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Problem Statement:

Detect occupancy of an office room from light, temperature, humidity and CO2 at a given time.

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.metrics import accuracy_score, plot_confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn import svm
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from sklearn import preprocessing
from sklearn.tree import DecisionTreeClassifier, export_graphviz,plot_tr
ee
from sklearn.ensemble import RandomForestClassifier
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import grangercausalitytests
from fbprophet import Prophet
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
plt.rcParams['figure.figsize'] = [10.0, 6.0]
```

In [2]:
```
# Read in data
df_train = pd.read_csv('train_data.txt')
df_val = pd.read_csv('validation_data.txt')
```

In [3]:
```
# Explore data
df_train.head()
```

Out[3]:

	date	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
1	2015-02-04 17:51:00	23.18	27.2720	426.0	721.25	0.004793	1
2	2015-02-04 17:51:59	23.15	27.2675	429.5	714.00	0.004783	1
3	2015-02-04 17:53:00	23.15	27.2450	426.0	713.50	0.004779	1
4	2015-02-04 17:54:00	23.15	27.2000	426.0	708.25	0.004772	1
5	2015-02-04 17:55:00	23.10	27.2000	426.0	704.50	0.004757	1

In [4]:
```
df_train.tail()
```

Out[4]:

	date	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
8139	2015-02-10 09:29:00	21.05	36.0975	433.0	787.250000	0.005579	1
8140	2015-02-10 09:29:59	21.05	35.9950	433.0	789.500000	0.005563	1
8141	2015-02-10 09:30:59	21.10	36.0950	433.0	798.500000	0.005596	1
8142	2015-02-10 09:32:00	21.10	36.2600	433.0	820.333333	0.005621	1
8143	2015-02-10 09:33:00	21.10	36.2000	447.0	821.000000	0.005612	1

Data seems to be ordered by date and time and appropriate for time series analysis. Time intervals seem to be about every minute. Dates are from 2015-02-04 to 2015-02-10 (6 days).

In [5]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8143 entries, 1 to 8143
Data columns (total 7 columns):
date             8143 non-null object
Temperature      8143 non-null float64
Humidity         8143 non-null float64
Light            8143 non-null float64
CO2              8143 non-null float64
HumidityRatio    8143 non-null float64
Occupancy        8143 non-null int64
dtypes: float64(5), int64(1), object(1)
memory usage: 508.9+ KB
```

There are no null values in the training data. May need to convert date to datetime object. Occupancy is the only int type.

```
In [6]: df_train.describe()
```

Out[6]:

	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
count	8143.000000	8143.000000	8143.000000	8143.000000	8143.000000	8143.000000
mean	20.619084	25.731507	119.519375	606.546243	0.003863	0.212330
std	1.016916	5.531211	194.755805	314.320877	0.000852	0.408982
min	19.000000	16.745000	0.000000	412.750000	0.002674	0.000000
25%	19.700000	20.200000	0.000000	439.000000	0.003078	0.000000
50%	20.390000	26.222500	0.000000	453.500000	0.003801	0.000000
75%	21.390000	30.533333	256.375000	638.833333	0.004352	0.000000
max	23.180000	39.117500	1546.333333	2028.500000	0.006476	1.000000

Occupancy seems to be binary: either 0 or 1. Assume 1 means occupied, and 0 means unoccupied.

```
In [7]: # Convert date column to datetime object
        df_train['date'] = pd.to_datetime(df_train['date'])
```

```
In [8]: # Verify changed datatype for date
        df_train.dtypes
```

```
Out[8]: date             datetime64[ns]
        Temperature             float64
        Humidity                float64
        Light                   float64
        CO2                     float64
        HumidityRatio           float64
        Occupancy                 int64
        dtype: object
```

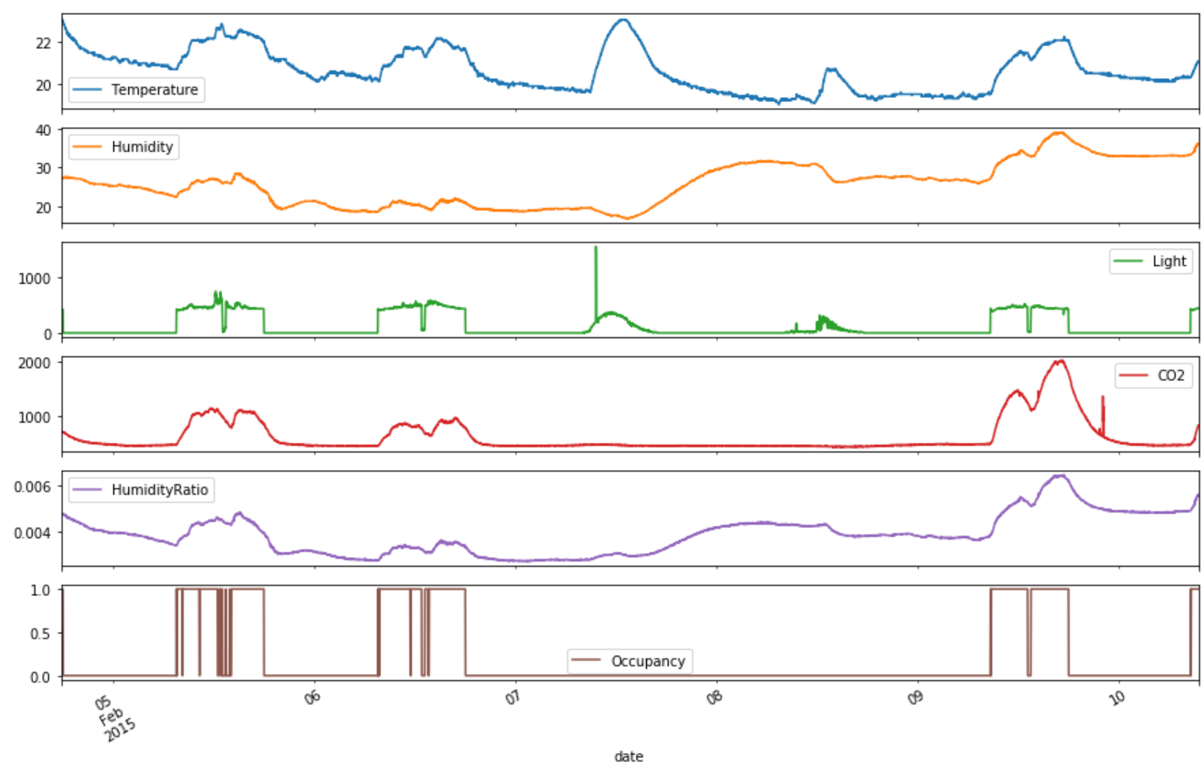
Date values are either at :00 or :59 seconds. Round all to nearest minute.

In [9]:
```python
# Set date to index and round to nearest minute for time series analysis
df_train = df_train.set_index('date')
df_train.index = df_train.index.round('min')
df_train.head()
```

Out[9]:

	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
date						
2015-02-04 17:51:00	23.18	27.2720	426.0	721.25	0.004793	1
2015-02-04 17:52:00	23.15	27.2675	429.5	714.00	0.004783	1
2015-02-04 17:53:00	23.15	27.2450	426.0	713.50	0.004779	1
2015-02-04 17:54:00	23.15	27.2000	426.0	708.25	0.004772	1
2015-02-04 17:55:00	23.10	27.2000	426.0	704.50	0.004757	1

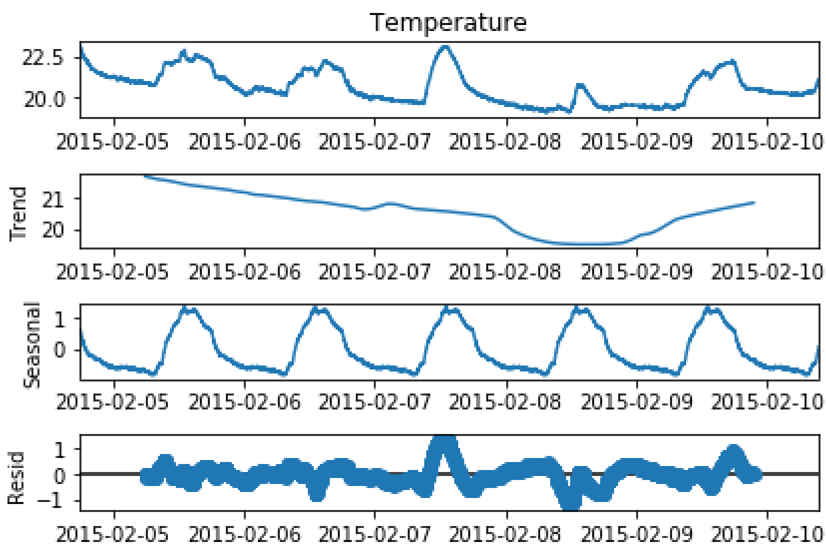
In [10]:
```python
pd.plotting.register_matplotlib_converters()
# Plot all columns vs. date
df_train.plot(subplots=True, figsize=(15,10))
plt.show()
```



There appears to be some correlation between the variables, which can be seen from when the peaks occur. The occupancy seems less correlated to Humidity than it does with Light and CO2. Light seems to be the most important factor, since there are dips in the occupancy that coincide with dips in Light. There seems to be periodicity in the occupancy, where the occupancy can be 1 during "normal working hours" (i.e., 9am-6pm). However, there was no occupancy on 2 consecutive dates, 2015-02-07 and 2015-02-08. Perhaps those dates were the weekend, which indicates conditional seasonality. For those 2 dates, the CO2 levels were also very low with no peaks. Since the date range is small, assume no overall underlying trends in the variables. There also seems to be a high outlier in the Light data, with the value of 1546.3 within the day of 2015-02-07.

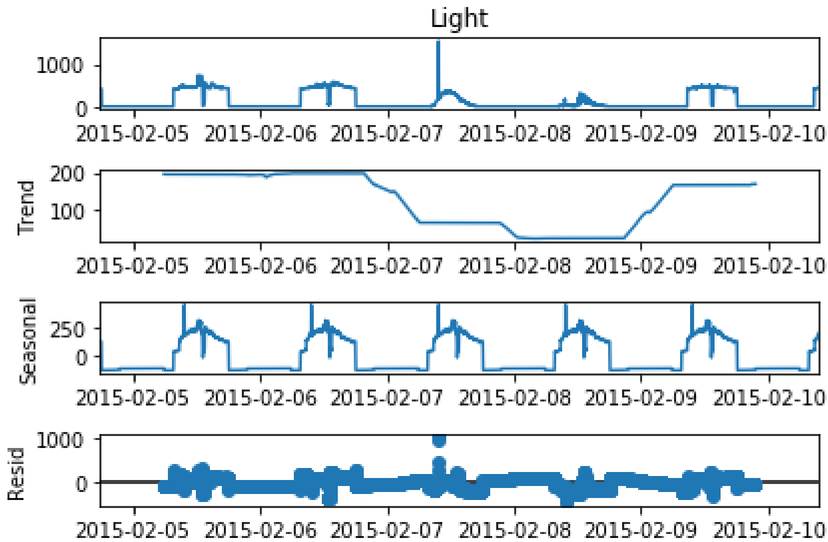
Check for Seasonality in parameters

In [11]:
```
# Perform seasonality decomposion for Temperature, period = 1 day
seas_d = seasonal_decompose(df_train['Temperature'], period = (60*24))
fig=seas_d.plot()
fig.set_figheight(4)
plt.show()
```



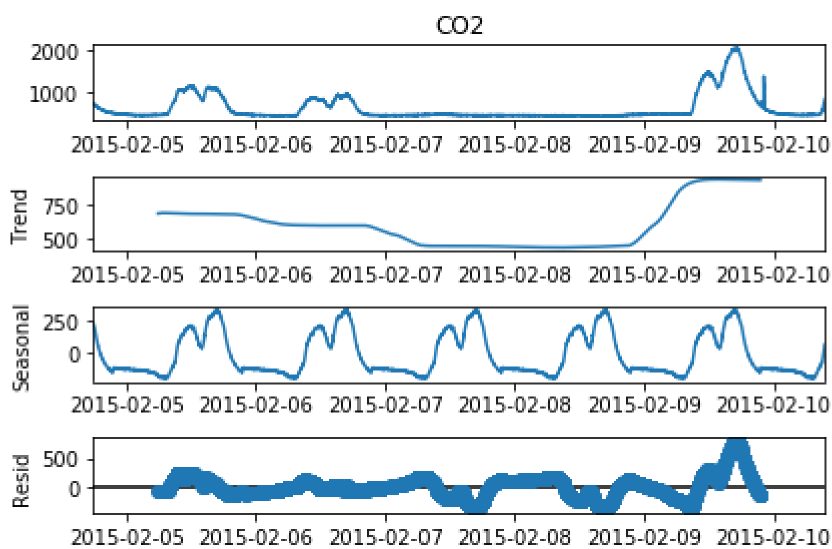
In [12]:

```
# Perform seasonality decomposion for Light, period = 1 day
seas_d = seasonal_decompose(df_train['Light'], period = (60*24))
fig=seas_d.plot()
fig.set_figheight(4)
plt.show()
```

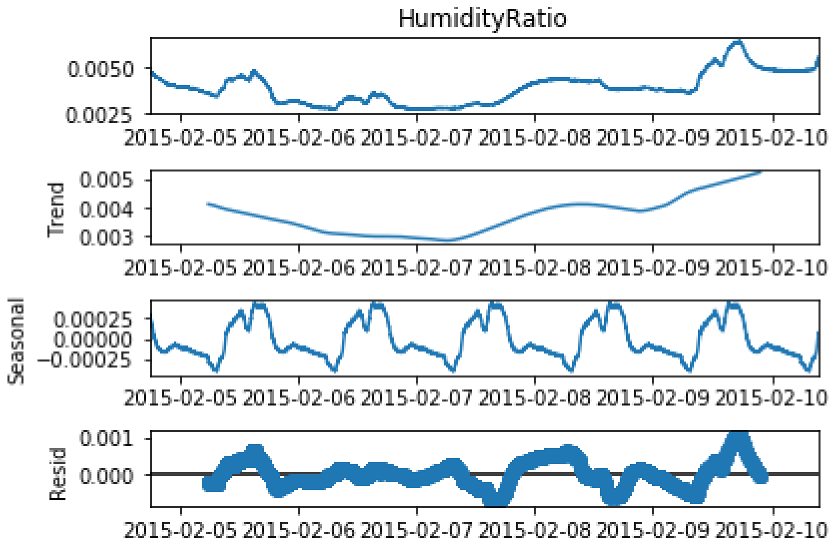


In [13]:

```
# Perform seasonality decomposion for CO2, period = 1 day
seas_d = seasonal_decompose(df_train['CO2'], period = (60*24))
fig=seas_d.plot()
fig.set_figheight(4)
plt.show()
```



In [14]:
```
# Perform seasonality decomposion for HumidityRatio, period = 1 day
seas_d = seasonal_decompose(df_train['HumidityRatio'], period = (60*24))
fig=seas_d.plot()
fig.set_figheight(4)
plt.show()
```



Perform Granger Causality Tests

In [15]:

```
# Examine Temperature causing Occupancy
print(grangercausalitytests(df_train[['Occupancy', 'Temperature']], maxl
ag=4))
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=10.5156 , p=0.0012  , df_denom=8139, df_num
=1
ssr based chi2 test:   chi2=10.5195 , p=0.0012  , df=1
likelihood ratio test: chi2=10.5127 , p=0.0012  , df=1
parameter F test:         F=10.5156 , p=0.0012  , df_denom=8139, df_num
=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=3.5933  , p=0.0276  , df_denom=8136, df_num
=2
ssr based chi2 test:   chi2=7.1910  , p=0.0274  , df=2
likelihood ratio test: chi2=7.1878  , p=0.0275  , df=2
parameter F test:         F=3.5933  , p=0.0276  , df_denom=8136, df_num
=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=1.1512  , p=0.3269  , df_denom=8133, df_num
=3
ssr based chi2 test:   chi2=3.4566  , p=0.3264  , df=3
likelihood ratio test: chi2=3.4559  , p=0.3265  , df=3
parameter F test:         F=1.1512  , p=0.3269  , df_denom=8133, df_num
=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.6326  , p=0.6392  , df_denom=8130, df_num
=4
ssr based chi2 test:   chi2=2.5331  , p=0.6387  , df=4
likelihood ratio test: chi2=2.5327  , p=0.6388  , df=4
parameter F test:         F=0.6326  , p=0.6392  , df_denom=8130, df_num
=4
{1: ({'ssr_ftest': (10.515600218091105, 0.0011884805851629405, 8139.0,
1), 'ssr_chi2test': (10.51947622259464, 0.0011812295962018446, 1), 'lrt
est': (10.512686480680713, 0.00118557768661934, 1), 'params_ftest': (1
0.515600218094972, 0.0011884805851604175, 8139.0, 1.0)}, [<statsmodels.
regression.linear_model.RegressionResultsWrapper object at 0x1215440d0
>, <statsmodels.regression.linear_model.RegressionResultsWrapper object
at 0x12d909b90>, array([[0., 1., 0.]])]), 2: ({'ssr_ftest': (3.59327014
28753764, 0.02755189101173785, 8136.0, 2), 'ssr_chi2test': (7.190956792
809351, 0.02744754922578252З, 2), 'lrtest': (7.1877827706048265, 0.0274
91143374182788, 2), 'params_ftest': (3.5932701428739904, 0.027551891011
77218, 8136.0, 2.0)}, [<statsmodels.regression.linear_model.RegressionR
esultsWrapper object at 0x12153c350>, <statsmodels.regression.linear_mo
del.RegressionResultsWrapper object at 0x12195b110>, array([[0., 0.,
1., 0., 0.],
       [0., 0., 0., 1., 0.]])]), 3: ({'ssr_ftest': (1.1512168877249138,
0.32689209422409926, 8133.0, 3), 'ssr_chi2test': (3.456623189258871, 0.
326431677123941, 3), 'lrtest': (3.455889475357253, 0.3265283318868665,
3), 'params_ftest': (1.1512168877277935, 0.32689209422298965, 8133.0,
3.0)}, [<statsmodels.regression.linear_model.RegressionResultsWrapper o
bject at 0x121534e50>, <statsmodels.regression.linear_model.RegressionR
esultsWrapper object at 0x12d9090d0>, array([[0., 0., 0., 1., 0., 0.,
0.],
```

```
        [0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 1., 0.]])]), 4: ({'ssr_ftest': (0.632582614
0788949, 0.6392277460576581, 8130.0, 4), 'ssr_chi2test': (2.53313156014
1759, 0.6387130628737945, 4), 'lrtest': (2.5327374439366395, 0.63878339
73927893, 4), 'params_ftest': (0.6325826140901567, 0.6392277460497593,
8130.0, 4.0)}, [<statsmodels.regression.linear_model.RegressionResultsW
rapper object at 0x1216f3f10>, <statsmodels.regression.linear_model.Reg
ressionResultsWrapper object at 0x12d8eca90>, array([[0., 0., 0., 0.,
1., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 1., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 1., 0.]])])}
```

For a lag <= 2, the Temperature seems to cause Occupancy based on the Granger Causality Test p-value < 0.05.

In [16]:

```
# Examine Humidity causing Occupancy
print(grangercausalitytests(df_train[['Occupancy', 'Humidity']], maxlag=
4))
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.5782  , p=0.4471  , df_denom=8139, df_num
=1
ssr based chi2 test:   chi2=0.5784  , p=0.4469  , df=1
likelihood ratio test: chi2=0.5784  , p=0.4470  , df=1
parameter F test:         F=0.5782  , p=0.4471  , df_denom=8139, df_num
=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=1.3368  , p=0.2628  , df_denom=8136, df_num
=2
ssr based chi2 test:   chi2=2.6752  , p=0.2625  , df=2
likelihood ratio test: chi2=2.6747  , p=0.2625  , df=2
parameter F test:         F=1.3368  , p=0.2628  , df_denom=8136, df_num
=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.6158  , p=0.6047  , df_denom=8133, df_num
=3
ssr based chi2 test:   chi2=1.8490  , p=0.6043  , df=3
likelihood ratio test: chi2=1.8488  , p=0.6044  , df=3
parameter F test:         F=0.6158  , p=0.6047  , df_denom=8133, df_num
=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.9867  , p=0.4133  , df_denom=8130, df_num
=4
ssr based chi2 test:   chi2=3.9510  , p=0.4127  , df=4
likelihood ratio test: chi2=3.9500  , p=0.4128  , df=4
parameter F test:         F=0.9867  , p=0.4133  , df_denom=8130, df_num
=4
{1: ({'ssr_ftest': (0.5781720070298837, 0.44705175496434246, 8139.0,
1), 'ssr_chi2test': (0.578385118716957, 0.4469459998686701, 1), 'lrtes
t': (0.5783645762421656, 0.4469540697217348, 1), 'params_ftest': (0.578
1720070245995, 0.44705175496647276, 8139.0, 1.0)}, [<statsmodels.regres
sion.linear_model.RegressionResultsWrapper object at 0x12d909c10>, <sta
tsmodels.regression.linear_model.RegressionResultsWrapper object at 0x1
2d909b90>, array([[0., 1., 0.]])]), 2: ({'ssr_ftest': (1.33676377023540
9, 0.2627521241567607, 8136.0, 2), 'ssr_chi2test': (2.675170563787233,
0.26247871606533607, 2), 'lrtest': (2.6747311232975335, 0.2625363942894
0245, 2), 'params_ftest': (1.336763770238285, 0.2627521241561952, 8136.
0, 2.0)}, [<statsmodels.regression.linear_model.RegressionResultsWrappe
r object at 0x12d8ecb50>, <statsmodels.regression.linear_model.Regressi
onResultsWrapper object at 0x12d8ecf50>, array([[0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.]])]), 3: ({'ssr_ftest': (0.6158148460645417,
0.6046860128780425, 8133.0, 3), 'ssr_chi2test': (1.8490346171026817, 0.
604323023923021l, 3), 'lrtest': (1.8488246409760904, 0.604368214741708
9, 3), 'params_ftest': (0.6158148460645266, 0.6046860128780425, 8133.0,
3.0)}, [<statsmodels.regression.linear_model.RegressionResultsWrapper o
bject at 0x12153c350>, <statsmodels.regression.linear_model.RegressionR
esultsWrapper object at 0x121954ad0>, array([[0., 0., 0., 1., 0., 0.,
0.],
       [0., 0., 0., 0., 1., 0., 0.],
```

```
       [0., 0., 0., 0., 0., 1., 0.]])]), 4: ({'ssr_ftest': (0.986655133
0898123, 0.4133429557230327, 8130.0, 4), 'ssr_chi2test': (3.95098948497
8097, 0.412679334524536, 4), 'lrtest': (3.9500308127244352, 0.412810681
76994806, 4), 'params_ftest': (0.9866551331015199, 0.4133429557167153,
8130.0, 4.0)}, [<statsmodels.regression.linear_model.RegressionResultsW
rapper object at 0x121954f50>, <statsmodels.regression.linear_model.Reg
ressionResultsWrapper object at 0x121954c50>, array([[0., 0., 0., 0.,
1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 1., 0.]])])}
```

The null hypothesis fails to be rejected at the p-value of 0.05, therefore Humidity does not cause Occupancy.

In [17]:

```
# Examine Light causing Occupancy
print(grangercausalitytests(df_train[['Occupancy', 'Light']], maxlag=4))
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=216.6264, p=0.0000  , df_denom=8139, df_num
=1
ssr based chi2 test:   chi2=216.7063, p=0.0000  , df=1
likelihood ratio test: chi2=213.8725, p=0.0000  , df=1
parameter F test:         F=216.6264, p=0.0000  , df_denom=8139, df_num
=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=152.1224, p=0.0000  , df_denom=8136, df_num
=2
ssr based chi2 test:   chi2=304.4318, p=0.0000  , df=2
likelihood ratio test: chi2=298.8777, p=0.0000  , df=2
parameter F test:         F=152.1224, p=0.0000  , df_denom=8136, df_num
=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=116.2704, p=0.0000  , df_denom=8133, df_num
=3
ssr based chi2 test:   chi2=349.1115, p=0.0000  , df=3
likelihood ratio test: chi2=341.8325, p=0.0000  , df=3
parameter F test:         F=116.2704, p=0.0000  , df_denom=8133, df_num
=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=83.6931 , p=0.0000  , df_denom=8130, df_num
=4
ssr based chi2 test:   chi2=335.1431, p=0.0000  , df=4
likelihood ratio test: chi2=328.4267, p=0.0000  , df=4
parameter F test:         F=83.6931 , p=0.0000  , df_denom=8130, df_num
=4
{1: ({'ssr_ftest': (216.62642993560382, 2.0562395592856343e-48, 8139.0,
1), 'ssr_chi2test': (216.70627749547688, 4.7299069898945616e-49, 1), 'l
rtest': (213.87253788191447, 1.9634670480476312e-48, 1), 'params_ftes
t': (216.62642993560408, 2.0562395592856343e-48, 8139.0, 1.0)}, [<stats
models.regression.linear_model.RegressionResultsWrapper object at 0x12d
909950>, <statsmodels.regression.linear_model.RegressionResultsWrapper
object at 0x1215446d0>, array([[0., 1., 0.]])]), 2: ({'ssr_ftest': (15
2.1223915307634, 1.3784532028737795e-65, 8136.0, 2), 'ssr_chi2test': (3
04.4317574857288, 7.824990229010475e-67, 2), 'lrtest': (298.87770134397
58, 1.2575688495486277e-65, 2), 'params_ftest': (152.12239153065397, 1.
3784532030197569e-65, 8136.0, 2.0)}, [<statsmodels.regression.linear_mo
del.RegressionResultsWrapper object at 0x121954590>, <statsmodels.regre
ssion.linear_model.RegressionResultsWrapper object at 0x121954650>, arr
ay([[0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.]])]), 3: ({'ssr_ftest': (116.27041836773999,
1.0028907212619656e-73, 8133.0, 3), 'ssr_chi2test': (349.1114738153462,
2.323097820054367e-75, 3), 'lrtest': (341.83245601379167, 8.75259793334
1622e-74, 3), 'params_ftest': (116.27041836773998, 1.0028907212628492e-
73, 8133.0, 3.0)}, [<statsmodels.regression.linear_model.RegressionResu
ltsWrapper object at 0x1215eb590>, <statsmodels.regression.linear_mode
l.RegressionResultsWrapper object at 0x121954050>, array([[0., 0., 0.,
1., 0., 0., 0.],
```

```
        [0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 1., 0.]])]), 4: ({'ssr_ftest': (83.69313503
029518, 9.349574743675364e-70, 8130.0, 4), 'ssr_chi2test': (335.1431370
290639, 2.827331931643635e-71, 4), 'lrtest': (328.4267270025739, 7.9631
98645095444e-70, 4), 'params_ftest': (83.69313503028006, 9.349574743941
627e-70, 8130.0, 4.0)}, [<statsmodels.regression.linear_model.Regressio
nResultsWrapper object at 0x12d8f2650>, <statsmodels.regression.linear_
model.RegressionResultsWrapper object at 0x12d8f2290>, array([[0., 0.,
0., 0., 1., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 1., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 1., 0.]])])}
```

Light seems to have a strong effect on Occupancy, since p-value is 0.000.

In [18]:

```
# Examine CO2 causing Occupancy
print(grangercausalitytests(df_train[['Occupancy', 'CO2']], maxlag=4))
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=34.9532 , p=0.0000  , df_denom=8139, df_num
=1
ssr based chi2 test:   chi2=34.9661 , p=0.0000  , df=1
likelihood ratio test: chi2=34.8912 , p=0.0000  , df=1
parameter F test:         F=34.9532 , p=0.0000  , df_denom=8139, df_num
=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=12.9394 , p=0.0000  , df_denom=8136, df_num
=2
ssr based chi2 test:   chi2=25.8947 , p=0.0000  , df=2
likelihood ratio test: chi2=25.8536 , p=0.0000  , df=2
parameter F test:         F=12.9394 , p=0.0000  , df_denom=8136, df_num
=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=5.3197  , p=0.0012  , df_denom=8133, df_num
=3
ssr based chi2 test:   chi2=15.9727 , p=0.0011  , df=3
likelihood ratio test: chi2=15.9571 , p=0.0012  , df=3
parameter F test:         F=5.3197  , p=0.0012  , df_denom=8133, df_num
=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=2.7232  , p=0.0279  , df_denom=8130, df_num
=4
ssr based chi2 test:   chi2=10.9050 , p=0.0277  , df=4
likelihood ratio test: chi2=10.8977 , p=0.0277  , df=4
parameter F test:         F=2.7232  , p=0.0279  , df_denom=8130, df_num
=4
{1: ({'ssr_ftest': (34.95321142853135, 3.513441792672317e-09, 8139.0,
1), 'ssr_chi2test': (34.9660950302374, 3.3549665099567356e-09, 1), 'lrt
est': (34.891227760119364, 3.486481577200691e-09, 1), 'params_ftest':
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s.regression.linear_model.RegressionResultsWrapper object at 0x12d909b9
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t at 0x121954650>, array([[0., 1., 0.]])]), 2: ({'ssr_ftest': (12.93940
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2.4319762667379205e-06, 2), 'params_ftest': (12.939402174147045, 2.4513
613633286006e-06, 8136.0, 2.0)}, [<statsmodels.regression.linear_model.
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n.linear_model.RegressionResultsWrapper object at 0x12d8f2410>, array
([[0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.]])]), 3: ({'ssr_ftest': (5.319664402728529,
0.0011641746096933505, 8133.0, 3), 'ssr_chi2test': (15.97272897019927,
0.0011486767474718582, 3), 'lrtest': (15.957078183288104, 0.00115719392
29575265, 3), 'params_ftest': (5.3196644026789315, 0.00116417460977454
9, 8133.0, 3.0)}, [<statsmodels.regression.linear_model.RegressionResul
tsWrapper object at 0x12d911710>, <statsmodels.regression.linear_model.
RegressionResultsWrapper object at 0x12d911150>, array([[0., 0., 0.,
1., 0., 0., 0.],
```

```
       [0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 1., 0.]])]), 4: ({'ssr_ftest': (2.723246955
2480016, 0.027863347815891896, 8130.0, 4), 'ssr_chi2test': (10.90504647
9096425, 0.027652144774908145, 4), 'lrtest': (10.897747430004529, 0.027
737549191175867, 4), 'params_ftest': (2.723246955187612, 0.027863347818
739642, 8130.0, 4.0)}, [<statsmodels.regression.linear_model.Regression
ResultsWrapper object at 0x121eeddd0>, <statsmodels.regression.linear_m
odel.RegressionResultsWrapper object at 0x12d911950>, array([[0., 0.,
0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 1., 0.]])])}
```

CO2 seems to have a strong effect on Occupancy, since p-value is < 0.05 for max_lag <= 4.

In [19]:
```
# Examine HumidityRatio causing Occupancy
print(grangercausalitytests(df_train[['Occupancy', 'HumidityRatio']], ma
xlag=4))
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=2.7994  , p=0.0943  , df_denom=8139, df_num
=1
ssr based chi2 test:   chi2=2.8005  , p=0.0942  , df=1
likelihood ratio test: chi2=2.8000  , p=0.0943  , df=1
parameter F test:         F=2.7994  , p=0.0943  , df_denom=8139, df_num
=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=1.7887  , p=0.1672  , df_denom=8136, df_num
=2
ssr based chi2 test:   chi2=3.5797  , p=0.1670  , df=2
likelihood ratio test: chi2=3.5789  , p=0.1671  , df=2
parameter F test:         F=1.7887  , p=0.1672  , df_denom=8136, df_num
=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.7380  , p=0.5293  , df_denom=8133, df_num
=3
ssr based chi2 test:   chi2=2.2158  , p=0.5289  , df=3
likelihood ratio test: chi2=2.2155  , p=0.5289  , df=3
parameter F test:         F=0.7380  , p=0.5293  , df_denom=8133, df_num
=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.9660  , p=0.4248  , df_denom=8130, df_num
=4
ssr based chi2 test:   chi2=3.8683  , p=0.4241  , df=4
likelihood ratio test: chi2=3.8674  , p=0.4243  , df=4
parameter F test:         F=0.9660  , p=0.4248  , df_denom=8130, df_num
=4
{1: ({'ssr_ftest': (2.7994495684347247, 0.09433510384211544, 8139.0,
1), 'ssr_chi2test': (2.8004814333696433, 0.0942360069980527, 1), 'lrtes
t': (2.799999924012809, 0.09426431130865497, 1), 'params_ftest': (2.799
449568434711, 0.09433510384211544, 8139.0, 1.0)}, [<statsmodels.regress
ion.linear_model.RegressionResultsWrapper object at 0x12d8ec850>, <stat
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153c350>, array([[0., 1., 0.]])]), 2: ({'ssr_ftest': (1.788748729481386
4, 0.16723494858875154, 8136.0, 2), 'ssr_chi2test': (3.579696019348074,
0.16698554792622738, 2), 'lrtest': (3.578909232201113, 0.16705125189055
7, 2), 'params_ftest': (1.7887487294809006, 0.16723494858883073, 8136.
0, 2.0)}, [<statsmodels.regression.linear_model.RegressionResultsWrappe
r object at 0x12d911b50>, <statsmodels.regression.linear_model.Regressi
onResultsWrapper object at 0x12d9115d0>, array([[0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.]])]), 3: ({'ssr_ftest': (0.7379510394387019,
0.5292573095580974, 8133.0, 3), 'ssr_chi2test': (2.2157585617967666, 0.
5288510996267659, 3), 'lrtest': (2.215457044883806, 0.5289102360516149,
3), 'params_ftest': (0.7379510394391602, 0.5292573095579194, 8133.0, 3.
0)}, [<statsmodels.regression.linear_model.RegressionResultsWrapper obj
ect at 0x1215348d0>, <statsmodels.regression.linear_model.RegressionRes
ultsWrapper object at 0x12d8f2e50>, array([[0., 0., 0., 1., 0., 0.,
0.],
       [0., 0., 0., 0., 1., 0., 0.],
```

```
        [0., 0., 0., 0., 0., 1., 0.]])]), 4: ({'ssr_ftest': (0.966003318
8057995, 0.42478433188508447, 8130.0, 4), 'ssr_chi2test': (3.8682907806
939246, 0.4241241083428684, 4), 'lrtest': (3.8673718144054874, 0.424252
58322177695, 4), 'params_ftest': (0.9660033188159165, 0.424784331879396
9, 8130.0, 4.0)}, [<statsmodels.regression.linear_model.RegressionResul
tsWrapper object at 0x12196be90>, <statsmodels.regression.linear_model.
RegressionResultsWrapper object at 0x121709ad0>, array([[0., 0., 0.,
0., 1., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 1., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 1., 0.]])])}
```

The null hypothesis fails to be rejected at the p-value of 0.05, therefore HumidityRatio does not cause Occupancy.

Check each parameter for stationarity using ADF Test

In [20]:

```python
# Check Temperature for stationarity
result = adfuller(df_train['Temperature'].values)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -2.694434
p-value: 0.075006
Critical Values:
	1%: -3.431
	5%: -2.862
	10%: -2.567
```

The p-value is above the rule-of-thumb threshold of 0.05, indicating that there is a unit root, and Temperature is NOT stationary.

In [21]:

```python
# Check Humidity for stationarity
result = adfuller(df_train['Humidity'].values)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -0.751632
p-value: 0.832919
Critical Values:
	1%: -3.431
	5%: -2.862
	10%: -2.567
```

The p-value is above the rule-of-thumb threshold of 0.05, indicating that there is a unit root, and Humidity is NOT stationary.

In [22]:
```
# Check Light for stationarity
result = adfuller(df_train['Light'].values)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -3.314650
p-value: 0.014236
Critical Values:
	1%: -3.431
	5%: -2.862
	10%: -2.567
```

The p-value is below the rule-of-thumb threshold of 0.05, indicating that there is no unit root, and Light IS stationary.

In [23]:
```
# Check CO2 for stationarity
result = adfuller(df_train['CO2'].values)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -3.639003
p-value: 0.005058
Critical Values:
	1%: -3.431
	5%: -2.862
	10%: -2.567
```

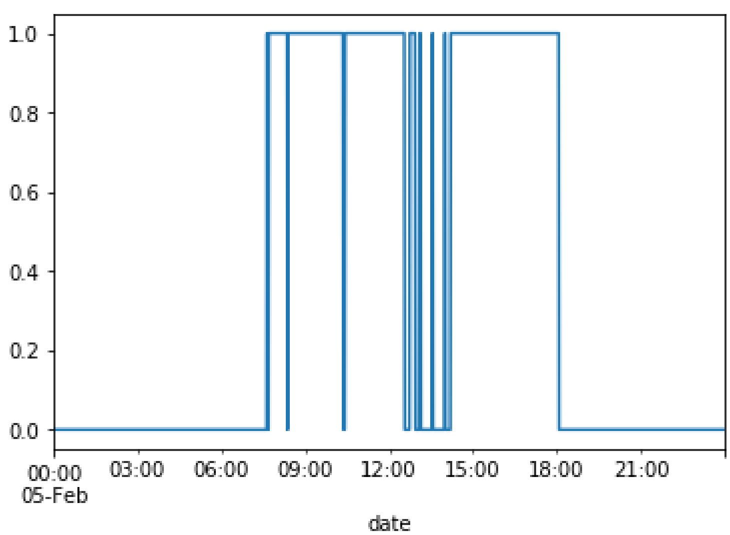
The p-value is below the rule-of-thumb threshold of 0.05, indicating that there is no unit root, and CO2 IS stationary.

In [24]:
```
# Check HumidityRatio for stationarity
result = adfuller(df_train['HumidityRatio'].values)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

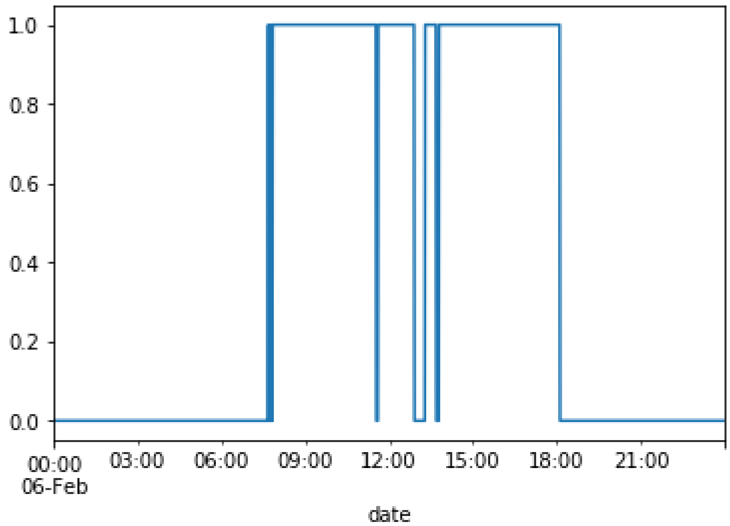
```
ADF Statistic: -1.279709
p-value: 0.638403
Critical Values:
        1%: -3.431
        5%: -2.862
        10%: -2.567
```

The p-value is above the rule-of-thumb threshold of 0.05, indicating that there is a unit root, and HumidityRatio is NOT stationary.

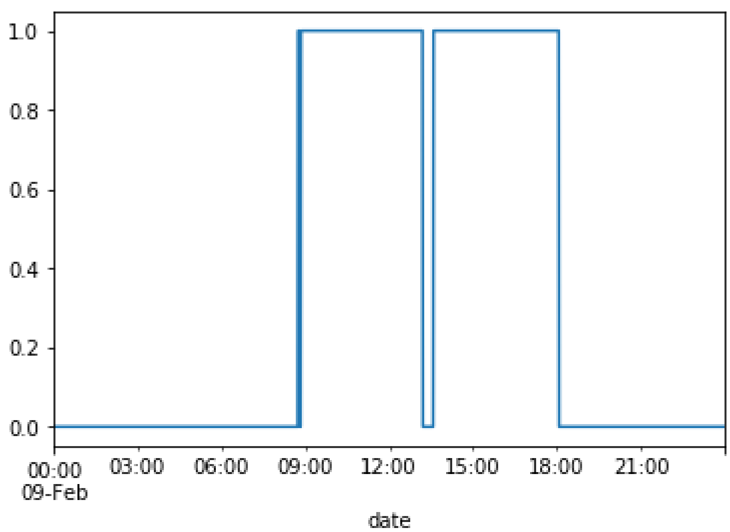
In [25]:
```
# Examine hours for Occupancy=1
df_train[df_train.index.day == 5]['Occupancy'].plot()
plt.show()
```



In [26]:
```
df_train[df_train.index.day == 6]['Occupancy'].plot()
plt.show()
```



In [27]:
```
df_train[df_train.index.day == 9]['Occupancy'].plot()
plt.show()
```



The plots confirm that the hours for occupancy tend to be roughly between 9am-6pm.

Since the day of the week and time of the day seem to be important factors in predicting occupancy and trends in the other variables, create new columns for "WorkHours" and "Weekday"

In [28]:
```
# Separate X and y
X_df_train = df_train.iloc[:,:5]
y_df_train = df_train['Occupancy']
```

In [29]:
```
# Add binary column for Weekday
X_df_train['Weekday'] = np.where((X_df_train.index.day == 7) | (X_df_tra
in.index.day == 8), 0, 1)
```

In [30]:
```
# Add binary column for WorkHours
X_df_train['WorkHours'] = np.where((X_df_train.index.hour >= 8) & (X_df_train.index.day <= 6), 1, 0)
```

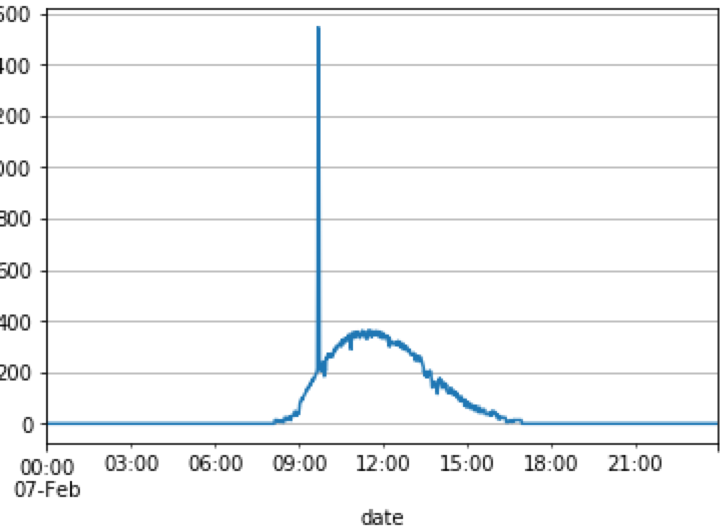
In [31]:
```
X_df_train
```

Out[31]:

date	Temperature	Humidity	Light	CO2	HumidityRatio	Weekday	WorkHours
2015-02-04 17:51:00	23.18	27.2720	426.0	721.250000	0.004793	1	1
2015-02-04 17:52:00	23.15	27.2675	429.5	714.000000	0.004783	1	1
2015-02-04 17:53:00	23.15	27.2450	426.0	713.500000	0.004779	1	1
2015-02-04 17:54:00	23.15	27.2000	426.0	708.250000	0.004772	1	1
2015-02-04 17:55:00	23.10	27.2000	426.0	704.500000	0.004757	1	1
...	...	...	...	...	...	...	...
2015-02-10 09:29:00	21.05	36.0975	433.0	787.250000	0.005579	1	0
2015-02-10 09:30:00	21.05	35.9950	433.0	789.500000	0.005563	1	0
2015-02-10 09:31:00	21.10	36.0950	433.0	798.500000	0.005596	1	0
2015-02-10 09:32:00	21.10	36.2600	433.0	820.333333	0.005621	1	0
2015-02-10 09:33:00	21.10	36.2000	447.0	821.000000	0.005612	1	0

8143 rows × 7 columns

In [32]:
```python
# Examine outlier for Light
X_df_train[X_df_train.index.day == 7]['Light'].plot(grid=True)
plt.show()
```



This is most likely an error, so we'll assume that the data for that spike can be removed and imputed.

In [33]:
```python
# Find time when spike occurred
X_df_train[(X_df_train.index.day == 7) & (X_df_train.index.hour == 9) &
(X_df_train['Light'] > 400)]['Light']
```

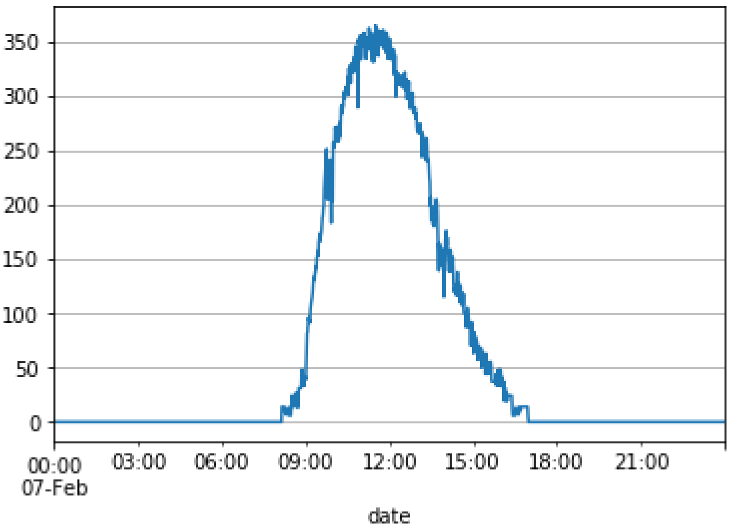
Out[33]:
```
date
2015-02-07 09:41:00     611.500000
2015-02-07 09:42:00    1546.333333
2015-02-07 09:43:00    1451.750000
2015-02-07 09:44:00     829.000000
Name: Light, dtype: float64
```

The data for Light was unusually high for 4 data points (09:40:59 through 09:43:59). To improve training the model, we'll change these values by imputing using simple linear regression.

In [34]:
```python
# Replace high values with NaN
X_df_train.at['2015-02-07 09:41:00', 'Light'] = np.nan
X_df_train.at['2015-02-07 09:42:00', 'Light'] = np.nan
X_df_train.at['2015-02-07 09:43:00', 'Light'] = np.nan
X_df_train.at['2015-02-07 09:44:00', 'Light'] = np.nan
```

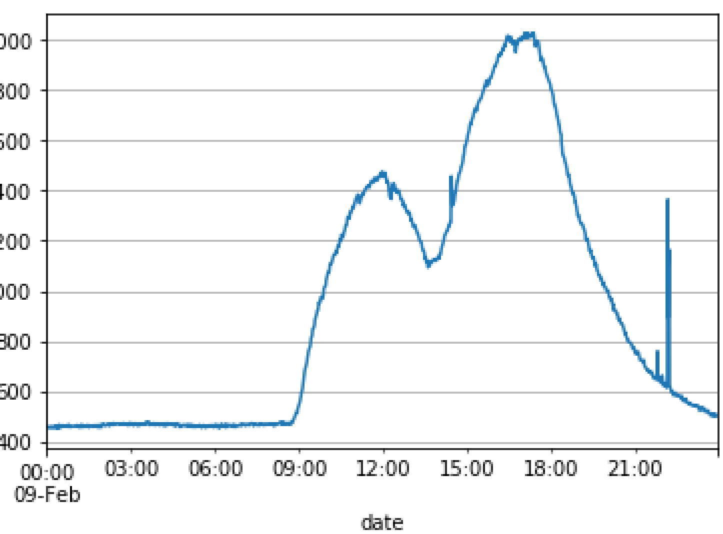
In [35]:
```python
# Interpolate NaN values using simple linear regression
X_df_train['Light'].interpolate(method='linear', inplace=True)
```

In [36]:
```
# Verify values were imputed
X_df_train[X_df_train.index.day == 7]['Light'].plot(grid=True)
plt.show()
```



CO2 also had some unusually high spikes near the end of the day on 2015-02-09. Let's zoom in and examine it.

In [37]:
```
# Examine spikes for CO2
df_train[df_train.index.day == 9]['CO2'].plot(grid=True)
plt.show()
```



However, the spike for CO2 is still in the range of the data, so we'll keep it and not bother smoothing it for now.

In [38]:
```
# Examine correlation matrix for predicting variables
X_df_train.corr()
```

Out[38]:

	Temperature	Humidity	Light	CO2	HumidityRatio	Weekday	WorkHours
Temperature	1.000000	-0.141759	0.654502	0.559894	0.151762	0.418657	0.532213
Humidity	-0.141759	1.000000	0.040864	0.439023	0.955198	0.108551	-0.327712
Light	0.654502	0.040864	1.000000	0.670003	0.234770	0.284592	0.404677
CO2	0.559894	0.439023	0.670003	1.000000	0.626556	0.394834	0.201954
HumidityRatio	0.151762	0.955198	0.234770	0.626556	1.000000	0.243146	-0.167921
Weekday	0.418657	0.108551	0.284592	0.394834	0.243146	1.000000	0.462569
WorkHours	0.532213	-0.327712	0.404677	0.201954	-0.167921	0.462569	1.000000

The correlation matrix shows that Humidity and HumidityRatio are highly correlated, so one of these may potentially be removed from the model to reduce multicollinearity. CO2 and HumidityRatio seem somewhat correlated, too. Therefore, let us drop HumidityRatio from the model.

In [39]:
```
X_df_train = X_df_train.drop(columns = 'HumidityRatio')
```

In [40]:
```
# Examine correlation matrix after dropping HumidityRatio
X_df_train.corr()
```

Out[40]:

	Temperature	Humidity	Light	CO2	Weekday	WorkHours
Temperature	1.000000	-0.141759	0.654502	0.559894	0.418657	0.532213
Humidity	-0.141759	1.000000	0.040864	0.439023	0.108551	-0.327712
Light	0.654502	0.040864	1.000000	0.670003	0.284592	0.404677
CO2	0.559894	0.439023	0.670003	1.000000	0.394834	0.201954
Weekday	0.418657	0.108551	0.284592	0.394834	1.000000	0.462569
WorkHours	0.532213	-0.327712	0.404677	0.201954	0.462569	1.000000

Inspect df_val:

In [41]:
```
df_val.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9752 entries, 1 to 9752
Data columns (total 7 columns):
date                 9752 non-null object
Temperature          9752 non-null float64
Humidity             9752 non-null float64
Light                9752 non-null float64
CO2                  9752 non-null float64
HumidityRatio        9752 non-null float64
Occupancy            9752 non-null int64
dtypes: float64(5), int64(1), object(1)
memory usage: 609.5+ KB
```

Again, no null values.

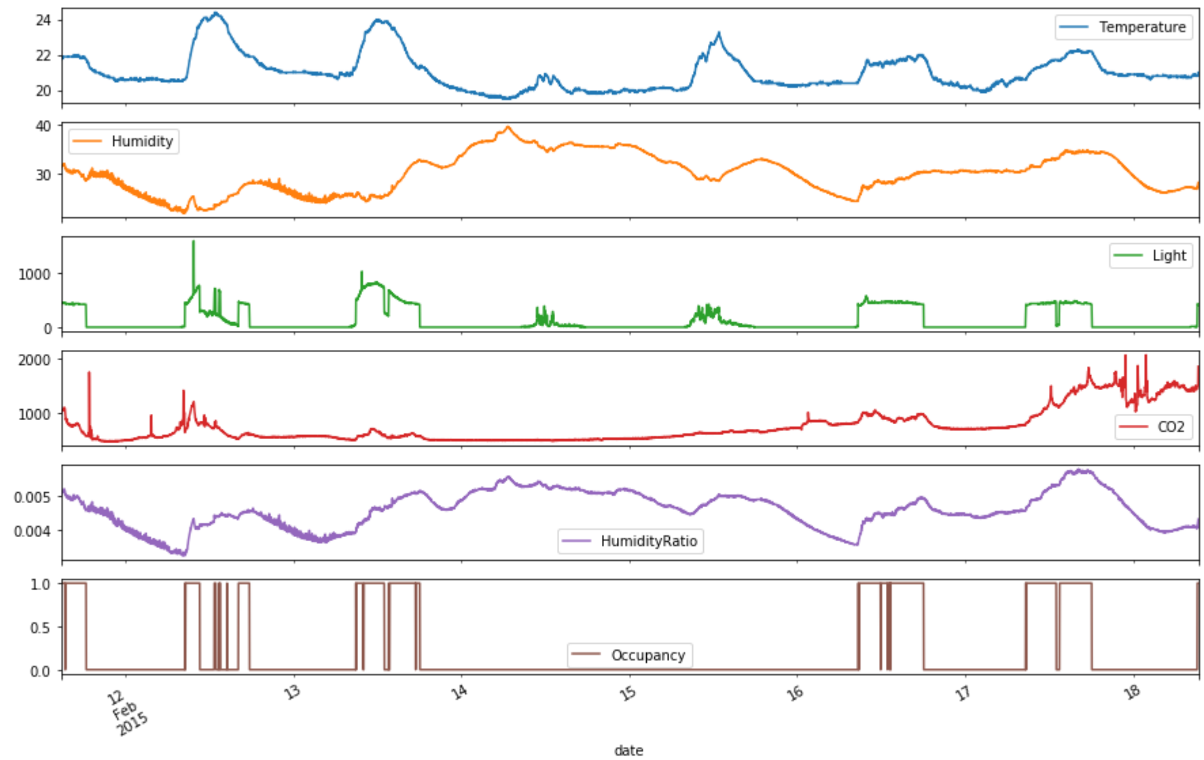
In [42]:
```
df_val.describe()
```

Out[42]:

	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
count	9752.000000	9752.000000	9752.000000	9752.000000	9752.000000	9752.000000
mean	21.001768	29.891910	123.067930	753.224832	0.004589	0.210111
std	1.020693	3.952844	208.221275	297.096114	0.000531	0.407408
min	19.500000	21.865000	0.000000	484.666667	0.003275	0.000000
25%	20.290000	26.642083	0.000000	542.312500	0.004196	0.000000
50%	20.790000	30.200000	0.000000	639.000000	0.004593	0.000000
75%	21.533333	32.700000	208.250000	831.125000	0.004998	0.000000
max	24.390000	39.500000	1581.000000	2076.500000	0.005769	1.000000

In [43]:
```python
# Convert date column to datetime object and set as index, round to nearest minute
df_val['date'] =  pd.to_datetime(df_val['date'])
df_val = df_val.set_index('date')
df_val.index = df_val.index.round('min')

# Plot df_val to visualize
df_val.plot(subplots=True, figsize=(15,10))
plt.show()
```



It can be seen that this is a continuation of the time series data from the training set. Now, the dates 2015-02-11 to 2015-02-19 are given. The same seasonality pattern of no occupancy for 2 consecutive days (2015-02-14 and 2015-02-15) can be observed, which indicates conditional seasonality. Add columns for Weekday or Weekend and Hour to take into account this seasonality for predicting Occupancy. Also, note that the time range is quite short here, and none of the variables lead us to predict that there is a trend component to this time series. Therefore, assume there is no trend component.

In [44]:
```python
# Drop HumidityRatio from df_val
df_val = df_val.drop(columns = 'HumidityRatio')
```

In [45]:
```python
# Separate X and y
X_df_val = df_val.iloc[:,:4]
y_df_val = df_val['Occupancy']
```

In [46]:
```python
# Add columns for Weekday and WorkHours
X_df_val['Weekday'] = np.where((X_df_val.index.day == 14) | (X_df_val.index.day == 15), 0, 1)
X_df_val['WorkHours'] = np.where((X_df_val.index.hour >= 8) & (X_df_val.index.hour <= 6), 1, 0)
```

Split the validation set into validation set for comparing models and test set for assessing model accuracy. Use dates from 2015-02-11 to 2015-02-14 for validation set, and 2015-02-15 to 2015-02-18 for test set. This gives a good balance by including a date in each set with a "weekend" day, and makes the test set the latest set in time.

In [47]:
```
X_df_test = X_df_val[df_val.index.day >= 15]
y_df_test = y_df_val[df_val.index.day >= 15]
X_df_val = X_df_val[df_val.index.day <= 14]
y_df_val = y_df_val[df_val.index.day <= 14]
```

In [48]:
```
X_df_val.head()
```

Out[48]:

	Temperature	Humidity	Light	CO2	Weekday	WorkHours
date						
2015-02-11 14:48:00	21.7600	31.133333	437.333333	1029.666667	1	0
2015-02-11 14:49:00	21.7900	31.000000	437.333333	1000.000000	1	0
2015-02-11 14:50:00	21.7675	31.122500	434.000000	1003.750000	1	0
2015-02-11 14:51:00	21.7675	31.122500	439.000000	1009.500000	1	0
2015-02-11 14:52:00	21.7900	31.133333	437.333333	1005.666667	1	0

In [49]:
```
y_df_val.head()
```

Out[49]:
```
date
2015-02-11 14:48:00    1
2015-02-11 14:49:00    1
2015-02-11 14:50:00    1
2015-02-11 14:51:00    1
2015-02-11 14:52:00    1
Name: Occupancy, dtype: int64
```

In [50]:
```
X_df_test.head()
```

Out[50]:

	Temperature	Humidity	Light	CO2	Weekday	WorkHours
date						
2015-02-15 00:00:00	19.89	35.745	0.0	535.500000	0	0
2015-02-15 00:01:00	19.89	35.700	0.0	541.000000	0	0
2015-02-15 00:02:00	20.00	35.700	0.0	539.333333	0	0
2015-02-15 00:03:00	20.00	35.700	0.0	541.000000	0	0
2015-02-15 00:04:00	20.00	35.700	0.0	542.000000	0	0

In [51]:
```
y_df_test.head()
```

Out[51]:
```
date
2015-02-15 00:00:00    0
2015-02-15 00:01:00    0
2015-02-15 00:02:00    0
2015-02-15 00:03:00    0
2015-02-15 00:04:00    0
Name: Occupancy, dtype: int64
```

In [52]:
```
# Normalize appropriate columns for building Classification Models
cols_to_norm = ['Temperature', 'Humidity', 'Light', 'CO2']
X_df_train[cols_to_norm] = X_df_train[cols_to_norm].apply(lambda x: (x -
x.min()) / (x.max() - x.min()))
```

In [53]:
```
X_df_val[cols_to_norm] = X_df_val[cols_to_norm].apply(lambda x: (x - x.m
in()) / (x.max() - x.min()))
X_df_test[cols_to_norm] = X_df_test[cols_to_norm].apply(lambda x: (x - x
.min()) / (x.max() - x.min()))
```

In [54]:
```
X_train = X_df_train
y_train = y_df_train
X_test = X_df_val
y_test = y_df_val
```

In [55]:
```
# Implement Logistic Regression
logreg = LogisticRegression(solver='lbfgs', max_iter=200)
# Fit model: Predict y from x_test after training on x_train and y_train
y_pred = logreg.fit(X_train, y_train).predict(X_test)
# Report testing accuracy
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.811576
```

In [56]:
```
# Implement the Gaussian Naive Bayes algorithm for classification
gnb = GaussianNB()
# Fit model: Predict y from x_test after training on x_train and y_train
y_pred = gnb.fit(X_train, y_train).predict(X_test)
# Report testing accuracy
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.888547
```

In [57]:
```
# Implement KNN
neigh = KNeighborsClassifier(n_neighbors=3) #Best: n_neighbors=3
# Fit model: Predict y from x_test after training on x_train and y_train
y_pred = neigh.fit(X_train, y_train).predict(X_test)
# Report testing accuracy
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.932471
```

In [58]:
```python
# Build classifier using svm
SVM = svm.SVC(C=1, kernel = 'rbf').fit(X_train, y_train) #Best: C=1, kernel = 'rbf'
y_pred = SVM.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.991379
```

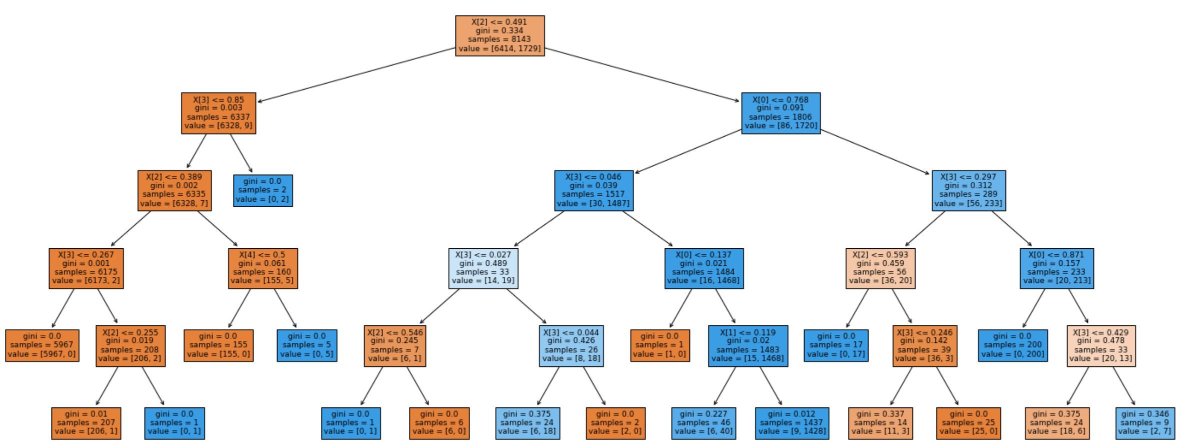
In [59]:
```python
# Build classifier using simple neural network
NN = MLPClassifier(solver = 'adam', learning_rate_init = 0.001, max_iter = 250, hidden_layer_sizes=(5, 2), random_state=99).fit(X_train, y_train)
y_pred = NN.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.837233
```

In [60]:
```python
# Build classifier using CART
dct = DecisionTreeClassifier(max_depth=5, random_state=99)
dct.fit(X_train, y_train)
y_pred = dct.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.880747
```

In [61]:
```python
# Plot decision tree to view feature importances
plt.figure(figsize=(25,10)) #Set figure size for legibility
plot_tree(dct, filled=True)
plt.show()
```



The Decision Tree plot shows that X[2] (Light) is the most important feature, followed by X[3] (CO2) and X[0] (Temperature).

In [62]:
```
# Build classifier using Random Forest
rf = RandomForestClassifier(n_estimators=100, max_depth=6, random_state=
99)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.838259
```

In [63]:
```
# Calculate feature importances
importances = rf.feature_importances_
print(importances)

# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]
print(indices)
```

```
[0.06784078 0.02669683 0.64817013 0.21166027 0.01187343 0.03375856]
[2 3 0 5 1 4]
```

The rank and weights of the features from the Random Forest classifier confirm that X[2] (Light) is the most important feature.

SVM model with C=1 and kernel='rbf' performed the best on the validation set. Assess the true accuracy of the model using the test set.

In [64]:
```
X_test = X_df_test
y_test = y_df_test
```

In [65]:
```
# Build classifier using svm
SVM = svm.SVC(C=1, kernel = 'rbf').fit(X_train, y_train) #Best: C=1, ker
nel = 'rbf'
y_pred = SVM.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

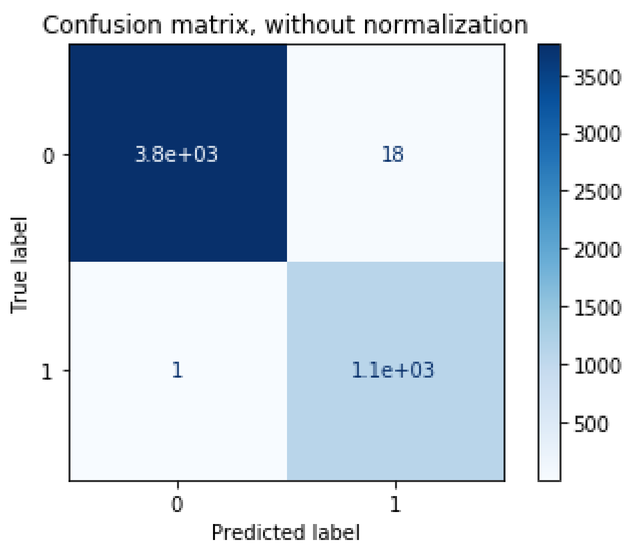
```
Testing accuracy out of a total 4880 points : 0.996107
```

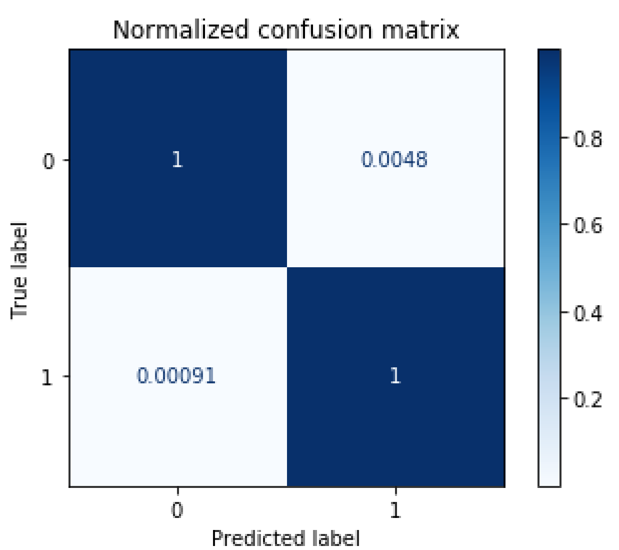
The accuracy on the test set is 0.996107, which is very high!

In [66]:
```
# Plot confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(SVM, X_test, y_test,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)
```

```
Confusion matrix, without normalization
[[3765   18]
 [   1 1096]]
Normalized confusion matrix
[[9.95241872e-01 4.75812847e-03]
 [9.11577028e-04 9.99088423e-01]]
```





The model above only predicts based on the variables Temperature, Humidity, CO2, Weekday, and WorkHours. It assumes that the information on the variables is known. For further exploration, subsets of the variables could be used to train more models. For a more difficult problem, forecast the variables and make predictions from the forecast, and compare the predictions with the actual results.

Fit time series forecasting models with Facebook Prophet

The range of date for the df_train set is 2015-02-04 17:51:00 (Wed) through 2015-02-10 09:33:00 (Tues).
The range of date for the df_val set is 2015-02-11 14:48:00 (Wed) through 2015-02-14 23:59:00 (Sat).
The range of date for the df_test set is 2015-02-15 through (Sun) 2015-02-18 09:19:00 (Wed).
Fit the predicted time series for the individual parameters to align with the day of week and time on the df_val set.

In [67]:
```
# Prophet requires columns ds (Date) and y (value)
X_df_train_forecast = df_train[['Temperature', 'Humidity', 'Light', 'CO
2']]
X_df_train_forecast['ds'] = df_train.index
X_df_train_forecast['y'] = df_train['Temperature']
```

In [68]:
```
X_df_train_forecast
```

Out[68]:

	Temperature	Humidity	Light	CO2	ds	y
date						
2015-02-04 17:51:00	23.18	27.2720	426.0	721.250000	2015-02-04 17:51:00	23.18
2015-02-04 17:52:00	23.15	27.2675	429.5	714.000000	2015-02-04 17:52:00	23.15
2015-02-04 17:53:00	23.15	27.2450	426.0	713.500000	2015-02-04 17:53:00	23.15
2015-02-04 17:54:00	23.15	27.2000	426.0	708.250000	2015-02-04 17:54:00	23.15
2015-02-04 17:55:00	23.10	27.2000	426.0	704.500000	2015-02-04 17:55:00	23.10
...	...	...	...	...	...	...
2015-02-10 09:29:00	21.05	36.0975	433.0	787.250000	2015-02-10 09:29:00	21.05
2015-02-10 09:30:00	21.05	35.9950	433.0	789.500000	2015-02-10 09:30:00	21.05
2015-02-10 09:31:00	21.10	36.0950	433.0	798.500000	2015-02-10 09:31:00	21.10
2015-02-10 09:32:00	21.10	36.2600	433.0	820.333333	2015-02-10 09:32:00	21.10
2015-02-10 09:33:00	21.10	36.2000	447.0	821.000000	2015-02-10 09:33:00	21.10

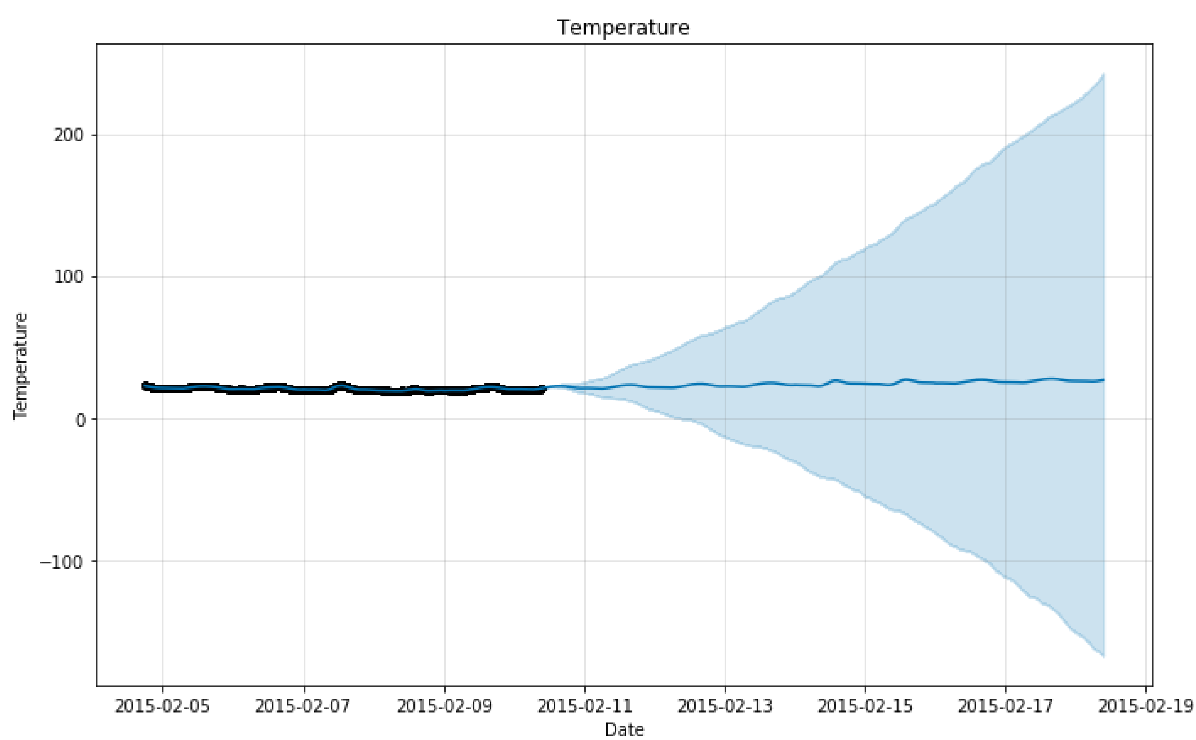
8143 rows × 6 columns

In [69]:
```
def is_weekday(ds):
    date = pd.to_datetime(ds)
    return (date.day != 7 and date.day != 8 and date.day != 14 and date.
day != 15)
```

In [70]:
```
X_df_train_forecast['weekday'] = X_df_train_forecast['ds'].apply(is_week
day)
X_df_train_forecast['weekend'] = ~X_df_train_forecast['ds'].apply(is_wee
kday)
```

In [71]:
```
# Model seasonality to make forecasts for Temperature
m = Prophet(daily_seasonality=False, weekly_seasonality=False, yearly_se
asonality=False)
m.add_seasonality(name='daily_weekday', period=1, fourier_order=3, condi
tion_name='weekday')
m.add_seasonality(name='daily_weekend', period=1, fourier_order=3, condi
tion_name='weekend')
m.fit(X_df_train_forecast)
# Make a future dataframe up to 2015-02-18 09:19:00
temp_forecast = m.make_future_dataframe(periods=60*24*8, freq='T')
temp_forecast['weekday'] = temp_forecast['ds'].apply(is_weekday)
temp_forecast['weekend'] = ~temp_forecast['ds'].apply(is_weekday)
# Make predictions
forecast = m.predict(temp_forecast)
```

In [72]:
```
m.plot(forecast, xlabel = 'Date', ylabel = 'Temperature')
plt.title('Temperature');
```



In [73]:
```
X_df_train_forecast['TempForecast'] = forecast['yhat']
```

In [74]:
```
temp_fc = forecast[['ds', 'yhat']].rename(columns={"ds": "date", "yhat":
"TempForecast"}).set_index('date')
```

In [75]:
```
temp_fc
```

Out[75]:

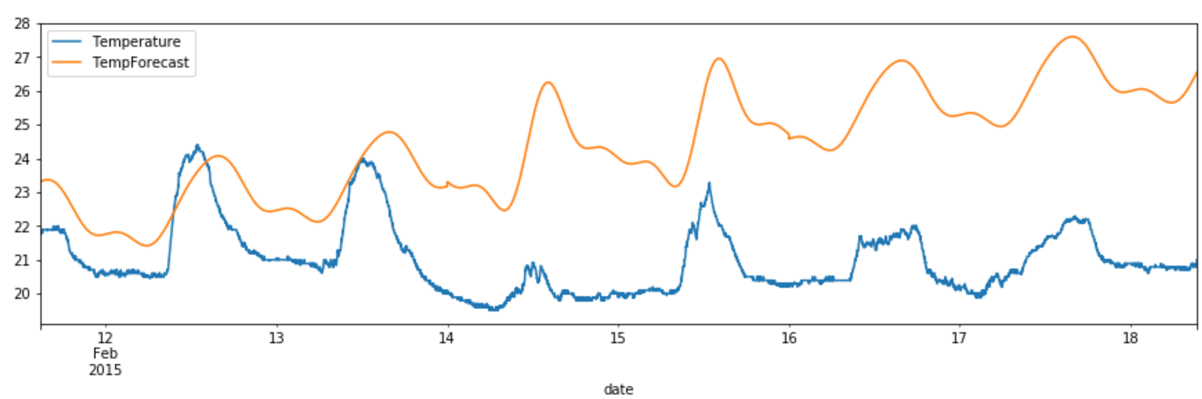
	TempForecast
date	
2015-02-04 17:51:00	22.825499
2015-02-04 17:52:00	22.819885
2015-02-04 17:53:00	22.814238
2015-02-04 17:54:00	22.808558
2015-02-04 17:55:00	22.802846
...	...
2015-02-18 09:29:00	26.606772
2015-02-18 09:30:00	26.613720
2015-02-18 09:31:00	26.620671
2015-02-18 09:32:00	26.627625
2015-02-18 09:33:00	26.634581

19663 rows × 1 columns

In [76]:
```
df_val = df_val.join(temp_fc, on='date', how='inner')
```

In [77]:
```
df_val.plot(y=["Temperature", "TempForecast"], figsize=(15,4))
```

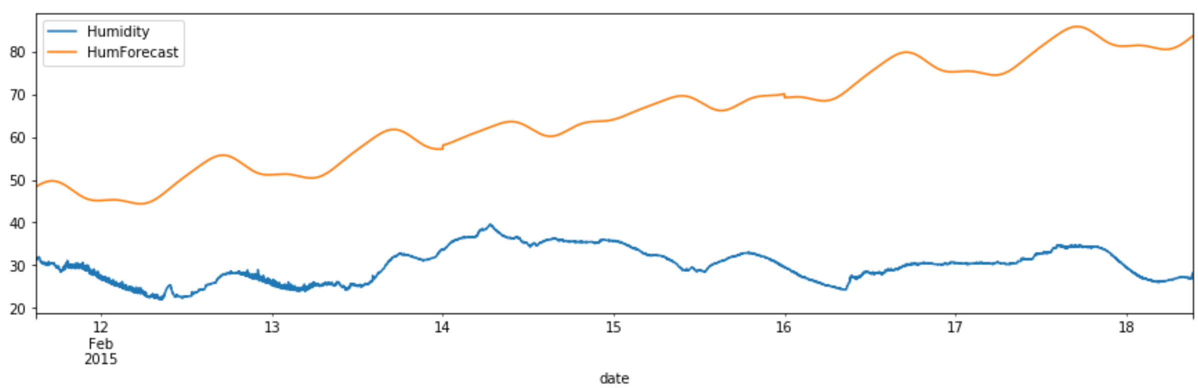
Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x12dc51b90>



In [78]:
```python
# Model seasonality to make forecasts for Humidity
m = Prophet(daily_seasonality=False, weekly_seasonality=False, yearly_se
asonality=False)
m.add_seasonality(name='daily_weekday', period=1, fourier_order=3, condi
tion_name='weekday')
m.add_seasonality(name='daily_weekend', period=1, fourier_order=3, condi
tion_name='weekend')
X_df_train_forecast['y'] = df_train['Humidity']
m.fit(X_df_train_forecast)
# Make a future dataframe up to 2015-02-18 09:19:00
hum_forecast = m.make_future_dataframe(periods=60*24*8, freq='T')
hum_forecast['weekday'] = hum_forecast['ds'].apply(is_weekday)
hum_forecast['weekend'] = ~hum_forecast['ds'].apply(is_weekday)
# Make predictions
forecast = m.predict(hum_forecast)
```

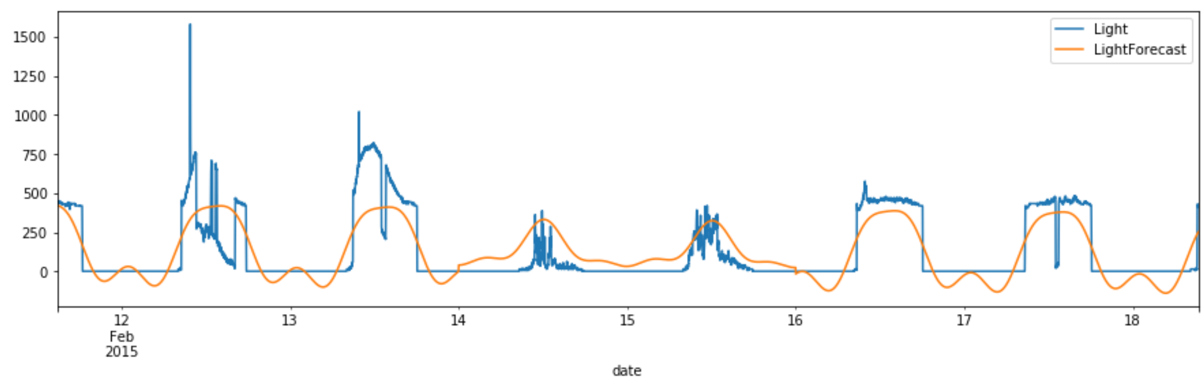
In [79]:
```python
X_df_train_forecast['HumForecast'] = forecast['yhat']
hum_fc = forecast[['ds', 'yhat']].rename(columns={"ds": "date", "yhat":
"HumForecast"}).set_index('date')
df_val = df_val.join(hum_fc, on='date', how='inner')
df_val.plot(y=["Humidity", "HumForecast"], figsize=(15,4))
```

Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x12de316d0>



In [80]:
```
# Model seasonality to make forecasts for Light
m = Prophet(daily_seasonality=False, weekly_seasonality=False, yearly_se
asonality=False)
m.add_seasonality(name='daily_weekday', period=1, fourier_order=3, condi
tion_name='weekday')
m.add_seasonality(name='daily_weekend', period=1, fourier_order=3, condi
tion_name='weekend')
X_df_train_forecast['y'] = df_train['Light']
m.fit(X_df_train_forecast)
# Make a future dataframe up to 2015-02-18 09:19:00
light_forecast = m.make_future_dataframe(periods=60*24*8, freq='T')
light_forecast['weekday'] = light_forecast['ds'].apply(is_weekday)
light_forecast['weekend'] = ~light_forecast['ds'].apply(is_weekday)
# Make predictions
forecast = m.predict(light_forecast)
X_df_train_forecast['LightForecast'] = forecast['yhat']
light_fc = forecast[['ds', 'yhat']].rename(columns={"ds": "date", "yhat"
: "LightForecast"}).set_index('date')
df_val = df_val.join(light_fc, on='date', how='inner')
# Plot Light vs. Forecasted Light
df_val.plot(y=["Light", "LightForecast"], figsize=(15,4))
```

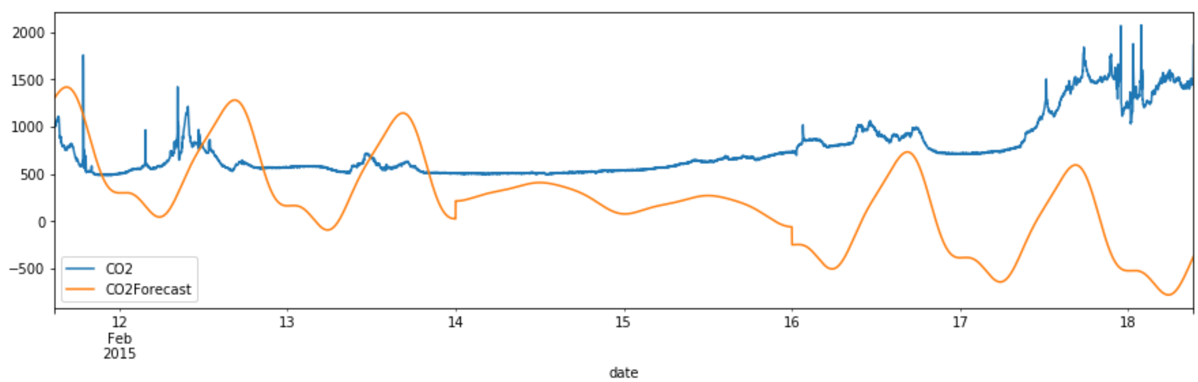
Out[80]: <matplotlib.axes._subplots.AxesSubplot at 0x103db8190>



In [81]:

```
# Model seasonality to make forecasts for CO2
m = Prophet(daily_seasonality=False, weekly_seasonality=False, yearly_se
asonality=False)
m.add_seasonality(name='daily_weekday', period=1, fourier_order=3, condi
tion_name='weekday')
m.add_seasonality(name='daily_weekend', period=1, fourier_order=3, condi
tion_name='weekend')
X_df_train_forecast['y'] = df_train['CO2']
m.fit(X_df_train_forecast)
# Make a future dataframe up to 2015-02-18 09:19:00
co2_forecast = m.make_future_dataframe(periods=60*24*8, freq='T')
co2_forecast['weekday'] = co2_forecast['ds'].apply(is_weekday)
co2_forecast['weekend'] = ~co2_forecast['ds'].apply(is_weekday)
# Make predictions
forecast = m.predict(co2_forecast)
X_df_train_forecast['CO2Forecast'] = forecast['yhat']
co2_fc = forecast[['ds', 'yhat']].rename(columns={"ds": "date", "yhat":
"CO2Forecast"}).set_index('date')
df_val = df_val.join(co2_fc, on='date', how='inner')
df_val.plot(y=["CO2", "CO2Forecast"], figsize=(15,4))
```

Out[81]: <matplotlib.axes._subplots.AxesSubplot at 0x138147810>



Predict Occupancy with forecasted parameters

In [82]:
```
# Separate X and y
X_df_val = df_val[['TempForecast', 'HumForecast', 'LightForecast', 'CO2F
orecast']]
y_df_val = df_val['Occupancy']

# Add columns for Weekday and WorkHours
X_df_val['Weekday'] = np.where((X_df_val.index.day == 14) | (X_df_val.in
dex.day == 15), 0, 1)
X_df_val['WorkHours'] = np.where((X_df_val.index.hour >= 8) & (X_df_val.
index.hour <= 6), 1, 0)

# Split into validation and test sets
X_df_test = X_df_val[df_val.index.day >= 15]
y_df_test = y_df_val[df_val.index.day >= 15]
X_df_val = X_df_val[df_val.index.day <= 14]
y_df_val = y_df_val[df_val.index.day <= 14]

# Normalize appropriate columns for building Classification Models
cols_to_norm = ['TempForecast', 'HumForecast', 'LightForecast', 'CO2Fore
cast']
X_df_val[cols_to_norm] = X_df_val[cols_to_norm].apply(lambda x: (x - x.m
in()) / (x.max() - x.min()))
X_df_test[cols_to_norm] = X_df_test[cols_to_norm].apply(lambda x: (x - x
.min()) / (x.max() - x.min()))

# Rename variables for easier implementation
X_train = X_df_train
y_train = y_df_train
X_test = X_df_val
y_test = y_df_val
```

In [83]:
```
# Implement Logistic Regression
logreg = LogisticRegression(solver='lbfgs', max_iter=100)
# Fit model: Predict y from x_test after training on x_train and y_train
y_pred = logreg.fit(X_train, y_train).predict(X_test)
# Report testing accuracy
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.791872
```

In [84]:
```
# Implement the Gaussian Naive Bayes algorithm for classification
gnb = GaussianNB()
# Fit model: Predict y from x_test after training on x_train and y_train
y_pred = gnb.fit(X_train, y_train).predict(X_test)
# Report testing accuracy
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.836412
```

In [85]:
```
# Implement KNN
neigh = KNeighborsClassifier(n_neighbors=3) #Best: n_neighbors=3
# Fit model: Predict y from x_test after training on x_train and y_train
y_pred = neigh.fit(X_train, y_train).predict(X_test)
# Report testing accuracy
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.853859
```

In [86]:
```
# Build classifier using SVM
SVM = svm.SVC(C=.01, kernel = 'rbf').fit(X_train, y_train) #Best: C=.01,
kernel = 'rbf'
y_pred = SVM.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.853243
```

In [87]:
```
# Build classifier using simple neural network
NN = MLPClassifier(solver = 'adam', learning_rate_init = 0.01, max_iter
= 150, hidden_layer_sizes=(5, 2), random_state=99).fit(X_train, y_train)
y_pred = NN.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.828818
```

In [88]:
```
# Build classifier using CART
dct = DecisionTreeClassifier(max_depth=4, random_state=99)
dct.fit(X_train, y_train)
y_pred = dct.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.821839
```

In [89]:
```
# Build classifier using Random Forest
rf = RandomForestClassifier(n_estimators=200, max_depth=1, random_state=
99)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

```
Testing accuracy out of a total 4872 points : 0.809524
```

SVM with C=0.01 and kernel='rbf' performed the best in the validation set. Test its true accuracy on the test set.

In [90]:
```
X_test = X_df_test
y_test = y_df_test
y_pred = SVM.predict(X_test)
print("Testing accuracy out of a total %d points : %f" % (X_test.shape[0
], accuracy_score(y_test, y_pred)))
```

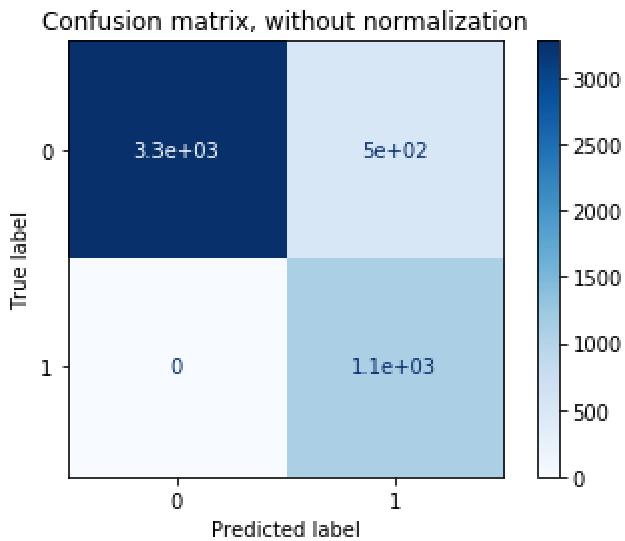
```
Testing accuracy out of a total 4880 points : 0.897336
```

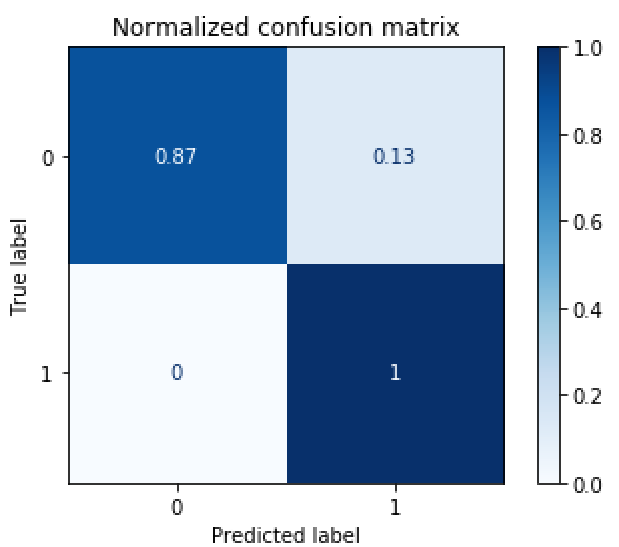
The accuracy on the test set was 0.897336. Not bad. The accuracy would be improved if the variables were forecasted better. Now plot the confusion matrix.

In [91]:
```python
# Plot confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(SVM, X_test, y_test,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)
```

```
Confusion matrix, without normalization
[[3282  501]
 [   0 1097]]
Normalized confusion matrix
[[0.86756542 0.13243458]
 [0.         1.        ]]
```





The final model chosen to predict Occupancy when the variables Temperature, Humidity, Light, and CO2 were forecasted from the training set was a Support Vector Model with margin C=0.01 and kernel='rbf'. This model performed the best in the validation set and resulted in a 89.7% accuracy in the test set. The confusion matrix shows that out of 4880 total test data points (minutes), 3282 points were correctly identified as unoccupied (true negatives), 1097 points were correctly identified as occupied (true positives), 501 points were incorrectly identified as occupied when they were unoccupied (false positives), and 0 points were incorrectly identified as unoccupied when they were occupied (false negatives). For the future, the model could be improved by tuning the trend component for forecasting the variables, and building and testing models on subsets of the parameters.

In [ ]: