Weather and Electric Load Forecasting
... (from scratch) with Python Data Science Tools

Nelson Correa, ***Ph.D.***
NLP, Data Science and Machine Learning
West Palm Beach, FL
@nelscorrea (https://twitter.com/nelscorrea) Jan. 10, 2019

PyData Miami 2019, Jan. 9-11, 2019

- https://pydata.org/miami2019/ (https://pydata.org/miami2019/) - @pydatamiami (https://twitter.com/pydatamiami)

Github Jupyter notebooks:

- https://github.com/u/nelscorrea/PyDataMiami2019/ (https://github.com/u/nelscorrea/PyDataMiami2019/)

Sources and acknowledgements, 1

NOAA/NCDC, National Oceanic and Atmospheric Administration

- https://www.ncdc.noaa.gov (https://www.ncdc.noaa.gov) - @NOAANCEIclimate (https://twitter.com/@NOAANCEIclimate)

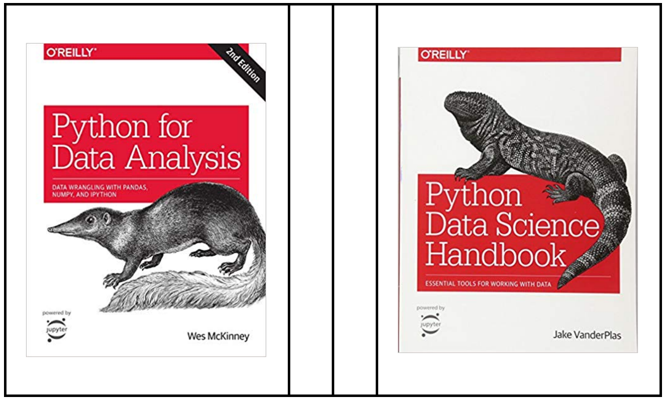
IEEE GEFCON2012 & Dr. Tao Hong, UNC Charlotte, NC

- http://www.gefcom.org (http://www.gefcom.org) - @DrHongTao (https://twitter.com/DrHongTao)

Sources and acknowledgements, 2

Wes McKinney, *Python for Data Analysis* (Pandas) - @wesmckinn (https://twitter.com/wesmckinn)

Jake van der Plas, *Python Data Science Handbook* (Scikit-Learn) - @jakevdp (https://twitter.com/jakevdp)



Outline

Preliminaries (~ 5 min)

- Python data science tools
- Time series and data forecasting

Weather forecasting (~ 10 min)

- Datasets (NOAA)
- Description & visualization
- Models, seasonality (yearly), model evaluation

Electric load forecasting (~ 7 min)

- Datasets (GEFCON2012 Load)
- Description & visualization
- Models, seasonality (yearly, hourly, other), model evaluation

Conclusion (~ 3 min)

- Advanced models and further work
- References, Github Jupyter notebooks

Preliminaries

Python data science tools

- Python, NumPy
    - numpy.ndarray; datetime
- Pandas
    - pandas.DataFrame, pivot_table, melt
    - time series, multidimensional indices
- Scikit-Learn
    - sklearn.linear_model.LinearRegression
    - sklearn.preprocessing.PolynomialFeatures
    - sklearn.pipeline.make_pipeline
- Matplotlib

Time series and data forecasting

Time series

A *time series* is a series of *values*, each with a *time stamp*. We may think of *time* as a single *input feature*, which defines an ordering of the values.

> y_t *is a scalar or vector variable, for independent time variable* t

Formally, in a *time series*, time t is the main or only input feature (independent variable), and there are one or more time-dependent variables $y_0, y_1, \ldots, y_t$ defining a univariate or multivariate time series. Time may be in any unit, year, month, day, hour, ..., datetime().

Time series may exhibit trends, seasonality and cycles, which are functions of time.

> *trends, seasonality and cycles*

Lastly, time-series may exhibit rare (gray swan) and extremely rare (black swan) events (cf. Nicolas Taleb, The Black Swan: The Impact of the Highly Improbable, 2010).

Time series forecasting

In *forecasting*, we want to make a *prediction* $\hat{y}_t = f(t)$ of the actual value of y_t at time t, with a *confidence interval* for the predicted value.

$$\hat{y_t} = f(t)$$

Feature engineering with time series analysis is usually limited to time-determined features that capture trends, seasonality and cycles of the time series:

- trends: increase, decrease of values y_t the time series with time
- seasonality: cycles with a fixed period (e.g., yearly or daily variation of values)
- cycles: recurring patterns without fixed period (e.g., economic cycles; warming or cooling periods, etc.)

Time series forecasting methods

The independent variable of a time series is time. It is often to include lagged values of the output variable or variables, leading to different models:

- Vector autoregressive (VAR)
- Exponential smoothing models
- Autoregressive Integrated Moving Average (ARIMA)
- Seasonal AutoRegressive Integrated Moving Average (SARIMA)
- Recurrent and autoregressive neural networks (RNN, NNAR)

In this talk we present a baseline model with *linear regression* and *seasonality* features added.

PyData Part I - Weather forecasting

- Datasets (NOAA)
- Visualization & analysis
- Features and models, model evaluation

NCDC Weather Data

GHCN-Daily: Global Historical Climate Network

- NOAA: 9,887 weather stations

Climate Data Online: https://www.ncdc.noaa.gov/cdo-web/datasets#GHCND (https://www.ncdc.noaa.gov/cdo-web/datasets#GHCND)

In [2]:

```
# Imports
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
```

In [3]:

```
# Read NOAA NCDC weather data: predownload from https://www.ncdc.noaa.gov/cdo-web
weather_SYR = pd.read_csv('NOAA_data/USSYR-ZIP13210-1922-2017-1526037.csv',
                          index_col='DATE', parse_dates=True)
weather = pd.read_csv('NOAA_data/USW00012839-FL-Miami-1927-2018-1535674.csv',
                          index_col='DATE', parse_dates=True)
print("SYR weather shape:", weather_SYR.shape,
                          " -- MIA weather shape:", weather.shape)
```

```
SYR weather shape: (11767, 16)  -- MIA weather shape: (54265, 87)

/Users/nelson/Dev/anaconda3/lib/python3.6/site-packages/IPython/core/interacti
veshell.py:2698: DtypeWarning: Columns (7,9,11,13,15,17,19,23,29,35,37,39,41,4
3,45,47,49,51,53,55,57,59,61,63,65,67,69,71,73,75,77,79,81,83,85,87) have mixe
d types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

```
In [4]: weather_SYR.head(3)
```

Out[4]:

	STATION	NAME	DAPR	MDPR	MDSF	PRCP	SNOW	S
DATE								
1922-01-01	USC00308380	SYRACUSE, NY US	NaN	NaN	NaN	0.42	0.0	5
1922-01-02	USC00308380	SYRACUSE, NY US	NaN	NaN	NaN	0.00	0.0	1
1922-01-03	USC00308380	SYRACUSE, NY US	NaN	NaN	NaN	0.23	0.0	3

In [5]:

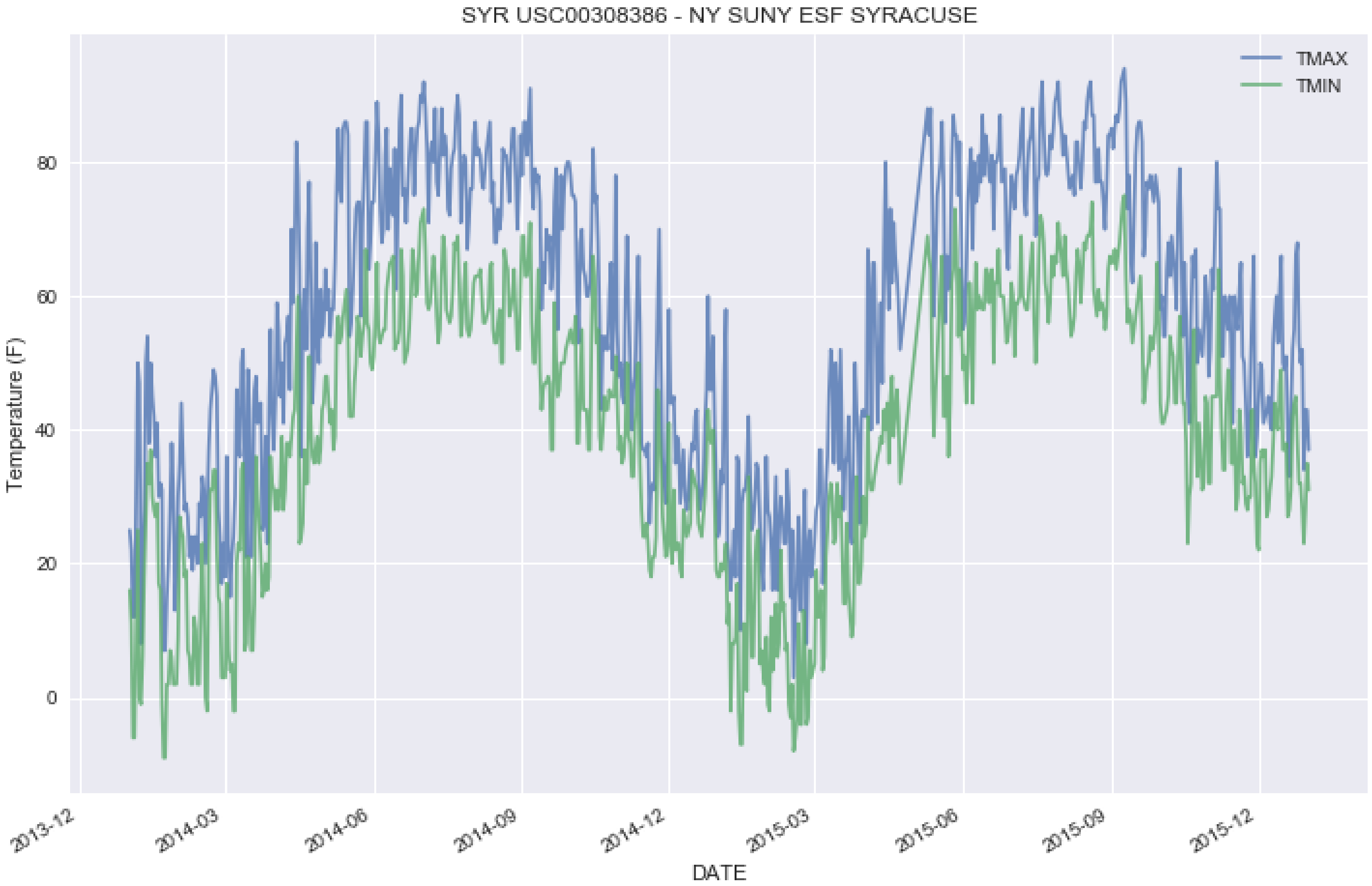
```python
# Select subset of MIA features
weather_features = ['STATION', 'NAME', 'LATITUDE', 'LONGITUDE', 'ELEVATION',
                    'TMAX', 'TMIN', 'PRCP', 'SNOW', 'TAVG', 'AWND', 'WSF1', 'WSF5', 'W
DF1', 'WDF5']
weather[weather_features].head(3)
```

Out[5]:

	STATION	NAME	LATITUDE	LONGITUDE	ELEVATIC
DATE					
1948-01-01	USW00012839	MIAMI INTERNATIONAL AIRPORT, FL US	25.7881	-80.3169	8.8
1948-01-02	USW00012839	MIAMI INTERNATIONAL AIRPORT, FL US	25.7881	-80.3169	8.8
1948-01-03	USW00012839	MIAMI INTERNATIONAL AIRPORT, FL US	25.7881	-80.3169	8.8

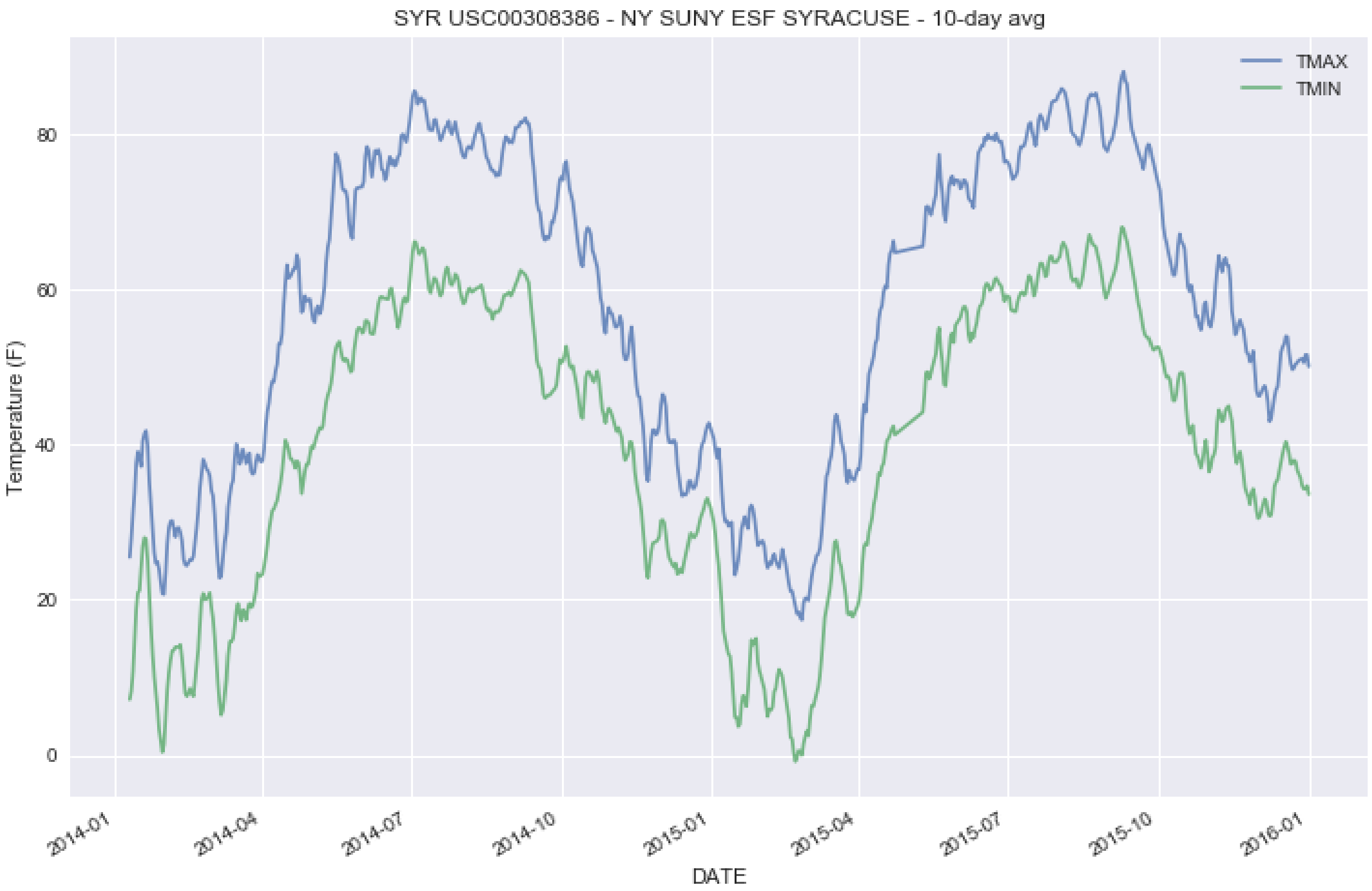
In [7]:

```
# USC00308386 SYR, 2 year plot 2014-2016; yearly seasonality
weather_SYR[weather_SYR['STATION']=='USC00308386']['2014-01-01':'2016-01-01'][['TM
AX', 'TMIN']].plot(alpha=0.8,
        title='SYR USC00308386 - NY SUNY ESF SYRACUSE', figsize=(12,8));
plt.ylabel('Temperature (F)');
```

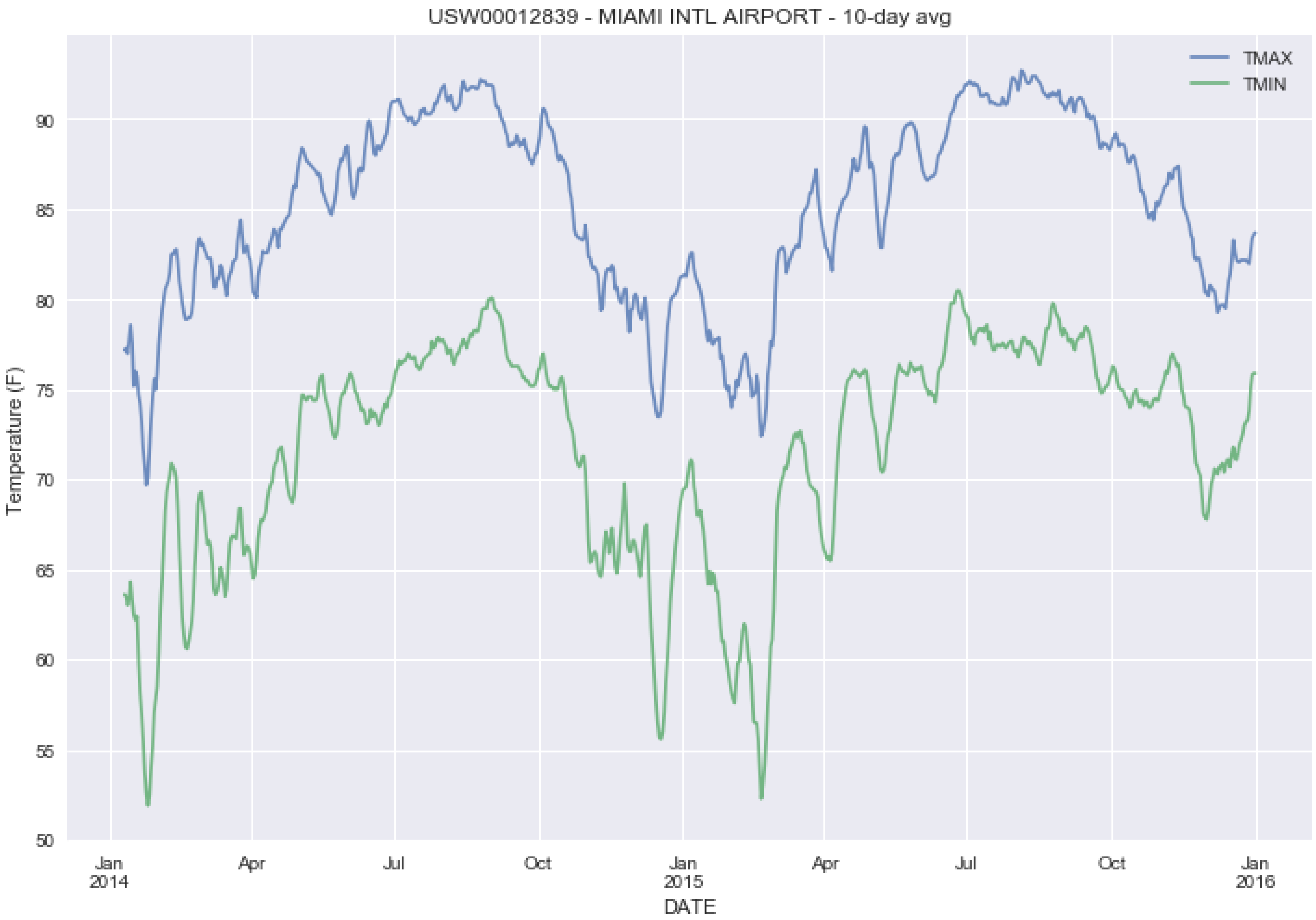


In [8]:

```
# USC00308386 SYR, 2 year plot 2014-2016; yearly seasonality
# SYR 10-day Moving Average (MA) TMAX, TMIN - pandas.DataFrame.rolling() window
weather_SYR[weather_SYR['STATION']=='USC00308386']['2014-01-01':'2016-01-01'][['TM
AX', 'TMIN']].rolling(10).mean().plot(alpha=0.8,
                        title='SYR USC00308386 - NY SUNY ESF SYRACUSE - 10-day av
g', figsize=(12,8));
plt.ylabel('Temperature (F)');
```



In [9]:
```
# MIA, 2 year plot 2014-01-01:2016-01-01; USW00012839
# MIA 10-day Moving Average (MA) TMAX, TMIN - pandas.DataFrame.rolling() window
weather[weather['STATION']=='USW00012839']['2014-01-01':'2016-01-01'][['TMAX','TMI
N']].rolling(10
    ).mean().plot(alpha=0.8, title='USW00012839 - MIAMI INTL AIRPORT - 10-day avg'
, figsize=(12,8));
plt.ylabel('Temperature (F)');
```



Temperature differences: Season and Location

The TMAX-TMIN temperature difference is about 20F degree for SYR, and about 15F degrees for MIA.

Season vs. Location (SYR, MIA)

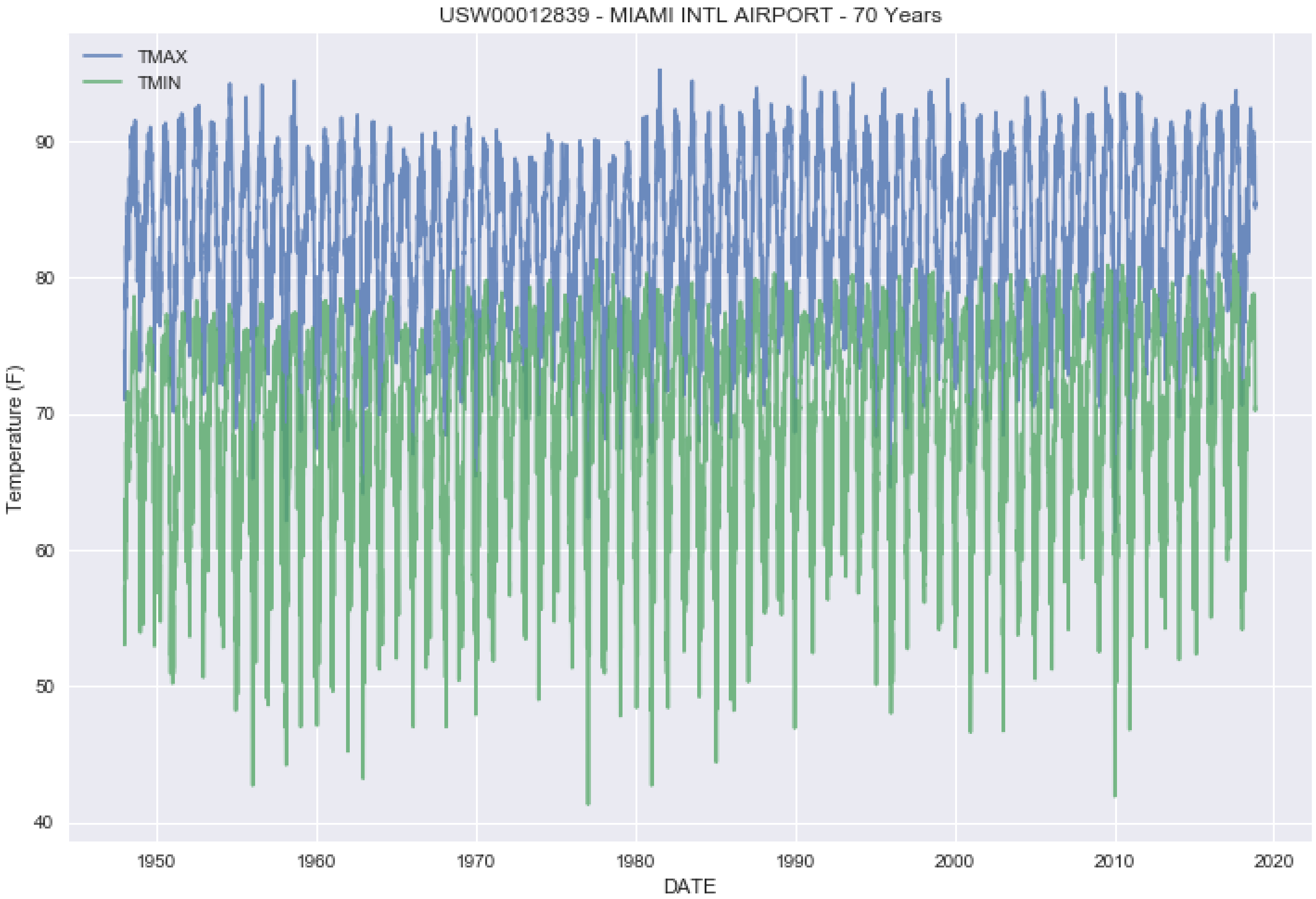
- Winter SYR 5-25F, MIA 60-75F
- Summer SYR 60-80F, MIA 78-93F

Full dataset date-ranges (TMAX, TMIN)

- MIA USW00012839 - MIAMI INTERNATIONAL AIRPORT, FL US
    - (date range 1948-2017, 70 years)
- MIA USW00092811 - MIAMI BEACH, FL US
    - (date range 1925-2017, 92 years; gaps 1931-1940; 2001-2003)

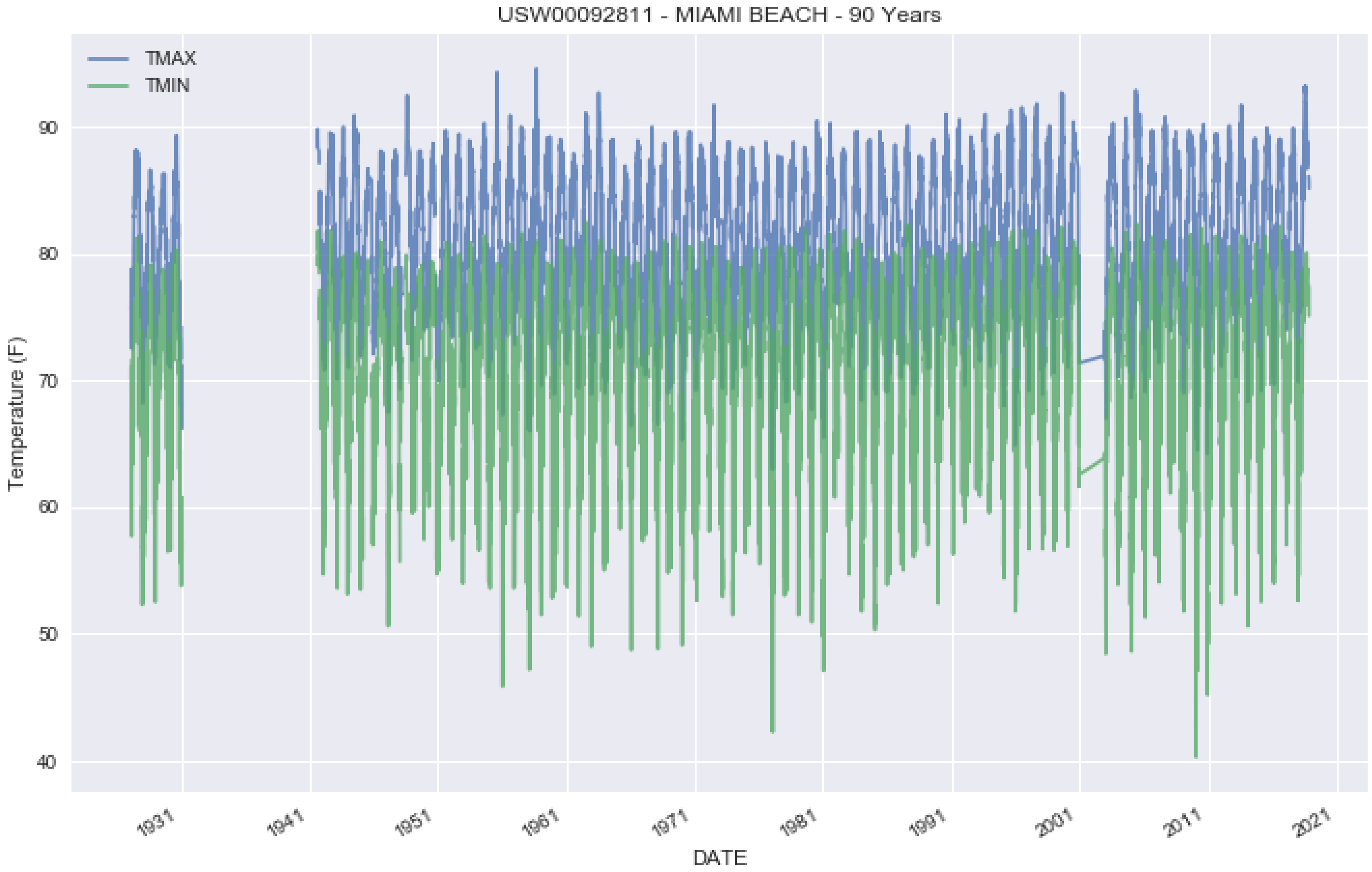
In [10]:

```
# MIA USW00012839 - MIAMI INTL AIRPORT, 1948-2017, Temperature
weather[weather['STATION']=='USW00012839'][['TMAX','TMIN']].rolling(10).mean(
    ).plot(alpha=0.8, title='USW00012839 - MIAMI INTL AIRPORT - 70 Years', figsize
=(12,8));
plt.ylabel('Temperature (F)');
```



In [11]:

```
# MIA USW00092811 - MIAMI BEACH, 1948-2017, Temperature
weather[weather['STATION']=='USW00092811'][['TMAX','TMIN']].rolling(10).mean(
    ).plot(alpha=0.8, title='USW00092811 - MIAMI BEACH - 90 Years', figsize=(12,8
));
plt.ylabel('Temperature (F)');
```



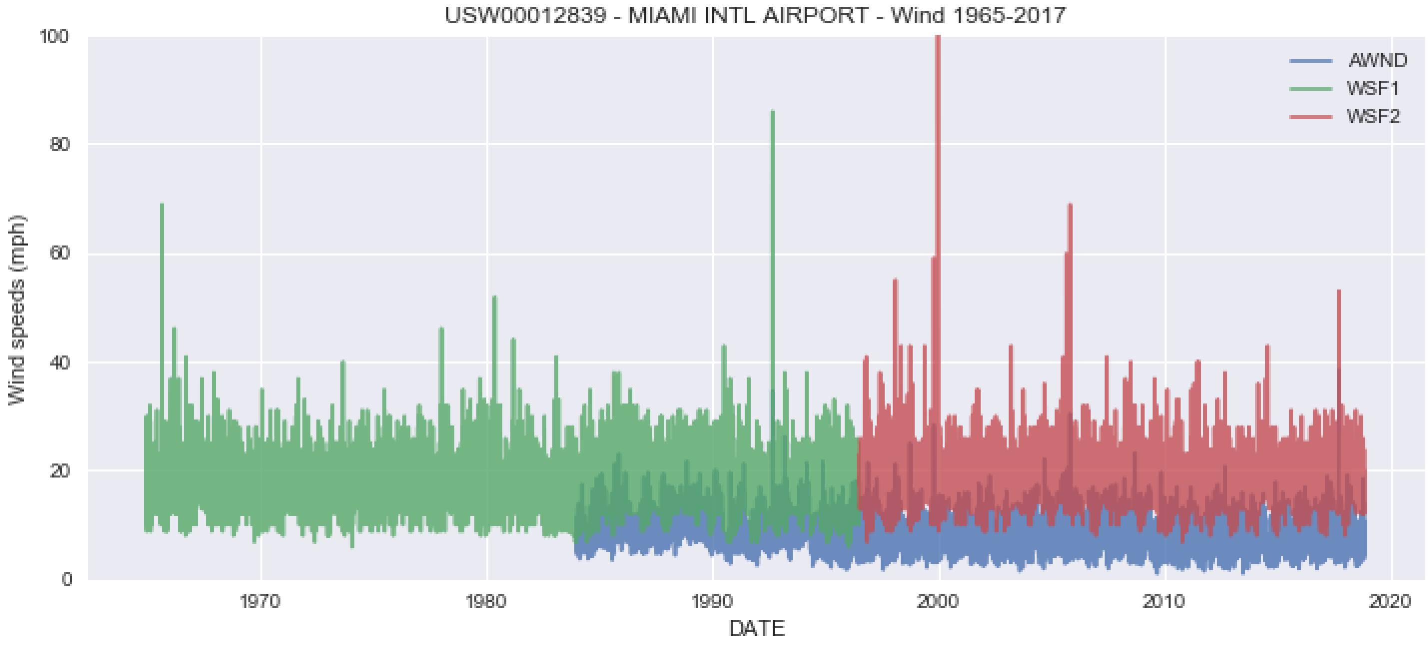
Major Florida hurricanes 1965 - 2017

Wind Speed Data - AWND, WSF1, WSF2, WSF5

- MIA USW00012839 - MIAMI INTL AIRPORT, 1948-2017
- Major Florida hurricanes
    - 1965, 1975, 1980, 1992 (Andrew), 1999, 2005, 2017 (Irma)
- WSF2 data outlier in 1999 (780 mph)

In [38]:
```
# MIA USW00012839, 1948-2017, Wind - different date ranges for AWND, WSF1, WSF2
weather[weather['STATION']=='USW00012839'][['AWND','WSF1','WSF2']].plot(alpha=0.8,

    title='USW00012839 - MIAMI INTL AIRPORT - Wind 1965-2017', figsize=(12,5));
plt.ylim((0,100))
plt.ylabel('Wind speeds (mph)');
```



In [14]:

```
# MIA USW00012839 - MIAMI INTL AIRPORT, weather feature description
weather[weather['STATION']=='USW00012839'][weather_features].describe()
```

Out[14]:

	LATITUDE	LONGITUDE	ELEVATION	TMAX	
count	2.587700e+04	2.587700e+04	2.587700e+04	25876.000000	25876.
mean	2.578810e+01	-8.031690e+01	8.800000e+00	83.535284	69.482
std	4.636381e-12	2.035034e-11	3.758844e-12	6.515358	8.4181
min	2.578810e+01	-8.031690e+01	8.800000e+00	45.000000	30.000
25%	2.578810e+01	-8.031690e+01	8.800000e+00	80.000000	65.000
50%	2.578810e+01	-8.031690e+01	8.800000e+00	84.000000	72.000
75%	2.578810e+01	-8.031690e+01	8.800000e+00	89.000000	75.000
max	2.578810e+01	-8.031690e+01	8.800000e+00	98.000000	84.000

Weather Forecasting - Temperature

Climate is the statistics of weather over long periods of time.

Reference

- https://en.wikipedia.org/wiki/Climate (https://en.wikipedia.org/wiki/Climate)
- https://en.wikipedia.org/wiki/Weather (https://en.wikipedia.org/wiki/Weather)

Input features: Date (DATE) ; target feature: temperature (TMAX, TMIN)

- Temperature prediction as a function of time (DATE) and previous temperature only
- Seasonality variable `season` introduced, as np.sin(date), with period 365.25, phase 0-90 days
- Train on historical data (e.g., past 10, 30, 50, 70 years)

Linear Prediction Model - Part I

- Training data: 1948-01-01 to 2010-12-31 (62 years)
- Model input feature: data index 'DATE', with no seasonality
- Time index is datetime(); 1 nanosecond time resolution

In [15]:

```
# imports and models
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline

model_mia_linear = LinearRegression(fit_intercept=True)
model_mia_polynomial = make_pipeline(PolynomialFeatures(7), LinearRegression())
```

In [16]:

```
# Define training data and outputs: train dates 1948-01-01 to 2010-12-31 (62 year
s)
train_end_date = '2010-12-31'
train_dates = weather[weather['STATION']=='USW00012839'][:train_end_date].index

X = train_dates[:, np.newaxis].astype('float64') * 1e-17
y = weather[weather['STATION']=='USW00012839'][:train_end_date][['TMAX','TMIN']]
print("X.shape:", X.shape, "y.shape:", y.shape)

# Train model
model_mia_linear.fit(X, y)
```

```
X.shape: (23011, 1) y.shape: (23011, 2)

/Users/nelson/Dev/anaconda3/lib/python3.6/site-packages/scipy/linalg/basic.py:
884: RuntimeWarning: internal gelsd driver lwork query error, required iwork d
imension not returned. This is likely the result of LAPACK bug 0038, fixed in
LAPACK 3.2.2 (released July 21, 2010). Falling back to 'gelss' driver.
  warnings.warn(mesg, RuntimeWarning)
```

Out[16]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [17]:

```
# Model score and coefficients: X as training date_range()
start_date = '1948-01-01'
end_date = '2010-12-31'
score_dates = pd.date_range(start_date, end_date)[:, np.newaxis]
score_dates_float64 = score_dates.astype('float64') * 1e-17
print("model_mia_linear.coef_:", model_mia_linear.coef_)
print("model_mia_linear.intercept_:", model_mia_linear.intercept_)
print("model_mia_linear.score:", model_mia_linear.score(score_dates_float64, y))
```

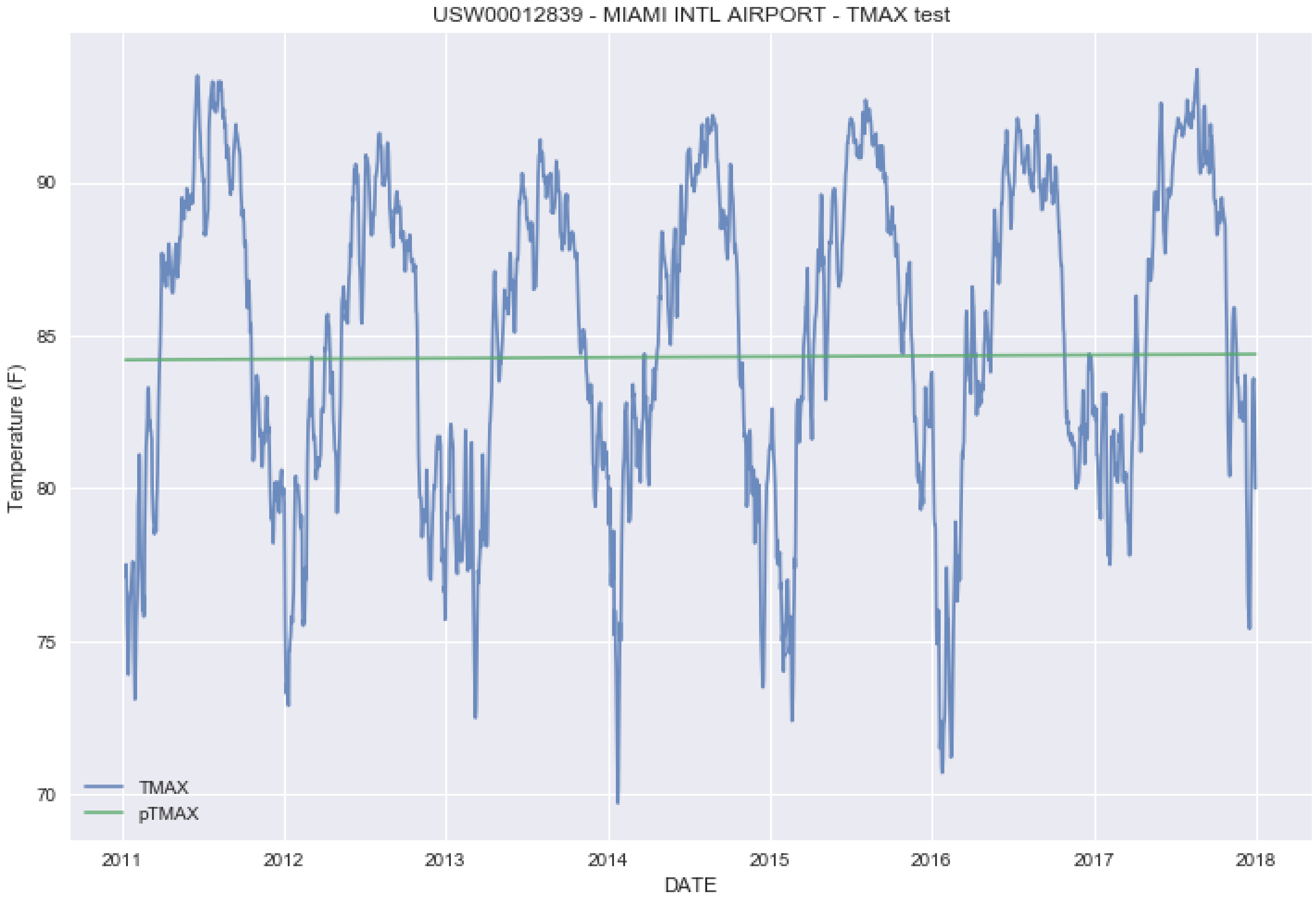
```
model_mia_linear.coef_: [[0.08521131]
 [0.14720108]]
model_mia_linear.intercept_: [83.10021582 68.79008727]
model_mia_linear.score: 0.008241949448928858
```

Model slope on 'date'

- slope: +0.14720108
- Pandas DatetimeIndex datetime() is converted to float64 - 1 ns resolution

In [24]:

```
# Plot USW00012839, 1948-2017, Temperature on Test data - Smooth 30-day window
weather_test[['TMAX','pTMAX']].rolling(10).mean().plot(alpha=0.8,
        figsize=(12,8), title='USW00012839 - MIAMI INTL AIRPORT - TMAX test');
plt.ylabel('Temperature (F)');
```



In [26]:

```
slope = model_mia_linear.coef_[1][0]
year_1 = slope * (365.25*24*60*60*10**9) * 1e-17
year_70 = slope * (365.25*24*60*60*10**9) * 1e-17 * 70
print("70-year temperature increase (F deg., MIA):", year_70)
print("Model slope (MIA):", slope, "(", year_1, "F degrees/ year)")
```

```
70-year temperature increase (F deg., MIA): 3.251718866134655
Model slope (MIA): 0.14720107568087085 ( 0.0464531266590665 F degrees/ year)
```

MIAMI Warming

MIA temperature increase on input variable 'date'

- model slope: +0.14720108 (0.04645 F deg/ year)

MIA 70 year temperature increase (1948-2017): +3.25 F

Linear Prediction Model - Part II, Yearly seasonality

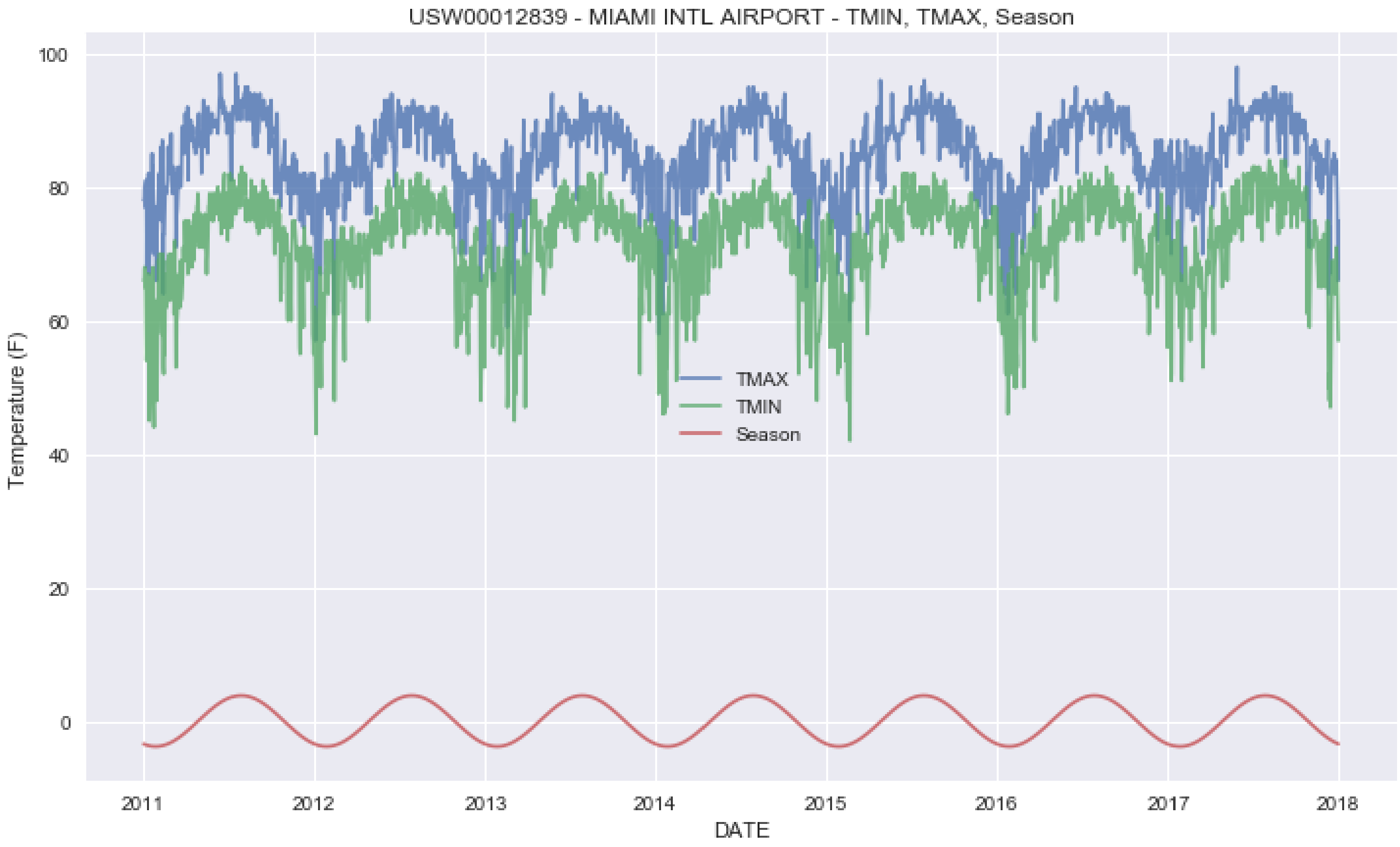
- Training data: 1948-01-01 to 2010-12-31 (62 years)
- Time index is datetime(); 1 nanosecond time resolution
- Seasonality feature added, one year period, with phase delay
- Model input features: data index 'DATE', 'SEASON'

In [27]:
```
# Yearly season variation, with phase delay
def season_year(date):
    """Compute season signal for input date"""
    phase_lag = -36   # lag in days
    days = (date - pd.datetime(1900, 12, 21)).days
    m = np.cos((days + phase_lag) * 2 * np.pi / 365.25)
    return 0.0 + 12. * np.degrees(-m) / 180.
```

In [39]:

```
weather_season = weather_test
weather_season['Season'] = list(map(season_year, weather_season.index))

weather_season[['TMAX','TMIN','Season']].plot(alpha=0.8,
    figsize=(12,7), title='USW00012839 - MIAMI INTL AIRPORT - TMIN, TMAX, Season')
plt.ylabel('Temperature (F)');
```



In [29]:

```
# Model score and coefficients: X as training date_range()
start_date = '1948-01-01'
end_date = '2010-12-31'
score_dates = pd.date_range(start_date, end_date)

X_train = pd.DataFrame(index=score_dates)
X_train['date'] = score_dates[:, np.newaxis].astype('float64') * 1e-17
X_train['season'] = list(map(season_year, score_dates))

y_train = weather[weather['STATION']=='USW00012839'][start_date:end_date][['TMAX',
'TMIN']]
X_train.head(3)
```

Out[29]:

	date	season
1948-01-01	-6.943104	-3.451062
1948-01-02	-6.942240	-3.478714
1948-01-03	-6.941376	-3.505336

In [30]:
```python
# Define and train season model
model_mia_season_linear = LinearRegression(fit_intercept=True)
model_mia_season_linear.fit(X_train, y_train)
```

Out[30]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [31]:
```python
# Model score and coefficients: X, y data
print("model coef_:", model_mia_season_linear.coef_)
print("model intercept_:", model_mia_season_linear.intercept_)
print("model score:", model_mia_season_linear.score(X_train, y_train))
```

```
model coef_: [[0.08049687 1.86322531]
 [0.14143504 2.27883374]]
model intercept_: [83.11441566 68.80745451]
model score: 0.5549477478135421
```

Model slope on 'date': +0.14143504

- vs. model slope +0.14720108 of previous model, with no seasonality

---

Test linear model with seasonality

Test/Training data

- Training data: 1948-01-01 to 2010-12-31 (62 years)
- Test data: 2011-01-01 to 2017-12-31 (7 years)

In [32]:
```
# Model score and coefficients: X as Test date_range()
start_date = '2011-01-01'
end_date = '2017-12-31'
score_dates = pd.date_range(start_date, end_date)

X_test = pd.DataFrame(index=score_dates)
X_test['date'] = score_dates[:, np.newaxis].astype('float64') * 2e-17
X_test['season'] = list(map(season_year, score_dates))

y_test = weather[weather['STATION']=='USW00012839'][start_date:end_date][['TMAX',
'TMIN']]
```

In [33]:

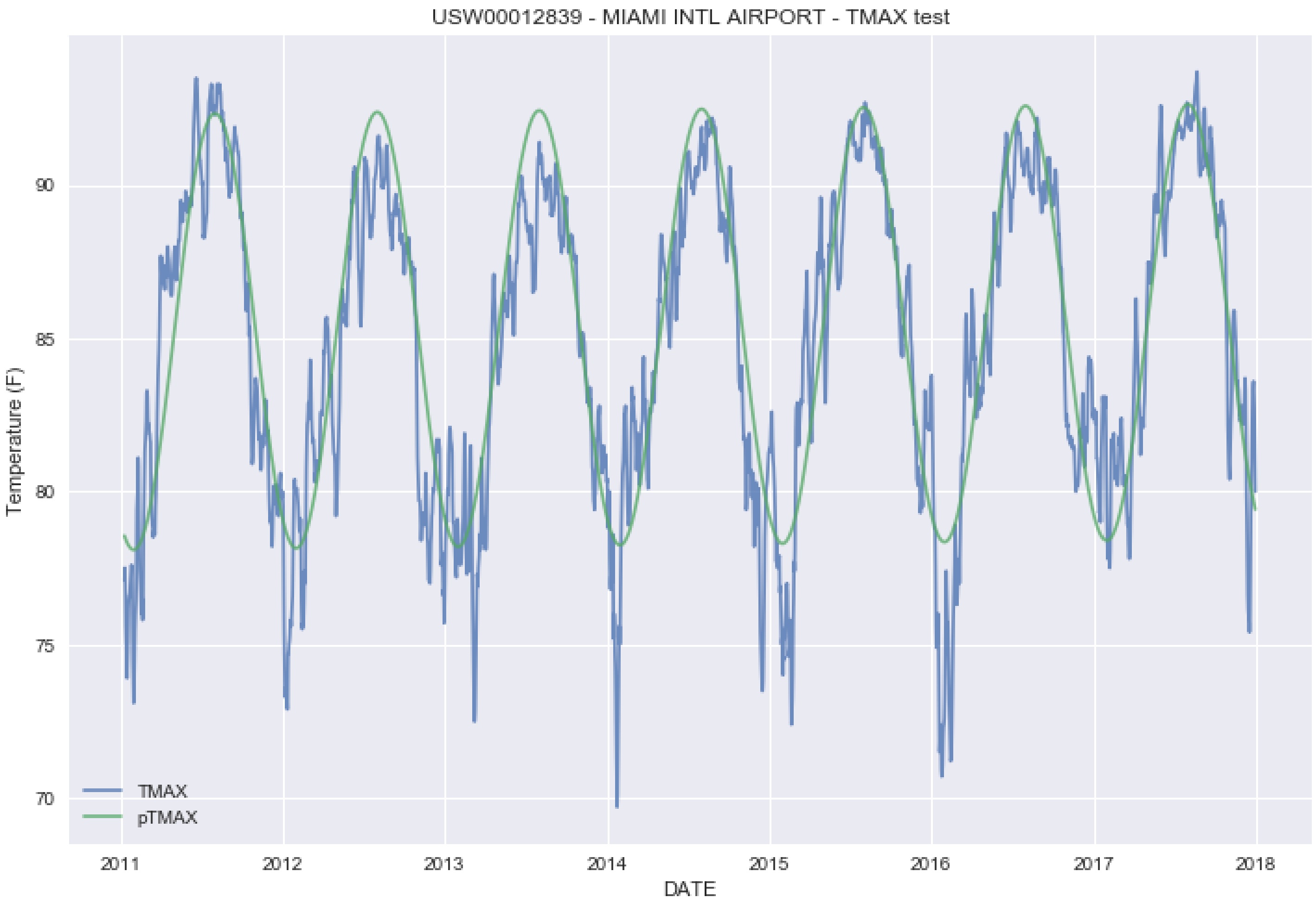
```
# Predict on test data
y_test_predict = y_test
y_test_predict['pTMAX'] = model_mia_season_linear.predict(X_test)[:,0]
y_test_predict['pTMIN'] = model_mia_season_linear.predict(X_test)[:,1]
y_test_predict.head(3)
```

Out[33]:

	TMAX	TMIN	pTMAX	pTMIN
DATE				
2011-01-01	78.0	66.0	78.754252	64.586972
2011-01-02	78.0	66.0	78.703348	64.524787
2011-01-03	80.0	68.0	78.654365	64.464953

In [34]:

```
# MIA USW00012839, 1948-2017, Temperature on test data - 10-day moving average
y_test_predict[['TMAX','pTMAX']].rolling(10).mean().plot(alpha=0.8,
        figsize=(12,8), title='USW00012839 - MIAMI INTL AIRPORT - TMAX test')
plt.ylabel('Temperature (F)');
```



In [36]:

```
# Prediction error TMAX, TMIN, on Test data - Smooth 10-day rolling window
_, rmse_tmax = prediction_error(y_test_predict['TMAX'].rolling(10).mean(), y_test_
predict['pTMAX'].rolling(10).mean())
_, rmse_tmin = prediction_error(y_test_predict['TMIN'].rolling(10).mean(), y_test_
predict['pTMIN'].rolling(10).mean())
print("rmse_tmax (F):", rmse_tmax, ", rmse_tmin (F):", rmse_tmin)
```

```
rmse_tmax (F): 2.257642393411309 , rmse_tmin (F): 3.491547236253771
```

In [37]:

```
slope = model_mia_season_linear.coef_[1][0]
year_1 = slope * (365.25*24*60*60*10**9) * 1e-17
year_70 = slope * (365.25*24*60*60*10**9) * 1e-17 * 70
print("70-year temperature increase (F deg., MIA):", year_70)
print("Model slope (MIA):", slope, "(", year_1, "F deg/ year)")
```

```
70-year temperature increase (F deg., MIA): 3.1243452370680074
Model slope (MIA): 0.14143503747650588 ( 0.04463350338668582 F deg/ year)
```

MIAMI Temperature increase on 'date' (model with seasonality)

- model slope: +0.14143504
- vs. previous model 0.14720108

MIA 70 year temperature increase: +3.12 F

- vs. previous linear model, no seasonality +3.25 F

Summary: Weather Prediction

We have presented a baseline linear weather prediction model with yearly seasonality.

Error difference, linear only vs. seasonality

Linear only model

- model_mia_linear.score: 0.008241949448928858
- rmse_tmax (F): 6.54348806133789 , rmse_tmin (F): 8.476266013127782

Model with seasonality

- model_mia_season_linear.score: 0.5549477478135421
- rmse_tmax (F): 2.257642393411309 , rmse_tmin (F): 3.491547236253771

Load Forecast continued (next notebook) ...

- PyDataMiami2019_ElectricLoadForecasting.ipynb (http://localhost:8888/notebooks/PyDataMiami2019/PyDataMiami2019_ElectricLoadF