Exploring tutorial:
Looking for another regression "better" than OLS
Will be exploring Lasso regression in this assignment to determine if it works better in predicting missing data than using OLS

Recap on previous assignment discussion
From the figures above where predicted and actual values were plotted:
1) S11-DRP - worked well
2) S11-TP - worked okay (within somewhat expected range, but the model had weak R2 and p-value)
3) S11-TSS - worked okay (within somewhat expected range)
4) S12- DRP - worked well
5) S12 - TP - worked well
6) S12 - TSS - did not work at all (some of the predicted TSS concentrations were negative)
In summary, this OLS model worked well for DRP and TP, but not TSS. Another suitable model is needed to predict TSS concentration. A potential approach is to multiple-linear-regression to incorporate several parameters such as precipitation data (antecedent condition) and time of the year (seasonality - land cover density).

So...in this assignment we will be exploring Lasso regression to determine if it works better in predicting missing data (especially TSS) than using OLS

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import linear_model
from scipy import stats
```

In [3]:
```
# import data from excel
data = pd.read_excel('JY_linear_reg_data.xlsx', sheet_name = 'Data')

# drop 'VSS' column, rename the columns into shorter names
data = data.drop(columns=['VSS (mg/L)'])
data = data.rename(columns={'Sample date': 'Date', 'Flow (cms)':'Flow', 'DRP
 (mg P/L)':'DRP', 'TP (mg P/L)':'TP', 'TSS (mg/L)':'TSS'})
data.head()
```

Out[3]:

	Date	Site	Flow	DRP	TP	TSS
0	2015-05-19	S11	0.028210	0.018	0.0015	22.333667
1	2015-06-16	S11	0.189993	0.027	0.1770	1006.666667
2	2015-06-30	S11	1.296460	0.203	1.2590	1338.666667
3	2015-08-18	S11	0.131722	0.050	1.3280	2026.000000
4	2015-08-25	S11	0.120204	0.010	3.1180	1722.000000

In [4]:
```
# separate data by site
data_11 = data[data['Site'] == 'S11']
data_12 = data[data['Site'] == 'S12']

# check the number of null values
print('S11')
print(data_11.isnull().sum())
print('S12')
print(data_12.isnull().sum())
```

```
S11
Date     0
Site     0
Flow     0
DRP      3
TP       3
TSS      3
dtype: int64
S12
Date     0
Site     0
Flow     0
DRP      4
TP       4
TSS      4
dtype: int64
```

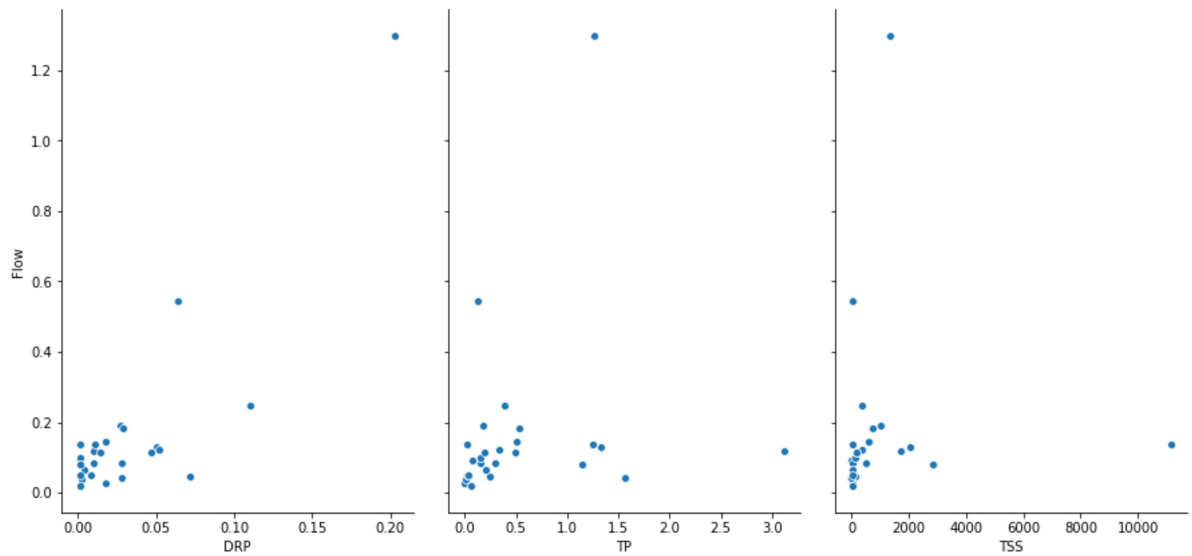
In [5]:
```
# create separate dataframe that only contain null values
data_11_null = data_11[data_11.isnull().any(axis=1)]
data_12_null = data_12[data_12.isnull().any(axis=1)]
print('S11')
print(data_11_null)
print('S12')
print(data_12_null)
```

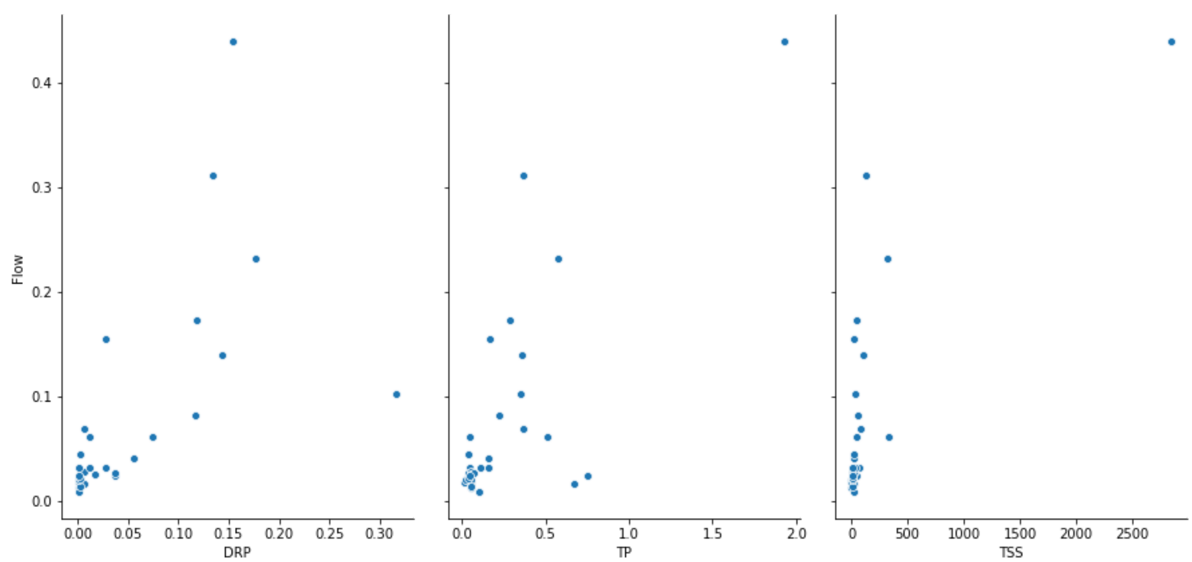
```
S11
          Date Site      Flow  DRP  TP  TSS
21 2018-06-22  S11  0.103414  NaN NaN  NaN
22 2018-06-27  S11  0.189099  NaN NaN  NaN
28 2018-10-11  S11  0.156634  NaN NaN  NaN
S12
          Date Site      Flow  DRP  TP  TSS
59 2018-08-21  S12  0.128687  NaN NaN  NaN
60 2018-08-31  S12  0.028923  NaN NaN  NaN
61 2018-09-06  S12  0.024730  NaN NaN  NaN
62 2018-09-26  S12  0.022594  NaN NaN  NaN
```

In [6]:
```
# drop the null values from the original dataset
data_11 = data_11.dropna()
data_12 = data_12.dropna()
print('S11')
print(data_11.isnull().sum())
print('S12')
print(data_12.isnull().sum())
```

```
S11
Date    0
Site    0
Flow    0
DRP     0
TP      0
TSS     0
dtype: int64
S12
Date    0
Site    0
Flow    0
DRP     0
TP      0
TSS     0
dtype: int64
```

In [7]:
```
# visualize the relationship between flow and responses
sns.pairplot(data_11, x_vars=['DRP', 'TP', 'TSS'], y_vars=['Flow'], height=6,
aspect=0.7)
sns.pairplot(data_12, x_vars=['DRP', 'TP', 'TSS'], y_vars=['Flow'], height=6,
aspect=0.7)
plt.show()
```





In [71]:
```
# there are 6 datasets, try to use 1 dataset to get the model to work first, t
hen incorporate the loop function later
import numpy as np

x = np.log(data_12['Flow'])
X = x[:, np.newaxis]
print(X.shape)

Y = data_12['DRP']
print(Y.shape)
```

```
(32, 1)
(32,)
```

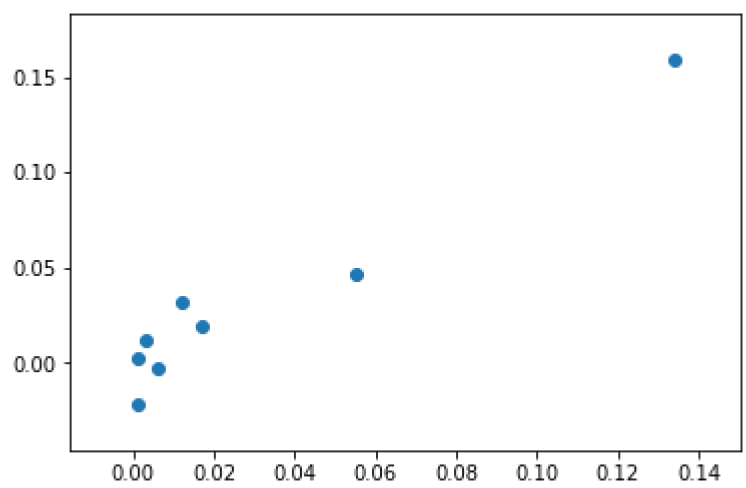
In [72]:
```
# split dataset into train and test

from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, ra
ndom_state = 0)
X_train.shape
```

Out[72]:
```
(24, 1)
```

In [73]:
```
#Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [74]:
```
# small alpha value is needed
reg = linear_model.Lasso(alpha=0.001)

# train the model
reg.fit(X_train, Y_train)

# predict outputs using test dataset
Y_pred = reg.predict(X_test)
```

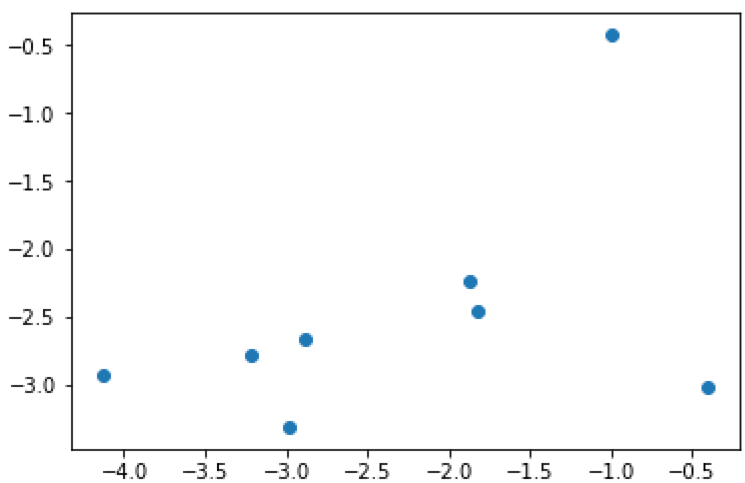
In [75]:
```
from sklearn.metrics import r2_score

# compare predict vs actual DRP
plt.scatter(Y_test, Y_pred)
plt.show()
print('R2 =',r2_score(Y_test, Y_pred))
```




```
R2 = 0.8831457973147876
```

R2 = 0.883 in this model is better than OLS prediction (R2 = 0.413) for S12 DRP.

In [85]:
```
# Sub 12 TP
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import numpy as np

x = np.log(data_12['Flow']) # try log and non log version, and see which one w
orks better
X = x[:, np.newaxis]
Y = np.log(data_12['TP']) # try log and non log version, and see which one wor
ks better

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, ra
ndom_state = 0)

reg = linear_model.Lasso(alpha=0.001) # try different alpha values to obtain h
igher r2

# train the model
reg.fit(X_train, Y_train)

# predict outputs using test dataset
Y_pred = reg.predict(X_test)

# compare predict vs actual values
plt.scatter(Y_test, Y_pred)
plt.show()
print('R2 =',r2_score(Y_test, Y_pred))
```

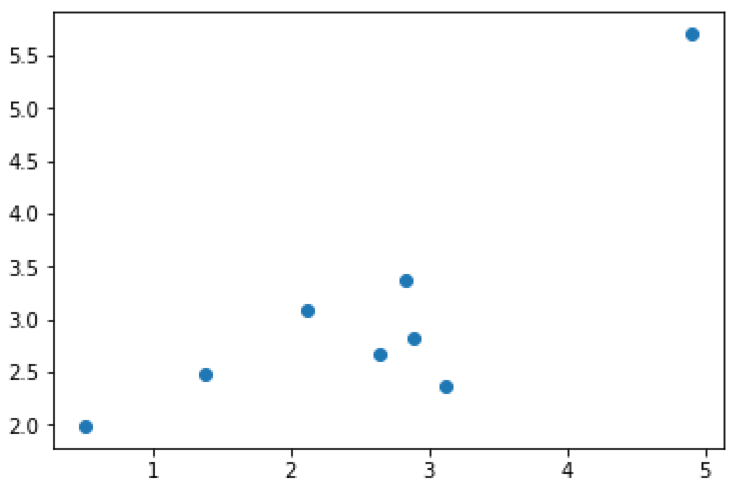



```
R2 = 0.11551245754515604
```

R2 using OLS was 0.558, so this model did not perform better in predicting S12-TP

In [95]:

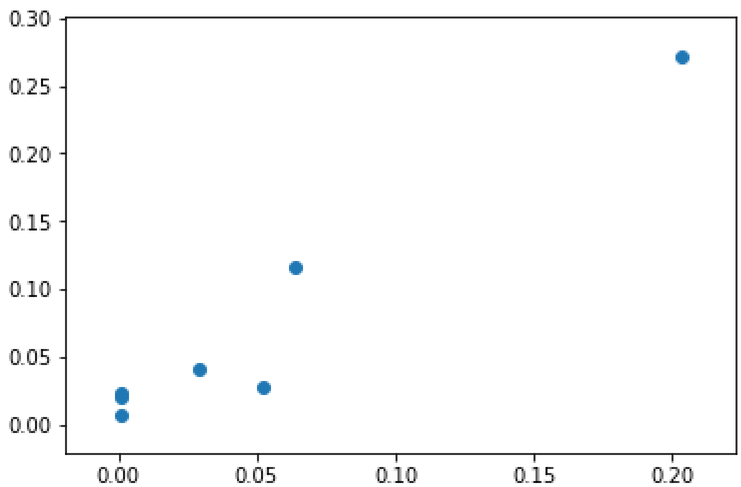
```
# Sub 12 TSS
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import numpy as np

x = np.log(data_12['Flow']) # try log and non log version, and see which one w
orks better
X = x[:, np.newaxis]
Y = np.log(data_12['TSS']) # try log and non log version, and see which one wo
rks better

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, ra
ndom_state = 0)

reg = linear_model.Lasso(alpha=0.0001) # try different alpha values to obtain
 higher r2

# train the model
reg.fit(X_train, Y_train)

# predict outputs using test dataset
Y_pred = reg.predict(X_test)

# compare predict vs actual values
plt.scatter(Y_test, Y_pred)
plt.show()
print('R2 =',r2_score(Y_test, Y_pred))
```




```
R2 = 0.5098497371312227
```

R2 using OLS was 0.556, so this model did not perform better in predicting S12-TSS but both model performances were close.

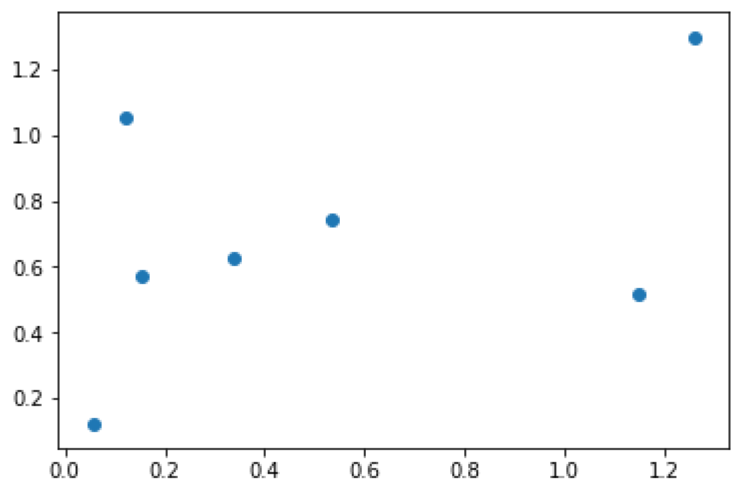
In [108]:
```
# Sub 11 DRP
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import numpy as np

x = (data_11['Flow']) # try log and non log version, and see which one works b
etter
X = x[:, np.newaxis]
Y = (data_11['DRP']) # try log and non log version, and see which one works be
tter

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, ra
ndom_state = 0)

reg = linear_model.Lasso(alpha=0.0001) # try different alpha values to obtain
 higher r2

# train the model
reg.fit(X_train, Y_train)

# predict outputs using test dataset
Y_pred = reg.predict(X_test)

# compare predict vs actual values
plt.scatter(Y_test, Y_pred)
plt.show()
print('R2 =',r2_score(Y_test, Y_pred))
```




```
R2 = 0.7049103617005045
```

R2 using OLS was 0.719, so this model did not perform better in predicting S11-DRP but both model performances were close.

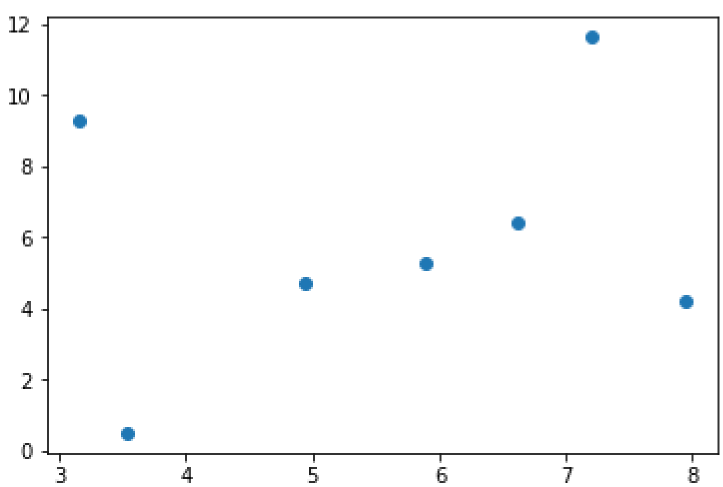
In [129]:
```
# Sub 11 TP
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import numpy as np

x = np.log(data_11['Flow']) # try log and non log version, and see which one w
orks better
X = x[:, np.newaxis]
Y = (data_11['TP']) # try log and non log version, and see which one works bet
ter

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, ra
ndom_state = 0)

reg = linear_model.Lasso(alpha=0.00001) # try different alpha values to obtain
higher r2

# train the model
reg.fit(X_train, Y_train)

# predict outputs using test dataset
Y_pred = reg.predict(X_test)

# compare predict vs actual values
plt.scatter(Y_test, Y_pred)
plt.show()
print('R2 =',r2_score(Y_test, Y_pred))
```




```
R2 = -0.06357470611670868
```

R2 using OLS was 0.036, so this model did not perform better in predicting S11-TP. Other parameters (besides flow) is probably needed to predict TSS more precisely.

In [154]:
```
# Sub 11 TSS
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
import numpy as np

x = np.log(data_11['Flow']) # try log and non log version, and see which one w
orks better
X = x[:, np.newaxis]
Y = np.log(data_11['TSS']) # try log and non log version, and see which one wo
rks better

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, ra
ndom_state = 0)

reg = linear_model.Lasso(alpha=0.1) # try different alpha values to obtain hig
her r2

# train the model
reg.fit(X_train, Y_train)

# predict outputs using test dataset
Y_pred = reg.predict(X_test)

# compare predict vs actual values
plt.scatter(Y_test, Y_pred)
plt.show()
print('R2 =',r2_score(Y_test, Y_pred))
```




```
R2 = -3.056273267276598
```

R2 using OLS was 0.003, so this model did not perform better in predicting S11-TSS. Other parameters (besides flow) is probably needed to predict TSS more precisely.

Discussion:

Based on tested parameter (changing lasso alpha, and log transforming dataset), some of the Lasso model can perdict better than OLS:
S12 DRP: improved r2 from 0.413 (OLS model) to 0.883 (Lasso model)
S12 TP: decreased r2 from 0.558 to 0.115
S12 TSS: slighlty decreased r2 from 0.556 to 0.510
S11 DRP: slighlty decreased r2 from 0.719 to 0.705
S11 TP: decreased r2 from 0.036 to -0.064 (it's not likely possible to improve model performance using only flow as predictor)
S11 TSS: decreased r2 from 0.003 to -3.056 (it's not likely possible to improve model performance using only flow as predictor)
In summary, multiple models can be tested while tweaking the model parameters (using loop iteration) to obtain the "best" prediction model. In future development, I can run the dataset through different potentially suitable model, and select the best model for each dataset. However, there is no guarantee that any models would work on a certain dataset (unpredictable using only flow as parameter) such as S11-TP and S11-TSS concentration. Other parameters such as antecedent soil moisture, land cover, and crop type should be considered in the model development.

```
In [ ]:
```