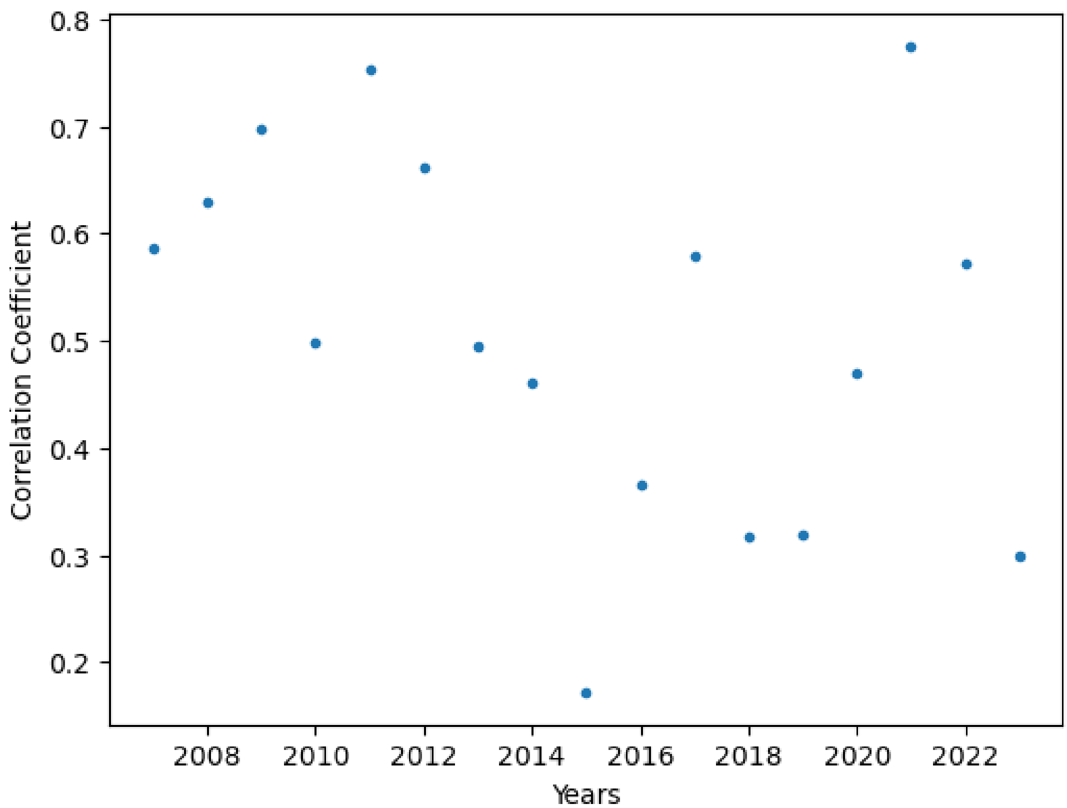

```
Gathering days for year 2022
The amount of data points is 3485925
The slope of the best fitting line is  0.664
The correlation coefficient is: 0.572
 The mean square error is: 0.02243
```

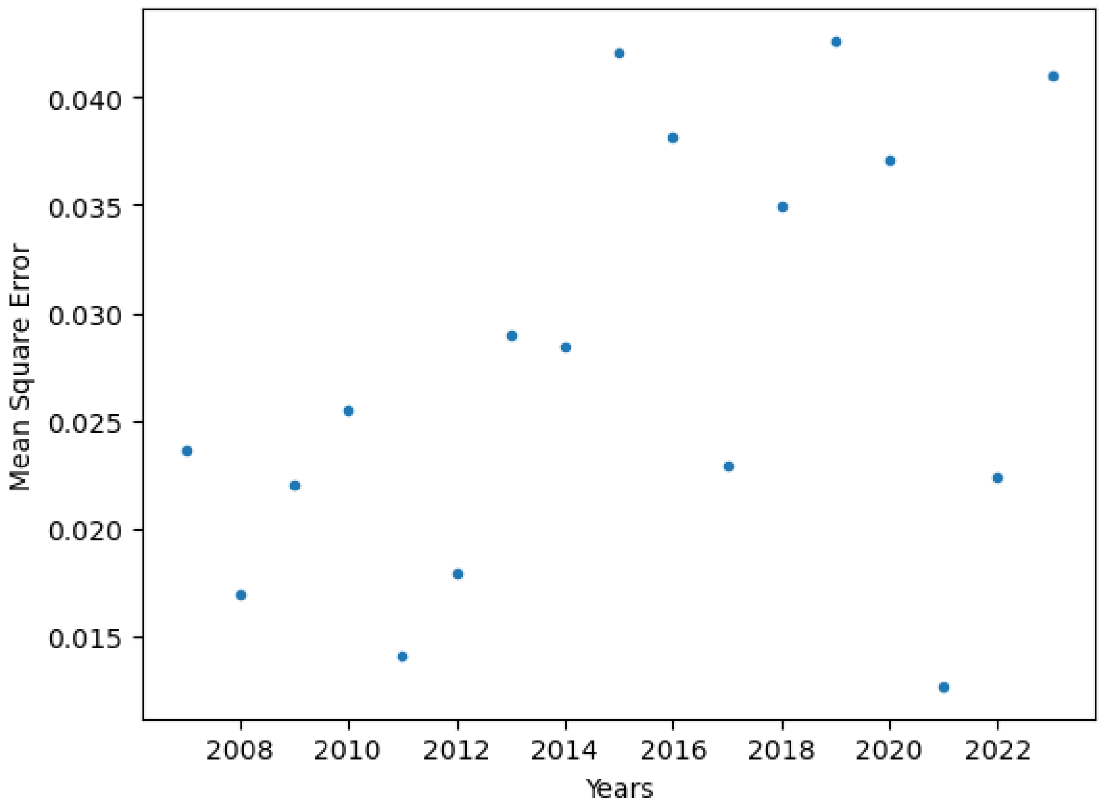



```
Gathering days for year 2023
The amount of data points is 3485925
The slope of the best fitting line is  0.305
The correlation coefficient is: 0.299
 The mean square error is: 0.041
```

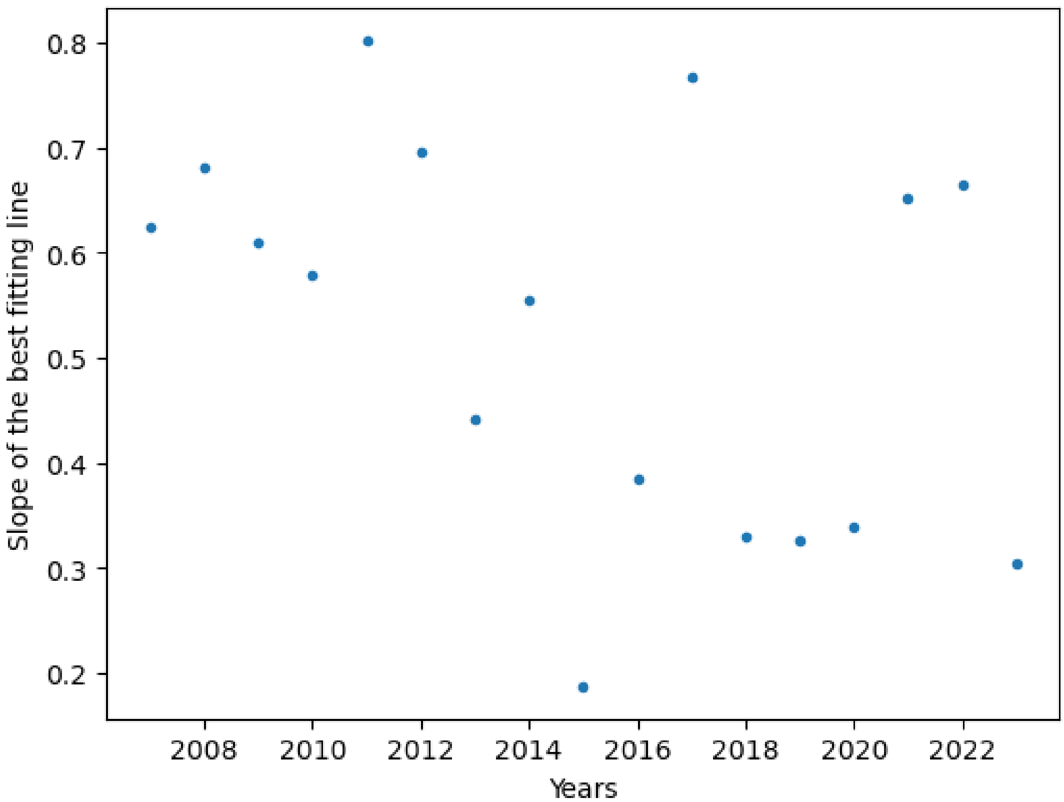


2023, Diatom (Testing dataset)
outputs
targets
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0.0
0.5
1.0
1.5
2.0


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



0.040
0.035
0.030
0.025
0.020
0.015
Mean Square Error
2008
2010
2012
2014
2016
2018
2020
2022
Years



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