

Predicting Future Ocean Acidification

Importing Data and Packages

```
In [2]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
pd.plotting.register_matplotlib_converters()
import matplotlib.dates as mdates
from sklearn.feature_selection import chi2
from sklearn.model_selection import train_test_split
import numpy as np
from scipy import stats
from statsmodels.tsa.vector_ar.vecm import coint_johansen
from statsmodels.tsa.vector_ar.var_model import VAR
from statsmodels.tsa.stattools import adfuller
from statsmodels.tools.eval_measures import rmse, aic
import matplotlib.pyplot as plt
%matplotlib inline
from statsmodels.stats.stattools import durbin_watson
```

```
In [3]: # reading CSV
df1 = pd.read_csv(r"C:\Users\datre\OneDrive\Documents\Graduate School\Spring '21\Project\2013_2014.csv")
```

```
In [4]: # Looking at data types and numbers
print(df1.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4123 entries, 0 to 4122
Data columns (total 26 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Mooring Name                          4123 non-null   object
1   Latitude                              4123 non-null   float64
2   Longitude                             4123 non-null   float64
3   Date                                  4123 non-null   object
4   Time                                  4123 non-null   object
5   xCO2 SW (wet) (umol/mol)              4123 non-null   float64
6   CO2 SW QF                             4123 non-null   int64
7   H2O SW (mmol/mol)                    4123 non-null   float64
8   xCO2 Air (wet) (umol/mol)             4123 non-null   float64
9   CO2 Air QF                             4123 non-null   int64
10  H2O Air (mmol/mol)                    4123 non-null   float64
11  Licor Atm Pressure (hPa)              4123 non-null   float64
12  Licor Temp (C)                        4123 non-null   float64
13  MAPCO2 %O2                            4123 non-null   float64
14  SST (C)                               4123 non-null   float64
15  Salinity                              4123 non-null   float64
16  xCO2 SW (dry) (umol/mol)              4123 non-null   float64
17  xCO2 Air (dry) (umol/mol)             4123 non-null   float64
18  fCO2 SW (sat) uatm                    4123 non-null   float64
19  fCO2 Air (sat) uatm                    4123 non-null   float64
20  dFCO2                                  4123 non-null   float64
21  pCO2 SW (sat) uatm                    4123 non-null   float64
22  pCO2 Air (sat) uatm                    4123 non-null   float64
23  dpCO2                                  4123 non-null   float64
24  pH (Total Scale)                      4123 non-null   float64
25  pH QF                                  4123 non-null   int64
dtypes: float64(20), int64(3), object(3)
memory usage: 837.6+ KB
None
```

```
In [4]: # Removing features where every instance has the same thing
# Data was taken from the same mooring, with the same Latitude and Longitude
del df1["Mooring Name"]
del df1["Latitude"]
del df1["Longitude"]
```

```
In [5]: # creating one datetime column with seperate date and time columns
df1["Datetime"] = pd.to_datetime(df1["Date"] + " " + df1["Time"])
```

```
In [6]: # setting index as datetime column
df1 = df1.set_index("Datetime")
```

In [7]:

```
# grouping data by day versus by hour
df1 = df1.groupby(pd.Grouper(freq='1D')).mean()
df1.head(3)
```

Out[7]:

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	CO2 SW QF	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	CO2 Air QF	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)	...	xCO2 SW (dry) (umol/mol)	xCO2 Air (dry) (umol/mol)
Datetime													
2013-04-24	7.464	151.898	397.9250	2.0	9.56000	394.375	2.0	8.70500	1006.9750	30.6750	...	401.7750	397.9250
2013-04-25	7.464	151.898	396.5750	2.0	10.11625	393.775	2.0	9.10875	1006.8125	30.9125	...	400.6250	393.775
2013-04-26	7.464	151.898	398.0875	2.0	10.34625	393.600	2.0	9.18375	1006.7750	31.2625	...	402.2625	393.600

3 rows × 23 columns

In [8]:

```
# Checking for Null values
df1.isnull().sum()
```

Out[8]:

Latitude	0
Longitude	0
xCO2 SW (wet) (umol/mol)	0
CO2 SW QF	0
H2O SW (mmol/mol)	0
xCO2 Air (wet) (umol/mol)	0
CO2 Air QF	0
H2O Air (mmol/mol)	0
Licor Atm Pressure (hPa)	0
Licor Temp (C)	0
MAPCO2 %O2	0
SST (C)	0
Salinity	0
xCO2 SW (dry) (umol/mol)	0
xCO2 Air (dry) (umol/mol)	0
fCO2 SW (sat) uatm	0
fCO2 Air (sat) uatm	0
dfCO2	0
pCO2 SW (sat) uatm	0
pCO2 Air (sat) uatm	0
dpCO2	0
pH (Total Scale)	0
pH QF	0
dtype:	int64

In [9]:

```
# Checking for recording errors, either extreme highs or extreme lows
df1.describe()
```

Out[9]:

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	CO2 SW QF	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	CO2 Air QF	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)
count	5.160000e+02	5.160000e+02	516.000000	516.000000	516.000000	516.000000	516.000000	516.000000	516.000000	516.000000
mean	7.464000e+00	1.518980e+02	406.902962	2.014535	8.971283	381.955655	2.014535	8.165870	1006.099062	30.692577
std	3.467257e-14	7.396815e-13	46.034660	0.061589	3.128491	42.350616	0.061589	2.975783	1.378662	1.067312
min	7.464000e+00	1.518980e+02	63.300000	2.000000	3.516250	43.437500	2.000000	3.041429	999.387500	27.537500
25%	7.464000e+00	1.518980e+02	398.065625	2.000000	6.370625	389.371875	2.000000	5.702813	1005.262500	29.971875
50%	7.464000e+00	1.518980e+02	410.993750	2.000000	9.059375	391.293750	2.000000	8.245000	1006.125000	30.706250
75%	7.464000e+00	1.518980e+02	430.593750	2.000000	11.713750	392.862500	2.000000	10.827188	1007.090625	31.450000
max	7.464000e+00	1.518980e+02	463.575000	2.500000	14.833750	398.862500	2.500000	13.052500	1008.925000	33.162500

8 rows × 23 columns

```
In [10]: chuuk = df1
```

```
In [11]: # Removing all extreme value instances
chuuk = chuuk[chuuk["xCO2 SW (wet) (umol/mol)"] != -999]
chuuk = chuuk[chuuk["xCO2 Air (wet) (umol/mol)"] != -999]
chuuk = chuuk[chuuk["SST (C)"] != -999]
chuuk = chuuk[(chuuk["SST (C)"] > 0) & (chuuk["pH (Total Scale)"] > 0) & (chuuk["dfCO2"] > 0) & (chuuk["dpCO2"] > 0)]
chuuk = chuuk[chuuk["xCO2 SW (dry) (umol/mol)"] != -999]
chuuk = chuuk[chuuk["xCO2 Air (dry) (umol/mol)"] != -999]
chuuk = chuuk[chuuk["fCO2 SW (sat) uatm"] != -999]
chuuk = chuuk[chuuk["fCO2 Air (sat) uatm"] != -999]
chuuk = chuuk[chuuk["dfCO2"] != -999]
chuuk = chuuk[chuuk["dpCO2"] != -999]
chuuk = chuuk[chuuk["pH (Total Scale)"] != -999]
# Dropping QF values
chuuk = chuuk.drop(["CO2 SW QF", "CO2 Air QF"], axis = 1)
```

```
In [12]: # checking that all extreme values were removed
chuuk.describe()
```

```
Out[12]:
```

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)	MAPCO2 %O2	SST (C)
count	3.790000e+02	3.790000e+02	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000
mean	7.464000e+00	1.518980e+02	416.996735	9.524825	391.358212	8.681078	1006.205541	30.793701	99.151405	29.439762
std	2.668057e-14	6.545634e-13	17.664458	3.127114	2.358320	2.942537	1.282512	1.037521	0.428422	0.489045
min	7.464000e+00	1.518980e+02	390.600000	4.002500	386.837500	3.295000	999.387500	27.937500	97.632500	28.331125
25%	7.464000e+00	1.518980e+02	400.931250	6.601875	389.400000	5.907500	1005.393750	30.131250	98.908125	29.089437
50%	7.464000e+00	1.518980e+02	413.337500	9.965000	391.575000	9.195000	1006.212500	30.800000	99.158750	29.429125
75%	7.464000e+00	1.518980e+02	430.687500	12.386875	393.006250	11.499375	1007.125000	31.493750	99.441250	29.799625
max	7.464000e+00	1.518980e+02	463.575000	14.833750	398.862500	13.052500	1008.925000	33.162500	100.767500	30.775875

8 rows × 21 columns



```
In [13]: # Copying dataset
chuuk_corr = chuuk.copy()
```

```
In [14]: chuuk_corr.describe()
```

```
Out[14]:
```

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)	MAPCO2 %O2	SST (C)
count	3.790000e+02	3.790000e+02	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000
mean	7.464000e+00	1.518980e+02	416.996735	9.524825	391.358212	8.681078	1006.205541	30.793701	99.151405	29.439762
std	2.668057e-14	6.545634e-13	17.664458	3.127114	2.358320	2.942537	1.282512	1.037521	0.428422	0.489045
min	7.464000e+00	1.518980e+02	390.600000	4.002500	386.837500	3.295000	999.387500	27.937500	97.632500	28.331125
25%	7.464000e+00	1.518980e+02	400.931250	6.601875	389.400000	5.907500	1005.393750	30.131250	98.908125	29.089437
50%	7.464000e+00	1.518980e+02	413.337500	9.965000	391.575000	9.195000	1006.212500	30.800000	99.158750	29.429125
75%	7.464000e+00	1.518980e+02	430.687500	12.386875	393.006250	11.499375	1007.125000	31.493750	99.441250	29.799625
max	7.464000e+00	1.518980e+02	463.575000	14.833750	398.862500	13.052500	1008.925000	33.162500	100.767500	30.775875

8 rows × 21 columns

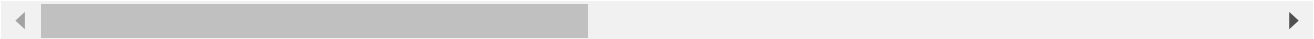


```
In [15]: # Creating correlation matrix
corr_matrix = chuuk_corr.corr()
corr_matrix
```

Out[15]:

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)	I
Latitude	1.000000e+00	-1.000000e+00	-2.429664e-14	-1.339909e-15	-6.852107e-15	-2.982314e-15	5.213248e-13	8.414180e-15	1.253
Longitude	-1.000000e+00	1.000000e+00	2.442846e-14	7.177709e-16	7.151686e-15	3.742963e-15	-5.213147e-13	-8.666888e-15	-1.253
xCO2 SW (wet) (umol/mol)	-2.429664e-14	2.442846e-14	1.000000e+00	-6.065765e-03	-2.730888e-01	-1.793784e-02	2.442229e-02	4.062362e-01	-1.162
H2O SW (mmol/mol)	-1.339909e-15	7.177709e-16	-6.065765e-03	1.000000e+00	-5.132088e-01	9.960826e-01	-4.135096e-02	3.332468e-01	4.114
xCO2 Air (wet) (umol/mol)	-6.852107e-15	7.151686e-15	-2.730888e-01	-5.132088e-01	1.000000e+00	-5.100476e-01	1.221732e-01	-2.138960e-01	-8.814
H2O Air (mmol/mol)	-2.982314e-15	3.742963e-15	-1.793784e-02	9.960826e-01	-5.100476e-01	1.000000e+00	-6.266097e-02	2.766740e-01	3.827
Licor Atm Pressure (hPa)	5.213248e-13	-5.213147e-13	2.442229e-02	-4.135096e-02	1.221732e-01	-6.266097e-02	1.000000e+00	1.644344e-01	3.983
Licor Temp (C)	8.414180e-15	-8.666888e-15	4.062362e-01	3.332468e-01	-2.138960e-01	2.766740e-01	1.644344e-01	1.000000e+00	5.033
MAPCO2 %O2	1.253603e-13	-1.252280e-13	-1.748042e-01	4.114359e-01	-8.814678e-02	3.821659e-01	3.983958e-02	5.033865e-01	1.000
SST (C)	3.363916e-14	-3.361552e-14	8.417755e-01	2.369253e-01	-3.200275e-01	2.104537e-01	1.166726e-01	6.572118e-01	2.196
Salinity	-3.747761e-15	3.710776e-15	-6.453285e-02	6.636009e-01	-3.326869e-01	6.461309e-01	3.318696e-02	3.317037e-01	3.259
xCO2 SW (dry) (umol/mol)	-2.282160e-15	2.678035e-15	9.971867e-01	6.885311e-02	-3.114377e-01	5.670892e-02	2.112733e-02	4.301949e-01	-1.424
xCO2 Air (dry) (umol/mol)	1.811631e-13	-1.812928e-13	-3.284913e-01	-2.579151e-02	8.700751e-01	-1.984712e-02	1.059009e-01	-9.062602e-02	1.162
fCO2 SW (sat) uatm	1.370838e-14	-1.360384e-14	9.971339e-01	6.254226e-02	-3.059022e-01	5.018098e-02	5.026538e-02	4.268245e-01	-1.151
fCO2 Air (sat) uatm	8.024809e-15	-7.979930e-15	-4.537848e-01	-7.866870e-02	8.630614e-01	-7.285439e-02	2.978609e-01	-1.747817e-01	6.738
dfCO2	-1.385843e-16	-9.104510e-16	9.917377e-01	6.834997e-02	-3.938823e-01	5.604111e-02	1.029266e-02	4.220163e-01	-1.151
pCO2 SW (sat) uatm	-2.994030e-15	3.123264e-15	9.971347e-01	6.242631e-02	-3.058729e-01	5.007342e-02	5.037229e-02	4.266586e-01	-1.151
pCO2 Air (sat) uatm	1.934314e-13	-1.934268e-13	-4.555326e-01	-7.934766e-02	8.630323e-01	-7.353538e-02	2.977787e-01	-1.759563e-01	6.723
dpCO2	1.312365e-15	-5.178742e-16	9.917409e-01	6.835485e-02	-3.938582e-01	5.604738e-02	1.038784e-02	4.219782e-01	-1.151
pH (Total Scale)	3.525734e-13	-3.526486e-13	-9.552045e-01	1.708242e-01	1.416996e-01	1.860399e-01	-1.006334e-01	-3.797438e-01	1.647
pH QF	4.491916e-15	-4.463443e-15	-1.330350e-01	-7.422357e-02	4.878880e-02	-7.427450e-02	-4.801234e-02	-6.347305e-02	-4.259

21 rows × 21 columns



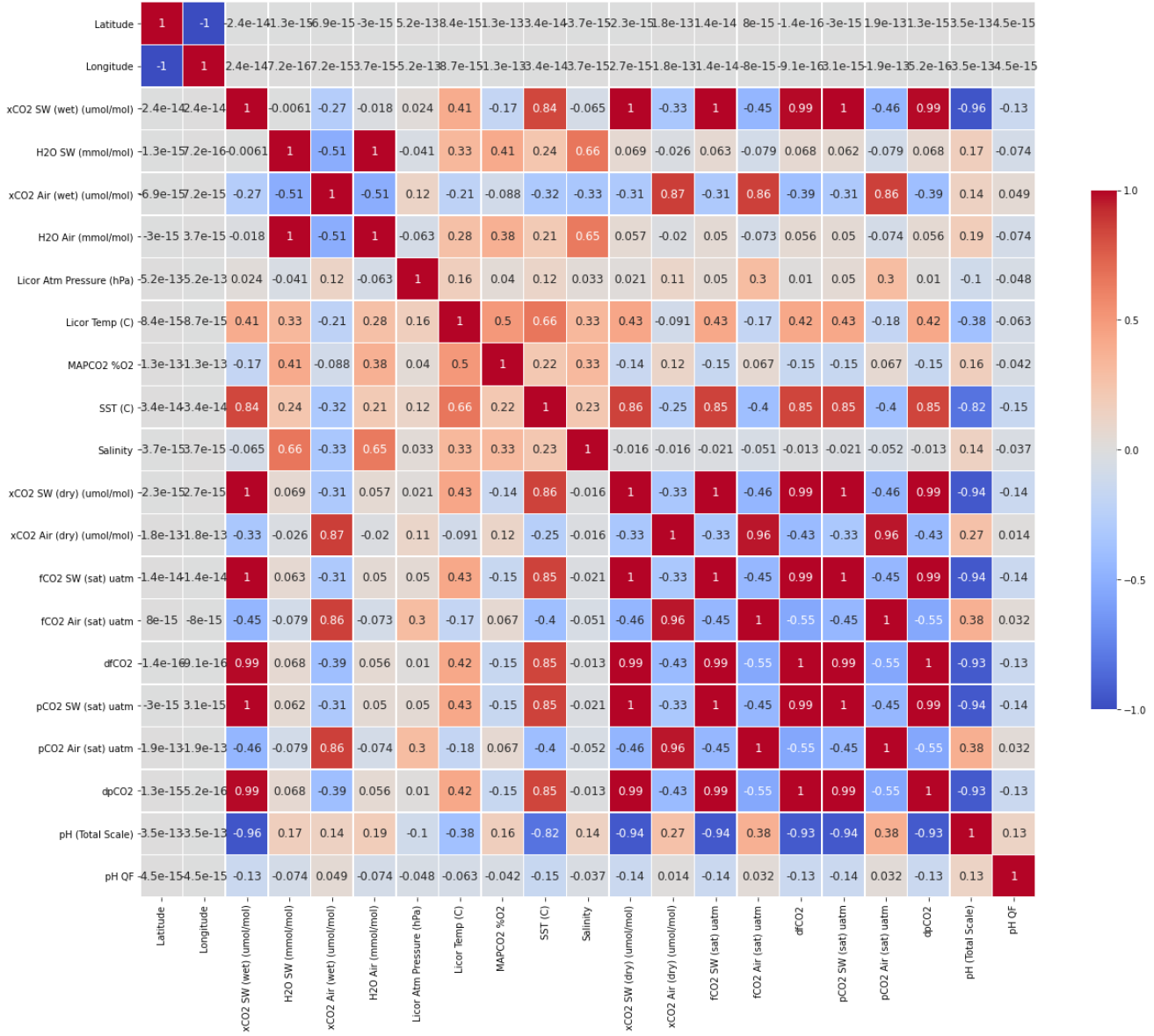
In [16]:

```
# setting figure size
f, ax = plt.subplots(figsize=(21,25))
heatmap = sns.heatmap(corr_matrix,
                        square = True,
                        linewidths = .5,
```

```
cmap = "coolwarm", # choosing color type for graph
cbar_kws = {"shrink": .4,
            "ticks" : [-1, -.5, 0, 0.5, 1]},

vmin = -1,
vmax = 1,
annot = True,
annot_kws = {"size": 12})

#add the column names as labels
ax.set_yticklabels(corr_matrix.columns, rotation = 0)
ax.set_xticklabels(corr_matrix.columns)
sns.set_style({'xtick.bottom': True}, {'ytick.left': True})
```



```
In [116... chuuk_df = chuuk.copy()
chuuk_df
```

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)	MAPCO2 %O2	SST (C)	...	xCO2 (umol/mol)
Datetime												
2013-04-24	7.464	151.898	397.9250	9.56000	394.3750	8.70500	1006.9750	30.6750	99.67750	28.855500	...	401.1
2013-04-25	7.464	151.898	396.5750	10.11625	393.7750	9.10875	1006.8125	30.9125	99.57625	28.933125	...	400.6
2013-04-26	7.464	151.898	398.0875	10.34625	393.6000	9.18375	1006.7750	31.2625	99.49250	28.989875	...	402.2

	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	H2O SW (mmol/mol)	xCO2 Air (wet) (umol/mol)	H2O Air (mmol/mol)	Licor Atm Pressure (hPa)	Licor Temp (C)	MAPCO2 %O2	SST (C)	...	xCO2 ((umol/r
Datetime												
2013-04-27	7.464	151.898	399.6750	10.49250	393.6625	9.42500	1006.7125	31.1000	99.44250	28.981000	...	403.9
2013-04-28	7.464	151.898	395.5625	10.24000	393.0375	9.39875	1007.1500	30.6375	99.57750	28.957750	...	399.6
...
2014-08-04	7.464	151.898	437.6375	4.93750	389.7375	3.80625	1008.1000	33.1125	99.15875	30.236125	...	439.8
2014-08-05	7.464	151.898	435.6250	5.13125	391.2875	3.98875	1007.7000	32.1500	99.17625	30.186875	...	437.8
2014-08-08	7.464	151.898	415.6625	4.00250	390.9625	3.29500	1008.0250	30.1875	99.24625	29.501750	...	417.3
2014-08-09	7.464	151.898	430.1250	4.17125	392.2500	3.63750	1006.9750	28.7625	98.73875	29.435375	...	431.9
2014-08-10	7.464	151.898	437.9625	4.35625	393.3250	3.76375	1006.3750	29.7625	98.43250	29.442875	...	439.8

379 rows × 21 columns



```
In [18]: # Dropping all features that did not have significant correlation with target, pH
chuuk_df = chuuk_df.drop(["H2O SW (mmol/mol)", "xCO2 Air (wet) (umol/mol)", "H2O Air (mmol/mol)",
                          "Licor Temp (C)", "MAPCO2 %O2", "Salinity", "xCO2 Air (dry) (umol/mol)", "fCO2 Air (sat) uatm",
                          "pCO2 Air (sat) uatm", "pH QF"],
                          axis = 1)
chuuk_df.head(3)
```

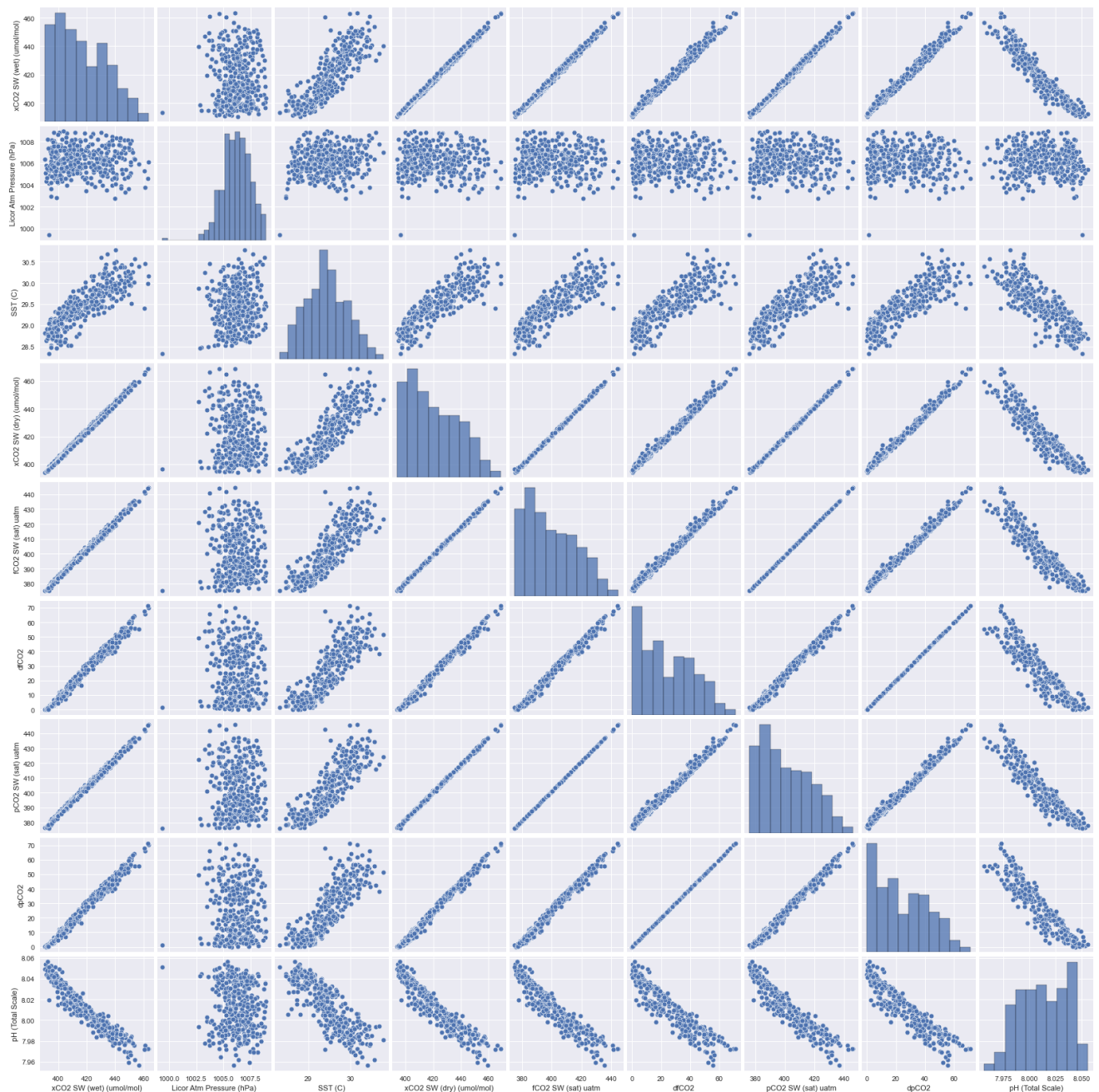
	Latitude	Longitude	xCO2 SW (wet) (umol/mol)	Licor Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	dfCO2	pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)
Datetime											
2013-04-24	7.464	151.898	397.9250	1006.9750	28.855500	401.7750	382.6750	3.7000	383.8250	3.7250	8.03300
2013-04-25	7.464	151.898	396.5750	1006.8125	28.933125	400.6250	381.4250	3.0500	382.5875	3.0625	8.04000
2013-04-26	7.464	151.898	398.0875	1006.7750	28.989875	402.2625	382.9375	4.7875	384.0875	4.8000	8.03475

```
In [24]: chuuk_df = chuuk_df.drop(["Latitude", "Longitude"], axis = 1)
```

```
In [19]: # creating easier reference for features
xCO2w = chuuk_df["xCO2 SW (wet) (umol/mol)"]
AtmP = chuuk_df["Licor Atm Pressure (hPa)"]
SST = chuuk_df["SST (C)"]
xCO2d = chuuk_df["xCO2 SW (dry) (umol/mol)"]
fCO2 = chuuk_df["fCO2 SW (sat) uatm"]
dfCO2 = chuuk_df["dfCO2"]
pCO2 = chuuk_df["pCO2 SW (sat) uatm"]
dpCO2 = chuuk_df["dpCO2"]
pH = chuuk_df["pH (Total Scale)"]
```

```
In [25]: # Pairplot to see correaltions and histograms
sns.pairplot(chuuk_df)
```

Out[25]: <seaborn.axisgrid.PairGrid at 0x1f24d065d90>



```
In [26]: # Subplot for boxplots of each feature
plt.style.use('seaborn')
fig, axis = plt.subplots(nrows = 5, ncols = 2)
fig.set_size_inches(10,10)
fig.subplots_adjust(wspace = 0.5, hspace = 0.8)

# plot 1
sns.boxplot(xCO2w, color = 'mistyrose', ax = axis[0,0]).set_title("Concentraiton of Carbon Dioxide (wet)")
# plot 2
sns.boxplot(AtmP, color = 'mistyrose', ax = axis[0,1]).set_title("Pressure (atm)")
# plot 3
sns.boxplot(SST, color = 'mistyrose', ax = axis[1,0]).set_title("Sea Surface Temperature (C)")
# plot 4
sns.boxplot(xCO2d, color = 'mistyrose', ax = axis[1,1]).set_title("Concentraiton of Carbon Dioxide (dry)")
# plot 5
sns.boxplot(fCO2, color = 'mistyrose', ax = axis[2,0]).set_title("Water Fungacity")
# plot 6
sns.boxplot(dfCO2, color = 'mistyrose', ax = axis[2,1]).set_title("Difference in Water and Air CO2")
# plot 7
sns.boxplot(pCO2, color = 'mistyrose', ax = axis[3,0]).set_title("Partial Pressure Carbon Dioxide")
# plot 8
sns.boxplot(dpCO2, color = 'mistyrose', ax = axis[3,1]).set_title("Difference in Water and Air Fungacity")
# plot 9
sns.boxplot(pH, color = 'mistyrose', ax = axis[4,0]).set_title("pH")
```



```
ax = axis[4,1].set_visible(False)
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

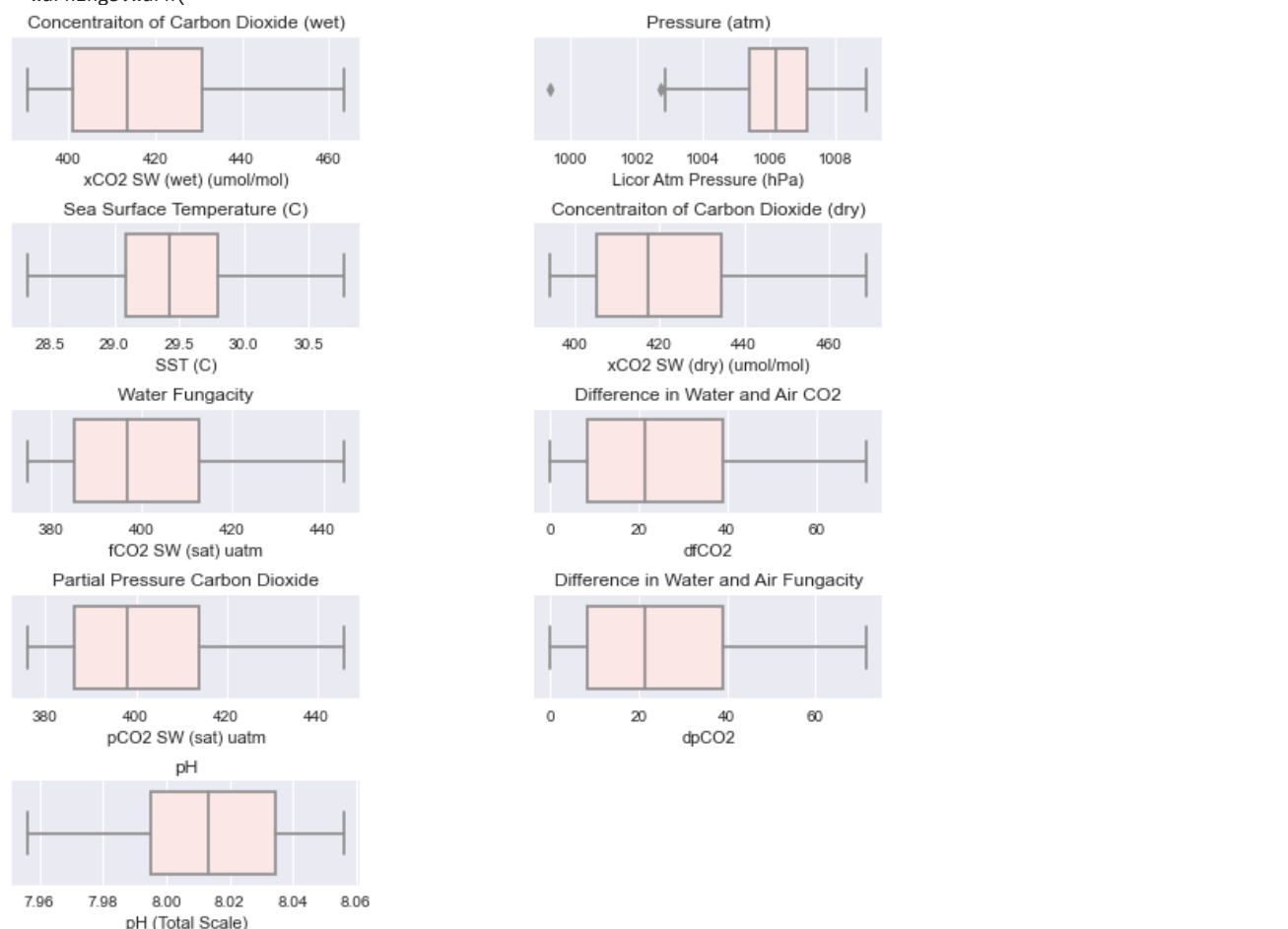
```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

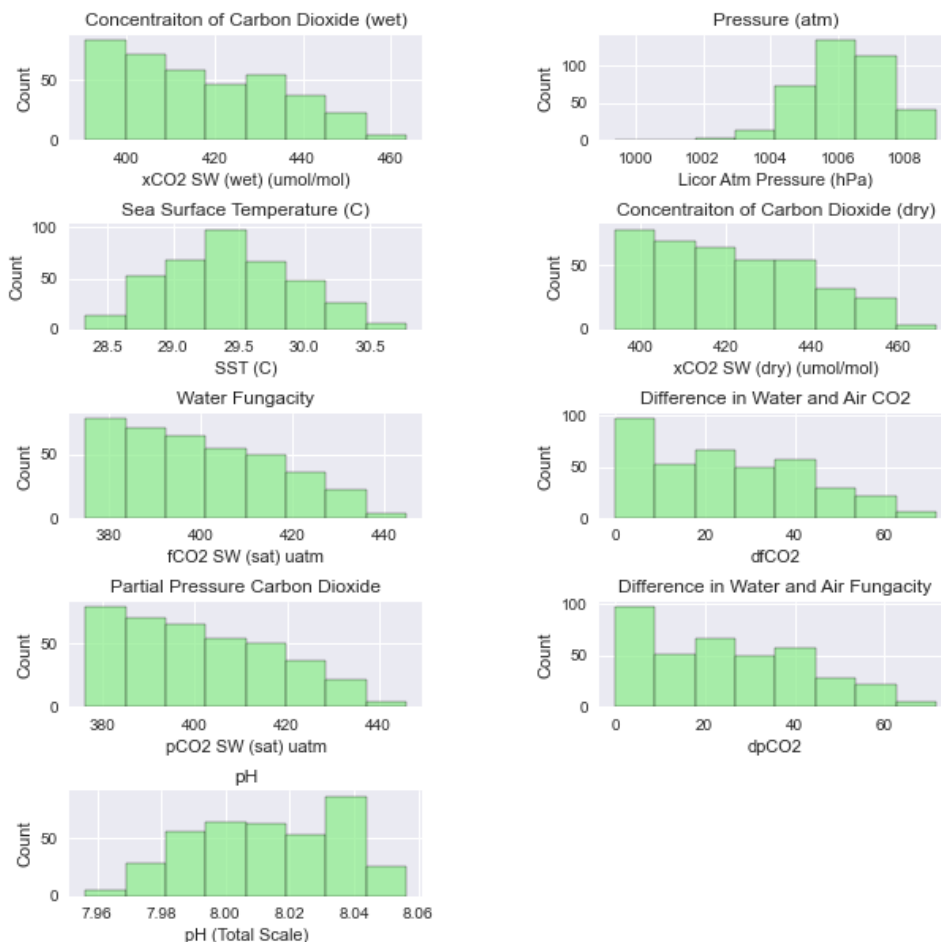


In [27]: `# Subplot for boxplots of each feature`


```
plt.style.use('seaborn')
fig, axis = plt.subplots(nrows = 5, ncols = 2)
fig.set_size_inches(10,10)
fig.subplots_adjust(wspace = 0.5, hspace = 0.8)

# plot 1
sns.histplot(xCO2w, color = 'lightgreen', bins = 8, ax = axis[0,0]).set_title("Concentraiton of Carbon Dioxide (wet)")
# plot 2
sns.histplot(AtmP, color = 'lightgreen', bins = 8, ax = axis[0,1]).set_title("Pressure (atm)")
# plot 3
sns.histplot(SST, color = 'lightgreen', bins = 8, ax = axis[1,0]).set_title("Sea Surface Temperature (C)")
# plot 4
sns.histplot(xCO2d, color = 'lightgreen', bins = 8, ax = axis[1,1]).set_title("Concentraiton of Carbon Dioxide (dry)")
# plot 5
sns.histplot(fCO2, color = 'lightgreen', bins = 8, ax = axis[2,0]).set_title("Water Fungacity")
# plot 6
sns.histplot(dfCO2, color = 'lightgreen', bins = 8, ax = axis[2,1]).set_title("Difference in Water and Air CO2")
# plot 7
sns.histplot(pCO2, color = 'lightgreen', bins = 8, ax = axis[3,0]).set_title("Partial Pressure Carbon Dioxide")
# plot 8
sns.histplot(dpCO2, color = 'lightgreen', bins = 8, ax = axis[3,1]).set_title("Difference in Water and Air Fungacity")
# plot 9
sns.histplot(pH, color = 'lightgreen', bins = 8, ax = axis[4,0]).set_title("pH")

ax = axis[4,1].set_visible(False)
```



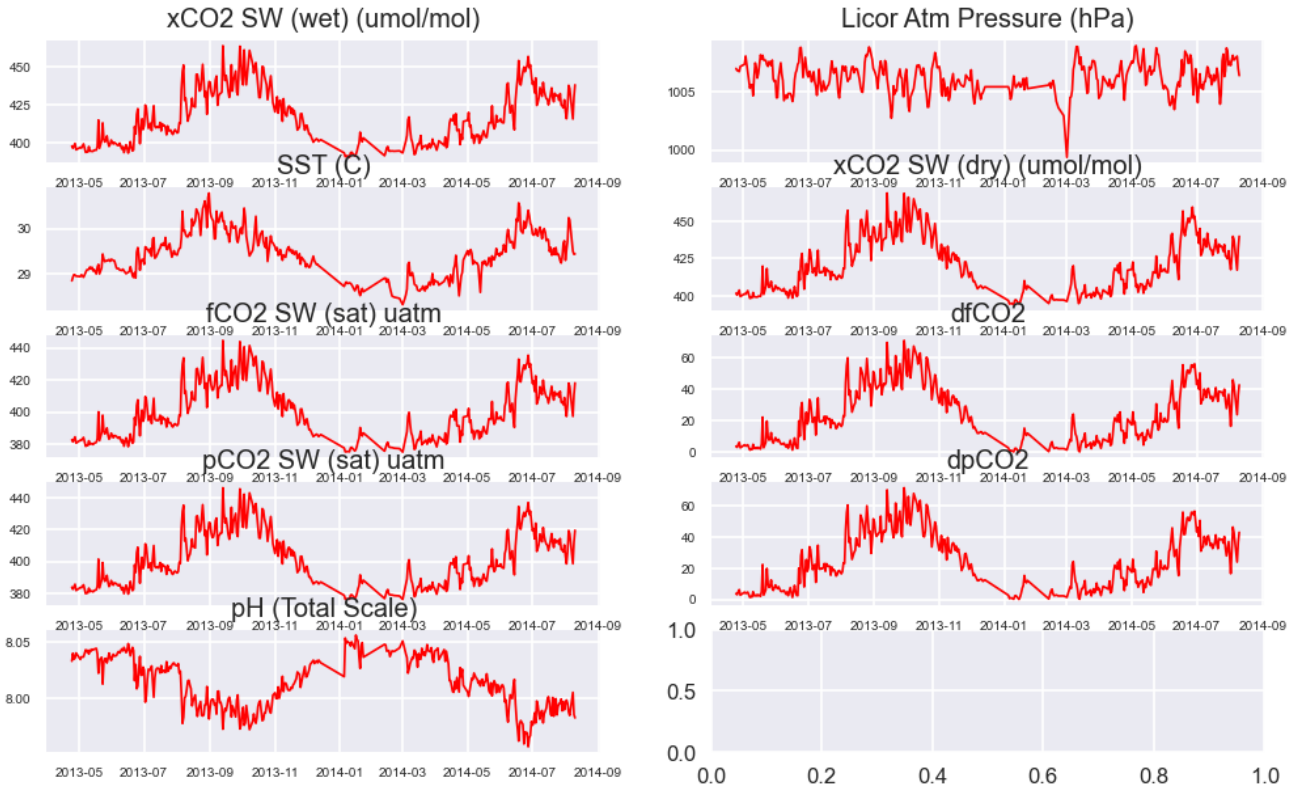
```
In [28]: # Looking at trends of all data
fig, axes = plt.subplots(nrows=5, ncols=2, dpi=120, figsize=(10,6), )
for i, ax in enumerate(axes.flatten()):
    data = chuuk_df[chuuk_df.columns[i]]
    ax.plot(data, color='red', linewidth=1)
    # Decorations
    ax.set_title(chuuk_df.columns[i])
    ax.xaxis.set_ticks_position('none')
    ax.yaxis.set_ticks_position('none')
    ax.spines["top"].set_alpha(0)
    ax.tick_params(labelsize=6)
```

```
subplots.adjust(wspace=4, hspace=20)
plt.show();
```

```
-----
IndexError                                Traceback (most recent call last)
<ipython-input-28-5383668cfd6b> in <module>
      2 fig, axes = plt.subplots(nrows=5, ncols=2, dpi=120, figsize=(10,6), )
      3 for i, ax in enumerate(axes.flatten()):
----> 4     data = chuuk_df[chuuk_df.columns[i]]
      5     ax.plot(data, color='red', linewidth=1)
      6     # Decorations

~\anaconda3\lib\site-packages\pandas\core\indexes\base.py in __getitem__(self, key)
    4099     if is_scalar(key):
    4100         key = com.cast_scalar_indexer(key, warn_float=True)
-> 4101     return getitem(key)
    4102
    4103     if isinstance(key, slice):
```

IndexError: index 9 is out of bounds for axis 0 with size 9



```
In [29]: # setting subplots to look at different ways pH can be grouped
fig = plt.figure(figsize=(18,16))
fig.subplots_adjust(hspace=.4)
# Daily average
ax1 = fig.add_subplot(5,1,1)
ax1.plot(chuuk_df['pH (Total Scale)'].resample('D').mean(),linewidth=1)
ax1.set_title('Mean pH (total scale) resampled over day')
ax1.tick_params(axis='both', which='major')
# Weekly Average
ax2 = fig.add_subplot(5,1,2, sharex=ax1)
ax2.plot(chuuk_df['pH (Total Scale)'].resample('W').mean(),linewidth=1)
ax2.set_title('Mean pH (total scale) resampled over week')
ax2.tick_params(axis='both', which='major')
# Monthly Average
ax3 = fig.add_subplot(5,1,3, sharex=ax1)
ax3.plot(chuuk_df['pH (Total Scale)'].resample('M').mean(),linewidth=1)
ax3.set_title('Mean pH (total scale) resampled over month')
ax3.tick_params(axis='both', which='major')
# Quarterly Average
ax4 = fig.add_subplot(5,1,4, sharex=ax1)
ax4.plot(chuuk_df['pH (Total Scale)'].resample('Q').mean(),linewidth=1)
ax4.set_title('Mean pH (total scale) resampled over quarter')
ax4.tick_params(axis='both', which='major')
# Yearly Average
ax5 = fig.add_subplot(5,1,5, sharex=ax1)
```

```
ax5.plot(chuuk_df['pH (Total Scale)'].resample('A').mean(),linewidth=1)
ax5.set_title('Mean pH (total scale) resampled over year')
ax5.tick_params(axis='both', which='major');
```



```
In [26]: chuuk_df.index = pd.DatetimeIndex(chuuk_df.index).to_period("D")
chuuk_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
PeriodIndex: 379 entries, 2013-04-24 to 2014-08-10
Freq: D
Data columns (total 9 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   xCO2 SW (wet) (umol/mol)              379 non-null    float64
1   Licor Atm Pressure (hPa)              379 non-null    float64
2   SST (C)                               379 non-null    float64
3   xCO2 SW (dry) (umol/mol)              379 non-null    float64
4   fCO2 SW (sat) uatm                    379 non-null    float64
5   dFCO2                                  379 non-null    float64
6   pCO2 SW (sat) uatm                    379 non-null    float64
7   dpCO2                                  379 non-null    float64
8   pH (Total Scale)                       379 non-null    float64
dtypes: float64(9)
memory usage: 29.6 KB
```

```
In [30]: # Splitting test and train set
train = chuuk_df[:int(0.8*(len(chuuk_df)))]
valid = chuuk_df[int(0.8*(len(chuuk_df))):]
print(train.shape)
print(valid.shape)
```

```
(303, 9)
```

(76, 9)

```
In [31]: def cointegration_test(df, alpha=0.05):
        """Perform Johanson's Cointegration Test and Report Summary"""
        out = coint_johansen(df,-1,5)
        d = {'0.90':0, '0.95':1, '0.99':2}
        traces = out.lr1
        cvts = out.cvt[:, d[str(1-alpha)]]
        def adjust(val, length= 6): return str(val).ljust(length)

        # Summary
        print('Name    :: Test Stat > C(95%)    => Signif \n', '--'*20)
        for col, trace, cvt in zip(df.columns, traces, cvts):
            print(adjust(col), ':: ', adjust(round(trace,2), 9), ">", adjust(cvt, 8), ' => ', trace > cvt)

        cointegration_test(chuuk_df)
```

```
Name    :: Test Stat > C(95%)    => Signif
-----
xCO2 SW (wet) (umol/mol) :: 285.21    > 179.5199 => True
Licor Atm Pressure (hPa) :: 202.63    > 143.6691 => True
SST (C) :: 131.67    > 111.7797 => True
xCO2 SW (dry) (umol/mol) :: 81.44    > 83.9383 => False
fCO2 SW (sat) uatm :: 47.12    > 60.0627 => False
dfCO2 :: 23.24    > 40.1749 => False
pCO2 SW (sat) uatm :: 9.84    > 24.2761 => False
dpCO2 :: 3.21    > 12.3212 => False
pH (Total Scale) :: 0.16    > 4.1296 => False
```

```
In [32]: def adfuller_test(series, signif=0.05, name='', verbose=False):
        """Perform ADFuller to test for Stationarity of given series and print report"""
        r = adfuller(series, autolag='AIC')
        output = {'test_statistic':round(r[0], 4), 'pvalue':round(r[1], 4), 'n_lags':round(r[2], 4), 'n_obs':r[3]}
        p_value = output['pvalue']
        def adjust(val, length= 6): return str(val).ljust(length)

        # Print Summary
        print(f'    Augmented Dickey-Fuller Test on "{name}"', "\n    ", '-'*47)
        print(f' Null Hypothesis: Data has unit root. Non-Stationary.')
        print(f' Significance Level      = {signif}')
        print(f' Test Statistic           = {output["test_statistic"]}')
        print(f' No. Lags Chosen          = {output["n_lags"]}')

        for key,val in r[4].items():
            print(f' Critical value {adjust(key)} = {round(val, 3)}')

        if p_value <= signif:
            print(f" => P-Value = {p_value}. Rejecting Null Hypothesis.")
            print(f" => Series is Stationary.")
        else:
            print(f" => P-Value = {p_value}. Weak evidence to reject the Null Hypothesis.")
            print(f" => Series is Non-Stationary.")
```

```
In [33]: # ADF Test on each column
        for name, column in train.iteritems():
            adfuller_test(column, name=column.name)
            print('\n')

        Augmented Dickey-Fuller Test on "xCO2 SW (wet) (umol/mol)"
        -----
        Null Hypothesis: Data has unit root. Non-Stationary.
        Significance Level      = 0.05
        Test Statistic          = -1.4415
        No. Lags Chosen         = 10
        Critical value 1%       = -3.453
        Critical value 5%      = -2.871
        Critical value 10%     = -2.572
        => P-Value = 0.5622. Weak evidence to reject the Null Hypothesis.
        => Series is Non-Stationary.
```

```
        Augmented Dickey-Fuller Test on "Licor Atm Pressure (hPa)"
        -----
        Null Hypothesis: Data has unit root. Non-Stationary.
        Significance Level      = 0.05
        Test Statistic          = -6.1375
        No. Lags Chosen         = 3
        Critical value 1%       = -3.452
        Critical value 5%      = -2.871
```

Critical value 10% = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.

Augmented Dickey-Fuller Test on "SST (C)"

Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -1.6993
No. Lags Chosen = 5
Critical value 1% = -3.453
Critical value 5% = -2.871
Critical value 10% = -2.572
=> P-Value = 0.4315. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.

Augmented Dickey-Fuller Test on "xCO2 SW (dry) (umol/mol)"

Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -1.398
No. Lags Chosen = 10
Critical value 1% = -3.453
Critical value 5% = -2.871
Critical value 10% = -2.572
=> P-Value = 0.5832. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.

Augmented Dickey-Fuller Test on "fCO2 SW (sat) uatm"

Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -1.4348
No. Lags Chosen = 10
Critical value 1% = -3.453
Critical value 5% = -2.871
Critical value 10% = -2.572
=> P-Value = 0.5655. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.

Augmented Dickey-Fuller Test on "dfCO2"

Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -1.3926
No. Lags Chosen = 10
Critical value 1% = -3.453
Critical value 5% = -2.871
Critical value 10% = -2.572
=> P-Value = 0.5858. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.

Augmented Dickey-Fuller Test on "pCO2 SW (sat) uatm"

Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -1.4353
No. Lags Chosen = 10
Critical value 1% = -3.453
Critical value 5% = -2.871
Critical value 10% = -2.572
=> P-Value = 0.5653. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.

Augmented Dickey-Fuller Test on "dpCO2"

Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -1.3925
No. Lags Chosen = 10
Critical value 1% = -3.453
Critical value 5% = -2.871
Critical value 10% = -2.572
=> P-Value = 0.5858. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.

Augmented Dickey-Fuller Test on "pH (Total Scale)"

```
-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -1.5639
No. Lags Chosen      = 6
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.5017. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.
```

```
In [34]: # 1st difference
train_diff = train.diff().dropna()
```

```
In [35]: # ADF Test on each column
for name, column in train_diff.iteritems():
    adfuller_test(column, name=column.name)
    print('\n')
```

Augmented Dickey-Fuller Test on "xCO2 SW (wet) (umol/mol)"

```
-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -8.012
No. Lags Chosen      = 9
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.
```

Augmented Dickey-Fuller Test on "Licor Atm Pressure (hPa)"

```
-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -7.3988
No. Lags Chosen      = 13
Critical value 1%    = -3.453
Critical value 5%    = -2.872
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.
```

Augmented Dickey-Fuller Test on "SST (C)"

```
-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -8.4613
No. Lags Chosen      = 8
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.
```

Augmented Dickey-Fuller Test on "xCO2 SW (dry) (umol/mol)"

```
-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -7.9435
No. Lags Chosen      = 9
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.
```

Augmented Dickey-Fuller Test on "fCO2 SW (sat) uatm"

```
-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -7.8566
No. Lags Chosen      = 9
```

```

Critical value 1%      = -3.453
Critical value 5%      = -2.871
Critical value 10%     = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.

```

Augmented Dickey-Fuller Test on "dfC02"

```

-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -7.7811
No. Lags Chosen      = 9
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.

```

Augmented Dickey-Fuller Test on "pC02 SW (sat) uatm"

```

-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -7.8536
No. Lags Chosen      = 9
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.

```

Augmented Dickey-Fuller Test on "dpC02"

```

-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -7.7804
No. Lags Chosen      = 9
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.

```

Augmented Dickey-Fuller Test on "pH (Total Scale)"

```

-----
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic       = -10.6787
No. Lags Chosen      = 5
Critical value 1%    = -3.453
Critical value 5%    = -2.871
Critical value 10%   = -2.572
=> P-Value = 0.0. Rejecting Null Hypothesis.
=> Series is Stationary.

```

```

In [36]: model = VAR(train_diff)
         x = model.select_order(maxlags=10)
         x.summary()

```

C:\Users\datre\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:581: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
warnings.warn('A date index has been provided, but it has no')

```

Out[36]: VAR Order Selection (* highlights the
          minimums)

```

	AIC	BIC	FPE	HQIC
0	-34.86	-34.75*	7.230e-16	-34.82
1	-35.81	-34.67	2.814e-16	-35.35
2	-36.28	-34.13	1.753e-16	-35.42*
3	-36.64*	-33.46	1.234e-16*	-35.37
4	-36.62	-32.43	1.263e-16	-34.94
5	-36.55	-31.34	1.370e-16	-34.46


```

6  -36.59  -30.36  1.333e-16  -34.10
7  -36.52  -29.26  1.475e-16  -33.61
8  -36.44  -28.17  1.646e-16  -33.13
9  -36.45  -27.16  1.698e-16  -32.73
10 -36.30  -25.99  2.088e-16  -32.17

```

```

In [37]: # Using fit 3 from results above
         model_fitted = model.fit(3)
         model_fitted.summary()

```

```
Out[37]: Summary of Regression Results
```

```

=====
Model:                                VAR
Method:                               OLS
Date:                                Thu, 03, Jun, 2021
Time:                                16:51:17
=====
No. of Equations:    9.00000    BIC:                -33.6672
Nobs:                299.000    HQIC:             -35.5377
Log likelihood:      1933.14    FPE:              1.06221e-16
AIC:                 -36.7860    Det(Omega_mle):   4.74593e-17
=====
Results for equation xCO2 SW (wet) (umol/mol)
=====

```

	coefficient	std. error	t-stat	prob
const	0.092659	0.370431	0.250	0.802
L1.xCO2 SW (wet) (umol/mol)	-1.697108	1.572509	-1.079	0.280
L1.Licor Atm Pressure (hPa)	4.253268	5.490276	0.775	0.439
L1.SST (C)	-7.749009	13.626843	-0.569	0.570
L1.xCO2 SW (dry) (umol/mol)	12.187276	12.809705	0.951	0.341
L1.fc02 SW (sat) uatm	11.733445	22.291591	0.526	0.599
L1.dfCO2	26.521244	23.037665	1.151	0.250
L1.pCO2 SW (sat) uatm	-21.782485	23.028528	-0.946	0.344
L1.dpCO2	-27.726482	22.966879	-1.207	0.227
L1.pH (Total Scale)	-47.685990	92.412470	-0.516	0.606
L2.xCO2 SW (wet) (umol/mol)	-1.783413	1.663797	-1.072	0.284
L2.Licor Atm Pressure (hPa)	-8.321198	5.367704	-1.550	0.121
L2.SST (C)	18.195817	13.228480	1.376	0.169
L2.xCO2 SW (dry) (umol/mol)	-17.627894	12.379860	-1.424	0.154
L2.fc02 SW (sat) uatm	-8.647903	24.211936	-0.357	0.721
L2.dfCO2	10.246204	26.618213	0.385	0.700
L2.pCO2 SW (sat) uatm	30.189244	24.505240	1.232	0.218
L2.dpCO2	-11.701242	26.539818	-0.441	0.659
L2.pH (Total Scale)	-12.199291	102.448626	-0.119	0.905
L3.xCO2 SW (wet) (umol/mol)	-0.575889	1.507157	-0.382	0.702
L3.Licor Atm Pressure (hPa)	-4.663817	5.459729	-0.854	0.393
L3.SST (C)	12.061142	13.441163	0.897	0.370
L3.xCO2 SW (dry) (umol/mol)	-8.038954	12.651793	-0.635	0.525
L3.fc02 SW (sat) uatm	26.234863	22.114256	1.186	0.235
L3.dfCO2	-16.486678	22.938355	-0.719	0.472
L3.pCO2 SW (sat) uatm	-16.372867	22.520665	-0.727	0.467
L3.dpCO2	15.549094	22.872544	0.680	0.497
L3.pH (Total Scale)	-91.223112	89.219420	-1.022	0.307

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Results for equation Licor Atm Pressure (hPa)
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	coefficient	std. error	t-stat	prob
const	0.003464	0.046752	0.074	0.941
L1.xCO2 SW (wet) (umol/mol)	-0.298861	0.198467	-1.506	0.132
L1.Licor Atm Pressure (hPa)	-1.743880	0.692928	-2.517	0.012
L1.SST (C)	4.267175	1.719846	2.481	0.013
L1.xCO2 SW (dry) (umol/mol)	-4.092935	1.616714	-2.532	0.011
L1.fc02 SW (sat) uatm	-0.143403	2.813424	-0.051	0.959
L1.dfCO2	-3.431241	2.907587	-1.180	0.238
L1.pCO2 SW (sat) uatm	4.758612	2.906433	1.637	0.102
L1.dpCO2	3.428710	2.898653	1.183	0.237
L1.pH (Total Scale)	8.785099	11.663389	0.753	0.451
L2.xCO2 SW (wet) (umol/mol)	-0.086561	0.209988	-0.412	0.680
L2.Licor Atm Pressure (hPa)	-1.529642	0.677459	-2.258	0.024
L2.SST (C)	2.828131	1.669568	1.694	0.090
L2.xCO2 SW (dry) (umol/mol)	-2.707458	1.562464	-1.733	0.083
L2.fc02 SW (sat) uatm	0.535578	3.055791	0.175	0.861
L2.dfCO2	-3.612027	3.359488	-1.075	0.282
L2.pCO2 SW (sat) uatm	2.464582	3.092809	0.797	0.426

L2.dpCO2	3.561548	3.349594	1.063	0.288
L2.pH (Total Scale)	16.531170	12.930054	1.279	0.201
L3.xCO2 SW (wet) (umol/mol)	-0.329881	0.190218	-1.734	0.083
L3.Licor Atm Pressure (hPa)	-0.732929	0.689073	-1.064	0.287
L3.SST (C)	2.133611	1.696411	1.258	0.208
L3.xCO2 SW (dry) (umol/mol)	-1.386550	1.596784	-0.868	0.385
L3.fCO2 SW (sat) uatm	-0.388050	2.791043	-0.139	0.889
L3.dfCO2	-3.455190	2.895053	-1.193	0.233
L3.pCO2 SW (sat) uatm	2.256208	2.842336	0.794	0.427
L3.dpCO2	3.393023	2.886747	1.175	0.240
L3.pH (Total Scale)	14.029620	11.260394	1.246	0.213

Results for equation SST (C)

	coefficient	std. error	t-stat	prob
const	0.002209	0.009134	0.242	0.809
L1.xCO2 SW (wet) (umol/mol)	-0.056959	0.038773	-1.469	0.142
L1.Licor Atm Pressure (hPa)	-0.258584	0.135373	-1.910	0.056
L1.SST (C)	0.484565	0.335995	1.442	0.149
L1.xCO2 SW (dry) (umol/mol)	-0.538131	0.315847	-1.704	0.088
L1.fCO2 SW (sat) uatm	0.137743	0.549640	0.251	0.802
L1.dfCO2	-0.033927	0.568036	-0.060	0.952
L1.pCO2 SW (sat) uatm	0.527215	0.567810	0.929	0.353
L1.dpCO2	-0.004108	0.566290	-0.007	0.994
L1.pH (Total Scale)	0.143478	2.278598	0.063	0.950
L2.xCO2 SW (wet) (umol/mol)	-0.027693	0.041024	-0.675	0.500
L2.Licor Atm Pressure (hPa)	-0.150573	0.132351	-1.138	0.255
L2.SST (C)	0.134937	0.326172	0.414	0.679
L2.xCO2 SW (dry) (umol/mol)	-0.311925	0.305248	-1.022	0.307
L2.fCO2 SW (sat) uatm	-0.001185	0.596989	-0.002	0.998
L2.dfCO2	0.074056	0.656321	0.113	0.910
L2.pCO2 SW (sat) uatm	0.382840	0.604221	0.634	0.526
L2.dpCO2	-0.098967	0.654388	-0.151	0.880
L2.pH (Total Scale)	0.531486	2.526058	0.210	0.833
L3.xCO2 SW (wet) (umol/mol)	-0.003007	0.037162	-0.081	0.936
L3.Licor Atm Pressure (hPa)	-0.391636	0.134620	-2.909	0.004
L3.SST (C)	0.916084	0.331416	2.764	0.006
L3.xCO2 SW (dry) (umol/mol)	-0.977053	0.311953	-3.132	0.002
L3.fCO2 SW (sat) uatm	0.576808	0.545267	1.058	0.290
L3.dfCO2	-0.258749	0.565587	-0.457	0.647
L3.pCO2 SW (sat) uatm	0.466794	0.555288	0.841	0.401
L3.dpCO2	0.250450	0.563964	0.444	0.657
L3.pH (Total Scale)	1.721753	2.199867	0.783	0.434

Results for equation xCO2 SW (dry) (umol/mol)

	coefficient	std. error	t-stat	prob
const	0.083434	0.375026	0.222	0.824
L1.xCO2 SW (wet) (umol/mol)	-1.249596	1.592017	-0.785	0.433
L1.Licor Atm Pressure (hPa)	4.392606	5.558385	0.790	0.429
L1.SST (C)	-7.713459	13.795889	-0.559	0.576
L1.xCO2 SW (dry) (umol/mol)	12.107051	12.968614	0.934	0.351
L1.fCO2 SW (sat) uatm	11.731047	22.568127	0.520	0.603
L1.dfCO2	27.344869	23.323456	1.172	0.241
L1.pCO2 SW (sat) uatm	-22.163864	23.314206	-0.951	0.342
L1.dpCO2	-28.543549	23.251792	-1.228	0.220
L1.pH (Total Scale)	-44.702176	93.558882	-0.478	0.633
L2.xCO2 SW (wet) (umol/mol)	-1.504923	1.684437	-0.893	0.372
L2.Licor Atm Pressure (hPa)	-8.298165	5.434293	-1.527	0.127
L2.SST (C)	17.940149	13.392584	1.340	0.180
L2.xCO2 SW (dry) (umol/mol)	-17.857475	12.533437	-1.425	0.154
L2.fCO2 SW (sat) uatm	-8.518789	24.512295	-0.348	0.728
L2.dfCO2	10.173068	26.948422	0.378	0.706
L2.pCO2 SW (sat) uatm	30.014711	24.809237	1.210	0.226
L2.dpCO2	-11.621240	26.869054	-0.433	0.665
L2.pH (Total Scale)	-3.494614	103.719541	-0.034	0.973
L3.xCO2 SW (wet) (umol/mol)	-0.335608	1.525854	-0.220	0.826
L3.Licor Atm Pressure (hPa)	-5.530004	5.527459	-1.000	0.317
L3.SST (C)	13.978028	13.607905	1.027	0.304
L3.xCO2 SW (dry) (umol/mol)	-10.324755	12.808743	-0.806	0.420
L3.fCO2 SW (sat) uatm	28.965959	22.388592	1.294	0.196
L3.dfCO2	-16.622964	23.222914	-0.716	0.474
L3.pCO2 SW (sat) uatm	-16.931223	22.800043	-0.743	0.458
L3.dpCO2	15.687631	23.156287	0.677	0.498
L3.pH (Total Scale)	-82.156275	90.326221	-0.910	0.363

Results for equation fCO2 SW (sat) uatm

	coefficient	std. error	t-stat	prob
const	0.078580	0.352747	0.223	0.824
L1.xCO2 SW (wet) (umol/mol)	-1.248528	1.497441	-0.834	0.404
L1.Licor Atm Pressure (hPa)	3.788152	5.228180	0.725	0.469
L1.SST (C)	-6.232155	12.976321	-0.480	0.631
L1.xCO2 SW (dry) (umol/mol)	10.515089	12.198192	0.862	0.389
L1.fCO2 SW (sat) uatm	10.332736	21.227430	0.487	0.626
L1.dfcO2	24.456185	21.937888	1.115	0.265
L1.pCO2 SW (sat) uatm	-19.182407	21.929187	-0.875	0.382
L1.dpCO2	-25.559329	21.870480	-1.169	0.243
L1.pH (Total Scale)	-38.770750	88.000861	-0.441	0.660
L2.xCO2 SW (wet) (umol/mol)	-1.435642	1.584370	-0.906	0.365
L2.Licor Atm Pressure (hPa)	-8.255483	5.111460	-1.615	0.106
L2.SST (C)	17.825060	12.596975	1.415	0.157
L2.xCO2 SW (dry) (umol/mol)	-17.517951	11.788867	-1.486	0.137
L2.fCO2 SW (sat) uatm	-8.427194	23.056101	-0.366	0.715
L2.dfcO2	7.953231	25.347506	0.314	0.754
L2.pCO2 SW (sat) uatm	29.437847	23.335403	1.262	0.207
L2.dpCO2	-9.326528	25.272853	-0.369	0.712
L2.pH (Total Scale)	2.477995	97.557909	0.025	0.980
L3.xCO2 SW (wet) (umol/mol)	-0.445770	1.435208	-0.311	0.756
L3.Licor Atm Pressure (hPa)	-5.051109	5.199091	-0.972	0.331
L3.SST (C)	12.949352	12.799505	1.012	0.312
L3.xCO2 SW (dry) (umol/mol)	-9.141870	12.047818	-0.759	0.448
L3.fCO2 SW (sat) uatm	26.392153	21.058560	1.253	0.210
L3.dfcO2	-16.817885	21.843318	-0.770	0.441
L3.pCO2 SW (sat) uatm	-15.514153	21.445568	-0.723	0.469
L3.dpCO2	15.912611	21.780649	0.731	0.465
L3.pH (Total Scale)	-73.972096	84.960242	-0.871	0.384

Results for equation dfCO2

	coefficient	std. error	t-stat	prob
const	0.085502	0.358798	0.238	0.812
L1.xCO2 SW (wet) (umol/mol)	-1.558477	1.523126	-1.023	0.306
L1.Licor Atm Pressure (hPa)	3.519844	5.317857	0.662	0.508
L1.SST (C)	-4.803112	13.198900	-0.364	0.716
L1.xCO2 SW (dry) (umol/mol)	10.764447	12.407424	0.868	0.386
L1.fCO2 SW (sat) uatm	11.371767	21.591538	0.527	0.598
L1.dfcO2	26.477545	22.314181	1.187	0.235
L1.pCO2 SW (sat) uatm	-19.472306	22.305331	-0.873	0.383
L1.dpCO2	-28.246858	22.245618	-1.270	0.204
L1.pH (Total Scale)	-41.538403	89.510313	-0.464	0.643
L2.xCO2 SW (wet) (umol/mol)	-1.336675	1.611546	-0.829	0.407
L2.Licor Atm Pressure (hPa)	-7.995554	5.199135	-1.538	0.124
L2.SST (C)	17.217440	12.813047	1.344	0.179
L2.xCO2 SW (dry) (umol/mol)	-16.817832	11.991078	-1.403	0.161
L2.fCO2 SW (sat) uatm	-12.888049	23.451575	-0.550	0.583
L2.dfcO2	13.767077	25.782284	0.534	0.593
L2.pCO2 SW (sat) uatm	33.442265	23.735668	1.409	0.159
L2.dpCO2	-15.503424	25.706351	-0.603	0.546
L2.pH (Total Scale)	3.010460	99.231290	0.030	0.976
L3.xCO2 SW (wet) (umol/mol)	0.164513	1.459826	0.113	0.910
L3.Licor Atm Pressure (hPa)	-5.485900	5.288269	-1.037	0.300
L3.SST (C)	14.873767	13.019051	1.142	0.253
L3.xCO2 SW (dry) (umol/mol)	-10.874368	12.254471	-0.887	0.375
L3.fCO2 SW (sat) uatm	25.532102	21.419771	1.192	0.233
L3.dfcO2	-12.792057	22.217990	-0.576	0.565
L3.pCO2 SW (sat) uatm	-13.286067	21.813417	-0.609	0.542
L3.dpCO2	11.755703	22.154246	0.531	0.596
L3.pH (Total Scale)	-69.829534	86.417539	-0.808	0.419

Results for equation pCO2 SW (sat) uatm

	coefficient	std. error	t-stat	prob
const	0.079086	0.353763	0.224	0.823
L1.xCO2 SW (wet) (umol/mol)	-1.262789	1.501752	-0.841	0.400
L1.Licor Atm Pressure (hPa)	3.791559	5.243233	0.723	0.470
L1.SST (C)	-6.255130	13.013684	-0.481	0.631
L1.xCO2 SW (dry) (umol/mol)	10.532871	12.233314	0.861	0.389
L1.fCO2 SW (sat) uatm	11.041147	21.288550	0.519	0.604
L1.dfcO2	24.509455	22.001053	1.114	0.265
L1.pCO2 SW (sat) uatm	-19.889548	21.992327	-0.904	0.366
L1.dpCO2	-25.616366	21.933451	-1.168	0.243
L1.pH (Total Scale)	-38.570252	88.254239	-0.437	0.662
L2.xCO2 SW (wet) (umol/mol)	-1.451897	1.588932	-0.914	0.361

L2.Licor Atm Pressure (hPa)	-8.279183	5.126177	-1.615	0.106
L2.SST (C)	17.845996	12.633245	1.413	0.158
L2.xCO2 SW (dry) (umol/mol)	-17.555099	11.822810	-1.485	0.138
L2.fCO2 SW (sat) uatm	-7.937543	23.122486	-0.343	0.731
L2.dfcO2	7.966565	25.420488	0.313	0.754
L2.pCO2 SW (sat) uatm	29.011724	23.402592	1.240	0.215
L2.dpCO2	-9.346441	25.345621	-0.369	0.712
L2.pH (Total Scale)	2.614778	97.838804	0.027	0.979
L3.xCO2 SW (wet) (umol/mol)	-0.455358	1.439340	-0.316	0.752
L3.Licor Atm Pressure (hPa)	-5.065401	5.214060	-0.971	0.331
L3.SST (C)	12.989717	12.836358	1.012	0.312
L3.xCO2 SW (dry) (umol/mol)	-9.159099	12.082507	-0.758	0.448
L3.fCO2 SW (sat) uatm	26.680817	21.119194	1.263	0.206
L3.dfcO2	-16.974872	21.906211	-0.775	0.438
L3.pCO2 SW (sat) uatm	-15.768379	21.507316	-0.733	0.463
L3.dpCO2	16.062845	21.843362	0.735	0.462
L3.pH (Total Scale)	-74.292738	85.204865	-0.872	0.383

Results for equation dpCO2

	coefficient	std. error	t-stat	prob
const	0.085789	0.359846	0.238	0.812
L1.xCO2 SW (wet) (umol/mol)	-1.565772	1.527576	-1.025	0.305
L1.Licor Atm Pressure (hPa)	3.518926	5.333394	0.660	0.509
L1.SST (C)	-4.795990	13.237463	-0.362	0.717
L1.xCO2 SW (dry) (umol/mol)	10.773844	12.443675	0.866	0.387
L1.fCO2 SW (sat) uatm	11.400152	21.654621	0.526	0.599
L1.dfcO2	27.310832	22.379376	1.220	0.222
L1.pCO2 SW (sat) uatm	-19.497779	22.370500	-0.872	0.383
L1.dpCO2	-29.083445	22.310613	-1.304	0.192
L1.pH (Total Scale)	-41.271882	89.771834	-0.460	0.646
L2.xCO2 SW (wet) (umol/mol)	-1.341758	1.616254	-0.830	0.406
L2.Licor Atm Pressure (hPa)	-8.036132	5.214325	-1.541	0.123
L2.SST (C)	17.312291	12.850483	1.347	0.178
L2.xCO2 SW (dry) (umol/mol)	-16.910472	12.026112	-1.406	0.160
L2.fCO2 SW (sat) uatm	-12.892249	23.520093	-0.548	0.584
L2.dfcO2	14.324418	25.857611	0.554	0.580
L2.pCO2 SW (sat) uatm	33.554133	23.805016	1.410	0.159
L2.dpCO2	-16.064717	25.781457	-0.623	0.533
L2.pH (Total Scale)	3.098095	99.521212	0.031	0.975
L3.xCO2 SW (wet) (umol/mol)	0.169428	1.464091	0.116	0.908
L3.Licor Atm Pressure (hPa)	-5.488298	5.303720	-1.035	0.301
L3.SST (C)	14.886692	13.057089	1.140	0.254
L3.xCO2 SW (dry) (umol/mol)	-10.877461	12.290275	-0.885	0.376
L3.fCO2 SW (sat) uatm	25.540628	21.482353	1.189	0.234
L3.dfcO2	-12.531884	22.282904	-0.562	0.574
L3.pCO2 SW (sat) uatm	-13.293905	21.877149	-0.608	0.543
L3.dpCO2	11.493638	22.218974	0.517	0.605
L3.pH (Total Scale)	-69.867510	86.670023	-0.806	0.420

Results for equation pH (Total Scale)

	coefficient	std. error	t-stat	prob
const	-0.000193	0.000432	-0.446	0.655
L1.xCO2 SW (wet) (umol/mol)	0.000427	0.001833	0.233	0.816
L1.Licor Atm Pressure (hPa)	-0.003322	0.006400	-0.519	0.604
L1.SST (C)	-0.000410	0.015885	-0.026	0.979
L1.xCO2 SW (dry) (umol/mol)	-0.007417	0.014932	-0.497	0.619
L1.fCO2 SW (sat) uatm	-0.025563	0.025986	-0.984	0.325
L1.dfcO2	-0.033246	0.026855	-1.238	0.216
L1.pCO2 SW (sat) uatm	0.030793	0.026845	1.147	0.251
L1.dpCO2	0.034841	0.026773	1.301	0.193
L1.pH (Total Scale)	-0.525504	0.107727	-4.878	0.000
L2.xCO2 SW (wet) (umol/mol)	0.001799	0.001940	0.927	0.354
L2.Licor Atm Pressure (hPa)	0.002632	0.006257	0.421	0.674
L2.SST (C)	-0.005165	0.015421	-0.335	0.738
L2.xCO2 SW (dry) (umol/mol)	0.002826	0.014431	0.196	0.845
L2.fCO2 SW (sat) uatm	0.003436	0.028224	0.122	0.903
L2.dfcO2	-0.003430	0.031029	-0.111	0.912
L2.pCO2 SW (sat) uatm	-0.009973	0.028566	-0.349	0.727
L2.dpCO2	0.005079	0.030938	0.164	0.870
L2.pH (Total Scale)	-0.324060	0.119426	-2.713	0.007
L3.xCO2 SW (wet) (umol/mol)	0.000850	0.001757	0.484	0.629
L3.Licor Atm Pressure (hPa)	0.004782	0.006364	0.751	0.452
L3.SST (C)	-0.013854	0.015669	-0.884	0.377
L3.xCO2 SW (dry) (umol/mol)	0.009078	0.014748	0.616	0.538
L3.fCO2 SW (sat) uatm	-0.041563	0.025779	-1.612	0.107
L3.dfcO2	0.038496	0.026740	1.440	0.150

L3.pCO2 SW (sat) uatm	0.030067	0.026253	1.145	0.252
L3.dpCO2	-0.037602	0.026663	-1.410	0.158
L3.pH (Total Scale)	-0.154808	0.104004	-1.488	0.137

=====

Correlation matrix of residuals

	xCO2 SW (wet) (umol/mol)	Licor Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)
fcO2 SW (sat) uatm	dfCO2	pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)
xCO2 SW (wet) (umol/mol)	1.000000	-0.016383	0.374658	0.999053
0.998142 0.973060	0.998138 0.973085	-0.832916		
Licor Atm Pressure (hPa)	-0.016383	1.000000	0.020791	-0.021967
0.031772 -0.010622	0.031790 -0.010468	-0.041978		
SST (C)	0.374658	0.020791	1.000000	0.395850
0.375797 0.414584	0.375321 0.414352	-0.267610		
xCO2 SW (dry) (umol/mol)	0.999053	-0.021967	0.395850	1.000000
0.998284 0.976087	0.998272 0.976102	-0.830490		
fcO2 SW (sat) uatm	0.998142	0.031772	0.375797	0.998284
1.000000 0.974394	0.999996 0.974423	-0.833739		
dfCO2	0.973060	-0.010622	0.414584	0.976087
0.974394 1.000000	0.974385 0.999997	-0.814025		
pCO2 SW (sat) uatm	0.998138	0.031790	0.375321	0.998272
0.999996 0.974385	1.000000 0.974414	-0.834033		
dpCO2	0.973085	-0.010468	0.414352	0.976102
0.974423 0.999997	0.974414 1.000000	-0.814034		
pH (Total Scale)	-0.832916	-0.041978	-0.267610	-0.830490
-0.833739 -0.814025	-0.834033 -0.814034	1.000000		

```
In [38]: out = durbin_watson(model_fitted.resid)

for col, val in zip(chuuk_df.columns, out):
    print(col, ': ', round(val, 2))
```

```
xCO2 SW (wet) (umol/mol) : 1.97
Licor Atm Pressure (hPa) : 2.0
SST (C) : 2.05
xCO2 SW (dry) (umol/mol) : 1.97
fcO2 SW (sat) uatm : 1.98
dfCO2 : 1.99
pCO2 SW (sat) uatm : 1.98
dpCO2 : 1.99
pH (Total Scale) : 1.98
```

```
In [39]: # Get the lag order
lag_order = model_fitted.k_ar
print(lag_order)

# Input data for forecasting
forecast_input = train_diff.values[-lag_order:]
forecast_input
```

3

```
Out[39]: array([[ 5.11250e+00,  8.75000e-02,  4.53750e-02,  5.13750e+00,
  4.87500e+00,  5.27500e+00,  4.88750e+00,  5.31250e+00,
 -6.00000e-03],
 [ 4.52500e+00,  3.12500e-01,  1.25125e-01,  4.73750e+00,
  4.52500e+00,  5.32500e+00,  4.51250e+00,  5.33750e+00,
 -8.87500e-03],
 [-7.50000e-02, -6.25000e-02, -1.50000e-02, -1.87500e-01,
 -2.00000e-01, -3.50000e-01, -2.00000e-01, -3.25000e-01,
 -2.25000e-03]])
```

```
In [40]: # Forecast
fc = model_fitted.forecast(y=forecast_input, steps = len(train_diff))
df_forecast = pd.DataFrame(fc, index=train_diff.index, columns = chuuk_df.columns + "_1d")
df_forecast
```

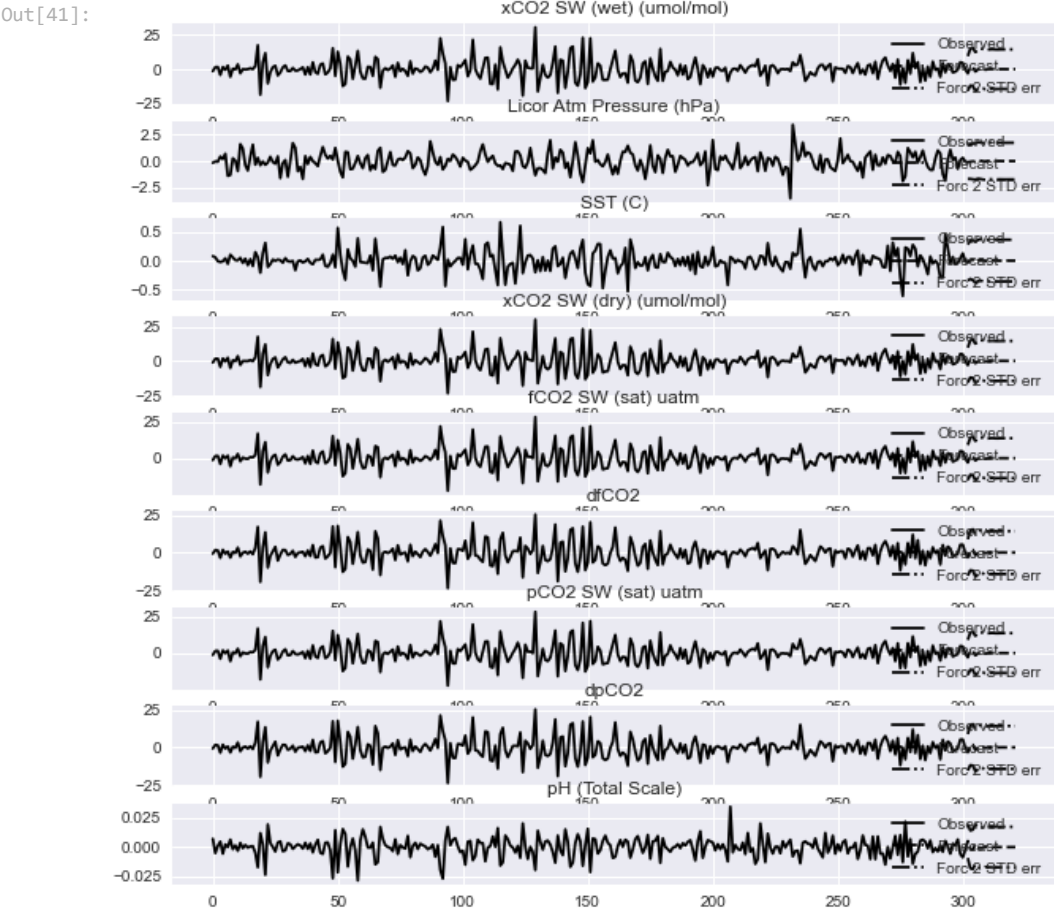
```
Out[40]:
```

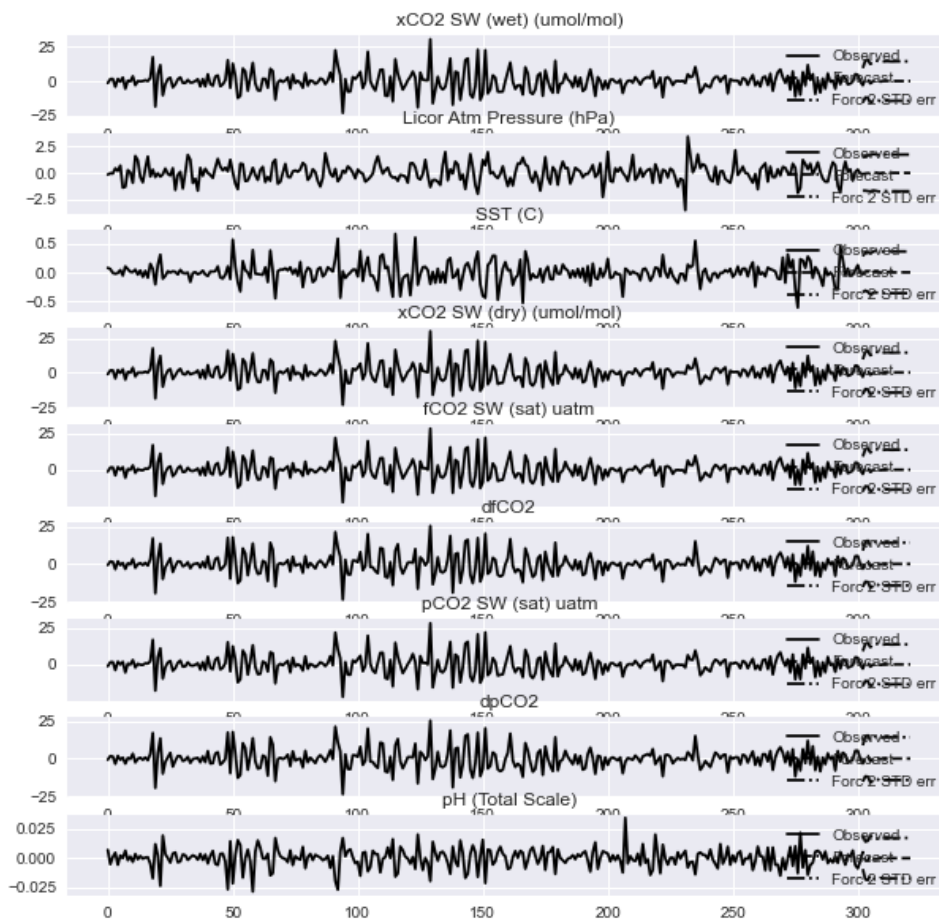
Datetime	xCO2 SW (wet) (umol/mol)_1d	Licor Atm Pressure (hPa)_1d	SST (C)_1d	xCO2 SW (dry) (umol/mol)_1d	fcO2 SW (sat) uatm_1d	dfCO2_1d	pCO2 SW (sat) uatm_1d	dpCO2_1d	pH (Total Scale)_1d
2013-04-25	-3.011511	-0.113039	-0.032469	-3.052355	-2.919747	-3.185919	-2.920522	-3.220280	0.005145
2013-04-26	1.503981	-0.063022	0.016578	1.531379	1.411335	1.539328	1.414204	1.548054	-0.002005
2013-04-27	1.754687	-0.029876	0.007649	1.746079	1.636270	1.805490	1.640750	1.812185	-0.002062

Datetime	xCO2 SW (wet) (umol/mol)_1d	Licor Atm Pressure (hPa)_1d	SST (C)_1d	xCO2 SW (dry) (umol/mol)_1d	fCO2 SW (sat) uatm_1d	dfCO2_1d	pCO2 SW (sat) uatm_1d	dpCO2_1d	pH (Total Scale)_1d
2013-04-28	-1.666134	-0.044382	-0.027470	-1.692304	-1.589906	-1.692350	-1.597855	-1.692765	0.002181
2013-05-02	-0.337657	0.052205	0.000268	-0.351231	-0.312635	-0.333211	-0.310113	-0.339033	0.000169
...
2014-05-18	0.043320	-0.001188	0.001062	0.038493	0.035133	0.041571	0.035227	0.041692	-0.000092
2014-05-19	0.043320	-0.001188	0.001062	0.038493	0.035133	0.041571	0.035227	0.041692	-0.000092
2014-05-20	0.043320	-0.001188	0.001062	0.038493	0.035133	0.041571	0.035227	0.041692	-0.000092
2014-05-21	0.043320	-0.001188	0.001062	0.038493	0.035133	0.041571	0.035227	0.041692	-0.000092
2014-05-22	0.043320	-0.001188	0.001062	0.038493	0.035133	0.041571	0.035227	0.041692	-0.000092

302 rows × 9 columns

```
In [41]: model_fitted.plot_forecast(20)
```





```
In [42]: fevd = model_fitted.fevd(5)
fevd.summary()
```

```
FEVD for xCO2 SW (wet) (umol/mol)
xCO2 SW (wet) (umol/mol)  Licor Atm Pressure (hPa)  SST (C)  xCO2 SW (dry) (umol/mol)  fCO2 SW (sat) uatm
dfCO2  pCO2 SW (sat) uatm  dpCO2  pH (Total Scale)
0      1.000000          0.000000  0.000000          0.000000          0.000000  0.
000000          0.000000  0.000000          0.000000          0.000000          0.
1      0.927590          0.000072  0.002589          0.000009          0.001887  0.
060801          0.001849  0.004411          0.000791          0.000025          0.005128  0.
2      0.902973          0.001953  0.011743          0.000025          0.005128  0.
060891          0.011055  0.005438          0.000794          0.000025          0.007405  0.
3      0.872782          0.005558  0.013027          0.000025          0.007405  0.
069973          0.017816  0.012222          0.001192          0.000845          0.007709  0.
4      0.865162          0.005593  0.012950          0.000845          0.007709  0.
073648          0.017696  0.014317          0.002080          0.000845          0.007709  0.
```

```
FEVD for Licor Atm Pressure (hPa)
xCO2 SW (wet) (umol/mol)  Licor Atm Pressure (hPa)  SST (C)  xCO2 SW (dry) (umol/mol)  fCO2 SW (sat) uatm
dfCO2  pCO2 SW (sat) uatm  dpCO2  pH (Total Scale)
0      0.000268          0.999732  0.000000          0.000000          0.000000  0.
000000          0.000000  0.000000          0.000000          0.000000          0.
1      0.000686          0.958052  0.000033          0.011521          0.016710  0.
000176          0.006489  0.004539          0.001794          0.011521          0.016710  0.
2      0.001939          0.941586  0.000590          0.010772          0.021175  0.
003848          0.006369  0.005578          0.008142          0.012698          0.021477  0.
3      0.003851          0.929918  0.002824          0.012698          0.021477  0.
008760          0.006271  0.005763          0.008439          0.014499          0.024451  0.
4      0.004272          0.917413  0.003469          0.014499          0.024451  0.
009209          0.006491  0.009469          0.010727          0.014499          0.024451  0.
```

```
FEVD for SST (C)
xCO2 SW (wet) (umol/mol)  Licor Atm Pressure (hPa)  SST (C)  xCO2 SW (dry) (umol/mol)  fCO2 SW (sat) uatm
dfCO2  pCO2 SW (sat) uatm  dpCO2  pH (Total Scale)
0      0.140368          0.000725  0.858906          0.000000          0.000000  0.
000000          0.000000  0.000000          0.000000          0.000000          0.
1      0.126070          0.002368  0.776007          0.001661          0.005496  0.
085941          0.002446  0.000000          0.000012          0.005496          0.005496  0.
2      0.140640          0.002733  0.765963          0.001673          0.005396          0.005396  0.
080648          0.002473  0.000001          0.000472          0.005396          0.005396  0.
3      0.136769          0.025534  0.718610          0.002169          0.021389          0.021389  0.
087900          0.002316  0.003809          0.001503          0.021389          0.021389  0.
```


4	0.137000	0.026785	0.713234	0.002713	0.024966	0.
087077	0.002292 0.004114	0.001820				
FEVD for xCO2 SW (dry) (umol/mol)						
xCO2 SW (wet) (umol/mol)	Licor	Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	
dfCO2 pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)				
0	0.998107	0.000031	0.000548	0.001313	0.000000	0.
000000	0.000000 0.000000	0.000000				
1	0.927157	0.000096	0.002971	0.001486	0.001947	0.
059187	0.001905 0.004571	0.000680				
2	0.900559	0.002014	0.013969	0.001421	0.005225	0.
059540	0.010840 0.005696	0.000737				
3	0.870568	0.005171	0.014784	0.001380	0.008391	0.
068835	0.017560 0.012220	0.001092				
4	0.862769	0.005186	0.014790	0.002416	0.008890	0.
072498	0.017537 0.014191	0.001722				
FEVD for fCO2 SW (sat) uatm						
xCO2 SW (wet) (umol/mol)	Licor	Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	
dfCO2 pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)				
0	0.996287	0.002317	0.000000	0.001374	0.000023	0.
000000	0.000000 0.000000	0.000000				
1	0.929031	0.002057	0.002876	0.001409	0.001691	0.
056594	0.001608 0.004152	0.000580				
2	0.902075	0.002836	0.013318	0.001339	0.005411	0.
057863	0.010915 0.005512	0.000731				
3	0.872220	0.006983	0.014427	0.001295	0.008062	0.
066079	0.017885 0.011969	0.001080				
4	0.864168	0.006918	0.014381	0.002169	0.008630	0.
070076	0.017825 0.014220	0.001613				
FEVD for dfCO2						
xCO2 SW (wet) (umol/mol)	Licor	Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	
dfCO2 pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)				
0	0.946846	0.000028	0.002896	0.005627	0.000250	0.
044353	0.000000 0.000000	0.000000				
1	0.816702	0.000048	0.005469	0.005337	0.002256	0.
163522	0.001466 0.004596	0.000604				
2	0.794952	0.001191	0.019797	0.005329	0.004607	0.
156728	0.011471 0.005171	0.000755				
3	0.767663	0.002758	0.020441	0.005235	0.008182	0.
163452	0.019003 0.012222	0.001043				
4	0.760630	0.002826	0.020395	0.007680	0.008402	0.
166014	0.018948 0.013705	0.001399				
FEVD for pCO2 SW (sat) uatm						
xCO2 SW (wet) (umol/mol)	Licor	Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	
dfCO2 pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)				
0	0.996279	0.002318	0.000000	0.001382	0.000014	0.
000000	0.000000 0.000000	0.000000				
1	0.928908	0.002057	0.002865	0.001408	0.001626	0.
056673	0.001748 0.004145	0.000570				
2	0.901973	0.002825	0.013337	0.001338	0.005342	0.
057947	0.011014 0.005505	0.000719				
3	0.872152	0.006973	0.014481	0.001295	0.007970	0.
066134	0.017927 0.011997	0.001072				
4	0.864006	0.006907	0.014428	0.002170	0.008536	0.
070187	0.017869 0.014282	0.001612				
FEVD for dpCO2						
xCO2 SW (wet) (umol/mol)	Licor	Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	
dfCO2 pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)				
0	0.946894	0.000030	0.002868	0.005613	0.000250	0.
044338	0.000000 0.000007	0.000000				
1	0.816539	0.000052	0.005461	0.005315	0.002246	0.
163492	0.001456 0.004847	0.000592				
2	0.794773	0.001213	0.019796	0.005311	0.004605	0.
156693	0.011459 0.005412	0.000738				
3	0.767505	0.002791	0.020439	0.005221	0.008144	0.
163422	0.018982 0.012474	0.001022				
4	0.760508	0.002861	0.020393	0.007683	0.008359	0.
165967	0.018926 0.013929	0.001374				
FEVD for pH (Total Scale)						
xCO2 SW (wet) (umol/mol)	Licor	Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	
dfCO2 pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)				
0	0.693749	0.003095	0.002458	0.000021	0.000529	0.
000990	0.008792 0.000069	0.290298				
1	0.570901	0.006868	0.015183	0.000801	0.000462	0.
082193	0.017320 0.004213	0.302061				
2	0.579775	0.009198	0.020795	0.001561	0.000459	0.
078065	0.021261 0.008165	0.280721				

3	0.560164	0.009211	0.020912	0.001541	0.008083	0.
089315	0.025524	0.015224	0.270025			
4	0.552060	0.009076	0.020606	0.002063	0.008645	0.
089891	0.026865	0.022284	0.268510			

```
In [43]: def invert_transformation(df_train, df_forecast, second_diff=False):
        """Revert back the differencing to get the forecast to original scale."""
        df_fc = df_forecast.copy()
        columns = df_train.columns
        for col in columns:
            # Roll back 2nd Diff
            if second_diff:
                df_fc[str(col)+'_1d'] = (df_train[col].iloc[-1]-df_train[col].iloc[-2]) + df_fc[str(col)+'_2d'].cumsum()
            # Roll back 1st Diff
            df_fc[col] = df_train[col].iloc[-1] + df_fc[str(col)+'_1d'].cumsum()
        return df_fc
```

```
In [45]: # Creating result dataframe
df_results = invert_transformation(train, df_forecast, second_diff=False)
df_results["Type"] = "Forecast"
df_results.head(2)
```

Out[45]:

	xCO2 SW (wet) (umol/mol)_1d	Licor Atm Pressure (hPa)_1d	SST (C)_1d	xCO2 SW (dry) (umol/mol)_1d	fCO2 SW (sat) uatm_1d	dfCO2_1d	pCO2 SW (sat) uatm_1d	dpCO2_1d	pH (Total Scale)_1d	xCO2 SW (wet) (umol/mol)	Lic P
Datetime											
2013-04-25	-3.011511	-0.113039	-0.032469	-3.052355	-2.919747	-3.185919	-2.920522	-3.220280	0.005145	410.188489	1006
2013-04-26	1.503981	-0.063022	0.016578	1.531379	1.411335	1.539328	1.414204	1.548054	-0.002005	411.692470	1006

```
In [46]: # Dropping all features that did not have significant correlation with target, pH
df_results = df_results.drop(["xCO2 SW (wet) (umol/mol)_1d", "Licor Atm Pressure (hPa)_1d", "SST (C)_1d", "xCO2 SW  
axis = 1)
df_results["Type"] = "Forecast"
df_results.head(3)
```

Out[46]:

	xCO2 SW (wet) (umol/mol)	Licor Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	dfCO2	pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)	Type
Datetime										
2013-04-25	410.188489	1006.661961	29.310906	412.885145	392.705253	16.126581	393.879478	16.167220	8.009645	Forecast
2013-04-26	411.692470	1006.598939	29.327484	414.416524	394.116588	17.665909	395.293681	17.715274	8.007640	Forecast
2013-04-27	413.447156	1006.569063	29.335133	416.162603	395.752858	19.471398	396.934431	19.527458	8.005578	Forecast

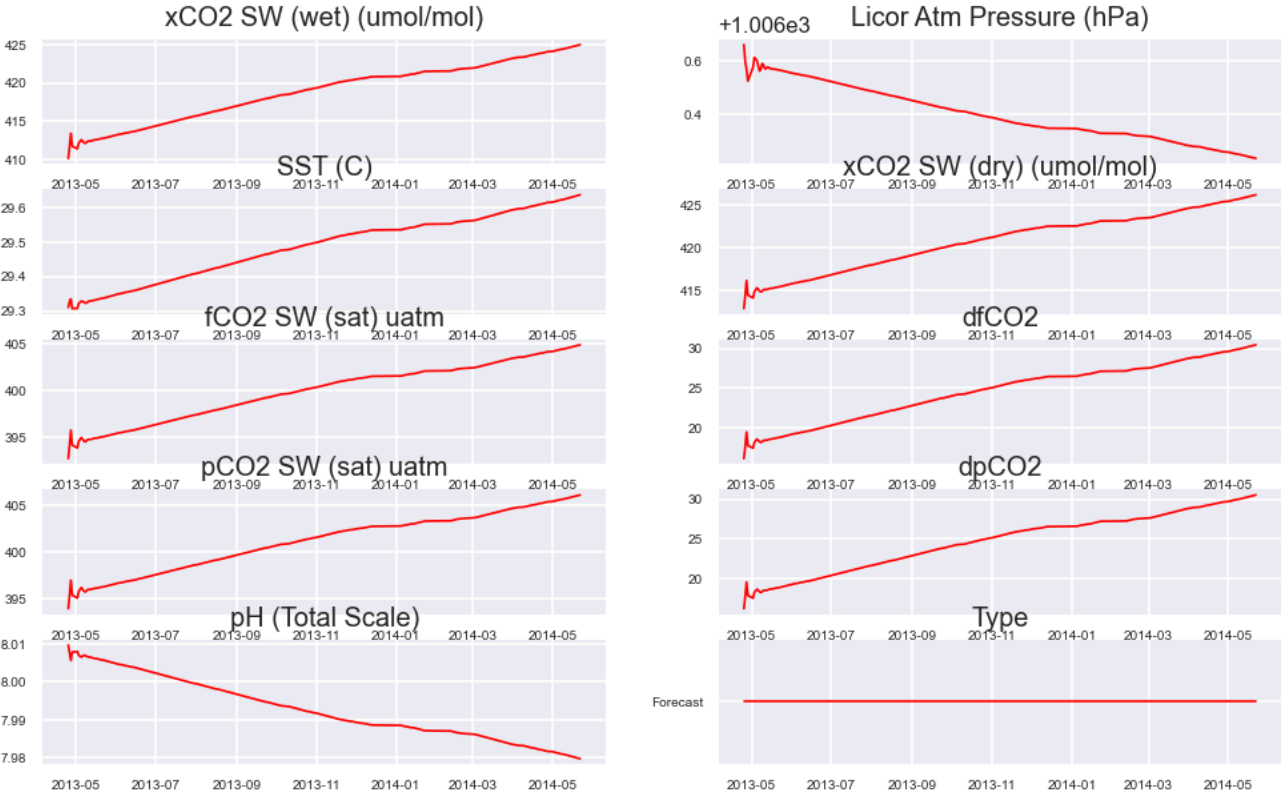
```
In [47]: df_results.index
```

Out[47]: DatetimeIndex(['2013-04-25', '2013-04-26', '2013-04-27', '2013-04-28',
'2013-05-02', '2013-05-03', '2013-05-05', '2013-05-07',
'2013-05-08', '2013-05-09',
...
'2014-05-13', '2014-05-14', '2014-05-15', '2014-05-16',
'2014-05-17', '2014-05-18', '2014-05-19', '2014-05-20',
'2014-05-21', '2014-05-22'],
dtype='datetime64[ns]', name='Datetime', length=302, freq=None)

```
In [44]: df_results.index = df_results.index.to_timestamp()
```

```
In [48]: fig, axes = plt.subplots(nrows=5, ncols=2, dpi=120, figsize=(10,6), )
for i, ax in enumerate(axes.flatten()):
    data = df_results[df_results.columns[i]]
    ax.plot(data, color='red', linewidth=1)
```

```
# Decorations
ax.set_title(df_results.columns[i])
ax.xaxis.set_ticks_position('none')
ax.yaxis.set_ticks_position('none')
ax.spines["top"].set_alpha(0)
ax.tick_params(labelsize=6)
plt.show();
```



```
In [49]: df_actual = pd.DataFrame(chuuk_df, index = df_results.index, columns = chuuk_df.columns)
df_actual["Type"] = "Actual"
df_actual
```

Out[49]:

	xCO2 SW (wet) (umol/mol)	Licor Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	dfCO2	pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)	Type
Datetime										
2013-04-25	396.5750	1006.8125	28.933125	400.6250	381.4250	3.0500	382.5875	3.0625	8.040000	Actual
2013-04-26	398.0875	1006.7750	28.989875	402.2625	382.9375	4.7875	384.0875	4.8000	8.034750	Actual
2013-04-27	399.6750	1006.7125	28.981000	403.9000	384.5125	6.2000	385.6500	6.2125	8.035625	Actual
2013-04-28	395.5625	1007.1500	28.957750	399.6500	380.6250	2.7375	381.7625	2.7625	8.040250	Actual
2013-05-02	397.1625	1007.3375	28.946375	401.4875	382.4500	4.6000	383.6250	4.6125	8.034500	Actual
...
2014-05-18	403.8875	1007.1750	29.228875	406.6750	387.0750	9.7500	388.2625	9.7875	8.015125	Actual
2014-05-19	403.6375	1006.4375	29.187875	406.2500	386.4250	9.0625	387.6000	9.0625	8.021625	Actual
2014-05-20	408.7500	1006.5250	29.233250	411.3875	391.3000	14.3375	392.4875	14.3750	8.015625	Actual
2014-05-21	413.2750	1006.8375	29.358375	416.1250	395.8250	19.6625	397.0000	19.7125	8.006750	Actual

	xCO2 SW (wet) (umol/mol)	Licor Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	dfCO2	pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)	Type
Datetime										
2014-05-22	413.2000	1006.7750	29.343375	415.9375	395.6250	19.3125	396.8000	19.3875	8.004500	Actual

302 rows × 10 columns

```
In [50]: # combining dataframes for better visual
dfs = [df_actual, df_results]
df_vis = df_actual.append(df_results)
df_vis
```

	xCO2 SW (wet) (umol/mol)	Licor Atm Pressure (hPa)	SST (C)	xCO2 SW (dry) (umol/mol)	fCO2 SW (sat) uatm	dfCO2	pCO2 SW (sat) uatm	dpCO2	pH (Total Scale)	Type
Datetime										
2013-04-25	396.575000	1006.812500	28.933125	400.625000	381.425000	3.050000	382.587500	3.062500	8.040000	Actual
2013-04-26	398.087500	1006.775000	28.989875	402.262500	382.937500	4.787500	384.087500	4.800000	8.034750	Actual
2013-04-27	399.675000	1006.712500	28.981000	403.900000	384.512500	6.200000	385.650000	6.212500	8.035625	Actual
2013-04-28	395.562500	1007.150000	28.957750	399.650000	380.625000	2.737500	381.762500	2.762500	8.040250	Actual
2013-05-02	397.162500	1007.337500	28.946375	401.487500	382.450000	4.600000	383.625000	4.612500	8.034500	Actual
...
2014-05-18	424.805184	1006.237609	29.631702	426.087817	404.788438	30.292703	405.993113	30.381310	7.980094	Forecast
2014-05-19	424.848504	1006.236421	29.632764	426.126310	404.823572	30.334274	406.028341	30.423002	7.980002	Forecast
2014-05-20	424.891824	1006.235234	29.633827	426.164803	404.858705	30.375845	406.063568	30.464694	7.979910	Forecast
2014-05-21	424.935143	1006.234046	29.634889	426.203297	404.893838	30.417416	406.098795	30.506387	7.979817	Forecast
2014-05-22	424.978463	1006.232859	29.635951	426.241790	404.928971	30.458987	406.134023	30.548079	7.979725	Forecast

604 rows × 10 columns

```
In [51]: type(df_vis.index)
```

```
Out[51]: pandas.core.indexes.datetimes.DatetimeIndex
```

```
In [52]: plt.style.use('seaborn')
fig, axis = plt.subplots(nrows = 5, ncols = 2)
fig.set_size_inches(10,10)
fig.subplots_adjust(wspace = 0.5, hspace = 0.8)

# plot 1
sns.lineplot(df_vis.index, df_vis["xCO2 SW (wet) (umol/mol)"], hue = df_vis["Type"], ax = axis[0,0]).set_title("Cor")
# plot 2
sns.lineplot(df_vis.index, df_vis["Licor Atm Pressure (hPa)"], hue = df_vis["Type"], ax = axis[0,1]).set_title("Pre")
# plot 3
sns.lineplot(df_vis.index, df_vis["SST (C)"], hue = df_vis["Type"], ax = axis[1,0]).set_title("Sea Surface Temperat")
# plot 4
sns.lineplot(df_vis.index, df_vis["xCO2 SW (dry) (umol/mol)"], hue = df_vis["Type"], ax = axis[1,1]).set_title("Cor")
# plot 5
sns.lineplot(df_vis.index, df_vis["fCO2 SW (sat) uatm"], hue = df_vis["Type"], ax = axis[2,0]).set_title("Water Fur")
# plot 6
sns.lineplot(df_vis.index, df_vis["dfCO2"], hue = df_vis["Type"], ax = axis[2,1]).set_title("Difference in Water ar")
```

```
# plot 7
sns.lineplot(df_vis.index, df_vis["pCO2 SW (sat) uatm"], hue = df_vis["Type"], ax = axis[3,0]).set_title("Partial P
# plot 8
sns.lineplot(df_vis.index, df_vis["dpCO2"], hue = df_vis["Type"], ax = axis[3,1]).set_title("Difference in Water ar
# plot 9
sns.lineplot(df_vis.index, df_vis["pH (Total Scale)"], hue = df_vis["Type"], ax = axis[4,0]).set_title("pH")

ax = axis[4,1].set_visible(False)
```

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

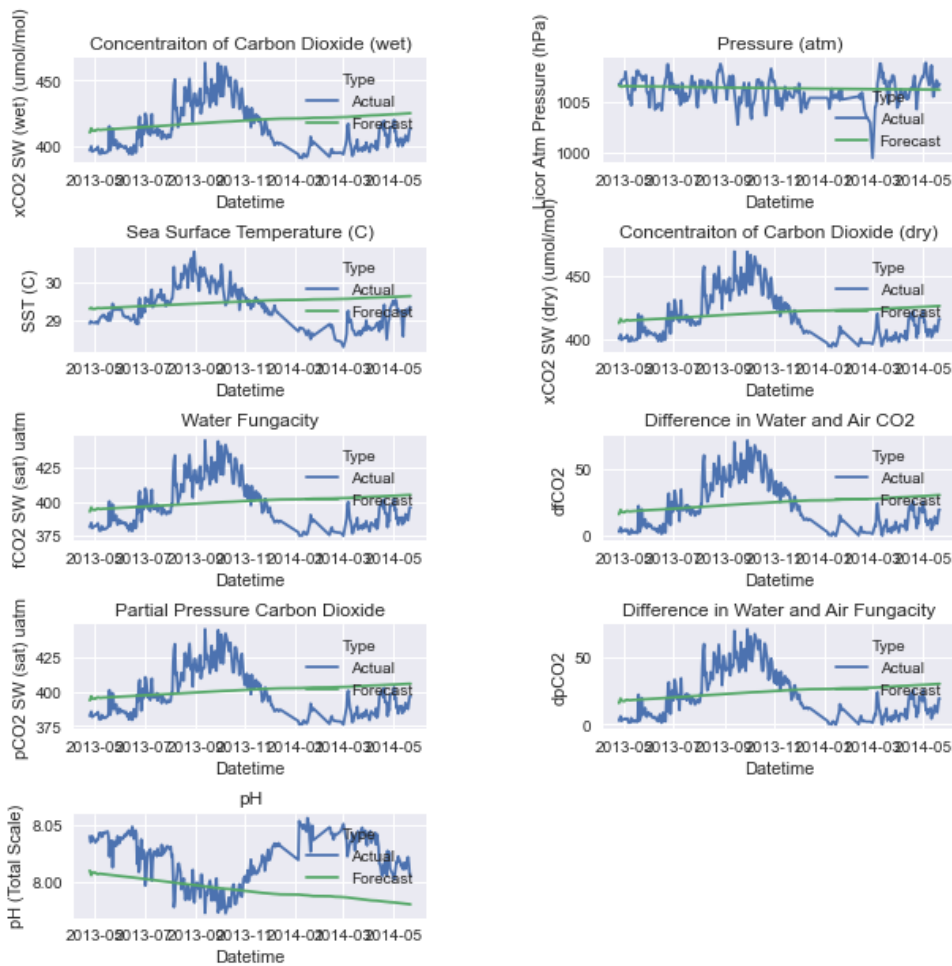
warnings.warn(

C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

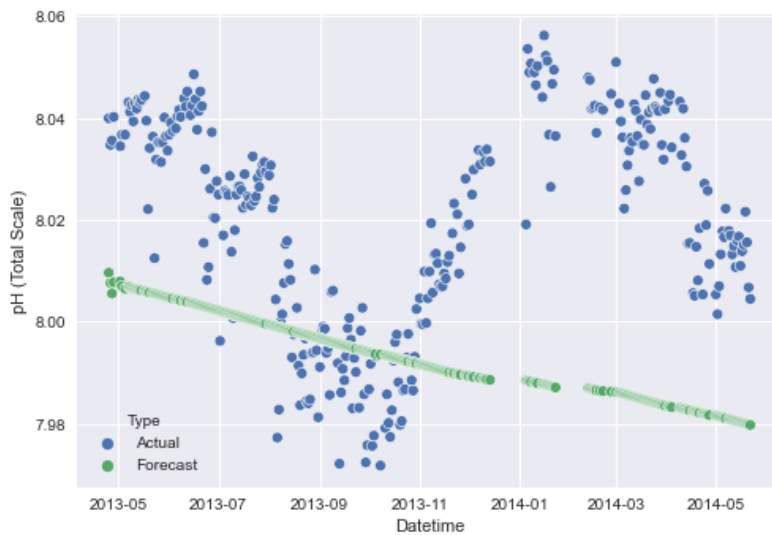
C:\Users\datre\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(



```
In [53]: # Isolating pH results
sns.scatterplot(x = df_vis.index, y = df_vis["pH (Total Scale)"], hue = df_vis.Type)
```

```
Out[53]: <AxesSubplot:xlabel='Datetime', ylabel='pH (Total Scale)'\>
```



```
In [ ]:
```

```
In [54]: from keras.preprocessing.sequence import TimeseriesGenerator
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten
from sklearn.preprocessing import MinMaxScaler
```

```

from sklearn.metrics import mean_squared_error
import math
from keras.models import load_model
from sklearn.metrics import r2_score
import plotly.graph_objects as go

```

```

In [55]: def create_dataset(dataset, lookback=1):
          dataX = []
          dataY = []
          for i in range(len(dataset) - lookback - 1):
              a = dataset[i: (i+lookback), 0]
              dataX.append(a)
              dataY.append(dataset[i+lookback,0])
          return np.array(dataX), np.array(dataY)

```

```

In [56]: # input data
data = chuuk_df["pH (Total Scale)"].values
data = data.astype("float32")

```

```

In [57]: # correcting shape of data
scaler = MinMaxScaler(feature_range=(0,1))
data = data.reshape(-1,1)
data = scaler.fit_transform(data)

```

```

In [58]: # Splitting into test and train sets
train = data[:int(len(data)*0.8), :]
test = data[int(len(data)*0.8):, :]

```

```

In [59]: lookback = 1
trainX, trainY = create_dataset(train, lookback)
testX, testY = create_dataset(test, lookback)

```

```

In [60]: trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))

```

```

In [61]: model = Sequential()
          # Check LSTM
          model.add(LSTM(4, input_shape=(1, lookback)))
          #return_sequences=True, model.add(LSTM(4))
          model.add(Dense(1))
          model.compile(loss='mean_squared_error', optimizer='adam', metrics=['mae'])
          model.fit(trainX, trainY, epochs=100, batch_size=1, verbose=2)

```

```

Epoch 1/100
301/301 - 5s - loss: 0.1952 - mae: 0.3815
Epoch 2/100
301/301 - 1s - loss: 0.0227 - mae: 0.1272
Epoch 3/100
301/301 - 1s - loss: 0.0180 - mae: 0.1118
Epoch 4/100
301/301 - 1s - loss: 0.0156 - mae: 0.1039
Epoch 5/100
301/301 - 1s - loss: 0.0135 - mae: 0.0952
Epoch 6/100
301/301 - 1s - loss: 0.0116 - mae: 0.0867
Epoch 7/100
301/301 - 1s - loss: 0.0099 - mae: 0.0780
Epoch 8/100
301/301 - 1s - loss: 0.0087 - mae: 0.0723
Epoch 9/100
301/301 - 1s - loss: 0.0079 - mae: 0.0674
Epoch 10/100
301/301 - 1s - loss: 0.0073 - mae: 0.0625
Epoch 11/100
301/301 - 1s - loss: 0.0071 - mae: 0.0621
Epoch 12/100
301/301 - 1s - loss: 0.0071 - mae: 0.0617
Epoch 13/100
301/301 - 1s - loss: 0.0070 - mae: 0.0610
Epoch 14/100
301/301 - 1s - loss: 0.0070 - mae: 0.0612
Epoch 15/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 16/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 17/100
301/301 - 1s - loss: 0.0069 - mae: 0.0606

```


Epoch 18/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 19/100
301/301 - 1s - loss: 0.0070 - mae: 0.0608
Epoch 20/100
301/301 - 1s - loss: 0.0069 - mae: 0.0605
Epoch 21/100
301/301 - 1s - loss: 0.0069 - mae: 0.0610
Epoch 22/100
301/301 - 0s - loss: 0.0069 - mae: 0.0606
Epoch 23/100
301/301 - 1s - loss: 0.0069 - mae: 0.0613
Epoch 24/100
301/301 - 0s - loss: 0.0069 - mae: 0.0609
Epoch 25/100
301/301 - 1s - loss: 0.0070 - mae: 0.0608
Epoch 26/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 27/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 28/100
301/301 - 1s - loss: 0.0069 - mae: 0.0600
Epoch 29/100
301/301 - 1s - loss: 0.0070 - mae: 0.0616
Epoch 30/100
301/301 - 1s - loss: 0.0069 - mae: 0.0601
Epoch 31/100
301/301 - 1s - loss: 0.0070 - mae: 0.0616
Epoch 32/100
301/301 - 1s - loss: 0.0070 - mae: 0.0609
Epoch 33/100
301/301 - 1s - loss: 0.0069 - mae: 0.0603
Epoch 34/100
301/301 - 1s - loss: 0.0069 - mae: 0.0606
Epoch 35/100
301/301 - 1s - loss: 0.0069 - mae: 0.0607
Epoch 36/100
301/301 - 1s - loss: 0.0070 - mae: 0.0607
Epoch 37/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 38/100
301/301 - 1s - loss: 0.0070 - mae: 0.0608
Epoch 39/100
301/301 - 1s - loss: 0.0069 - mae: 0.0606
Epoch 40/100
301/301 - 1s - loss: 0.0069 - mae: 0.0621
Epoch 41/100
301/301 - 1s - loss: 0.0068 - mae: 0.0600
Epoch 42/100
301/301 - 1s - loss: 0.0069 - mae: 0.0617
Epoch 43/100
301/301 - 1s - loss: 0.0069 - mae: 0.0605
Epoch 44/100
301/301 - 1s - loss: 0.0070 - mae: 0.0612
Epoch 45/100
301/301 - 1s - loss: 0.0068 - mae: 0.0605
Epoch 46/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 47/100
301/301 - 1s - loss: 0.0070 - mae: 0.0610
Epoch 48/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 49/100
301/301 - 0s - loss: 0.0067 - mae: 0.0596
Epoch 50/100
301/301 - 0s - loss: 0.0069 - mae: 0.0601
Epoch 51/100
301/301 - 0s - loss: 0.0069 - mae: 0.0610
Epoch 52/100
301/301 - 1s - loss: 0.0069 - mae: 0.0604
Epoch 53/100
301/301 - 1s - loss: 0.0069 - mae: 0.0609
Epoch 54/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 55/100
301/301 - 1s - loss: 0.0070 - mae: 0.0605
Epoch 56/100
301/301 - 1s - loss: 0.0069 - mae: 0.0612
Epoch 57/100
301/301 - 1s - loss: 0.0070 - mae: 0.0609
Epoch 58/100
301/301 - 1s - loss: 0.0069 - mae: 0.0604

Epoch 59/100
301/301 - 1s - loss: 0.0069 - mae: 0.0602
Epoch 60/100
301/301 - 1s - loss: 0.0069 - mae: 0.0614
Epoch 61/100
301/301 - 1s - loss: 0.0069 - mae: 0.0603
Epoch 62/100
301/301 - 1s - loss: 0.0070 - mae: 0.0605
Epoch 63/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 64/100
301/301 - 1s - loss: 0.0069 - mae: 0.0607
Epoch 65/100
301/301 - 1s - loss: 0.0070 - mae: 0.0604
Epoch 66/100
301/301 - 1s - loss: 0.0069 - mae: 0.0608
Epoch 67/100
301/301 - 1s - loss: 0.0069 - mae: 0.0605
Epoch 68/100
301/301 - 1s - loss: 0.0069 - mae: 0.0610
Epoch 69/100
301/301 - 1s - loss: 0.0067 - mae: 0.0612
Epoch 70/100
301/301 - 1s - loss: 0.0069 - mae: 0.0609
Epoch 71/100
301/301 - 1s - loss: 0.0069 - mae: 0.0610
Epoch 72/100
301/301 - 1s - loss: 0.0070 - mae: 0.0605
Epoch 73/100
301/301 - 1s - loss: 0.0069 - mae: 0.0603
Epoch 74/100
301/301 - 1s - loss: 0.0069 - mae: 0.0606
Epoch 75/100
301/301 - 1s - loss: 0.0068 - mae: 0.0603
Epoch 76/100
301/301 - 0s - loss: 0.0070 - mae: 0.0617
Epoch 77/100
301/301 - 0s - loss: 0.0069 - mae: 0.0607
Epoch 78/100
301/301 - 0s - loss: 0.0070 - mae: 0.0607
Epoch 79/100
301/301 - 1s - loss: 0.0069 - mae: 0.0596
Epoch 80/100
301/301 - 1s - loss: 0.0067 - mae: 0.0605
Epoch 81/100
301/301 - 1s - loss: 0.0069 - mae: 0.0607
Epoch 82/100
301/301 - 1s - loss: 0.0068 - mae: 0.0602
Epoch 83/100
301/301 - 1s - loss: 0.0070 - mae: 0.0601
Epoch 84/100
301/301 - 1s - loss: 0.0069 - mae: 0.0606
Epoch 85/100
301/301 - 1s - loss: 0.0070 - mae: 0.0608
Epoch 86/100
301/301 - 1s - loss: 0.0070 - mae: 0.0616
Epoch 87/100
301/301 - 1s - loss: 0.0068 - mae: 0.0604
Epoch 88/100
301/301 - 1s - loss: 0.0070 - mae: 0.0607
Epoch 89/100
301/301 - 1s - loss: 0.0069 - mae: 0.0598
Epoch 90/100
301/301 - 1s - loss: 0.0069 - mae: 0.0603
Epoch 91/100
301/301 - 1s - loss: 0.0069 - mae: 0.0612
Epoch 92/100
301/301 - 1s - loss: 0.0069 - mae: 0.0611
Epoch 93/100
301/301 - 1s - loss: 0.0069 - mae: 0.0606
Epoch 94/100
301/301 - 1s - loss: 0.0068 - mae: 0.0606
Epoch 95/100
301/301 - 1s - loss: 0.0069 - mae: 0.0607
Epoch 96/100
301/301 - 1s - loss: 0.0070 - mae: 0.0620
Epoch 97/100
301/301 - 1s - loss: 0.0069 - mae: 0.0607
Epoch 98/100
301/301 - 1s - loss: 0.0069 - mae: 0.0612
Epoch 99/100
301/301 - 1s - loss: 0.0070 - mae: 0.0609

Epoch 100/100
 301/301 - 1s - loss: 0.0068 - mae: 0.0597

Out[61]: <tensorflow.python.keras.callbacks.History at 0x1f25c186970>

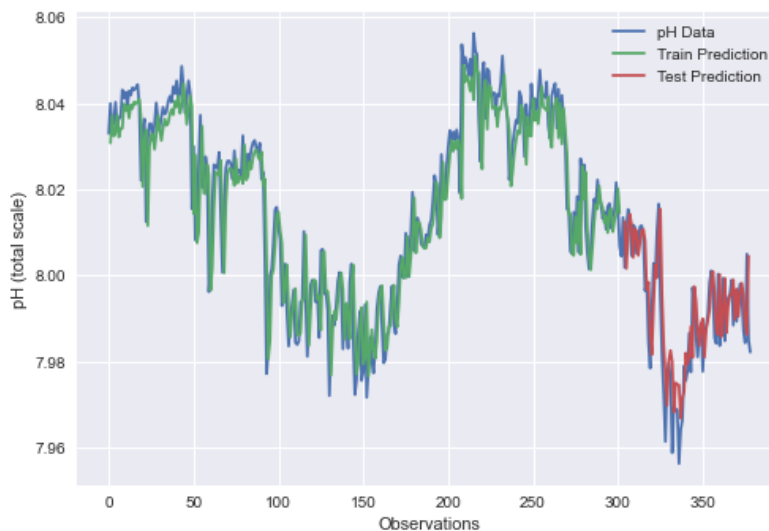
```
In [62]: # make predictions
trainPredict = model.predict(trainX)
testPredict = model.predict(testX)
```

```
In [63]: #nsamples, nx, ny = trainY.shape
#trainY = trainY.reshape((nsamples,nx*ny))
```

```
In [64]: # invert predictions
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
# calculate root mean squared error
trainScore = math.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = math.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

Train Score: 0.01 RMSE
 Test Score: 0.01 RMSE

```
In [65]: trainPredictPlot = np.empty_like(data)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[lookback:len(trainPredict)+lookback, :] = trainPredict
# shift test predictions for plotting
testPredictPlot = np.empty_like(data)
testPredictPlot[:, :] = np.nan
testPredictPlot[len(trainPredict)+(lookback*2)+1:len(data)-1, :] = testPredict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(data), label="pH Data")
plt.plot(trainPredictPlot, label="Train Prediction")
plt.plot(testPredictPlot, label="Test Prediction")
plt.xlabel("Observations")
plt.ylabel("pH (total scale)")
plt.legend()
plt.show()
```



```
In [66]: model.save("pH_model.h5")
```

```
In [67]: model = load_model("pH_model.h5")
```

```
In [68]: trainScore = math.sqrt(r2_score(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f R2' % (trainScore))
testScore = math.sqrt(r2_score(testY[0], testPredict[:,0]))
print('Test Score: %.2f R2' % (testScore))
```

Train Score: 0.92 R2
 Test Score: 0.77 R2

In []: