PCA is used here to determine if month, temperature, or precipitation has significant effect on the NOx concentration at each monitoring site

In [1]:
```
%matplotlib inline

import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

dataset = pd.read_excel('BHL PCA.xlsx', sheet_name='Monthly ppt and temp_trimmed')
dataset.head()
```

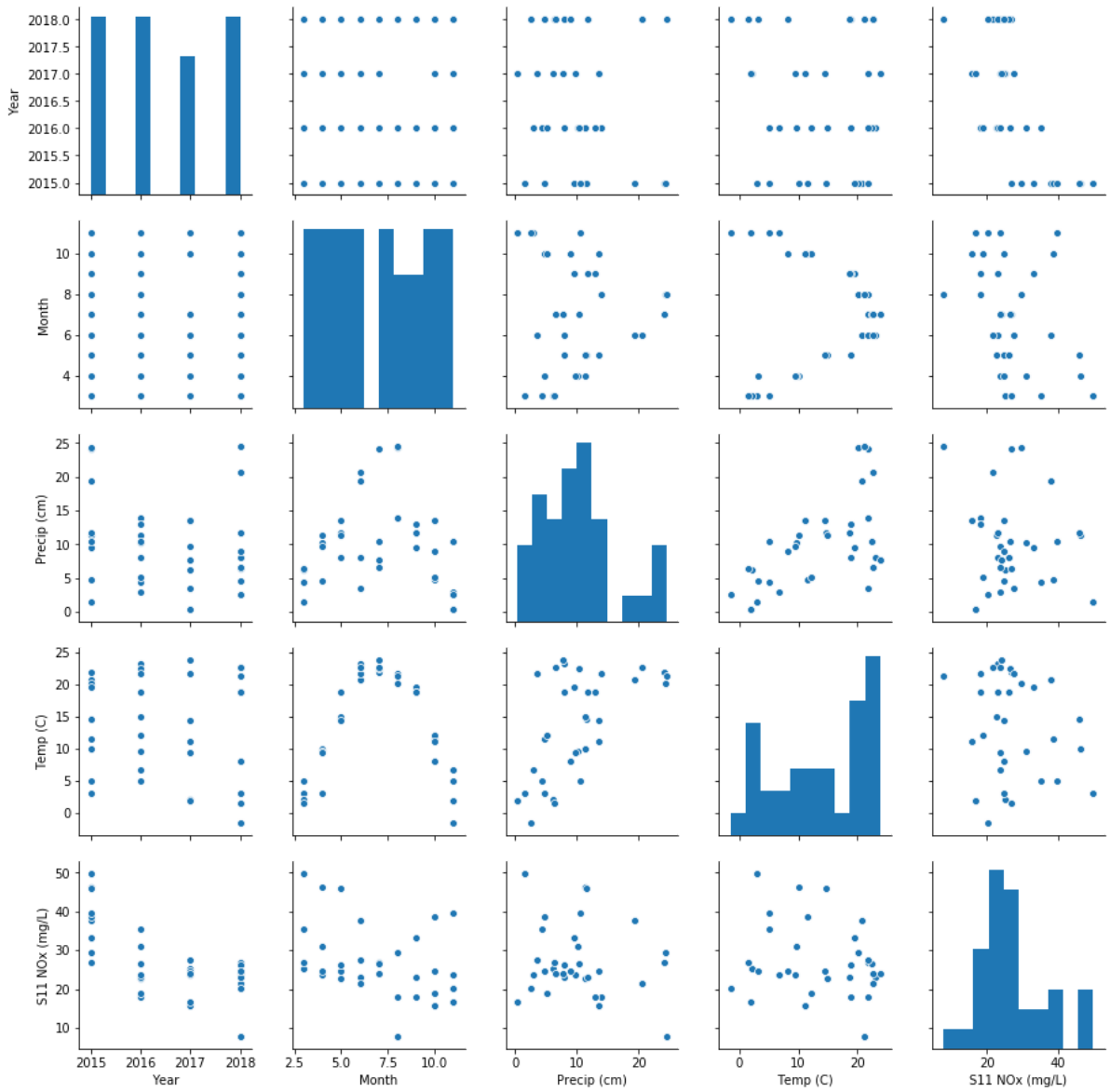
Out[1]:

	Year	Month	Precip (cm)	Temp (C)	S11 NOx (mg/L)	S12 NOx (mg/L)	T12 NOx (mg/L)
0	2015	3	1.4732	3.000000	49.881450	10.88840	13.020500
1	2015	4	11.3538	10.000000	46.129780	12.33426	13.993825
2	2015	5	11.6332	14.611111	45.923850	10.41450	15.625580
3	2015	6	19.4056	20.666667	37.787071	8.63195	16.626840
4	2015	7	24.0792	21.833333	26.937750	5.19046	16.490175

S11 dataset

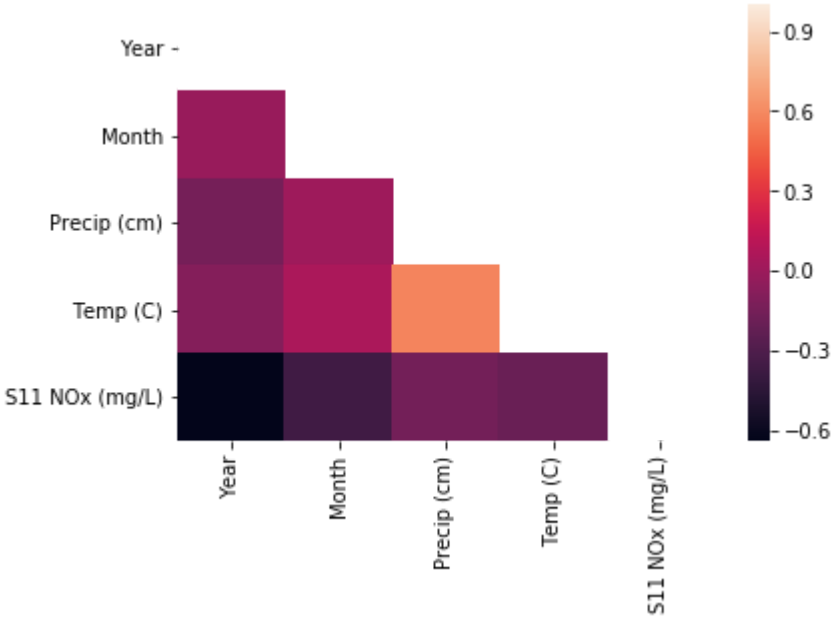
In [2]:
```
feature_list = list(dataset.columns[0:5])
feature = dataset[feature_list]
sns.pairplot(feature)
```

Out[2]: <seaborn.axisgrid.PairGrid at 0x1bf3482e3c8>



In [3]:
```
corr = feature.corr(method='pearson')
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

sns.heatmap(corr, mask=mask)
```

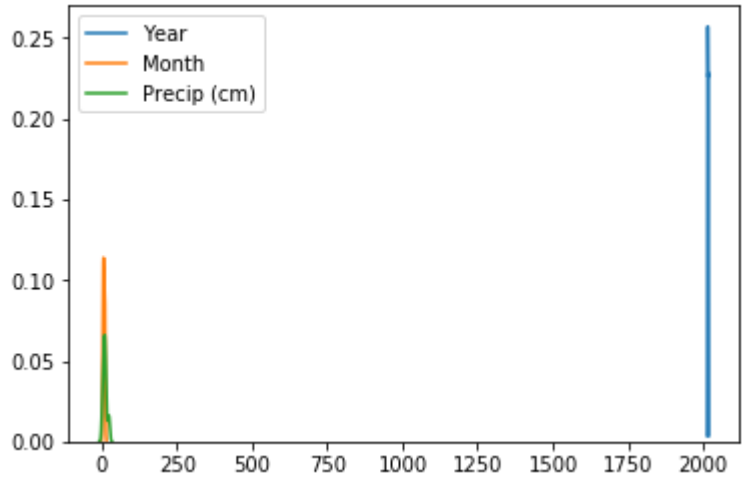
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf36c52160>



In [22]:
```
from sklearn.preprocessing import StandardScaler

X_data = feature.iloc[:,0:3]
Y_data = feature.iloc[:,4]

scaled_data = StandardScaler()
scaled_X = scaled_data.fit_transform(X_data)

sns.kdeplot(X_data.iloc[:,0])
sns.kdeplot(X_data.iloc[:,1])
sns.kdeplot(X_data.iloc[:,2])
```

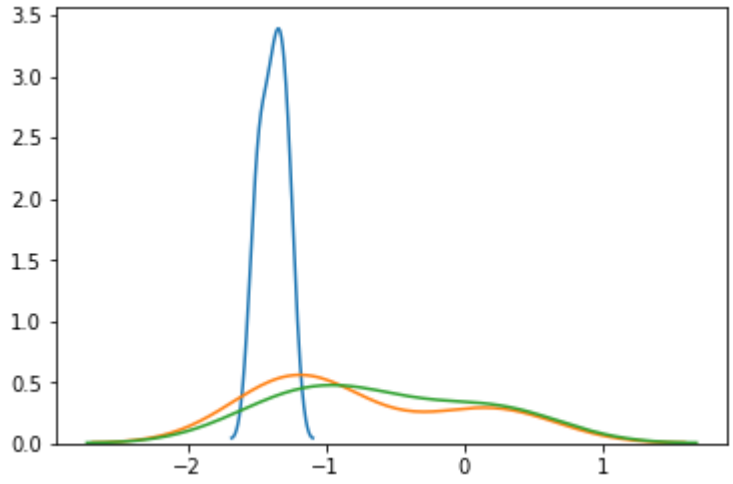
```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64, float64 were all converte
d to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversio
nWarning: Data with input dtype int64, float64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf391663c8>



In [15]:
```
sns.kdeplot(scaled_X[0])
sns.kdeplot(scaled_X[1])
sns.kdeplot(scaled_X[2])
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf38f12198>



In [17]:
```
from sklearn.decomposition import PCA
pcal = PCA(n_components =3)
pcal.fit(scaled_X)
trained_pcal = pcal.transform(scaled_X)

trained_pcal.shape
```

Out[17]: (34, 3)

In [23]:
```
pc_df = pd.DataFrame(data=trained_pcal, columns = ['PC1', 'PC2', 'PC3'])
pc_df['Cluster'] = Y_data
pc_df.head()
```

Out[23]:

	PC1	PC2	PC3	Cluster
0	-0.189061	-1.369321	-1.961303	49.881450
1	0.944161	-1.150936	-0.837798	46.129780
2	1.008921	-0.776976	-0.785239	45.923850
3	1.907534	-0.524431	0.103111	37.787071
4	2.461299	-0.221673	0.645811	26.937750

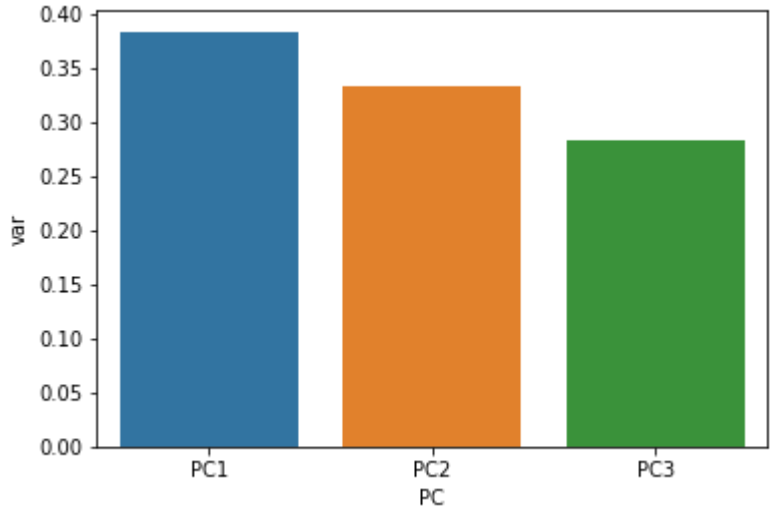
In [28]:
```
df = pd.DataFrame({'var':pcal.explained_variance_ratio_, 'PC':['PC1','PC2','PC3']})
df
```

Out[28]:

	var	PC
0	0.384051	PC1
1	0.333093	PC2
2	0.282855	PC3

In [20]:
```
sns.barplot(x='PC', y='var', data=df)
```

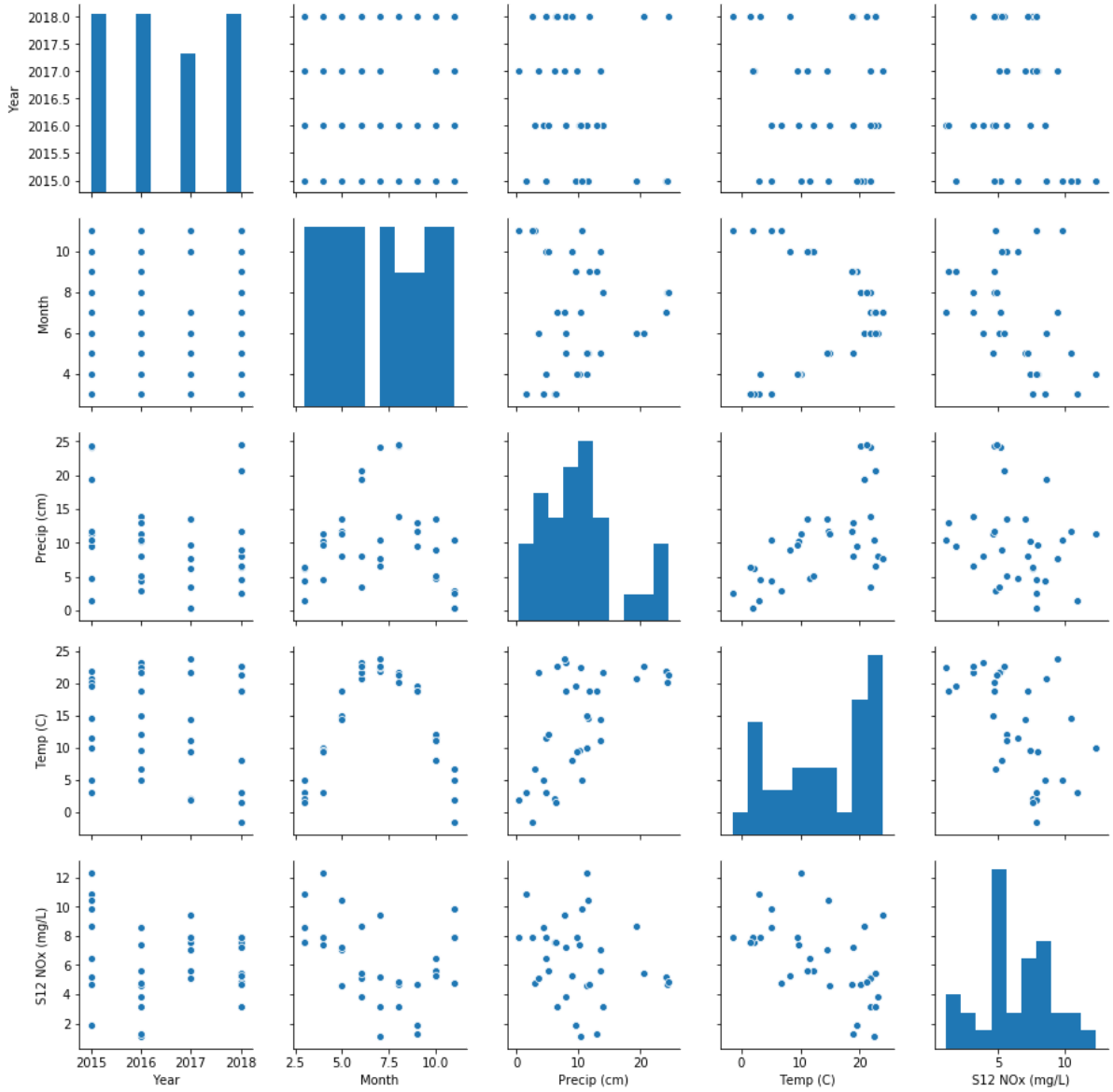
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf38fcdef0>



S12 dataset

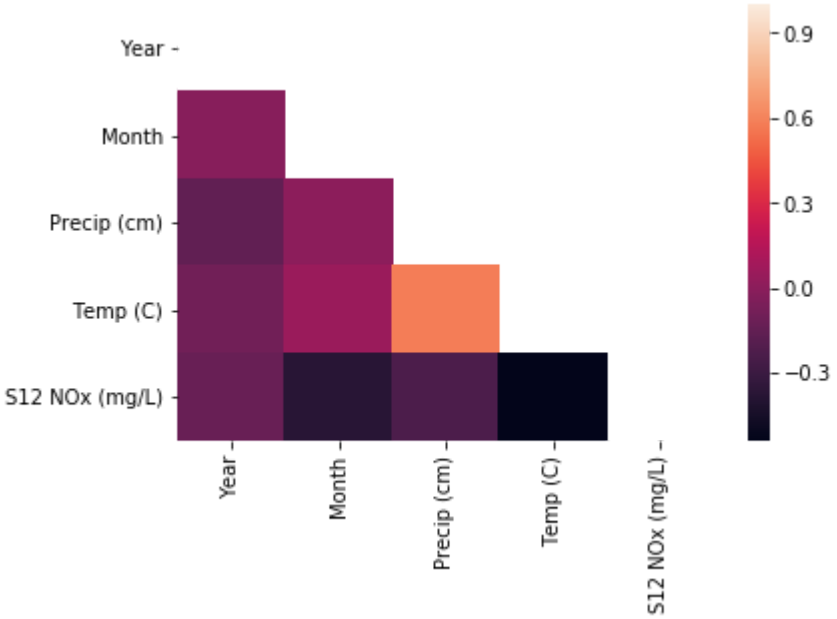
In [26]:
```
feature = dataset.iloc[:, [0,1,2,3,5]]
sns.pairplot(feature)
```

Out[26]: <seaborn.axisgrid.PairGrid at 0x1bf39302d30>



In [27]:
```
corr = feature.corr(method='pearson')
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

sns.heatmap(corr, mask=mask)
```

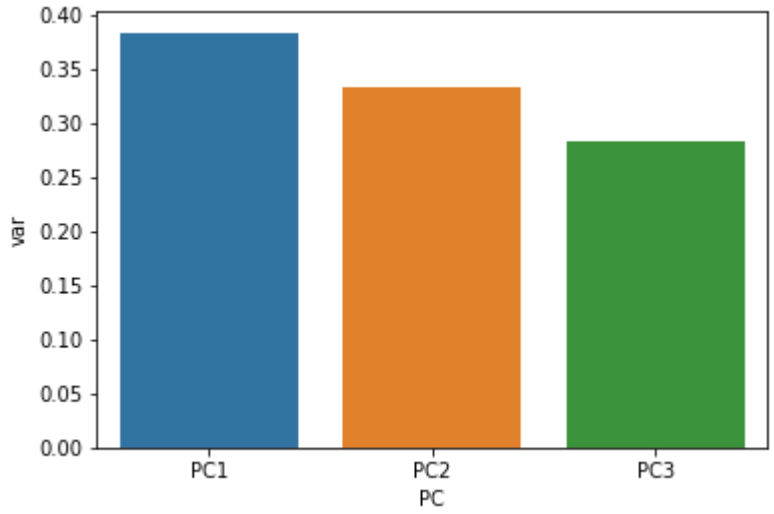
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf39c00d68>



In [29]:
```
from sklearn.preprocessing import StandardScaler

X_data = feature.iloc[:,0:3]
Y_data = feature.iloc[:,4]

scaled_data = StandardScaler()
scaled_X = scaled_data.fit_transform(X_data)

from sklearn.decomposition import PCA
pcal = PCA(n_components =3)
pcal.fit(scaled_X)
trained_pcal = pcal.transform(scaled_X)

pc_df = pd.DataFrame(data=trained_pcal, columns = ['PC1', 'PC2', 'PC3'])
pc_df['Cluster'] = Y_data

df = pd.DataFrame({'var':pcal.explained_variance_ratio_, 'PC':['PC1','PC2','PC
3']})
sns.barplot(x='PC', y='var', data=df)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64, float64 were all converte
d to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversio
nWarning: Data with input dtype int64, float64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

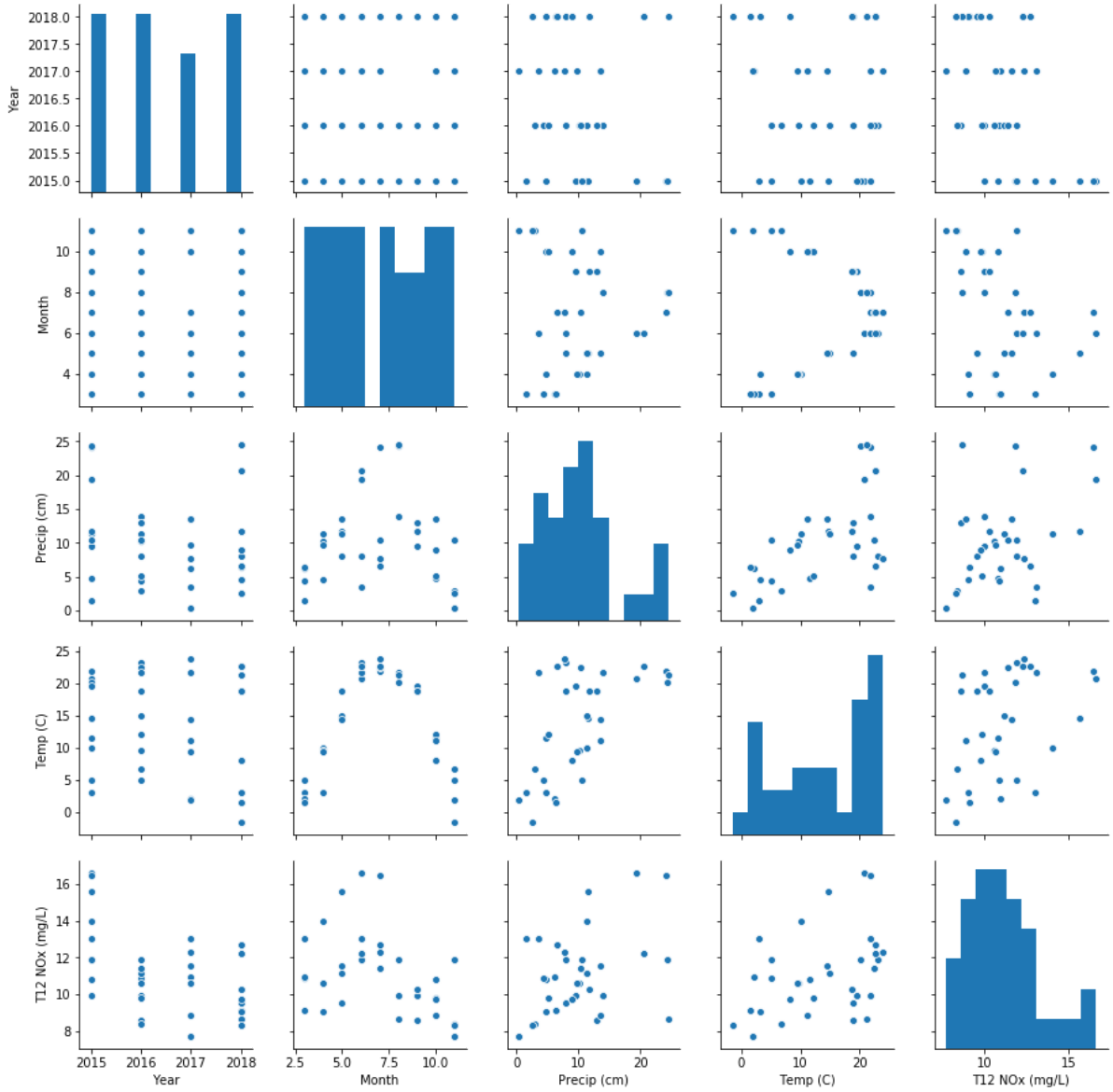
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf3a338be0>



T12 dataset

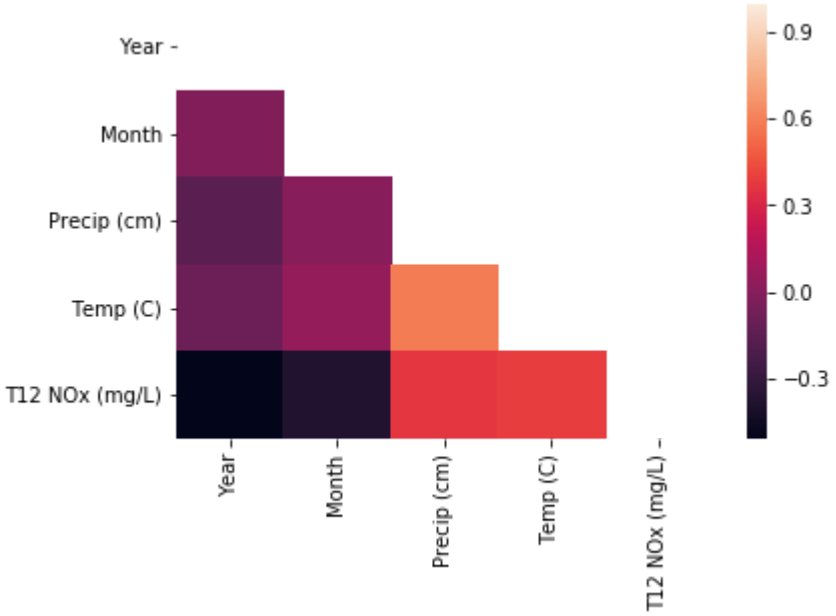
In [30]:
```
feature = dataset.iloc[:, [0,1,2,3,6]]
sns.pairplot(feature)
```

Out[30]: <seaborn.axisgrid.PairGrid at 0x1bf3a386a58>



In [31]:
```
corr = feature.corr(method='pearson')
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

sns.heatmap(corr, mask=mask)
```

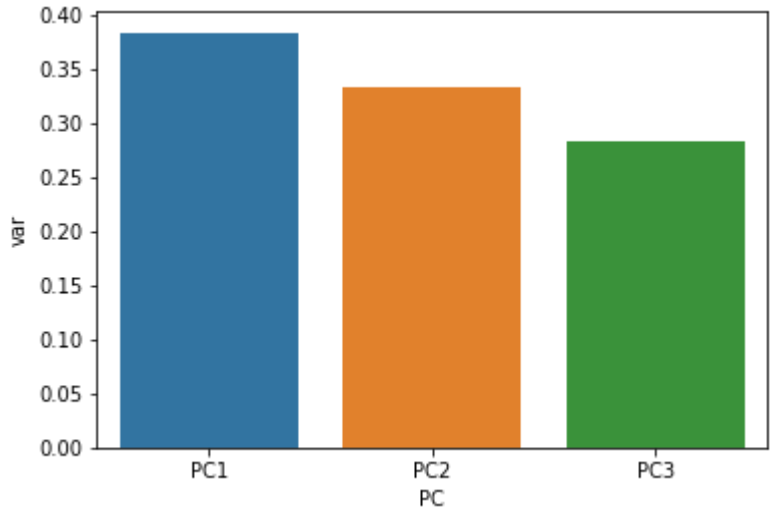
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf3bf4a160>



In [32]:
```
from sklearn.preprocessing import StandardScaler

X_data = feature.iloc[:,0:3]
Y_data = feature.iloc[:,4]

scaled_data = StandardScaler()
scaled_X = scaled_data.fit_transform(X_data)

from sklearn.decomposition import PCA
pcal = PCA(n_components =3)
pcal.fit(scaled_X)
trained_pcal = pcal.transform(scaled_X)

pc_df = pd.DataFrame(data=trained_pcal, columns = ['PC1', 'PC2', 'PC3'])
pc_df['Cluster'] = Y_data

df = pd.DataFrame({'var':pcal.explained_variance_ratio_, 'PC':['PC1','PC2','PC
3']})
sns.barplot(x='PC', y='var', data=df)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64, float64 were all converte
d to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversio
nWarning: Data with input dtype int64, float64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1bf3c36ee48>



Discussions:

High PC1, PC2, and PC3 variances were observed in PCAs of NOx concentration vs all three parameters (month, precipitation, and temperature) at all monitoring sites.
All three parameters were equally significant in explaining NOx concentration at each monitoring site.
The result was somewhat unsurprising because PCA is typically used to eliminate factors that have little effect on the responding variables, while these three factors (month, precip, temperature) were commonly known to affect NOx concentration.

In [ ]: