Jupyter_Notebook_Wind_Energy_Planning_Analysis_for_Locations_in

August 31, 2021

0.1 Planning and Analysis for Wind in Libya

0.1.1 Comparison of Capacity Factor and Variability of Wind Enery for Coast, Southern, Western and Eastern Libyan Cities

Data have already been downloaded and stored

```
In [1]: import os  # for getting environment variables
        import pathlib  # for finding the example dataset
        import pvlib
        import pandas as pd  # for data wrangling
        import matplotlib.pyplot as plt  # for visualization

        from pvlib.iotools import get_pvgis_tmy
        from pvlib import clearsky, solarposition, irradiance
        import numpy as np
```

0.1.2 Reading a TMY dataset

```
In [2]: import os
        import pathlib  # for finding the example dataset
        os.getcwd()
        os.chdir("C:/Users/Mhdella/Desktop/TMY Libyan Cities")
```

```
In [3]: cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata','S
                 'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

        df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan'
               'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Gad
               'df_Kufra','df_Jaghbub', 'df_Berlin']

        for i in np.arange(len(cities)):

            data = pd.read_csv(cities[i]+'_get_pvgis_tmy.csv',index_col='time(UTC)')
            vars()[df_dt[i]] = data
            vars()[df_dt[i]].index=pd.to_datetime(vars()[df_dt[i]].index, format='%Y-%m-%d')
```

```
    vars()[df_dt[i]]['Year']=vars()[df_dt[i]].index.year
    vars()[df_dt[i]]['Month']=vars()[df_dt[i]].index.month
    vars()[df_dt[i]]['Day']=vars()[df_dt[i]].index.day
    vars()[df_dt[i]]['Hour']=vars()[df_dt[i]].index.hour
    vars()[df_dt[i]]['Year'] = 2021
    vars()[df_dt[i]].index=pd.to_datetime(df_Trip[['Year', 'Month', 'Day', 'Hour']])

# df_Berlin
```

0.1.3 Wind speed at 10 meter (WS10m) for some Libyan CIties

WS10m: 10-m total wind speed (m/s)

```
In [4]: cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata','S
        'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

        df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan'
               'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
               'df_Kufra','df_Jaghbub', 'df_Berlin']


        df_tem=pd.DataFrame({'Tripoli':df_Trip['WS10m'].resample('M').mean()})
        df_tem
        for i in np.arange(len(cities)):
            df_tem[cities[i]]=vars()[df_dt[i]]['WS10m'].resample('M').mean()

        Wind10m_comparison=df_tem

        # Wind10m_comparison.describe()
        Wind10m_comparison
```

Out[4]:

	Tripoli	Zuwara	Tarhunah	Msallata	Ghanima	Gharyan	\
2021-01-31	6.394113	3.921089	5.527608	5.325591	4.859341	4.193978	
2021-02-28	6.317589	5.745610	6.136042	5.213274	4.760432	3.987083	
2021-03-31	4.051640	4.336747	4.823172	5.626317	5.627164	4.389933	
2021-04-30	4.400028	4.227639	5.032042	5.312806	5.649750	5.206111	
2021-05-31	3.546062	3.509637	5.294825	4.723374	4.729906	4.543293	
2021-06-30	4.923917	5.390097	4.822375	4.201042	3.909625	3.898389	
2021-07-31	4.810202	3.655282	4.421815	3.740202	3.554005	3.525417	
2021-08-31	3.637594	4.040027	3.911075	3.359610	3.198495	3.862513	
2021-09-30	4.427556	3.588278	4.452806	3.344556	3.501819	4.281306	
2021-10-31	3.890954	3.731263	3.794583	4.274207	3.959368	3.800887	
2021-11-30	4.442611	3.477889	4.642319	4.404361	4.301431	3.659153	
2021-12-31	4.176116	3.768656	3.718387	5.010067	4.653642	3.474933	

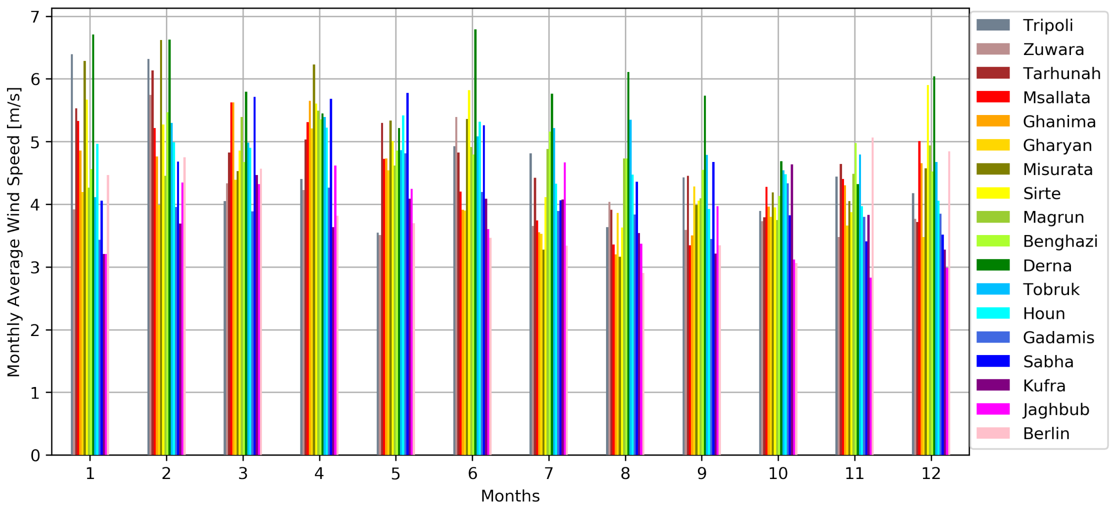
	Misurata	Sirte	Magrun	Benghazi	Derna	Tobruk	\
2021-01-31	6.287204	5.667231	4.263737	4.561129	6.709933	4.114530	
2021-02-28	6.621682	5.272128	4.450997	5.466920	6.627321	5.297634	

2021-03-31	4.527137	4.859247	5.391465	4.673710	5.793602	4.983925
2021-04-30	6.228361	5.606972	5.494014	5.350847	5.448764	5.392069
2021-05-31	5.335954	5.007513	4.620161	4.853925	5.217312	4.864624
2021-06-30	5.360847	5.822528	4.914861	4.790958	6.792208	5.083278
2021-07-31	3.278159	4.112433	4.878602	5.161694	5.760726	5.215296
2021-08-31	3.159798	3.628414	4.731358	4.727876	6.109341	5.350296
2021-09-30	3.988472	4.054931	4.093750	4.547625	5.729458	4.786306
2021-10-31	4.188723	3.947110	3.745901	4.131935	4.683253	4.539570
2021-11-30	4.047472	3.874056	4.486778	4.973750	4.323903	4.793139
2021-12-31	4.575202	5.902581	4.939167	4.521922	6.037876	4.672110

	Houn	Gadamis	Sabha	Kufra	Jaghbub	Berlin
2021-01-31	4.963978	3.436196	4.054597	3.205618	3.205336	4.462917
2021-02-28	4.988631	3.956012	4.683036	3.689836	4.343750	4.750818
2021-03-31	4.901237	3.886949	5.715027	4.465336	4.321828	4.567110
2021-04-30	5.222653	4.264514	5.682056	3.634667	4.617347	3.814361
2021-05-31	5.417298	4.813118	5.777903	4.088078	4.243642	3.698911
2021-06-30	5.319028	4.193597	5.257264	4.089528	3.602681	3.465681
2021-07-31	4.325874	3.893199	4.064704	4.073535	4.665497	3.341317
2021-08-31	4.470927	3.835161	4.361680	3.537876	3.373253	2.901949
2021-09-30	3.924097	3.443347	4.674139	3.215569	3.965444	3.343597
2021-10-31	4.475860	4.334261	3.826505	4.635578	3.118871	3.062392
2021-11-30	3.968806	3.798972	3.406056	3.832472	2.827222	5.062264
2021-12-31	4.057702	3.848804	3.512728	3.276129	2.987567	4.846237

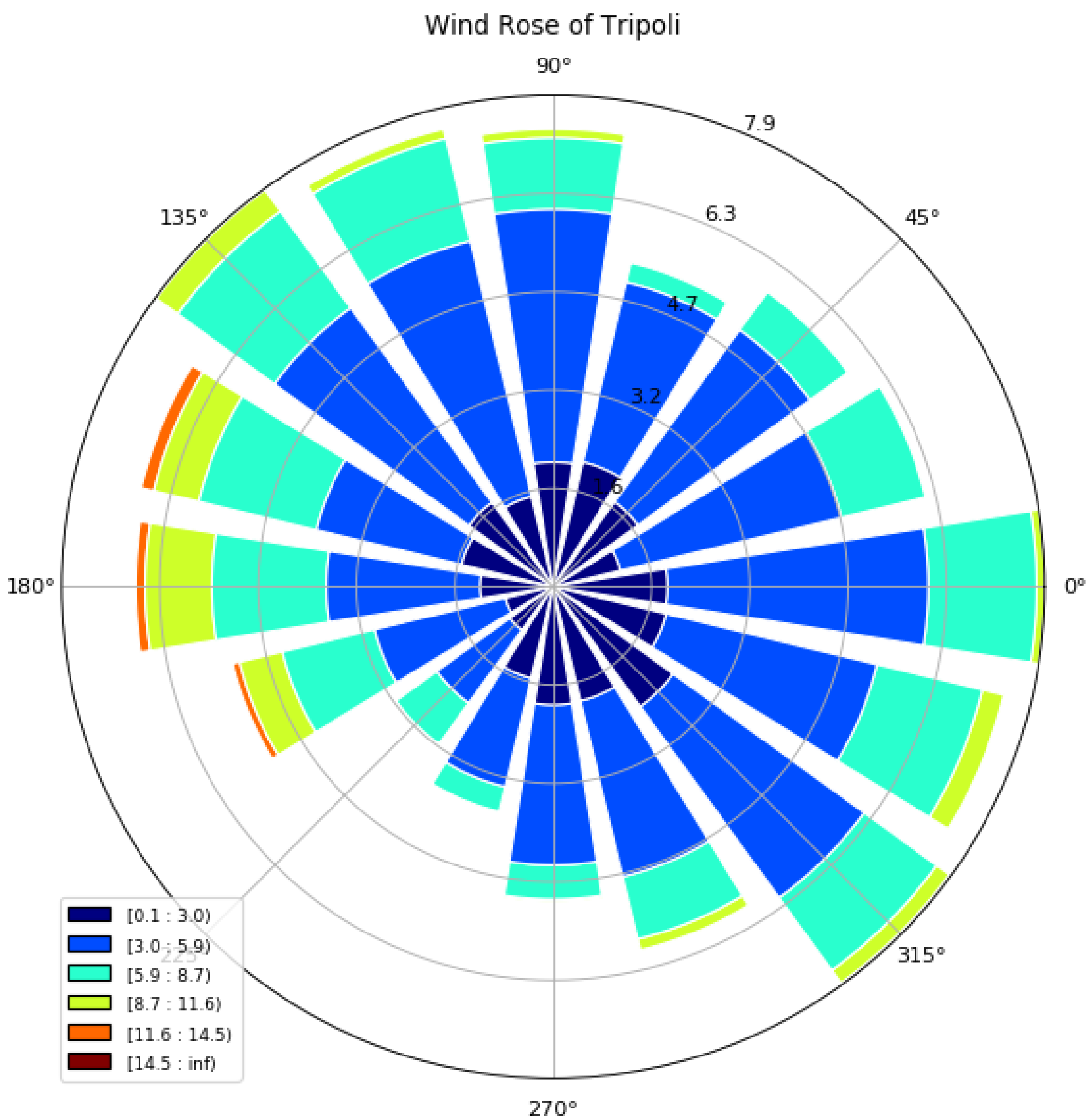
In [5]:
```
Wind10m_comparison.index=Wind10m_comparison.index.month
```

In [6]:
```
plt.rcParams['figure.figsize'] = [10, 5.0]
plt.rcParams['figure.dpi'] = 300

c = ['slategrey','rosybrown','brown','red','orange','gold','olive','yellow','yellowgre
     'greenyellow','green','deepskyblue','cyan','royalblue','blue','purple', 'magenta'

Wind10m_comparison.plot.bar(zorder=3,color=c)

plt.xticks(rotation=0)
plt.xlabel('Months');
plt.ylabel('Monthly Average Wind Speed [m/s]');
plt.legend(bbox_to_anchor=(1.16, 1.01),loc='upper right')
plt.grid()
```

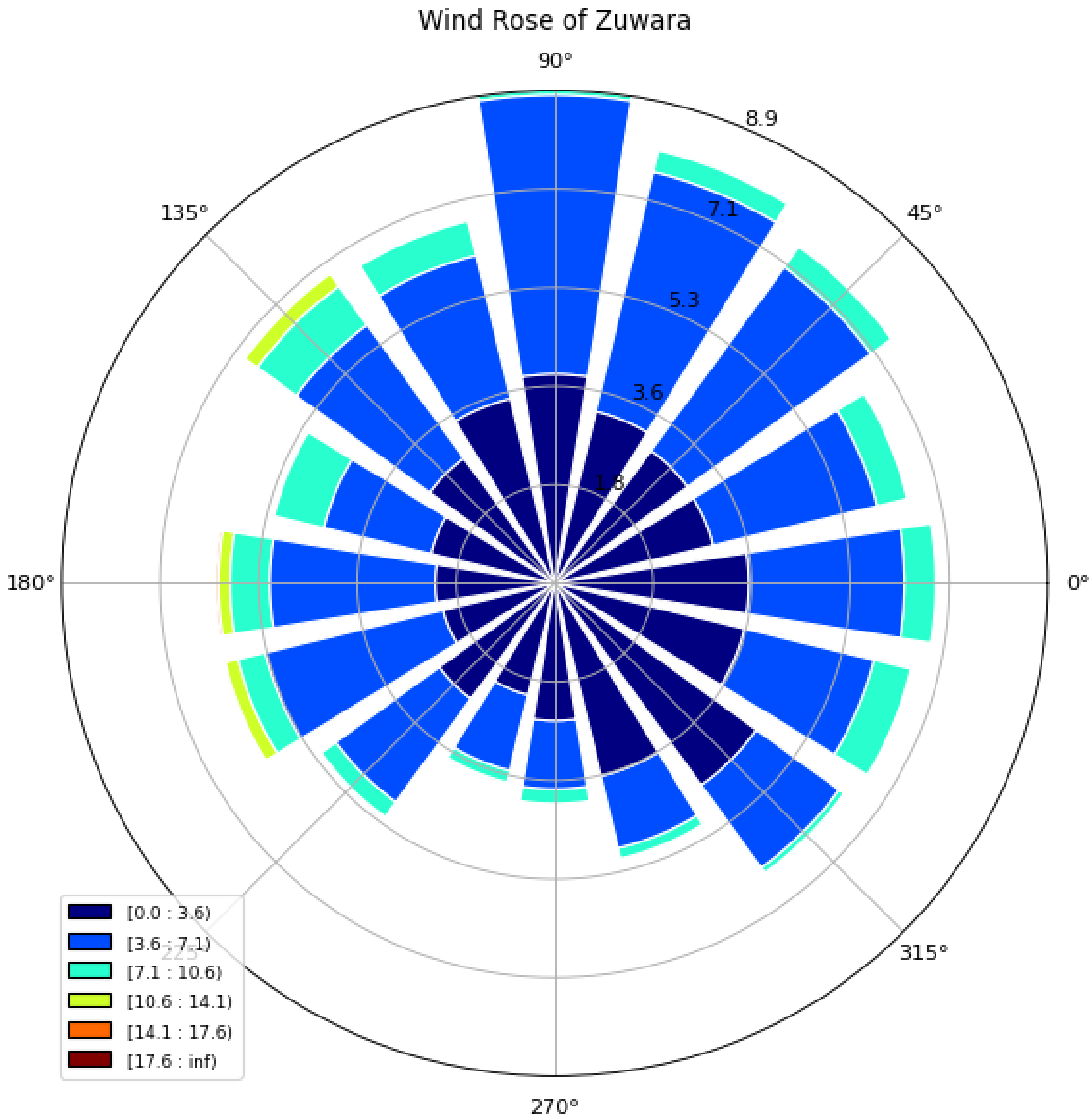


0.1.4 Plot wind roses

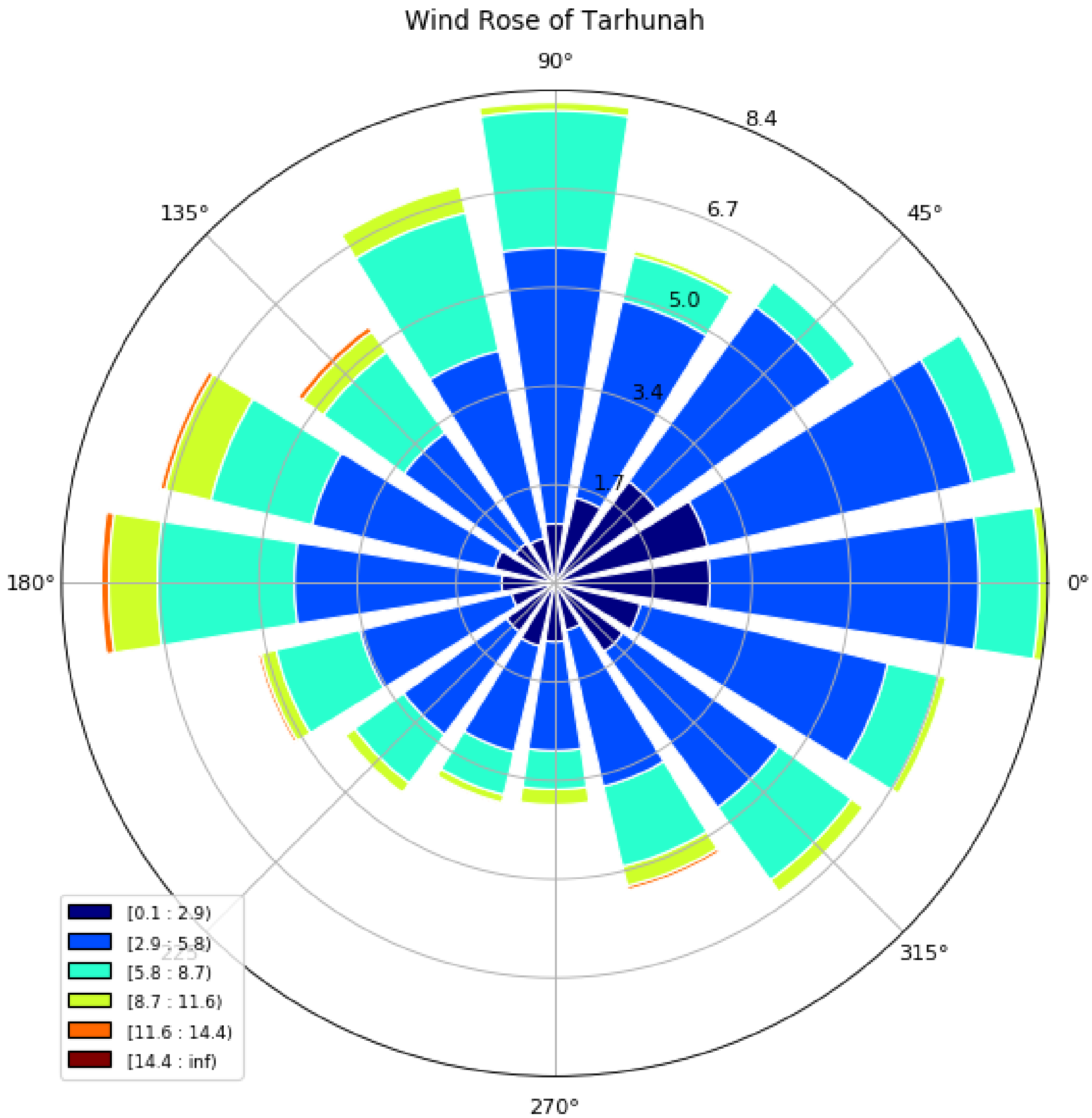
In [7]:
```
import matplotlib.pyplot as plt
from windrose import WindroseAxes
import matplotlib.cm as cm
import numpy as np

cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata','S
        'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan'
       'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Gad
       'df_Kufra','df_Jaghbub', 'df_Berlin']

for i in np.arange(len(cities)):
    dt_tem=vars()[df_dt[i]][['WS10m','WD10m']]

    ax = WindroseAxes.from_ax()
    ax.bar(dt_tem['WD10m'], dt_tem['WS10m'], normed=True, opening=0.8, edgecolor='white
    ax.set_legend()
    ax.set_title('Wind Rose of '+ cities[i])
```



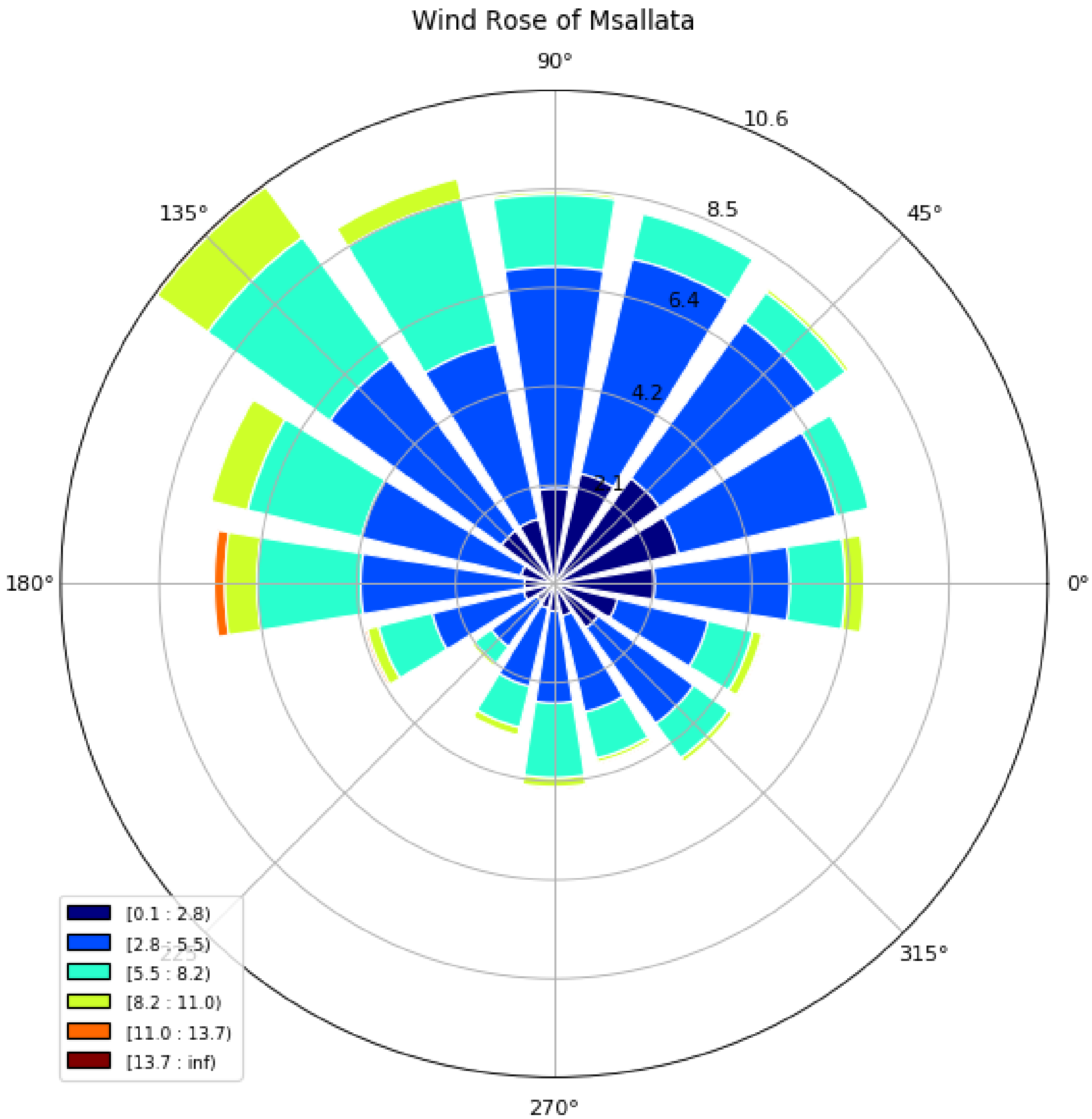
Wind Rose of Tripoli
90°
135°
45°
180°
0°
225°
315°
270°
1.6
3.2
4.7
6.3
7.9
[0.1 : 3.0)
[3.0 : 5.9)
[5.9 : 8.7)
[8.7 : 11.6)
[11.6 : 14.5)
[14.5 : inf)



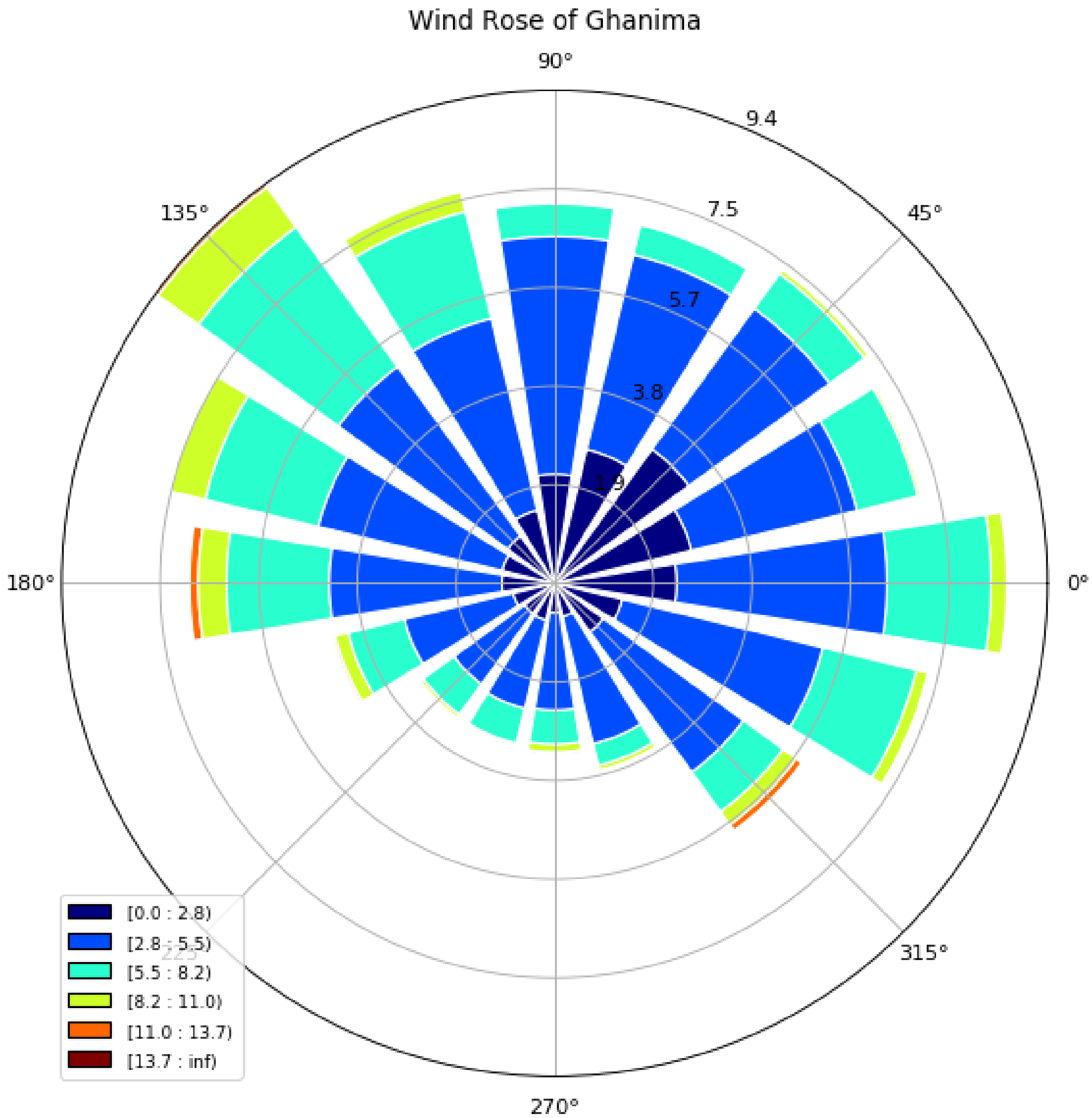
Wind Rose of Zuwara
90°
45°
0°
315°
270°
180°
135°
1.8
3.6
5.3
7.1
8.9
[0.0 : 3.6)
[3.6 : 7.1)
[7.1 : 10.6)
[10.6 : 14.1)
[14.1 : 17.6)
[17.6 : inf)

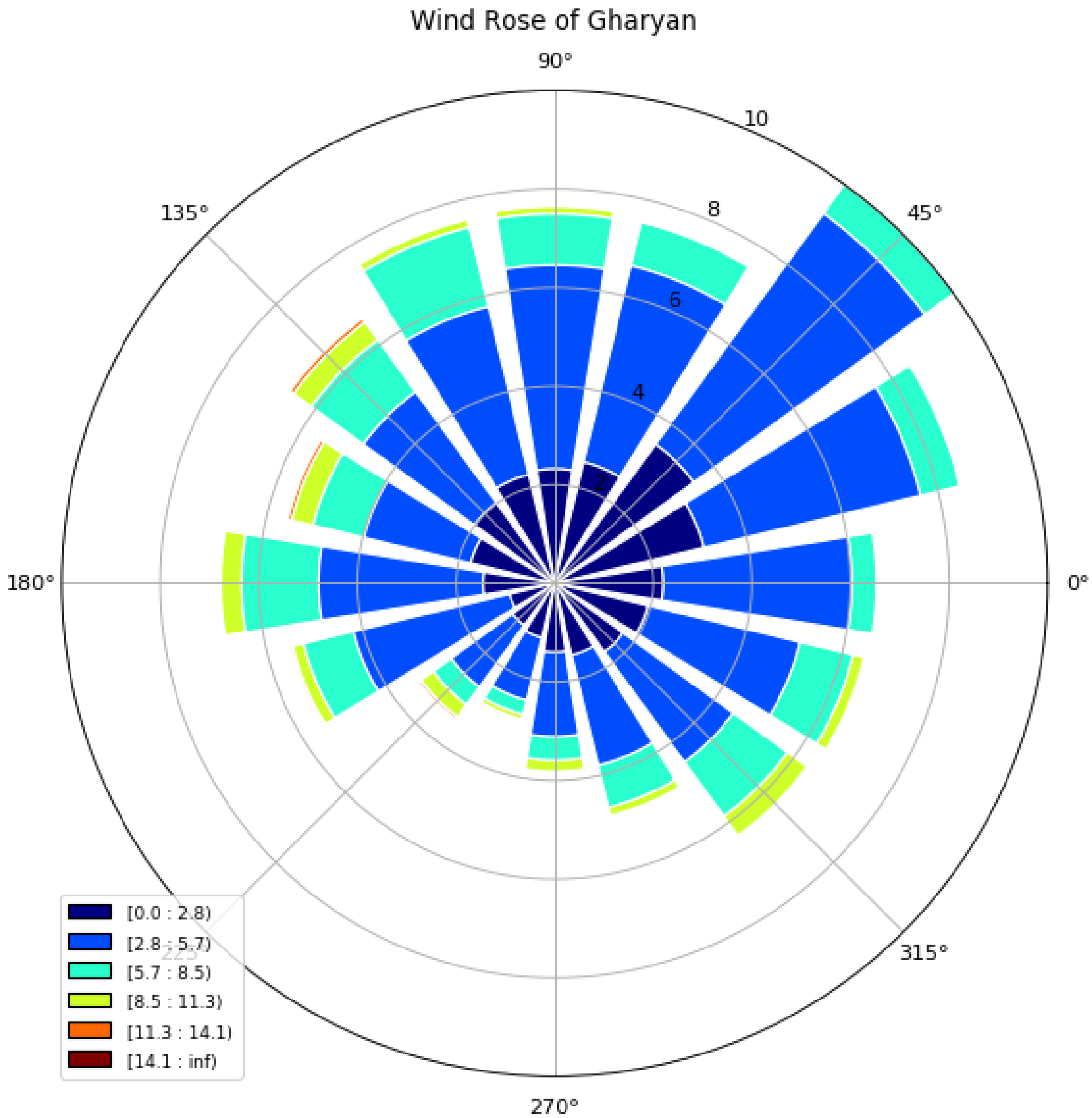


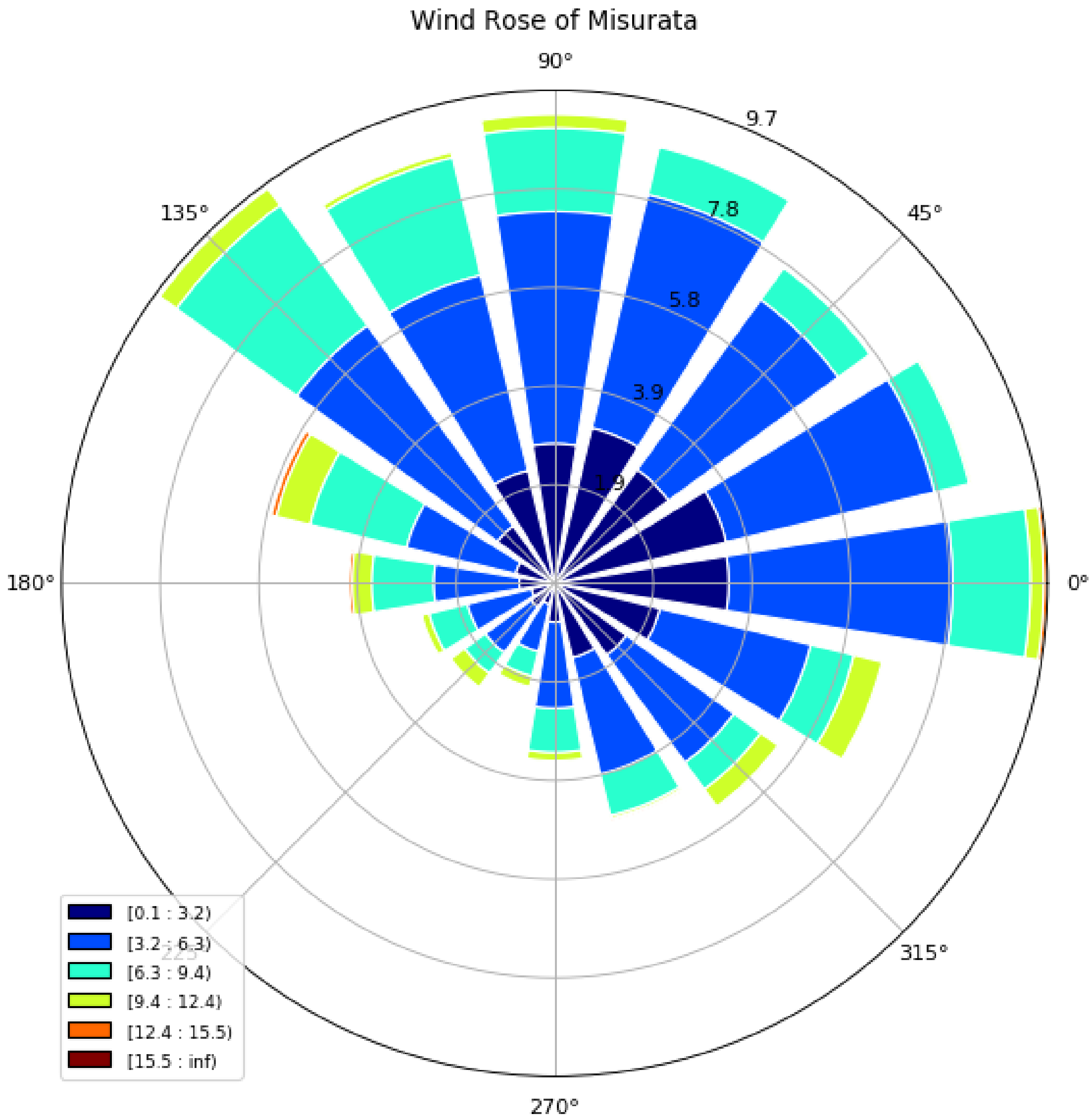
Wind Rose of Tarhunah
90°
45°
0°
315°
270°
225
180°
135°
1.7
3.4
5.0
6.7
8.4
[0.1 : 2.9)
[2.9 : 5.8)
[5.8 : 8.7)
[8.7 : 11.6)
[11.6 : 14.4)
[14.4 : inf)



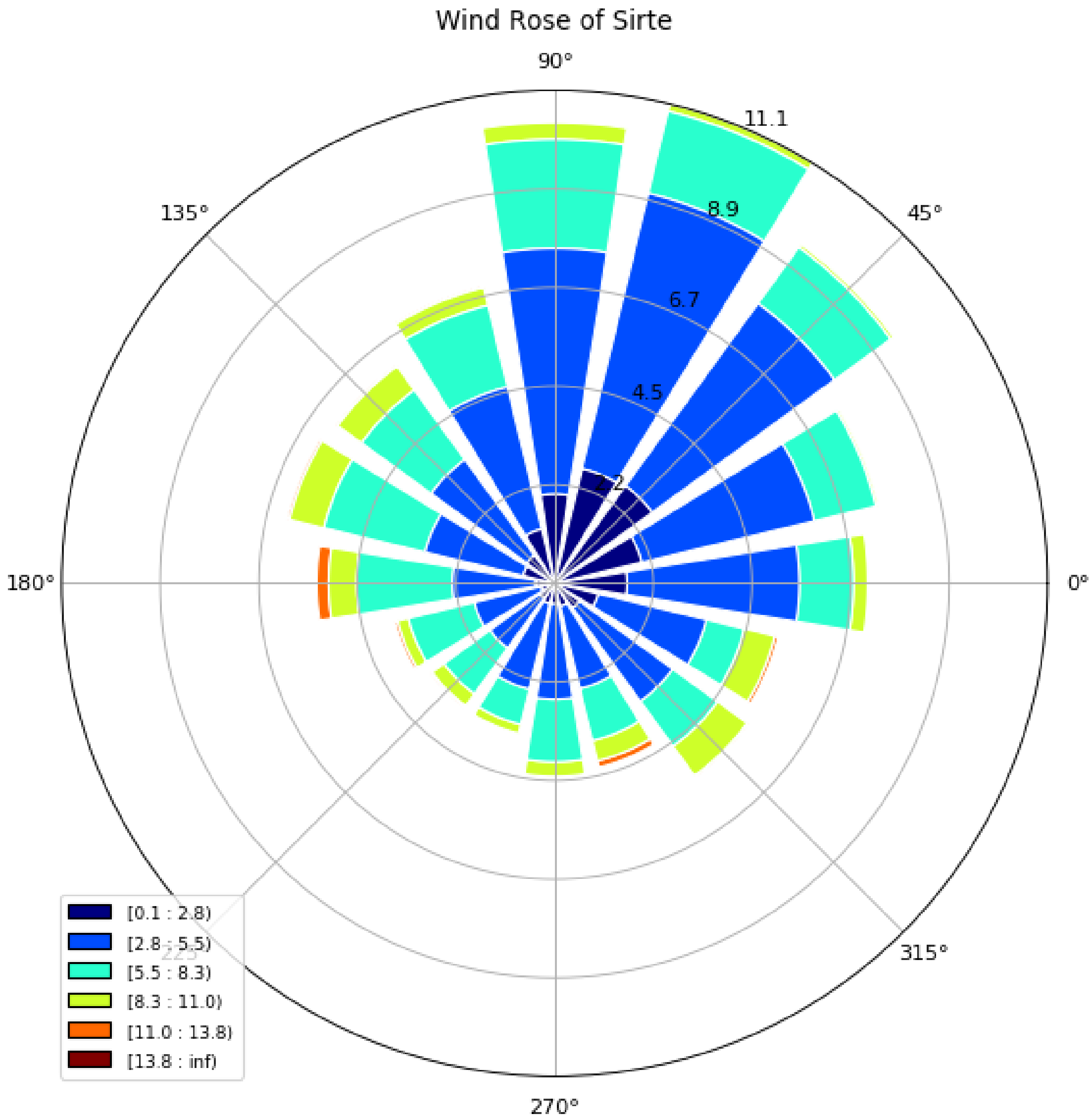
Wind Rose of Msallata
90°
135°
45°
180°
0°
315°
270°
10.6
8.5
6.4
4.2
2.1
[0.1 : 2.8)
[2.8 : 5.5)
[5.5 : 8.2)
[8.2 : 11.0)
[11.0 : 13.7)
[13.7 : inf)

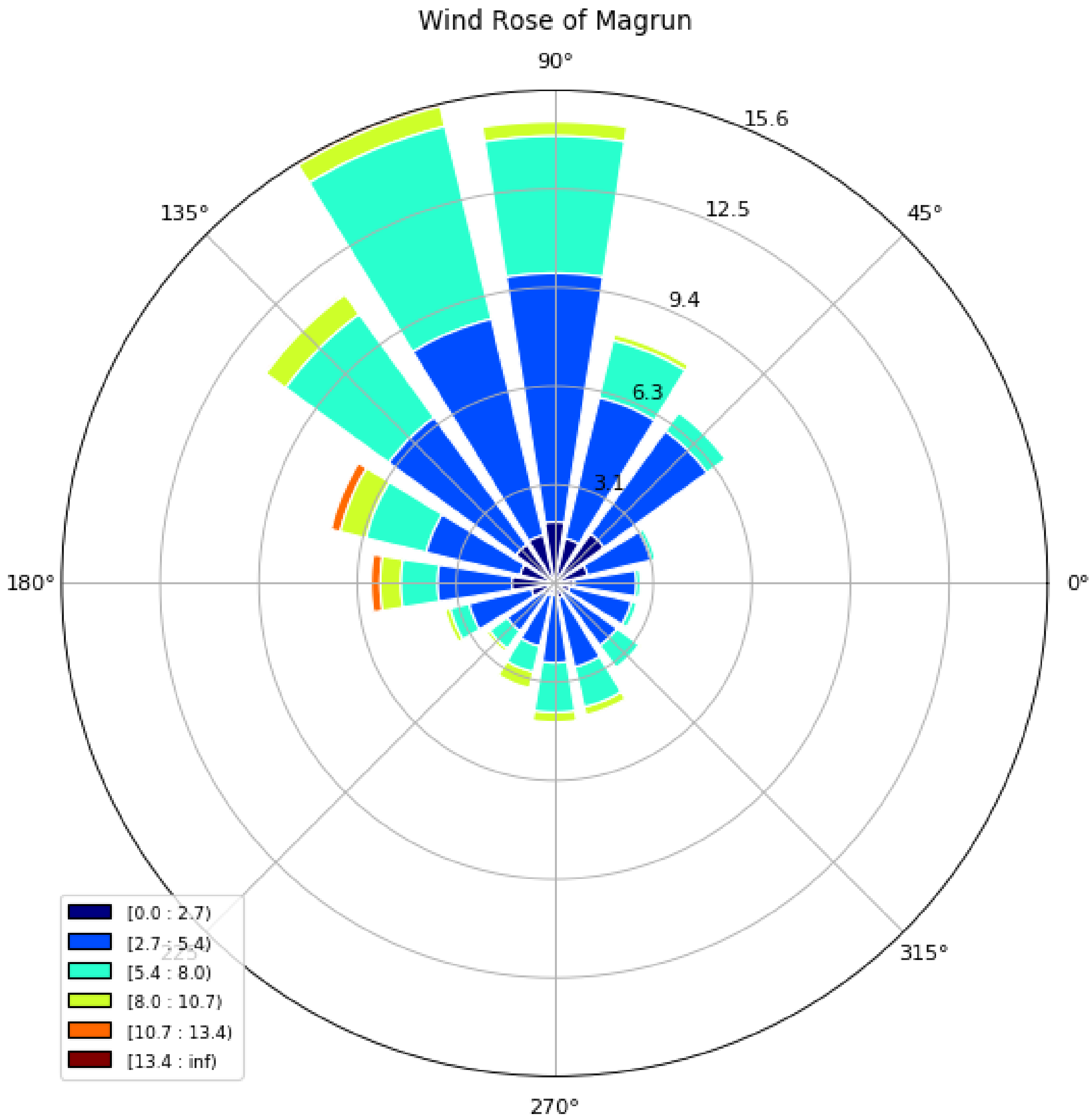

Wind Rose of Ghanima
90°
135°
45°
180°
0°
315°
270°
9.4
7.5
5.7
3.8
1.9
[0.0 : 2.8)
[2.8 : 5.5)
[5.5 : 8.2)
[8.2 : 11.0)
[11.0 : 13.7)
[13.7 : inf)


Wind Rose of Gharyan
90°
135°
45°
180°
0°
315°
270°
10
8
6
4
2
[0.0 : 2.8)
[2.8 : 5.7)
[5.7 : 8.5)
[8.5 : 11.3)
[11.3 : 14.1)
[14.1 : inf)

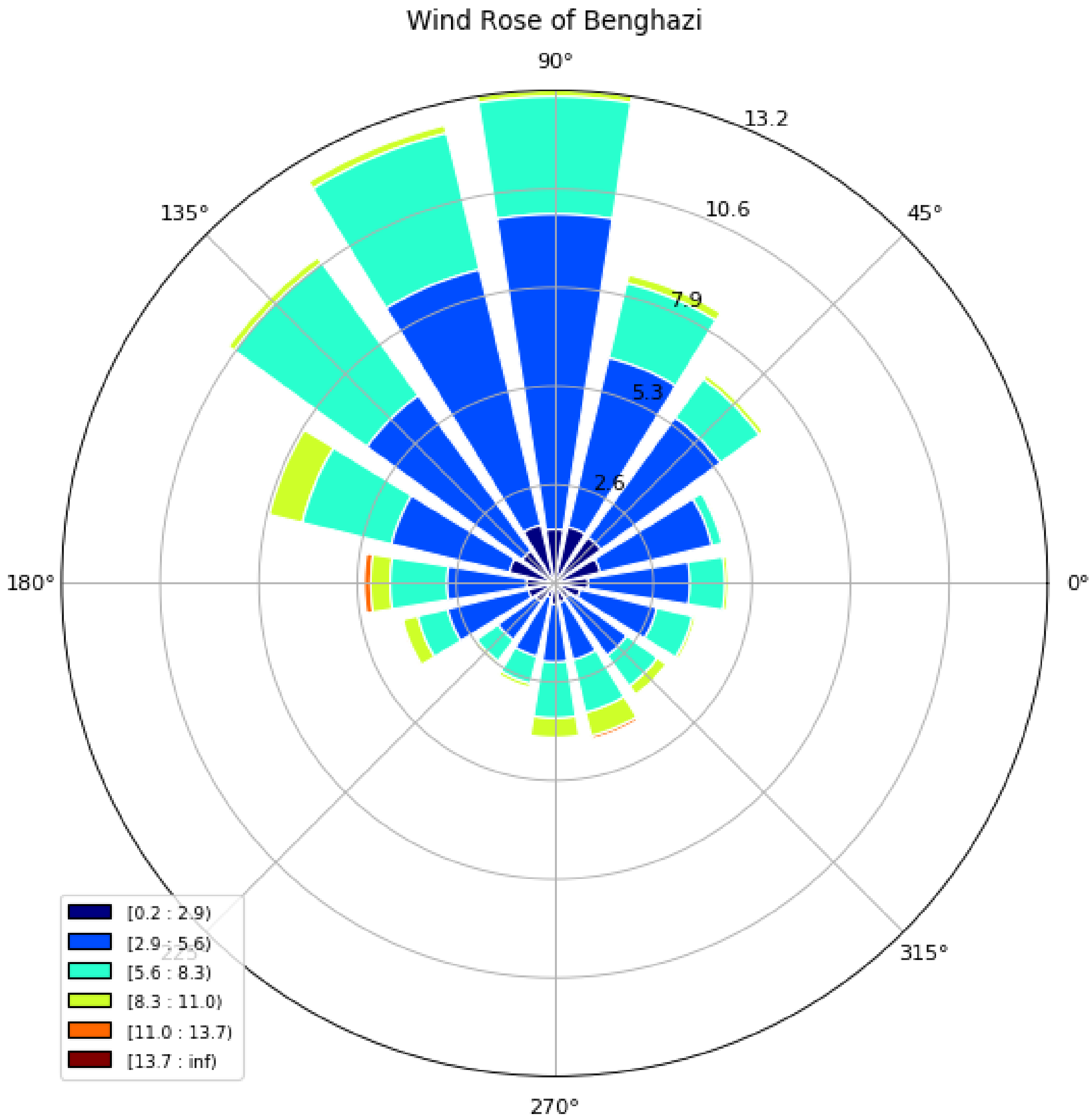


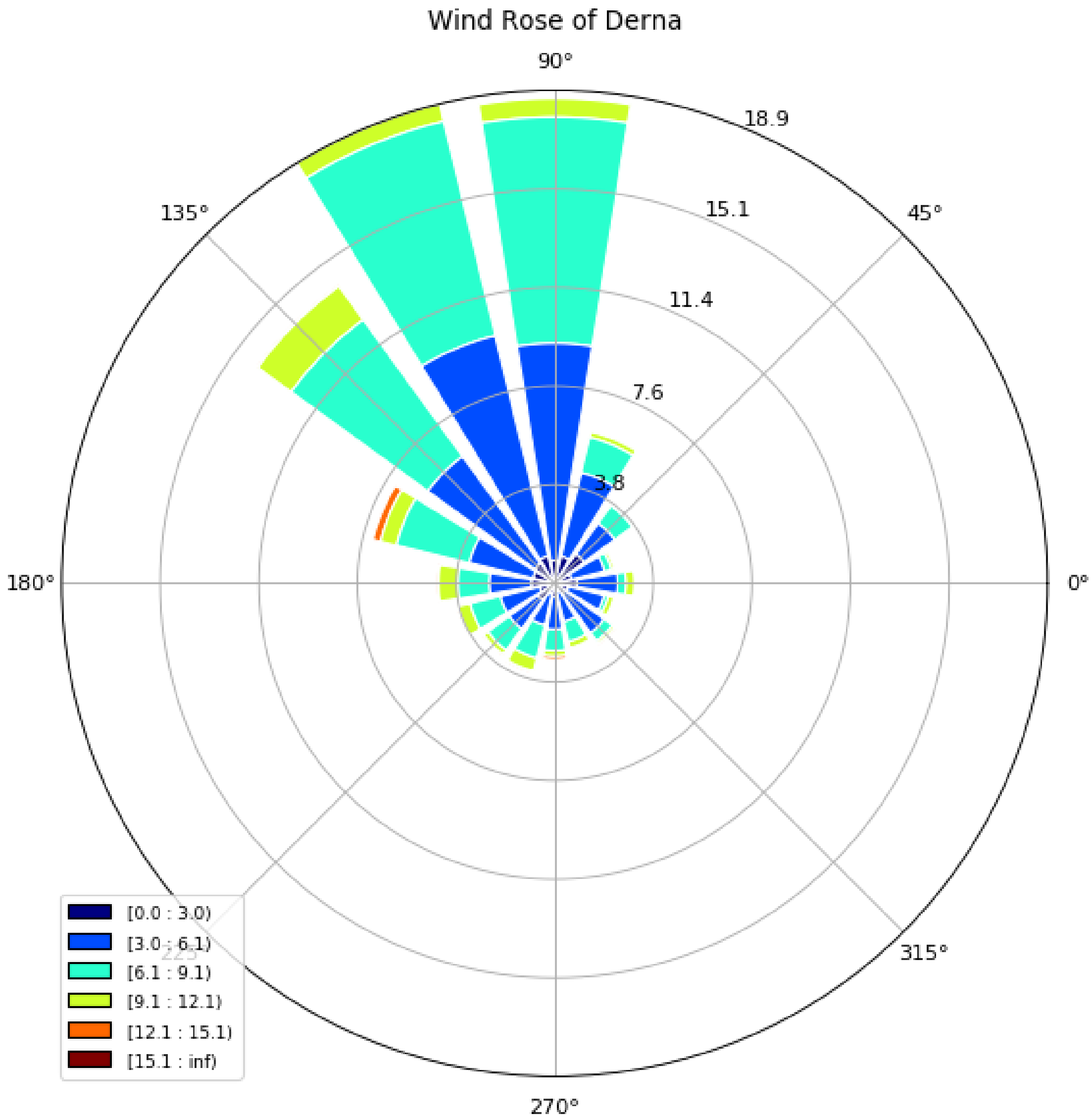
Wind Rose of Misurata
90°
45°
0°
315°
270°
225°
180°
135°
9.7
7.8
5.8
3.9
1.9
[0.1 : 3.2)
[3.2 : 6.3)
[6.3 : 9.4)
[9.4 : 12.4)
[12.4 : 15.5)
[15.5 : inf)


Wind Rose of Sirte
90°
45°
0°
315°
270°
135°
180°
2.2
4.5
6.7
8.9
11.1
[0.1 : 2.8)
[2.8 : 5.5)
[5.5 : 8.3)
[8.3 : 11.0)
[11.0 : 13.8)
[13.8 : inf)

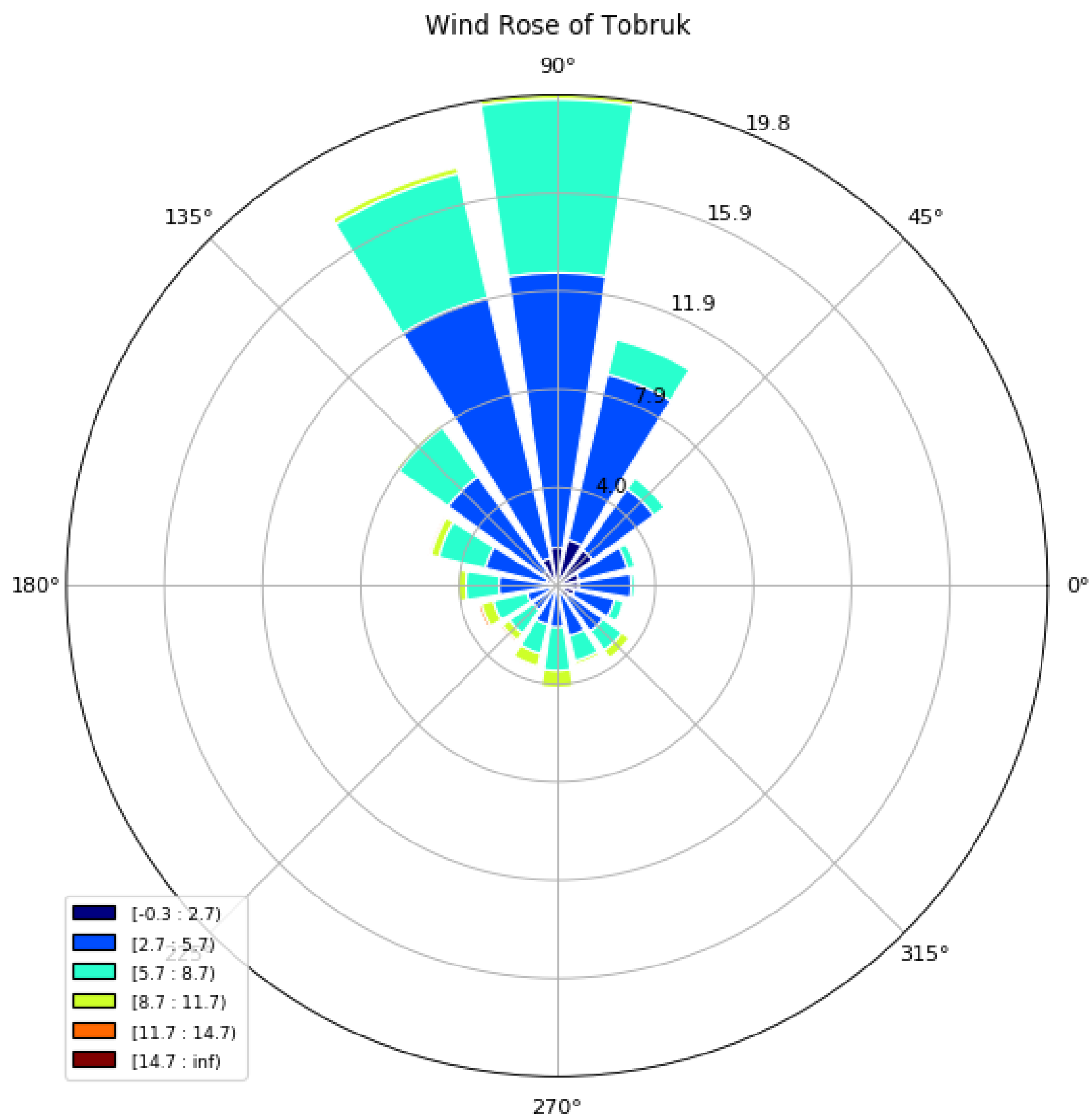


Wind Rose of Magrun
90°
135°
45°
180°
0°
225
315°
270°
3.1
6.3
9.4
12.5
15.6
[0.0 : 2.7)
[2.7 : 5.4)
[5.4 : 8.0)
[8.0 : 10.7)
[10.7 : 13.4)
[13.4 : inf)

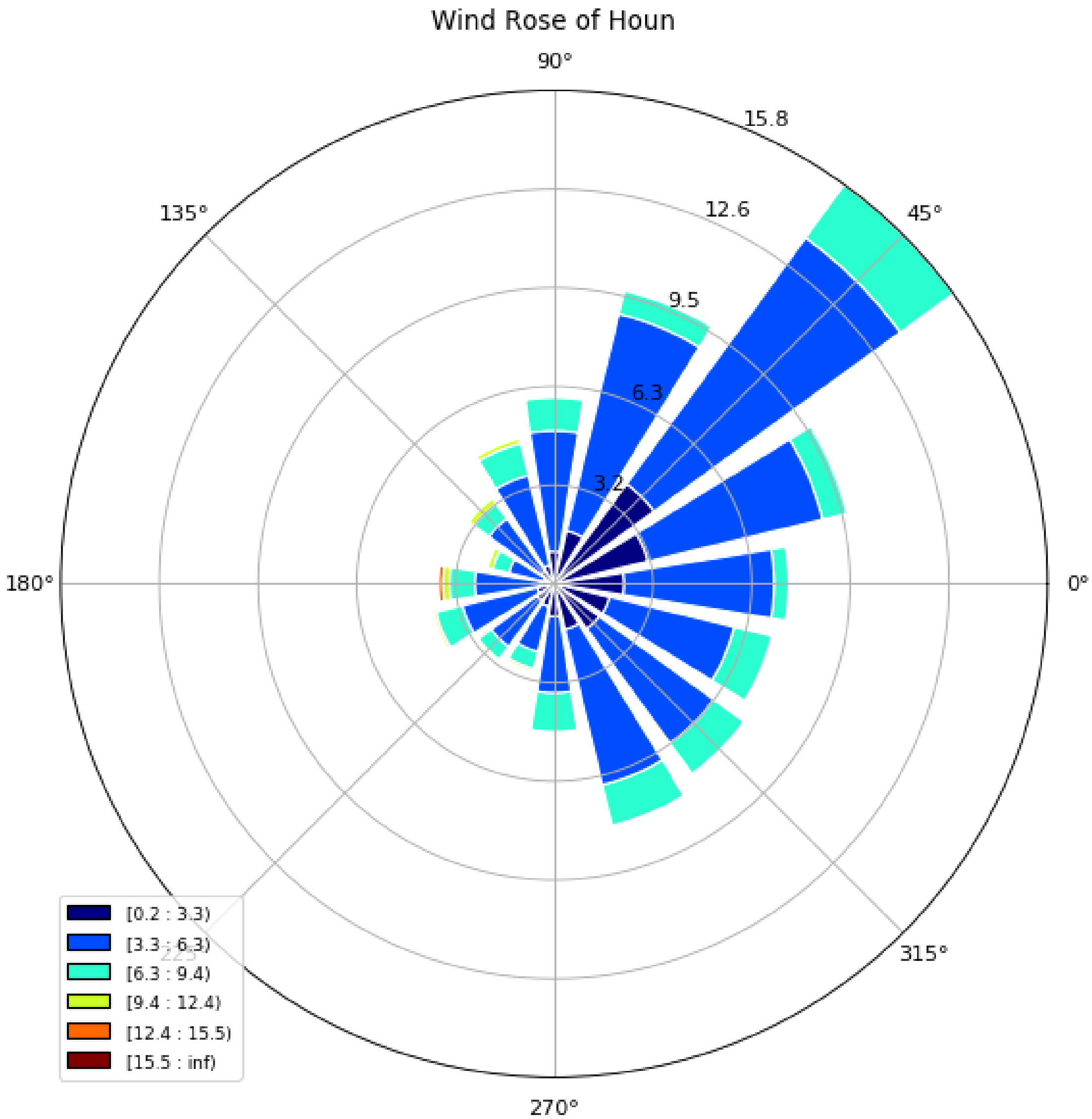

Wind Rose of Benghazi
90°
135°
45°
180°
0°
225
315°
270°
2.6
5.3
7.9
10.6
13.2
[0.2 : 2.9)
[2.9 : 5.6)
[5.6 : 8.3)
[8.3 : 11.0)
[11.0 : 13.7)
[13.7 : inf)



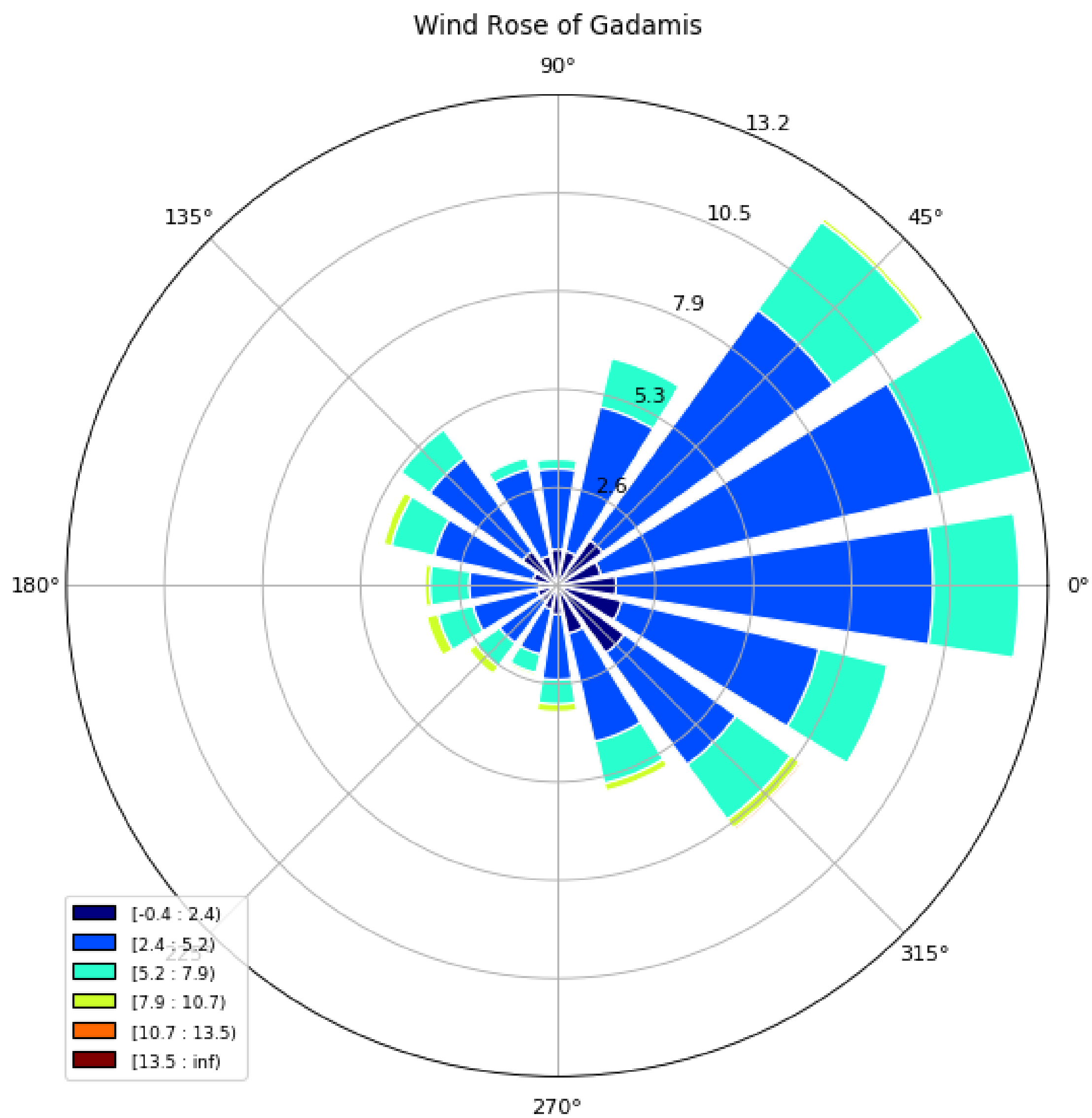
Wind Rose of Derna
90°
135°
45°
180°
0°
225°
315°
270°
3.8
7.6
11.4
15.1
18.9
[0.0 : 3.0)
[3.0 : 6.1)
[6.1 : 9.1)
[9.1 : 12.1)
[12.1 : 15.1)
[15.1 : inf)



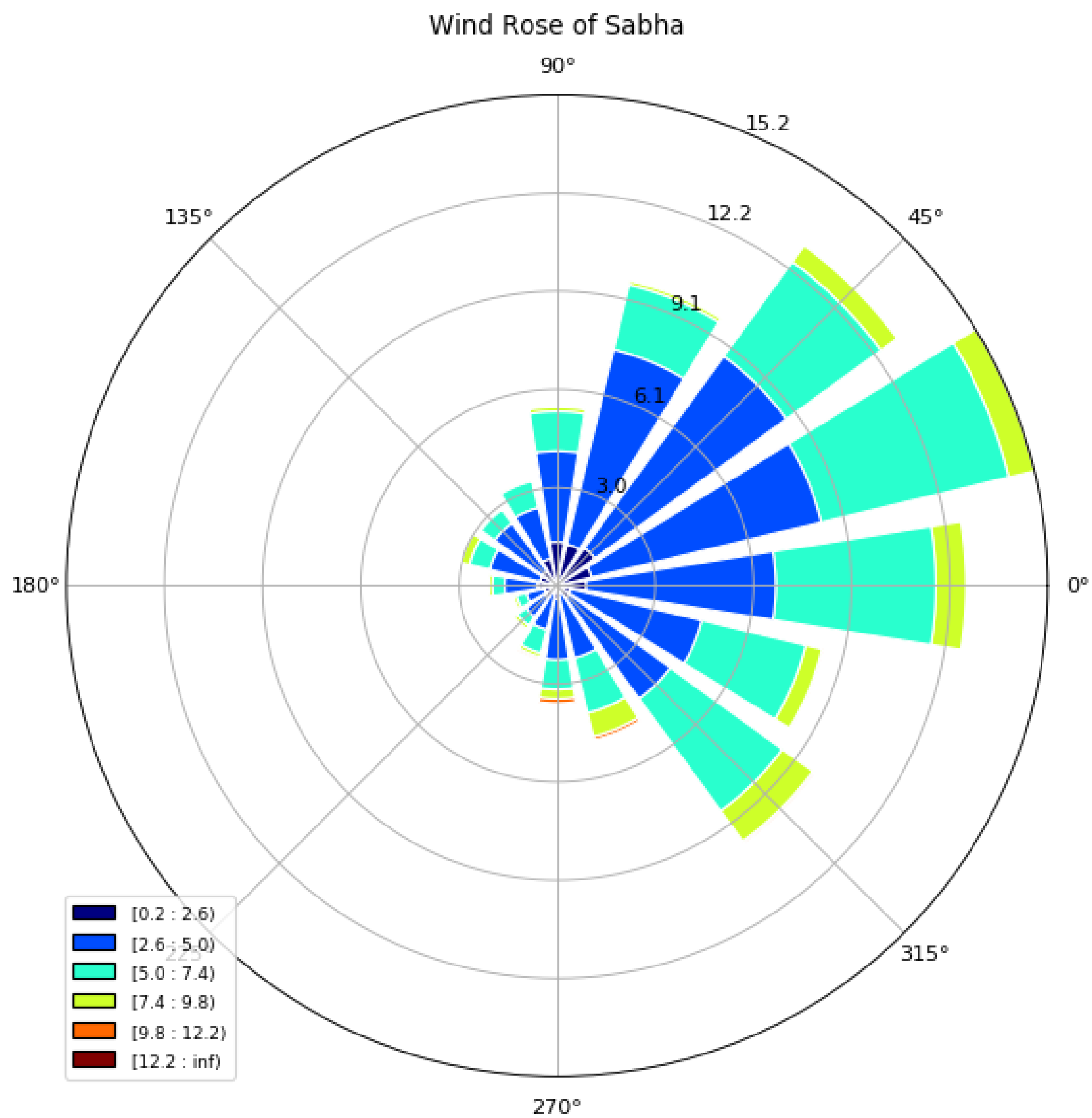
Wind Rose of Tobruk
90°
45°
0°
315°
270°
135°
180°
225°
4.0
7.9
11.9
15.9
19.8
[-0.3 : 2.7)
[2.7 : 5.7)
[5.7 : 8.7)
[8.7 : 11.7)
[11.7 : 14.7)
[14.7 : inf)

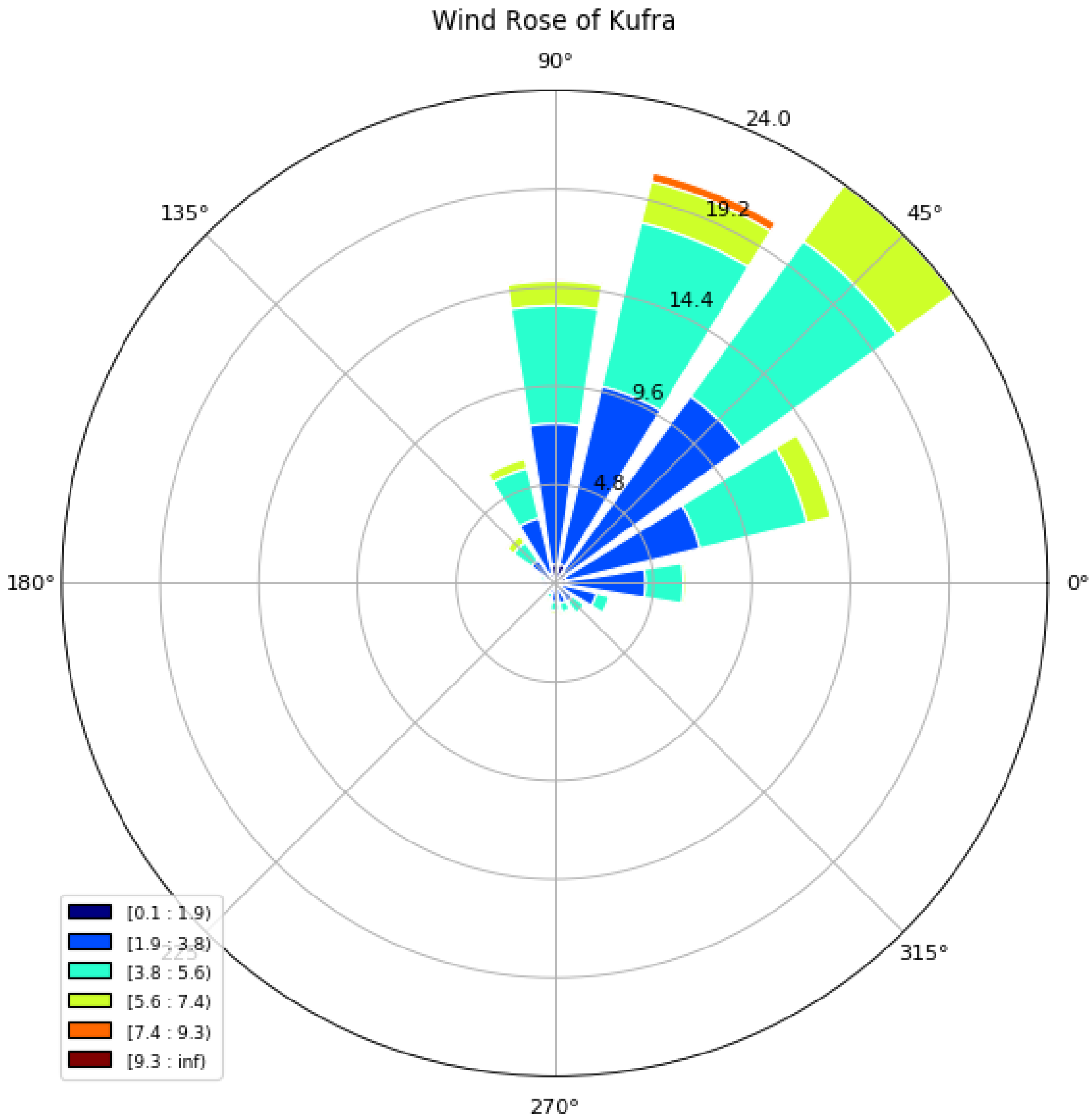


Wind Rose of Houn
90°
45°
0°
315°
270°
225°
180°
135°
3.2
6.3
9.5
12.6
15.8
[0.2 : 3.3)
[3.3 : 6.3)
[6.3 : 9.4)
[9.4 : 12.4)
[12.4 : 15.5)
[15.5 : inf)

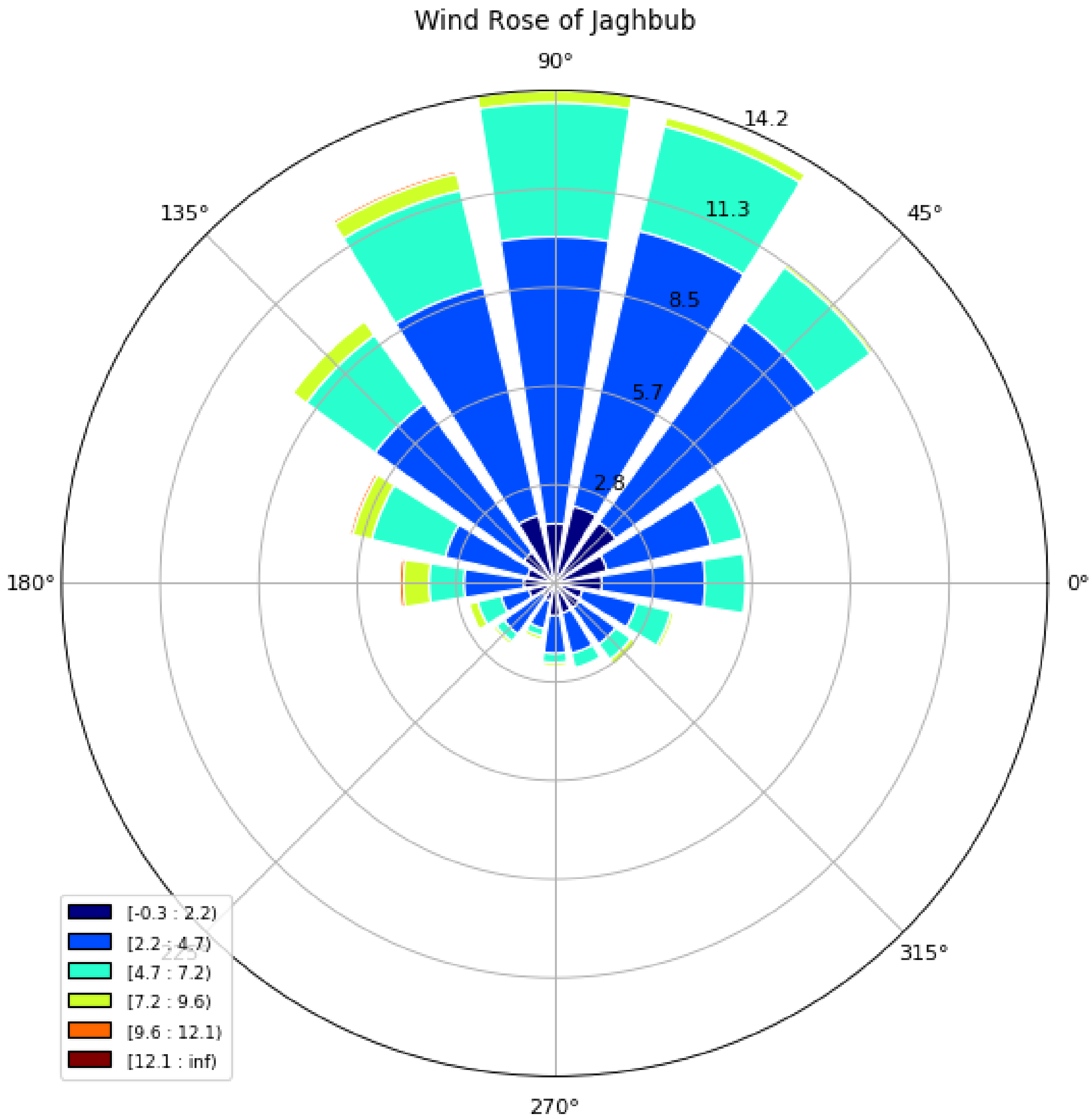


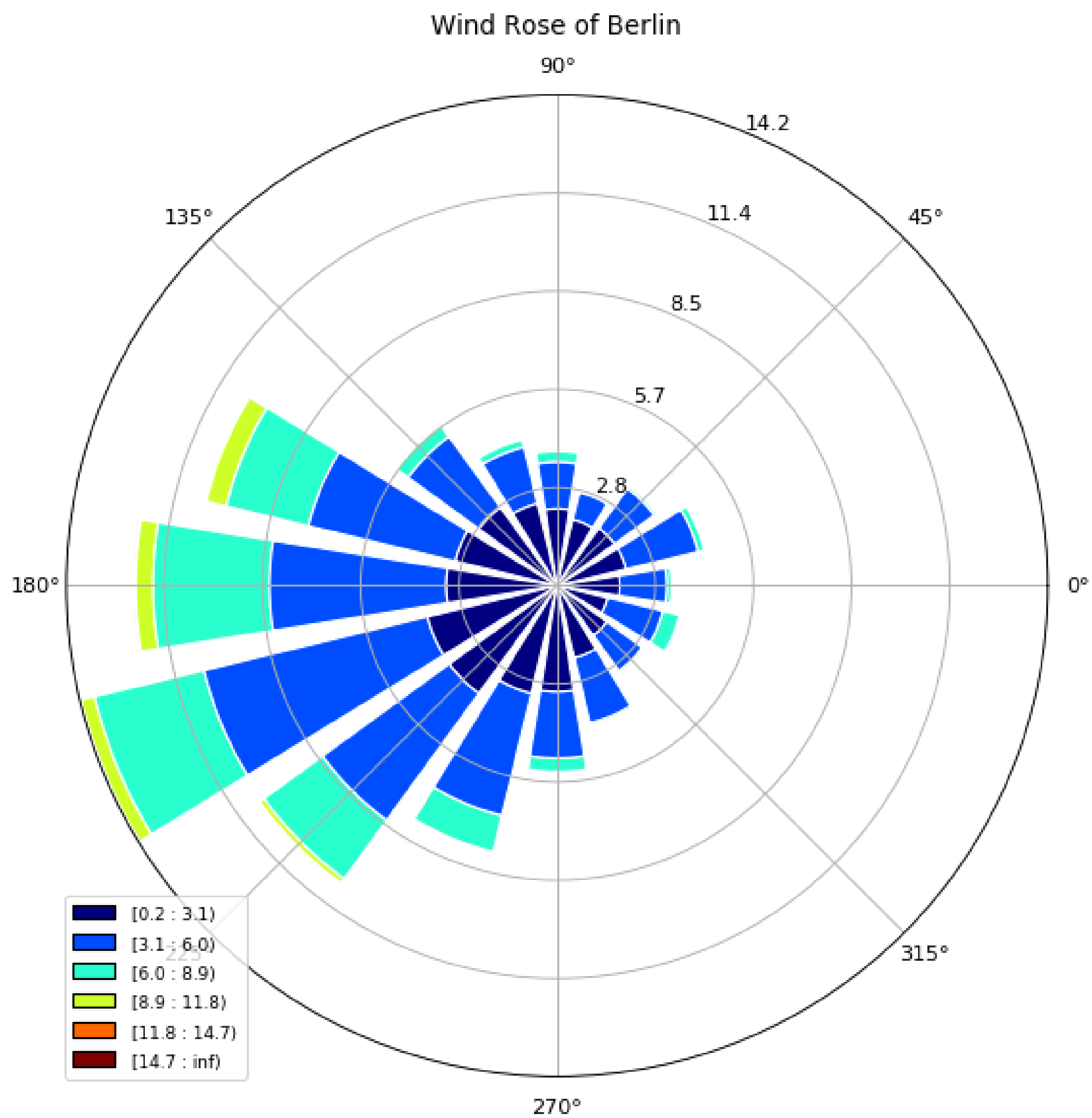
Wind Rose of Gadamis
90°
135°
45°
180°
0°
315°
270°
13.2
10.5
7.9
5.3
2.6
[-0.4 : 2.4)
[2.4 : 5.2)
[5.2 : 7.9)
[7.9 : 10.7)
[10.7 : 13.5)
[13.5 : inf)


Wind Rose of Sabha
90°
135°
45°
180°
0°
315°
270°
15.2
12.2
9.1
6.1
3.0
[0.2 : 2.6)
[2.6 : 5.0)
[5.0 : 7.4)
[7.4 : 9.8)
[9.8 : 12.2)
[12.2 : inf)



Wind Rose of Kufra
90°
45°
0°
315°
270°
225°
180°
135°
24.0
19.2
14.4
9.6
4.8
[0.1 : 1.9)
[1.9 : 3.8)
[3.8 : 5.6)
[5.6 : 7.4)
[7.4 : 9.3)
[9.3 : inf)


Wind Rose of Jaghbub
90°
45°
0°
315°
270°
225°
180°
135°
2.8
5.7
8.5
11.3
14.2
[-0.3 : 2.2)
[2.2 : 4.7)
[4.7 : 7.2)
[7.2 : 9.6)
[9.6 : 12.1)
[12.1 : inf)




```
In [9]: plt.rcParams['figure.figsize'] = [10, 5.0]
        plt.rcParams['figure.dpi'] = 300
```

0.2 Correlation of wind speed and solar irradiance

0.2.1 Correlation without considering night hours, becasue there is no solar irradiance at night

```
In [10]: from sklearn.metrics import r2_score
         # plt.rcParams['figure.figsize']=[5, 4.8]  ### default figure size

         cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
                 'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']
```

```python
df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan
       'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
       'df_Kufra','df_Jaghbub', 'df_Berlin']

Corr_solar_wind=pd.DataFrame({'tem':[0]},index=['Corr_GHI_WS','Corr_DNI_WS'])

##### Since correlation is same for non-nomalized or nomralized no need for nomalized
# Corr_solar_wind=pd.DataFrame({'tem':[0]},index=['Corr_GHI_WS','Corr_DNI_WS','Corrno

df_windsp=pd.DataFrame({'Tripoli':df_Trip['WS10m']})
df_ghi=pd.DataFrame({'Tripoli':df_Trip['G(h)']})
df_dni=pd.DataFrame({'Tripoli':df_Trip['Gb(n)']})

# for i in np.arange(len(cities)):
for i in np.arange(len(cities)-1):
    vars()[df_dt[i]]=vars()[df_dt[i]][vars()[df_dt[i]]['G(h)']>0.01]
    df_windsp[cities[i]]=vars()[df_dt[i]]['WS10m']
    df_ghi[cities[i]]=vars()[df_dt[i]]['G(h)']
    df_dni[cities[i]]=vars()[df_dt[i]]['Gb(n)']
#     day_hrs=df_Sirte[df_Sirte['G(h)']>0.01].count()[0]

    windspeed_comparison=df_windsp
    ghi_comparison=df_ghi
    dni_comparison=df_dni

    df_tem=vars()[df_dt[i]][['WS10m','G(h)','Gb(n)']]
    df_tem_norm=0+(df_tem-df_tem.min())/(df_tem.max()-df_tem.min())*(1-0)

    Corr_solar_wind.at['Corr_GHI_WS',cities[i]]=df_tem['G(h)'].corr(df_tem['WS10m'])
    Corr_solar_wind.at['Corr_DNI_WS',cities[i]]=df_tem['Gb(n)'].corr(df_tem['WS10m'])

#     Corr_solar_wind.at['Corrnorm_GHI_WS',cities[i]]=df_tem_norm['G(h)'].corr(df_tem
#     Corr_solar_wind.at['Corrnorm_DNI_WS',cities[i]]=df_tem_norm['Gb(n)'].corr(df_te

Corr_solar_wind.drop(['tem'], axis=1, inplace=True)

Corr_solar_wind
```

Out[10]:

	Tripoli	Zuwara	Tarhunah	Msallata	Ghanima	Gharyan
Corr_GHI_WS	-0.018879	0.066374	0.016751	-0.040884	-0.022189	0.030488
Corr_DNI_WS	-0.067343	-0.023226	-0.048938	-0.146477	-0.152906	-0.031215

	Misurata	Sirte	Magrun	Benghazi	Derna	Tobruk
Corr_GHI_WS	-0.056642	-0.017901	0.066411	0.070508	0.038926	0.132381
Corr_DNI_WS	-0.117396	-0.056006	-0.007122	-0.024761	-0.062727	0.057894

	Houn	Gadamis	Sabha	Kufra	Jaghbub
Corr_GHI_WS	0.041430	0.063430	0.076660	-0.001165	0.062920

```
Corr_DNI_WS -0.024885  0.010074 -0.044828  0.025716 -0.011235
```

In [11]:
```python
Corr_solar_wind.loc['Corr_GHI_WS'].describe()
# Corr_solar_wind.loc['Corr_DNI_WS'].describe()
```

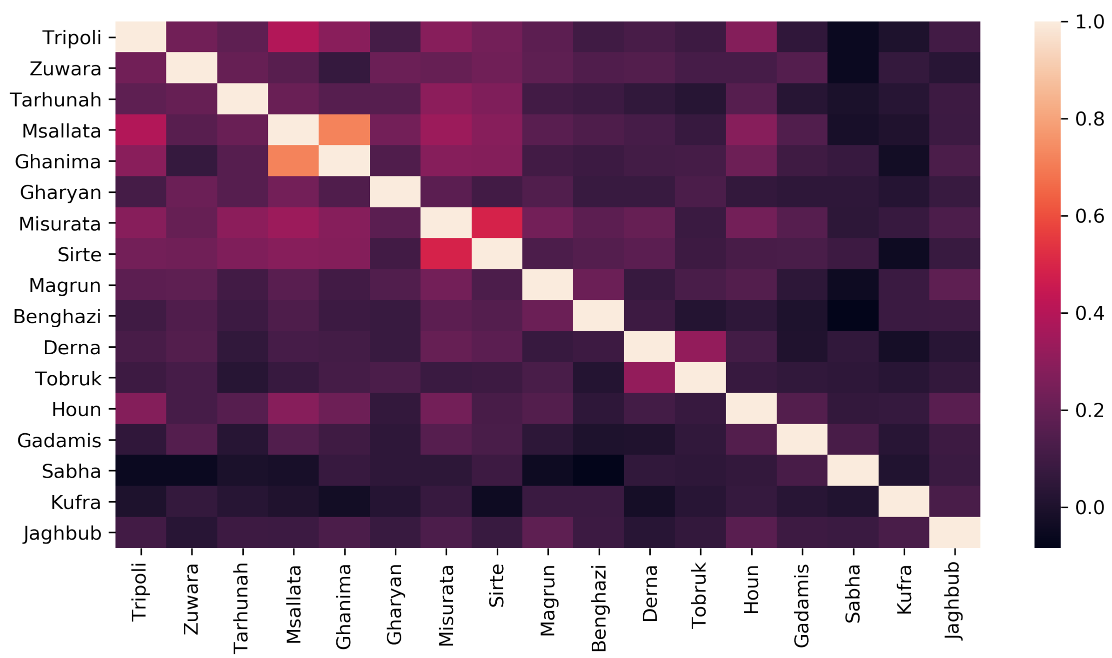
Out[11]:
```
count    17.000000
mean      0.029919
std       0.050278
min      -0.056642
25%      -0.017901
50%       0.038926
75%       0.066374
max       0.132381
Name: Corr_GHI_WS, dtype: float64
```

In [12]:
```python
# windspeed_comparison
# ghi_comparison
# dni_comparison

windspeed_comparison.shape
# ghi_comparison.shape
# dni_comparison.shape
```

Out[12]:
```
(8760, 17)
```

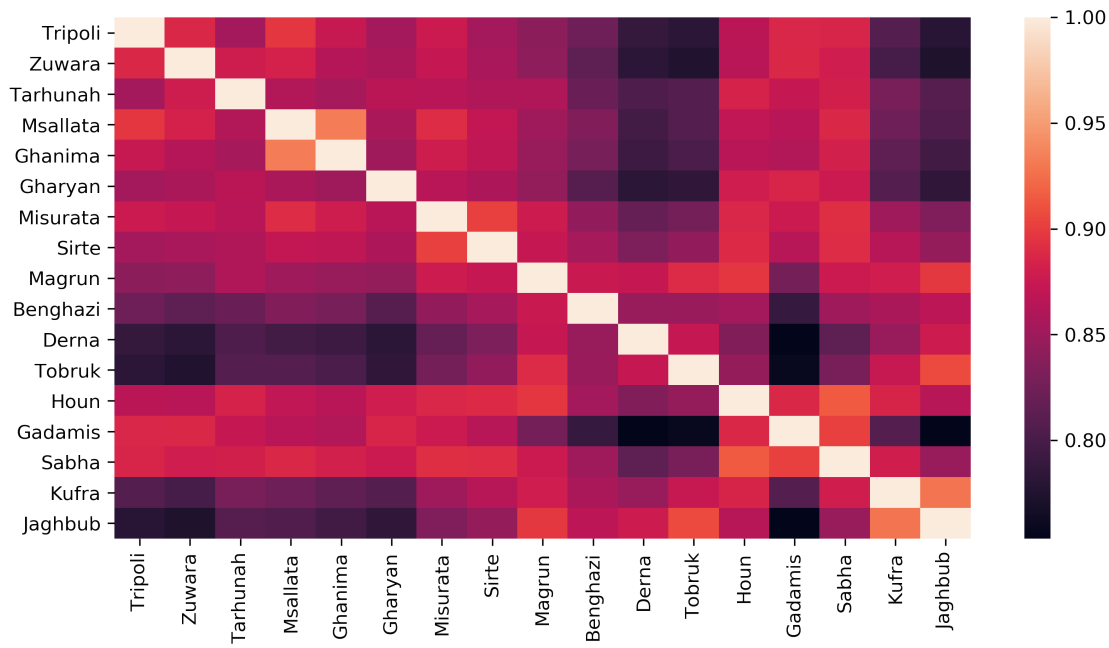
In [13]:
```python
import seaborn as sns
sns.heatmap(windspeed_comparison.corr())
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21c090c3278>
```



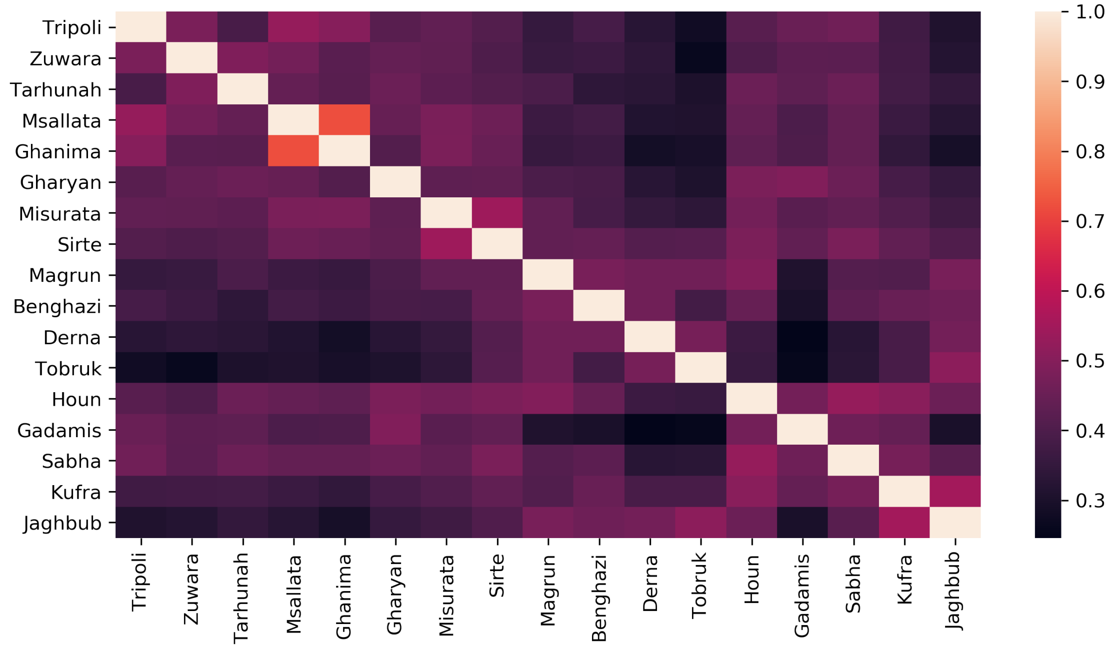
```
In [14]: sns.heatmap(ghi_comparison.corr())
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x21c091915c0>
```




```
In [15]: sns.heatmap(dni_comparison.corr())
```

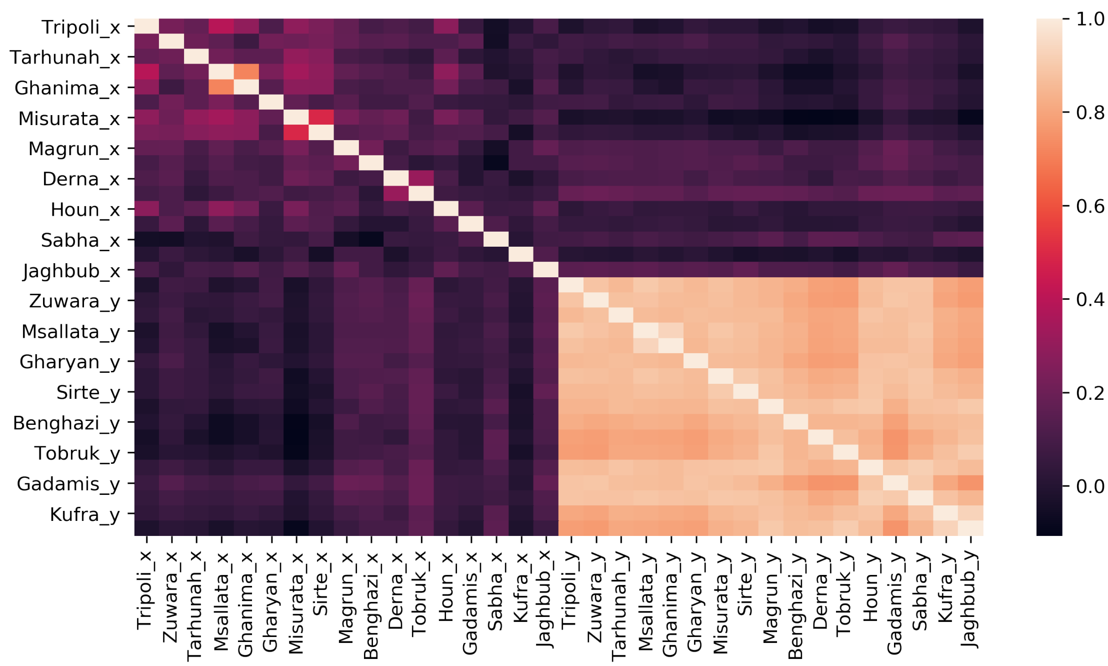
```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x21c09202860>
```



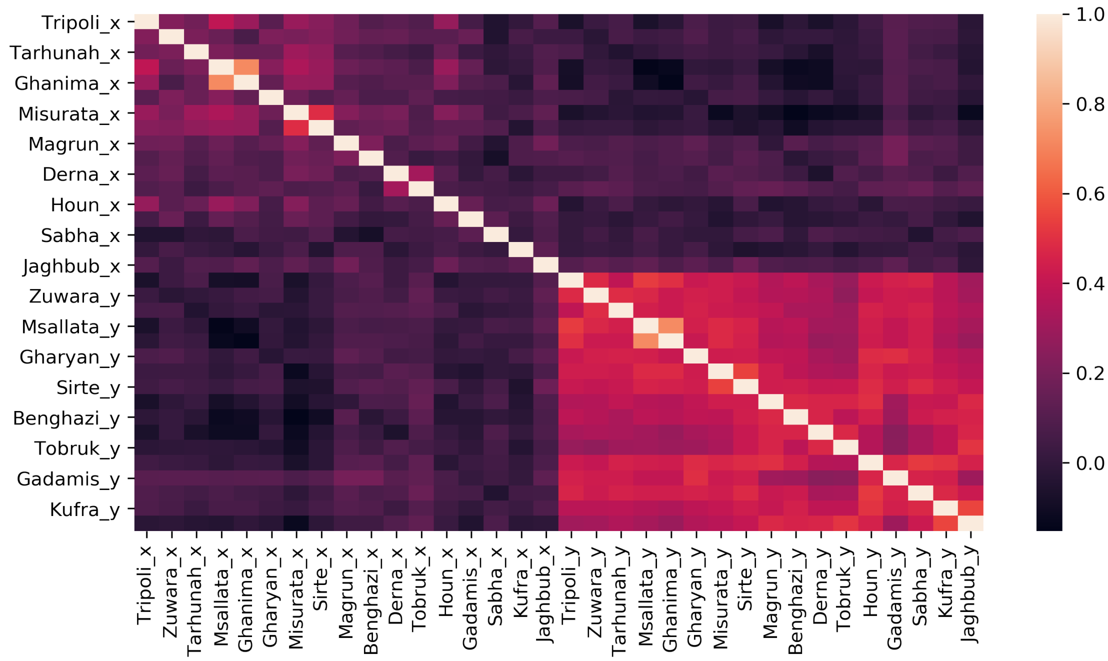

```
In [16]: df_ws_ghi = pd.merge(windspeed_comparison, ghi_comparison, left_index =True, right_ind
         df_ws_dni = pd.merge(windspeed_comparison, dni_comparison, left_index =True, right_ind
         # df_ws_ghi
         # df_ws_ghi.describe()
```

```
In [17]: sns.heatmap(df_ws_ghi.corr())
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x21c0566f7b8>
```



```
In [18]: sns.heatmap(df_ws_dni.corr())

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x21c051ae2e8>
```



0.3 Modeling Wind Speed to Wind Output Power for a Particular Wind Turbine

Using windpowerlib https://windpowerlib.readthedocs.io/en/stable/
https://github.com/mhdella/windpowerlib

```
In [19]: from windpowerlib import ModelChain, WindTurbine, create_power_curve
         from windpowerlib import data as wt
```

0.3.1 Import weather data

In order to use the windpowerlib you need to at least provide wind speed data for the time frame you want to analyze. The function below imports example weather data from the weather.csv file provided along with the windpowerlib. The data includes wind speed at two different heights in m/s, air temperature in two different heights in K, surface roughness length in m and air pressure in Pa.

To find out which weather data in which units need to be provided to use the ModelChain or other functions of the windpowerlib see the individual function documentation.

```
In [20]: cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
                 'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

         df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan
                'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
                'df_Kufra','df_Jaghbub', 'df_Berlin']

         for i in np.arange(len(cities)):

             data = pd.read_csv(cities[i]+'_get_pvgis_tmy.csv',index_col='time(UTC)')
             vars()[df_dt[i]] = data
             vars()[df_dt[i]].index=pd.to_datetime(vars()[df_dt[i]].index, format='%Y-%m-%d')

             vars()[df_dt[i]]['Year']=vars()[df_dt[i]].index.year
             vars()[df_dt[i]]['Month']=vars()[df_dt[i]].index.month
             vars()[df_dt[i]]['Day']=vars()[df_dt[i]].index.day
             vars()[df_dt[i]]['Hour']=vars()[df_dt[i]].index.hour
             vars()[df_dt[i]]['Year'] = 2021
             vars()[df_dt[i]].index=pd.to_datetime(df_Trip[['Year', 'Month', 'Day', 'Hour']])

         # df_Berlin

In [21]: weather=[]
         cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
                 'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

         df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan
                'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
                'df_Kufra','df_Jaghbub', 'df_Berlin']


         for i in np.arange(len(cities)):

             weather =vars()[df_dt[i]]
             # weather.index.name = None
             temp=weather['T2m']
             weather=weather.rename(columns={'WS10m':'wind_speed',  'T2m':'temperature', 'SP':
             weather['roughness_length'] = 0.15
             weather['temperature'] =273.15+temp
             weather.drop(['RH','G(h)','Gb(n)','Gd(h)','IR(h)','WD10m','Year', 'Month', 'Day',

             weather.columns=[['temperature', 'wind_speed', 'pressure', 'roughness_length'],[2
             vars()[df_dt[i]]=weather

         # vars()[df_dt[i]]
         # weather
         # df_Mis
```

0.3.2 Initialize wind turbine

There are three ways to initialize a WindTurbine object in the windpowerlib. You can either use turbine data from the OpenEnergy Database (oedb) turbine library that is provided along with the windpowerlib, as done for the 'enercon_e126', or specify your own turbine by directly providing a power (coefficient) curve, as done below for 'my_turbine', or provide your own turbine data in csv files, as done for 'my_turbine2'.

You can execute the following to get a table of all wind turbines for which power and/or power coefficient curves are provided.

We will use a wind trubine from GE, which is GE120/2500 https://www.thewindpower.net/turbine_en_592_ge-energy_2.5-120.php

```
In [22]: # get power curves
         # get names of wind turbines for which power curves and/or are provided
         # set print_out=True to see the list of all available wind turbines
         df = wt.get_turbine_types(print_out=False)

         # find all Enercons
         # print(df[df["manufacturer"].str.contains("Enercon")])
         print(df[df["manufacturer"].str.contains("GE")])
```

```
   manufacturer turbine_type  has_power_curve  has_cp_curve
21      GE Wind   GE100/2500             True         False
22      GE Wind   GE103/2750             True          True
23      GE Wind   GE120/2500             True          True
24      GE Wind   GE120/2750             True          True
25      GE Wind   GE130/3200             True          True
```

```
In [23]: # specification of wind turbine where power curve is provided in the
         # oedb turbine library

         ge_120 = {
                 'turbine_type': 'GE120/2500',  # turbine type as in oedb turbine library
                 'hub_height': 100  # in m
             }
         # initialize WindTurbine object
         ge120 = WindTurbine(**ge_120)
```

0.3.3 Use the ModelChain to calculate turbine power output

The ModelChain is a class that provides all necessary steps to calculate the power output of a wind turbine. When calling the 'run_model' method, first the wind speed and density (if necessary) at hub height are calculated and then used to calculate the power output.

```
In [24]: #### power output calculation for ge120
         cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
                 'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']
```

```
df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan
       'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
       'df_Kufra','df_Jaghbub', 'df_Berlin']



for i in np.arange(len(cities)):

    weather =vars()[df_dt[i]]
    #### own specifications for ModelChain setup
    modelchain_data = {
        'wind_speed_model': 'logarithmic',      # 'logarithmic' (default),
                                                # 'hellman' or
                                                # 'interpolation_extrapolation'
        'density_model': 'ideal_gas',           # 'barometric' (default), 'ideal_gas'
                                                #  or 'interpolation_extrapolation'
        'temperature_model': 'linear_gradient', # 'linear_gradient' (def.) or
                                                # 'interpolation_extrapolation'
        'power_output_model':
            'power_coefficient_curve',          # 'power_curve' (default) or
                                                # 'power_coefficient_curve'
        'density_correction': True,             # False (default) or True
        'obstacle_height': 0,                   # default: 0
        'hellman_exp': None}                    # None (default) or None

    # initialize ModelChain with own specifications and use run_model method to
    # calculate power output
    mc_ge120 = ModelChain(ge120, **modelchain_data).run_model(
        weather)
    # write power output time series to WindTurbine object
    ge120.power_output = mc_ge120.power_output

    vars()[df_dt[i]]['PW_Wind']=ge120.power_output
    vars()[df_dt[i]+'_PW_Curve']=ge120.power_curve
    vars()[df_dt[i]+'_PW_Cp']=ge120.power_coefficient_curve

# vars()[df_dt[i]]
# vars()[df_dt[i]]['PW_Wind']
```

In [25]:
```
cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
        'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan
       'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
       'df_Kufra','df_Jaghbub', 'df_Berlin']
```

```python
df_tem=pd.DataFrame({'Tripoli':df_Trip['PW_Wind',].resample('M').sum()})
df_tem
for i in np.arange(len(cities)):
    df_tem[cities[i]]=vars()[df_dt[i]]['PW_Wind',].resample('M').sum()

PW_Wind_comparison=df_tem

# # PW_Wind_comparison.describe()
PW_Wind_comparison
```

```
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performanc
  raw_cell, store_history, silent, shell_futures)
```

Out[25]:

	Tripoli	Zuwara	Tarhunah	Msallata	\
2021-01-31	1.233823e+09	6.563418e+08	1.072380e+09	1.055705e+09	
2021-02-28	1.232927e+09	1.065110e+09	1.159623e+09	9.861940e+08	
2021-03-31	6.840335e+08	7.589762e+08	8.782608e+08	1.057770e+09	
2021-04-30	7.975678e+08	7.148443e+08	9.418069e+08	1.039795e+09	
2021-05-31	5.213789e+08	4.840239e+08	9.634585e+08	8.989776e+08	
2021-06-30	8.850381e+08	1.096890e+09	8.484234e+08	7.085471e+08	
2021-07-31	9.846533e+08	5.610340e+08	7.718120e+08	5.483634e+08	
2021-08-31	5.452158e+08	7.112266e+08	5.983949e+08	4.434599e+08	
2021-09-30	7.999770e+08	4.926898e+08	7.690518e+08	4.187425e+08	
2021-10-31	6.382198e+08	5.594551e+08	5.472171e+08	7.673814e+08	
2021-11-30	8.181772e+08	4.881820e+08	8.167281e+08	7.731433e+08	
2021-12-31	7.116705e+08	5.167463e+08	5.576381e+08	1.014080e+09	

	Ghanima	Gharyan	Misurata	Sirte	\
2021-01-31	9.472439e+08	6.837305e+08	1.280761e+09	1.136600e+09	
2021-02-28	8.682733e+08	5.899248e+08	1.281676e+09	9.244250e+08	
2021-03-31	1.079482e+09	7.260579e+08	7.624387e+08	9.548665e+08	
2021-04-30	1.181007e+09	9.282684e+08	1.239411e+09	1.096995e+09	
2021-05-31	9.236674e+08	7.560305e+08	1.093043e+09	9.858632e+08	
2021-06-30	6.139530e+08	5.862362e+08	1.069205e+09	1.199379e+09	
2021-07-31	4.868493e+08	4.912442e+08	4.664368e+08	7.120975e+08	
2021-08-31	3.857082e+08	5.940871e+08	4.317863e+08	5.497205e+08	
2021-09-30	4.821710e+08	7.106109e+08	6.567398e+08	6.667348e+08	
2021-10-31	6.044576e+08	5.936234e+08	7.203912e+08	6.335377e+08	
2021-11-30	7.656827e+08	5.398451e+08	6.590450e+08	6.430542e+08	
2021-12-31	9.041625e+08	4.687127e+08	8.847158e+08	1.288761e+09	

	Magrun	Benghazi	Derna	Tobruk	\
2021-01-31	7.506282e+08	8.829393e+08	1.400028e+09	6.685409e+08	
2021-02-28	7.243157e+08	9.150553e+08	1.218404e+09	9.343409e+08	
2021-03-31	1.021578e+09	9.190877e+08	1.237225e+09	9.175855e+08	
2021-04-30	1.121674e+09	1.066776e+09	1.121666e+09	1.010394e+09	
2021-05-31	8.618430e+08	9.577347e+08	1.089353e+09	9.602590e+08	

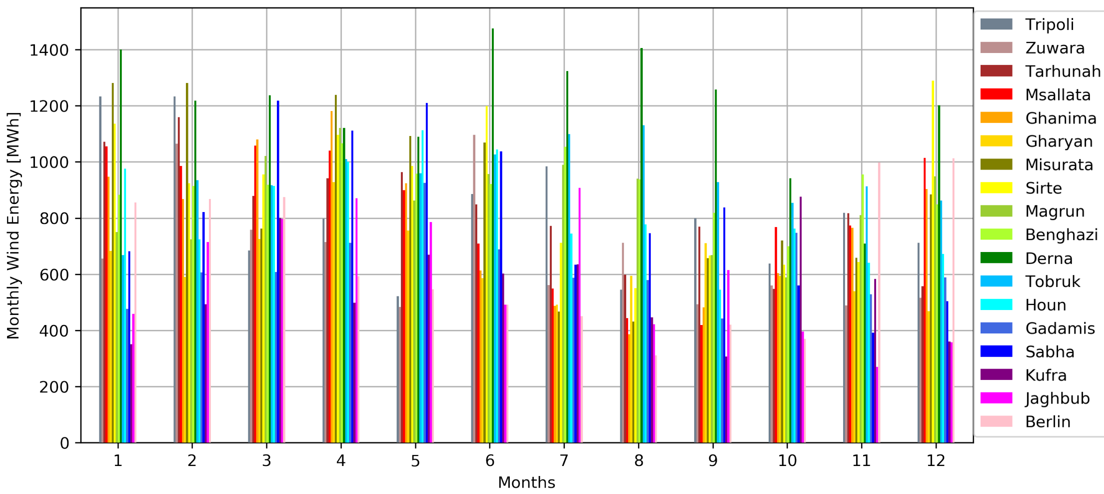
```
2021-06-30  9.565255e+08  9.207377e+08  1.476126e+09  1.027179e+09
2021-07-31  9.890508e+08  1.054671e+09  1.323571e+09  1.099174e+09
2021-08-31  9.398077e+08  9.380734e+08  1.406133e+09  1.130710e+09
2021-09-30  6.676445e+08  8.184178e+08  1.258601e+09  9.286683e+08
2021-10-31  5.882051e+08  6.997753e+08  9.422476e+08  8.538214e+08
2021-11-30  8.097814e+08  9.558372e+08  7.098323e+08  9.129622e+08
2021-12-31  9.490383e+08  8.493525e+08  1.202426e+09  8.620006e+08

                    Houn       Gadamis         Sabha         Kufra  \
2021-01-31  9.756065e+08  4.770973e+08  6.811497e+08  3.507817e+08
2021-02-28  7.243111e+08  6.068439e+08  8.219009e+08  4.935132e+08
2021-03-31  9.148067e+08  6.080890e+08  1.218285e+09  8.004039e+08
2021-04-30  1.000001e+09  7.116468e+08  1.112154e+09  4.981017e+08
2021-05-31  1.112512e+09  9.250209e+08  1.210722e+09  6.694428e+08
2021-06-30  1.044626e+09  6.879866e+08  1.037125e+09  6.023965e+08
2021-07-31  7.451443e+08  5.867695e+08  6.337102e+08  6.357442e+08
2021-08-31  7.778566e+08  5.789876e+08  7.455438e+08  4.467794e+08
2021-09-30  5.442506e+08  4.422653e+08  8.378133e+08  3.074311e+08
2021-10-31  7.623670e+08  7.472764e+08  5.601609e+08  8.755263e+08
2021-11-30  6.404036e+08  5.282371e+08  3.921635e+08  5.826436e+08
2021-12-31  6.728102e+08  5.888288e+08  5.036680e+08  3.596595e+08

                 Jaghbub        Berlin
2021-01-31  4.580622e+08  8.553083e+08
2021-02-28  7.151638e+08  8.684264e+08
2021-03-31  7.969964e+08  8.750233e+08
2021-04-30  8.710807e+08  5.932219e+08
2021-05-31  7.864301e+08  5.464065e+08
2021-06-30  4.912357e+08  4.918726e+08
2021-07-31  9.071451e+08  4.499309e+08
2021-08-31  4.215692e+08  3.111526e+08
2021-09-30  6.149091e+08  4.203312e+08
2021-10-31  3.956638e+08  3.693392e+08
2021-11-30  2.694907e+08  9.985872e+08
2021-12-31  3.570939e+08  1.012789e+09
```

In [26]:
```
PW_Wind_comparison.index=PW_Wind_comparison.index.month
PW_Wind_MW_comparison=PW_Wind_comparison/1000000
```

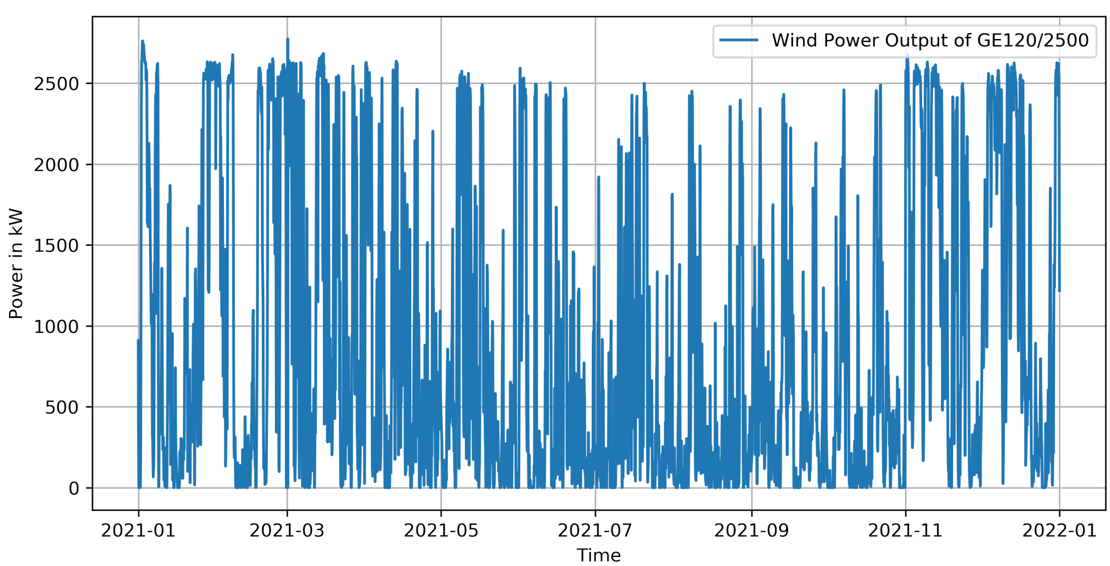
In [27]:
```
plt.rcParams['figure.figsize'] = [10, 5.0]
plt.rcParams['figure.dpi'] = 300

c = ['slategrey','rosybrown','brown','red','orange','gold','olive','yellow','yellowgre
     'greenyellow','green','deepskyblue','cyan','royalblue','blue','purple', 'magenta

PW_Wind_MW_comparison.plot.bar(zorder=3,color=c)

plt.xticks(rotation=0)
```

```python
plt.xlabel('Months');
plt.ylabel('Monthly Wind Energy [MWh]');
plt.legend(bbox_to_anchor=(1.16, 1.01),loc='upper right')
plt.grid()
print(PW_Wind_MW_comparison.describe())
```

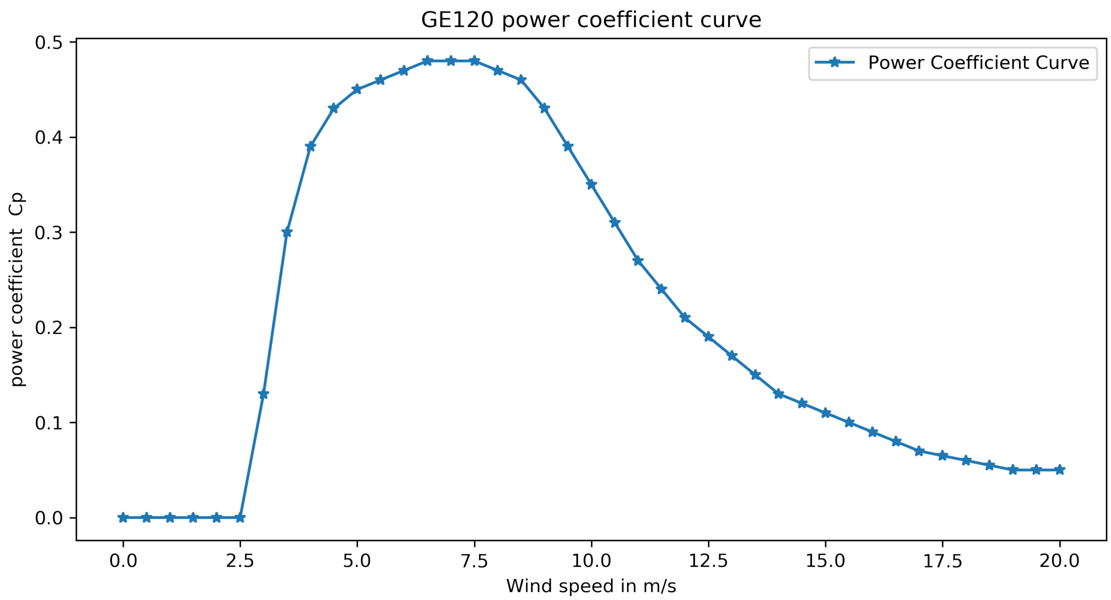
```
           Tripoli       Zuwara     Tarhunah     Msallata      Ghanima  \
count    12.000000    12.000000    12.000000    12.000000    12.000000
mean    821.056825   675.459966   827.066221   809.346621   770.221524
std     233.926976   212.446201   194.314965   238.275413   254.033909
min     521.378879   484.023854   547.217134   418.742487   385.708200
25%     672.580098   510.732170   726.387538   668.501164   575.055547
50%     798.772396   608.687876   832.575722   836.060412   816.977995
75%     909.941860   725.877305   947.219776  1020.508948   929.561518
max    1233.823277  1096.890154  1159.622684  1057.769908  1181.007409

          Gharyan     Misurata        Sirte       Magrun     Benghazi  \
count   12.000000    12.000000    12.000000    12.000000    12.000000
mean   639.030969   878.804142   899.336128   865.007682   914.871523
std    128.632750   307.809254   251.533855   159.065176    98.906348
min    468.712677   431.786324   549.720532   588.205146   699.775317
25%    574.638401   658.468730   660.814631   744.050056   874.542593
50%    593.855246   823.577259   939.645751   900.825343   919.912686
75%    714.472663  1129.635029  1106.896059   964.656818   956.311536
max    928.268427  1281.675922  1288.760593  1121.674038  1066.776437

             Derna       Tobruk         Houn      Gadamis        Sabha  \
count    12.000000    12.000000    12.000000    12.000000    12.000000
mean   1198.800997   942.136276   826.224600   624.087428   812.866307
std     214.103690   121.809220   178.624010   130.231251   278.576773
min     709.832314   668.540870   544.250580   442.265342   392.163546
25%    1113.587365   900.221765   711.435863   566.299973   615.322884
50%    1227.814324   931.504600   770.111790   597.836342   783.722317
75%    1342.685355  1014.589927   981.705039   693.901624  1055.881889
max    1476.126486  1130.709742  1112.512367   925.020885  1218.285181

            Kufra     Jaghbub       Berlin
count   12.000000   12.000000    12.000000
mean   551.868665  590.403390   649.365745
std    177.188393  219.000429   255.653201
min    307.431126  269.490707   311.152557
25%    424.999445  415.092845   442.530979
50%    540.372668  553.072423   569.814212
75%    644.168827  789.071642   870.075631
max    875.526262  907.145077  1012.788923
```

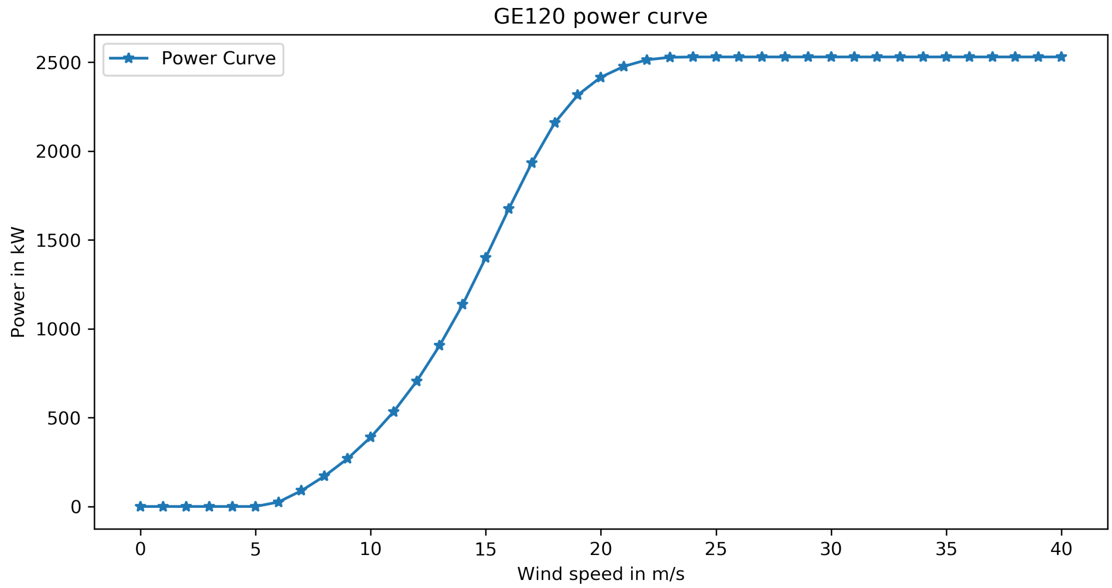


In [28]:
```python
plt.rcParams['figure.figsize'] = [10, 5.0]
plt.rcParams['figure.dpi'] = 300

#### plot turbine power output

plt.plot(ge120.power_output/1000)

# plt.legend(['Enercon E126'], bbox_to_anchor=(1.2, 1.02),loc='upper right')
plt.legend(['Wind Power Output of GE120/2500'],loc='upper right')

plt.xlabel('Time')
plt.ylabel('Power in kW')
plt.grid()
plt.show()
```



In [29]:
```
#### plot power (coefficient) curves
ge120pcrv_kw=ge120.power_curve['value']/1000

if plt:
    if ge120.power_coefficient_curve is not None:
        ge120.power_coefficient_curve.plot(
        x='wind_speed', y='value', style='-*',
        title='GE120 power coefficient curve')
        plt.xlabel('Wind speed in m/s')
        plt.ylabel('power coefficient  Cp')
        plt.legend(['Power Coefficient Curve'],loc='upper right')
        plt.show()

    if ge120.power_curve is not None:
        ge120pcrv_kw.plot(x='wind_speed', y='value', style='-*',
        title='GE120 power curve')
        plt.xlabel('Wind speed in m/s')
        plt.ylabel('Power in kW')
        plt.legend(['Power Curve'],loc='upper left')
        plt.show()
```





0.4 Calculating Net Capacity Factor

For demonstration purposes, we'll assume a 1kW array with a temperature coefficient of -0.4%/řC:

0.4.1 Capacity Factor for all locations

In [30]: PW_Wind_comparison

Out[30]:

	Tripoli	Zuwara	Tarhunah	Msallata	Ghanima
1	1.233823e+09	6.563418e+08	1.072380e+09	1.055705e+09	9.472439e+08
2	1.232927e+09	1.065110e+09	1.159623e+09	9.861940e+08	8.682733e+08
3	6.840335e+08	7.589762e+08	8.782608e+08	1.057770e+09	1.079482e+09
4	7.975678e+08	7.148443e+08	9.418069e+08	1.039795e+09	1.181007e+09
5	5.213789e+08	4.840239e+08	9.634585e+08	8.989776e+08	9.236674e+08
6	8.850381e+08	1.096890e+09	8.484234e+08	7.085471e+08	6.139530e+08
7	9.846533e+08	5.610340e+08	7.718120e+08	5.483634e+08	4.868493e+08
8	5.452158e+08	7.112266e+08	5.983949e+08	4.434599e+08	3.857082e+08
9	7.999770e+08	4.926898e+08	7.690518e+08	4.187425e+08	4.821710e+08
10	6.382198e+08	5.594551e+08	5.472171e+08	7.673814e+08	6.044576e+08
11	8.181772e+08	4.881820e+08	8.167281e+08	7.731433e+08	7.656827e+08
12	7.116705e+08	5.167463e+08	5.576381e+08	1.014080e+09	9.041625e+08

	Gharyan	Misurata	Sirte	Magrun	Benghazi
1	6.837305e+08	1.280761e+09	1.136600e+09	7.506282e+08	8.829393e+08
2	5.899248e+08	1.281676e+09	9.244250e+08	7.243157e+08	9.150553e+08
3	7.260579e+08	7.624387e+08	9.548665e+08	1.021578e+09	9.190877e+08
4	9.282684e+08	1.239411e+09	1.096995e+09	1.121674e+09	1.066776e+09

```
5    7.560305e+08  1.093043e+09  9.858632e+08  8.618430e+08  9.577347e+08
6    5.862362e+08  1.069205e+09  1.199379e+09  9.565255e+08  9.207377e+08
7    4.912442e+08  4.664368e+08  7.120975e+08  9.890508e+08  1.054671e+09
8    5.940871e+08  4.317863e+08  5.497205e+08  9.398077e+08  9.380734e+08
9    7.106109e+08  6.567398e+08  6.667348e+08  6.676445e+08  8.184178e+08
10   5.936234e+08  7.203912e+08  6.335377e+08  5.882051e+08  6.997753e+08
11   5.398451e+08  6.590450e+08  6.430542e+08  8.097814e+08  9.558372e+08
12   4.687127e+08  8.847158e+08  1.288761e+09  9.490383e+08  8.493525e+08

            Derna        Tobruk          Houn       Gadamis         Sabha  \
1    1.400028e+09  6.685409e+08  9.756065e+08  4.770973e+08  6.811497e+08
2    1.218404e+09  9.343409e+08  7.243111e+08  6.068439e+08  8.219009e+08
3    1.237225e+09  9.175855e+08  9.148067e+08  6.080890e+08  1.218285e+09
4    1.121666e+09  1.010394e+09  1.000001e+09  7.116468e+08  1.112154e+09
5    1.089353e+09  9.602590e+08  1.112512e+09  9.250209e+08  1.210722e+09
6    1.476126e+09  1.027179e+09  1.044626e+09  6.879866e+08  1.037125e+09
7    1.323571e+09  1.099174e+09  7.451443e+08  5.867695e+08  6.337102e+08
8    1.406133e+09  1.130710e+09  7.778566e+08  5.789876e+08  7.455438e+08
9    1.258601e+09  9.286683e+08  5.442506e+08  4.422653e+08  8.378133e+08
10   9.422476e+08  8.538214e+08  7.623670e+08  7.472764e+08  5.601609e+08
11   7.098323e+08  9.129622e+08  6.404036e+08  5.282371e+08  3.921635e+08
12   1.202426e+09  8.620006e+08  6.728102e+08  5.888288e+08  5.036680e+08

            Kufra       Jaghbub        Berlin
1    3.507817e+08  4.580622e+08  8.553083e+08
2    4.935132e+08  7.151638e+08  8.684264e+08
3    8.004039e+08  7.969964e+08  8.750233e+08
4    4.981017e+08  8.710807e+08  5.932219e+08
5    6.694428e+08  7.864301e+08  5.464065e+08
6    6.023965e+08  4.912357e+08  4.918726e+08
7    6.357442e+08  9.071451e+08  4.499309e+08
8    4.467794e+08  4.215692e+08  3.111526e+08
9    3.074311e+08  6.149091e+08  4.203312e+08
10   8.755263e+08  3.956638e+08  3.693392e+08
11   5.826436e+08  2.694907e+08  9.985872e+08
12   3.596595e+08  3.570939e+08  1.012789e+09
```

In [31]:
```
typical_hrs=8760
```

In [32]:
```
# ghi_comparison_and_Berlin.describe()
rating_pw=2500000    ##2,500 kW
day_hrs=typical_hrs
PW_Wind_comparison.sum()
PW_CFs=PW_Wind_comparison.sum()/(day_hrs*rating_pw)

PW_CFs
```

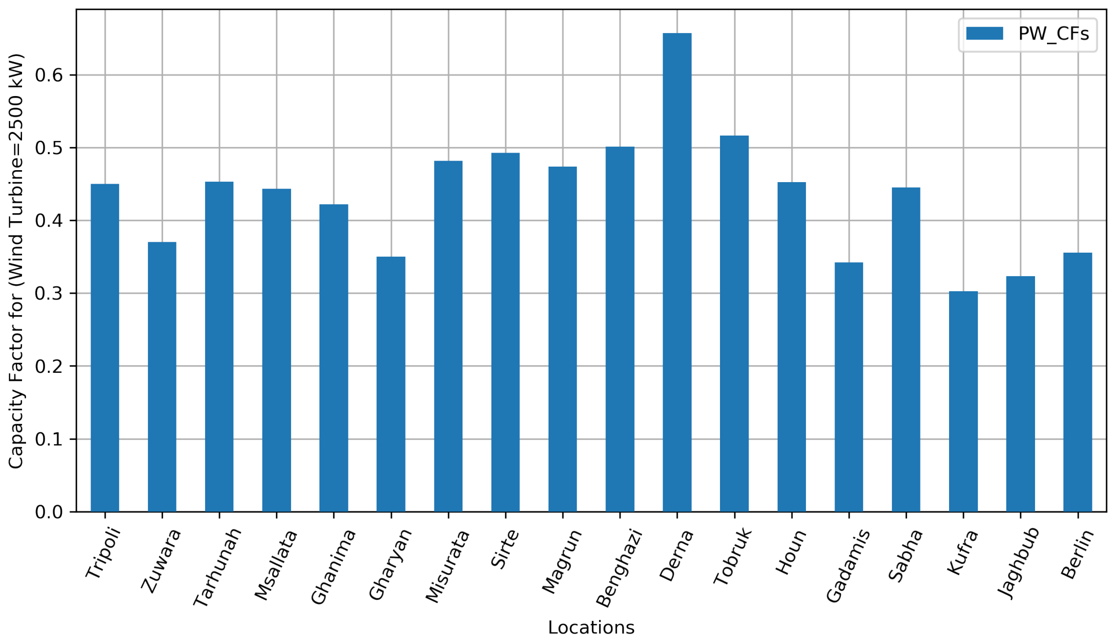
Out[32]:
```
Tripoli      0.449894
Zuwara       0.370115
```

```
Tarhunah    0.453187
Msallata    0.443478
Ghanima     0.422039
Gharyan     0.350154
Misurata    0.481537
Sirte       0.492787
Magrun      0.473977
Benghazi    0.501299
Derna       0.656877
Tobruk      0.516239
Houn        0.452726
Gadamis     0.341966
Sabha       0.445406
Kufra       0.302394
Jaghbub     0.323509
Berlin      0.355817
dtype: float64
```

In [42]:
```
# CFs_dict={'GHI': GHI_CFs, 'DNI':DNI_CFs}
CFs_dict={'PW_CFs': PW_CFs}

df_pw_cfs=pd.DataFrame(CFs_dict)
df_pw_cfs.T
```

Out[42]:
```
         Tripoli    Zuwara  Tarhunah  Msallata   Ghanima   Gharyan  Misurata  \
PW_CFs  0.449894  0.370115  0.453187  0.443478  0.422039  0.350154  0.481537

           Sirte    Magrun  Benghazi     Derna    Tobruk      Houn   Gadamis  \
PW_CFs  0.492787  0.473977  0.501299  0.656877  0.516239  0.452726  0.341966

           Sabha     Kufra   Jaghbub    Berlin
PW_CFs  0.445406  0.302394  0.323509  0.355817
```

In [34]:
```
plt.rcParams['figure.figsize'] = [10, 5.0]
plt.rcParams['figure.dpi'] = 300

df_pw_cfs.plot.bar(zorder=3)
# plt.yticks(np.arange(0, 1, 0.1))
plt.xticks(rotation=0)
# plt.title('Capacity Factors Based on GHI and DNI')
plt.xlabel('Locations');
plt.ylabel('Capacity Factor for (Wind Turbine=2500 kW)');
# plt.legend(bbox_to_anchor=(1.2, 1.02),loc='upper right')
# plt.legend(bbox_to_anchor=(1.08,1.01),loc='upper right')

plt.xticks(rotation=65)
plt.grid()
```



0.5 Wind Power Variability for given locations

In [35]:
```
# ge120.power_output.describe()
# ge120.power_output.max()
```

In [36]:
```
df_pw_variability=[]

cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
        'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

i=0
dt=[df_Trip,df_Zuwara, df_Tarhunah, df_Msallata, df_Ghanima, df_Gharyan, df_Misurata,
    df_Benghazi, df_Derna, df_Tobruk, df_Houn, df_Gadamis, df_Sabha, df_Kufra, df_Jag

for dti in dt:
    dti_pw=dti['PW_Wind',]/ge120.power_output.max()
    dti_pw[dti_pw>10]=0
    dti_pw[dti_pw>1]=1
# #    dti_pw_variability=1-dti_pw.describe()[1]#mean
    dti_pw_variability=dti_pw.describe()[2]#std deviation

    df_pw_variability.append(dti_pw_variability)
    print('Wind Power Variability of', cities[i],'=', round(dti_pw_variability,4))
    i=i+1

PW_Var_dict= {'Wind Power Variability':df_pw_variability}
```

```
    df_pw_var=pd.DataFrame(PW_Var_dict)
    df_pw_var.index=cities
```

```
Wind Power Variability of Tripoli = 0.3259
Wind Power Variability of Zuwara = 0.3134
Wind Power Variability of Tarhunah = 0.3076
Wind Power Variability of Msallata = 0.315
Wind Power Variability of Ghanima = 0.3163
Wind Power Variability of Gharyan = 0.295
Wind Power Variability of Misurata = 0.3329
Wind Power Variability of Sirte = 0.3259
Wind Power Variability of Magrun = 0.3182
Wind Power Variability of Benghazi = 0.3159
Wind Power Variability of Derna = 0.3144
Wind Power Variability of Tobruk = 0.3136
Wind Power Variability of Houn = 0.2798
Wind Power Variability of Gadamis = 0.2785
Wind Power Variability of Sabha = 0.2867
Wind Power Variability of Kufra = 0.2351
Wind Power Variability of Jaghbub = 0.2863
Wind Power Variability of Berlin = 0.3257
```

```
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
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  raw_cell, store_history, silent, shell_futures)
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  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
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  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
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  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
```

```
  raw_cell, store_history, silent, shell_futures)
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  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
C:\Users\Mhdella\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2899: Performance
  raw_cell, store_history, silent, shell_futures)
```
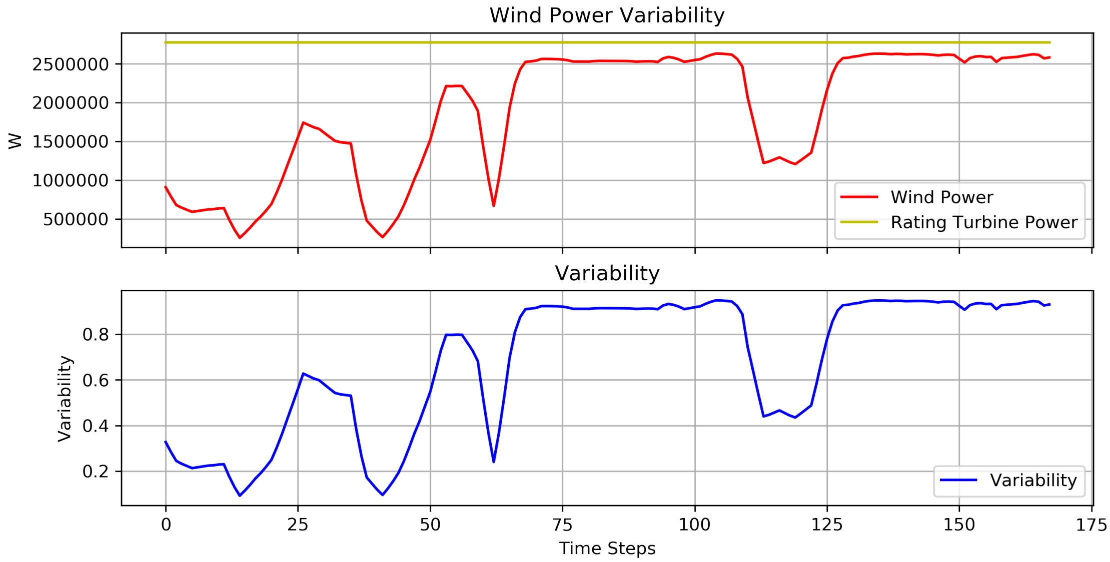

In [37]:
```
df_noise=1-dti_pw
dti_pw.describe()
df_noise.describe()
```

Out[37]:
```
count    8760.000000
mean        0.679462
std         0.325731
min         0.000000
25%         0.434836
50%         0.822675
75%         0.949489
max         1.000000
Name: (PW_Wind,), dtype: float64
```

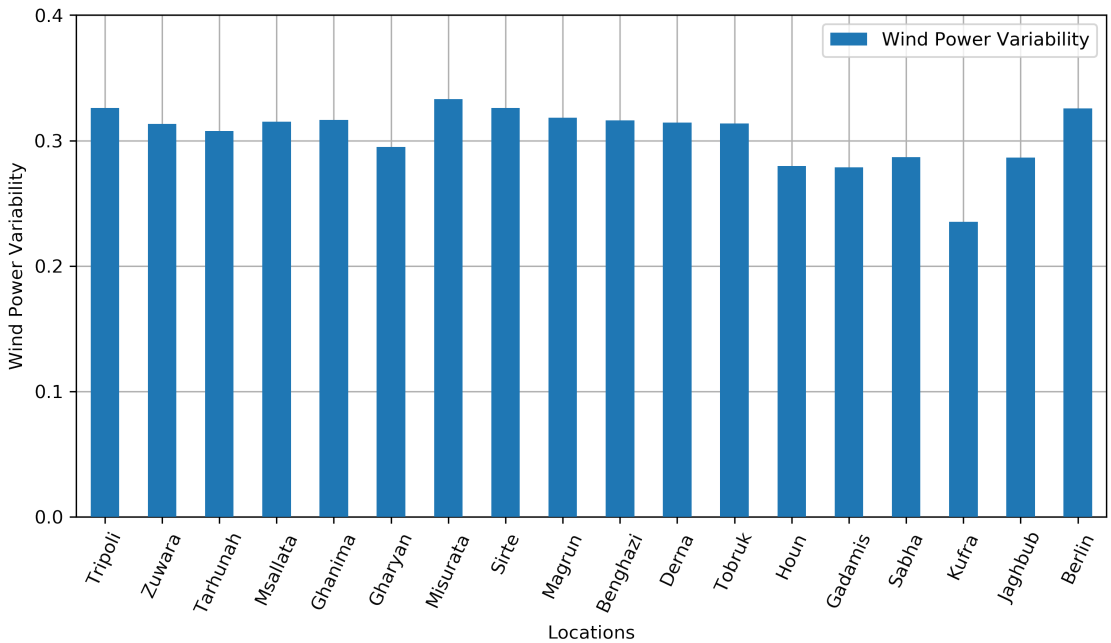
In [38]:
```
# Const_PW=ge120.power_output.max()*np.ones(8760)
dti['Const_PW']=ge120.power_output.max()
```

In [76]:
```
fig, axs = plt.subplots(2)
axs[0].plot(
dti['2021-01-24':'2021-01-30'][['PW_Wind',]].values,'r-',
dti['2021-01-24':'2021-01-30'][['Const_PW']].values,'y-',zorder=3)
axs[0].set_title('Wind Power Variability')
axs[0].set(xlabel='Time Steps', ylabel='W')
axs[0].legend(['Wind Power', 'Rating Turbine Power'], loc='lower right')
axs[0].label_outer()
axs[0].grid()


axs[1].plot(dti_pw['2021-01-24':'2021-01-30'].values,'b-',zorder=3)
axs[1].set_title('Variability')
axs[1].set(xlabel='Time Steps', ylabel='Variability')
axs[1].legend(['Variability'], loc='lower right')
axs[1].label_outer()
axs[1].grid()
```

```
# fig.suptitle('GHI Variability', color='orange')

for ax in axs.flat:
    ax.label_outer()
```




```
In [77]: plt.rcParams['figure.figsize'] = [10, 5.0]
         plt.rcParams['figure.dpi'] = 300

         df_pw_var.plot.bar(zorder=3)
         plt.xticks(rotation=0)
         plt.xlabel('Locations');
         plt.ylabel('Wind Power Variability');
         plt.yticks(np.arange(0, 0.5, 0.1))

         plt.xticks(rotation=65)
         plt.grid()
```



0.6 Aggregation of Some Locations and then Calculate the Variability Factors the Wind Power

In [78]:
```
cities=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata',
        'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub','Berlin']

df_dt=['df_Trip','df_Zuwara', 'df_Tarhunah', 'df_Msallata', 'df_Ghanima', 'df_Gharyan
       'df_Sirte','df_Magrun','df_Benghazi', 'df_Derna', 'df_Tobruk', 'df_Houn','df_Ga
       'df_Kufra','df_Jaghbub', 'df_Berlin']


df_tem=pd.DataFrame({'Tripoli':df_Trip['PW_Wind']})

for i in np.arange(len(cities)):
    df_tem[cities[i]]=vars()[df_dt[i]]['PW_Wind']

df_pwi=df_tem
df_pwi=df_pwi.drop(df_pwi.columns[-1], axis = 1) ### drop Berlin Column

df_pwi.describe()
```

Out[78]:

	Tripoli	Zuwara	Tarhunah	Msallata	Ghanima	\
count	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03	
mean	1.124735e+06	9.252876e+05	1.132967e+06	1.108694e+06	1.055098e+06	
std	9.045518e+05	8.697813e+05	8.536700e+05	8.740421e+05	8.777576e+05	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	

```
25%    2.849261e+05  1.778221e+05  3.281590e+05  2.773044e+05  2.412286e+05
50%    8.864910e+05  5.692916e+05  9.798336e+05  9.390867e+05  8.290779e+05
75%    2.117460e+06  1.696361e+06  2.045035e+06  2.018223e+06  1.925031e+06
max    2.701884e+06  2.751882e+06  2.572662e+06  2.559644e+06  2.614749e+06

            Gharyan      Misurata         Sirte        Magrun     Benghazi  \
count  8.760000e+03  8.760000e+03  8.760000e+03  8.760000e+03  8.760000e+03
mean   8.753849e+05  1.203841e+06  1.231967e+06  1.184942e+06  1.253249e+06
std    8.185537e+05  9.237246e+05  9.045546e+05  8.830059e+05  8.767755e+05
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    1.598462e+05  2.872960e+05  3.781087e+05  3.713953e+05  4.411392e+05
50%    5.717048e+05  1.076485e+06  1.101054e+06  1.008379e+06  1.105333e+06
75%    1.543270e+06  2.226730e+06  2.238574e+06  2.151313e+06  2.225949e+06
max    2.505678e+06  2.750912e+06  2.712657e+06  2.693715e+06  2.702251e+06

              Derna        Tobruk          Houn       Gadamis         Sabha  \
count  8.760000e+03  8.760000e+03  8.760000e+03  8.760000e+03  8.760000e+03
mean   1.642193e+06  1.290598e+06  1.131815e+06  8.549143e+05  1.113515e+06
std    8.726092e+05  8.703866e+05  7.763619e+05  7.729529e+05  7.957098e+05
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    8.661029e+05  4.672832e+05  4.291030e+05  2.055079e+05  3.891420e+05
50%    2.026356e+06  1.222763e+06  1.033785e+06  5.869258e+05  9.608268e+05
75%    2.403194e+06  2.235560e+06  1.920503e+06  1.419236e+06  1.928967e+06
max    2.768783e+06  2.664395e+06  2.501903e+06  2.540151e+06  2.487014e+06

              Kufra       Jaghbub
count  8.760000e+03  8.760000e+03
mean   7.559845e+05  8.087718e+05
std    6.524434e+05  7.946478e+05
min    0.000000e+00  0.000000e+00
25%    2.384865e+05  1.431595e+05
50%    5.465814e+05  5.113383e+05
75%    1.134275e+06  1.324050e+06
max    2.452718e+06  2.631017e+06
```

In [79]:
```
west_locs=[df_pwi['Tripoli'],df_pwi['Zuwara'], df_pwi['Tarhunah'],df_pwi['Msallata'],
           df_pwi['Gharyan'],df_pwi['Misurata'], df_pwi['Sirte'], df_pwi['Houn'], df_p

east_locs=[df_pwi['Magrun'],df_pwi['Benghazi'], df_pwi['Derna'], df_pwi['Tobruk'],df_p

df_agg_west_pw=pd.DataFrame(sum(west_locs))
df_agg_east_pw=pd.DataFrame(sum(east_locs))
df_agg_all_pw=pd.DataFrame(df_pwi.sum(axis=1))

df_agg_west_maxpw=len(list(west_locs))*ge120.power_output.max()
df_agg_east_maxpw=len(list(east_locs))*ge120.power_output.max()
df_agg_all_maxpw=len(list(df_pwi))*ge120.power_output.max()
```

```
        # df_agg_west_pw
        # df_agg_east_pw
        # df_agg_all_pw
```

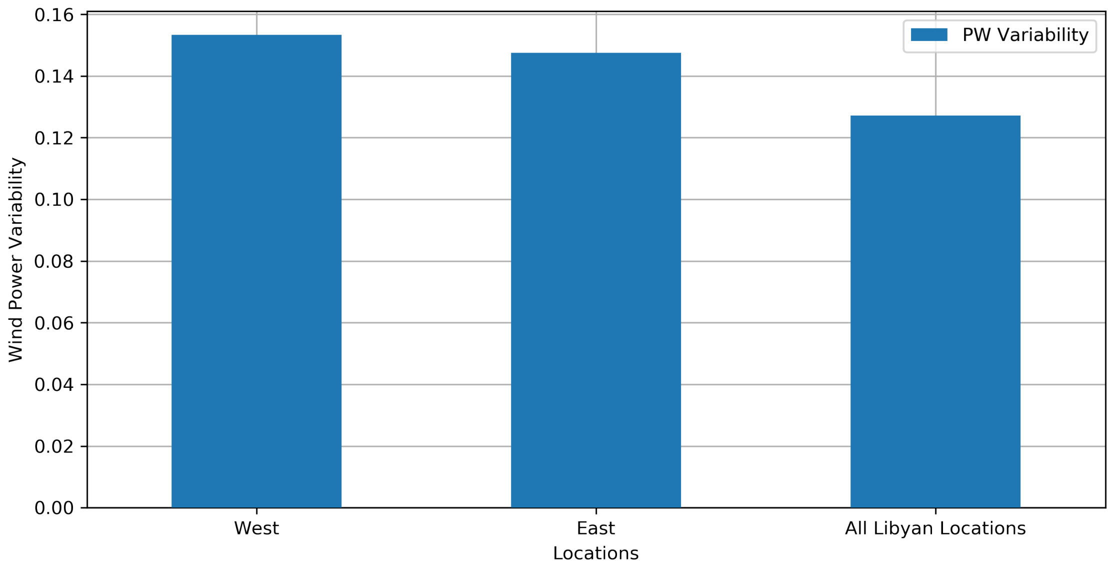
```
In [80]: df_aggi_pw_variability=[]
         cities=['West','East', 'All Libyan Locations']
         i=0
         dagg=[df_agg_west_pw, df_agg_east_pw, df_agg_all_pw]
         dagg_max=[df_agg_west_maxpw, df_agg_east_maxpw, df_agg_all_maxpw]

         for daggi in dagg:
             dagg_pw=daggi/dagg_max[i]
             dagg_pw[dagg_pw>10]=0
             dagg_pw[dagg_pw>1]=1
         # #     dfagg_pw_variability=1-dagg_pw[0].describe()[1]#mean
             dfagg_pw_variability=dagg_pw[0].describe()[2]#std deviation

             df_aggi_pw_variability.append(dfagg_pw_variability)
             print('PW Variability of', cities[i],'=', round(dfagg_pw_variability,4))
             i=i+1

         AggPW_Var_dict= {'PW Variability':df_aggi_pw_variability}
         df_aggpw_var=pd.DataFrame(AggPW_Var_dict)
         df_aggpw_var.index=cities
         df_aggpw_var
```

```
PW Variability of West = 0.1534
PW Variability of East = 0.1475
PW Variability of All Libyan Locations = 0.1272
```

Out[80]:

	PW Variability
West	0.153398
East	0.147481
All Libyan Locations	0.127237

```
In [81]: plt.rcParams['figure.figsize'] = [10, 5.0]
         plt.rcParams['figure.dpi'] = 300

         df_aggpw_var.plot.bar(zorder=3)
         # plt.yticks(np.arange(0, 1, 0.1))
         plt.xticks(rotation=0)
         plt.xlabel('Locations');
         plt.ylabel('Wind Power Variability');
         # plt.legend(bbox_to_anchor=(1.16, 1.01),loc='upper right')
         plt.grid()
```



0.6.1 Wind Power Capacity Factor for aggregated locations

In [82]:
```
# df_agg_all_pw.describe()
```

In [83]:
```
typical_hrs=8760
rating_pw=2500000
day_hrs=typical_hrs
# Agg_All_PW_CFs=df_agg_all_pw.sum()/(9*day_hrs*rating_pw)
# Agg_All_PW_CFs=df_agg_all_pw.sum()/(10*day_hrs*rating_pw)
Agg_All_PW_CFs=df_agg_all_pw.sum()/(17*day_hrs*rating_pw)

Agg_All_PW_CFs
```

Out[83]:
```
0    0.439858
dtype: float64
```

In [84]:
```
# df_pw_cfs.min()
# df_pw_cfs.max()
df_pw_cfs.mean()
```

Out[84]:
```
PW_CFs    0.435189
dtype: float64
```

In [85]:
```
PW_AggPW_CFs=pd.DataFrame(df_pw_cfs)
df2 = pd.DataFrame([Agg_All_PW_CFs], index=['Aggregated'])
PW_AggPW_CFs=PW_AggPW_CFs.append(df2)
PW_AggPW_CFs=PW_AggPW_CFs.drop('Berlin')
PW_AggPW_CFs=PW_AggPW_CFs.rename({0: 'PW_CFs'}, axis=1)
PW_AggPW_CFs
```

Out[85]:

	PW_CFs	PW_CFs
Tripoli	0.449894	NaN
Zuwara	0.370115	NaN
Tarhunah	0.453187	NaN
Msallata	0.443478	NaN
Ghanima	0.422039	NaN
Gharyan	0.350154	NaN
Misurata	0.481537	NaN
Sirte	0.492787	NaN
Magrun	0.473977	NaN
Benghazi	0.501299	NaN
Derna	0.656877	NaN
Tobruk	0.516239	NaN
Houn	0.452726	NaN
Gadamis	0.341966	NaN
Sabha	0.445406	NaN
Kufra	0.302394	NaN
Jaghbub	0.323509	NaN
Aggregated	NaN	0.439858

In [86]:

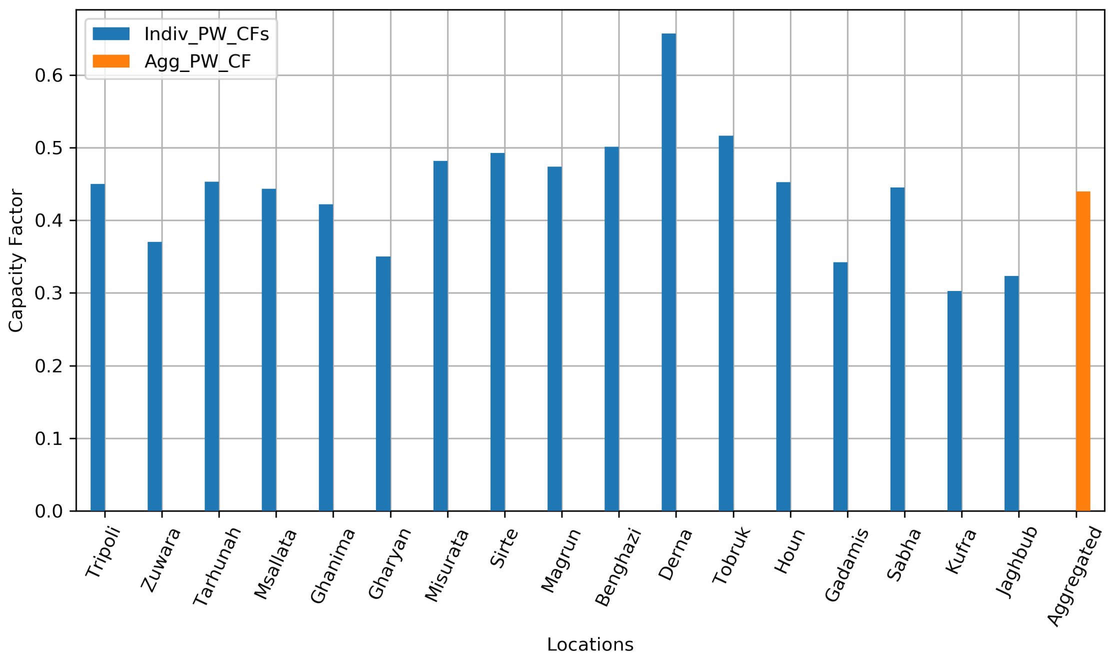
```
PW_AggPW_CFs.describe()   #mean of CFs = Agg CF
```

Out[86]:

	PW_CFs	PW_CFs
count	17.000000	1.000000
mean	0.439858	0.439858
std	0.085929	NaN
min	0.302394	0.439858
25%	0.370115	0.439858
50%	0.449894	0.439858
75%	0.481537	0.439858
max	0.656877	0.439858

In [87]:

```
plt.rcParams['figure.figsize'] = [10, 5.0]
plt.rcParams['figure.dpi'] = 300

PW_AggPW_CFs.plot.bar(zorder=3)
# plt.yticks(np.arange(0, 1, 0.1))
plt.xticks(rotation=0)
# plt.title('Capacity Factors')
plt.xlabel('Locations');
plt.ylabel('Capacity Factor');

plt.legend(['Indiv_PW_CFs','Agg_PW_CF'],loc='upper left')


plt.xticks(rotation=65)
plt.grid()
```



0.6.2 Improvement of aggregation vs. other best variability for each region

In [88]:
```
West_locs=['Tripoli','Zuwara','Tarhunah','Msallata','Ghanima','Gharyan','Misurata','Si
           'Sabha']

East_locs=['Magrun','Benghazi','Derna','Tobruk','Kufra','Jaghbub']

All_locs=['Tripoli','Zuwara', 'Tarhunah', 'Msallata', 'Ghanima', 'Gharyan', 'Misurata
        'Derna', 'Tobruk','Houn','Gadamis','Sabha','Kufra', 'Jaghbub']

min_west=df_pw_var.loc[West_locs].min()
min_east=df_pw_var.loc[East_locs].min()
min_all=df_pw_var.loc[All_locs].min()

pw_improvement_agg_west=(1-(df_aggpw_var/min_west.values))*100
pw_improvement_agg_east=(1-(df_aggpw_var/min_east.values))*100
pw_improvement_agg_all=(1-(df_aggpw_var/min_all.values))*100

df_pw_improv = pd.concat([pw_improvement_agg_west, pw_improvement_agg_east, pw_improve
df_pw_improv.columns=['Agg vs. Best West','Agg vs. Best East','Agg vs. Best All']

df_pw_improv
```

Out[88]:

	Agg vs. Best West	Agg vs. Best East	Agg vs. Best All
West	44.925192	34.752601	34.752601

```
East                          47.049281         37.269021         37.269021
All Libyan Locations          54.317646         45.879888         45.879888
```

In [89]:
```python
# df_agg_all_PW=df_agg_all_pw/9
# df_agg_all_PW=df_agg_all_pw/10
df_agg_all_PW=df_agg_all_pw/17


df_indiv_PW=df_Trip['PW_Wind']
print('Avg Aggregated PW:',df_agg_all_PW.mean(),
'Avg individual PW:',df_indiv_PW.mean())

print('Std Aggregated PW:',df_agg_all_PW.std(),
'Std individual PW:',df_indiv_PW.std())
```

```
Avg Aggregated PW: 0    1.099645e+06
dtype: float64 Avg individual PW: 1124735.3772854137
Std Aggregated PW: 0    353103.104608
dtype: float64 Std individual PW: 904551.7877033348
```

In [90]:
```python
df_pwi.describe()
```

Out[90]:

	Tripoli	Zuwara	Tarhunah	Msallata	Ghanima
count	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03
mean	1.124735e+06	9.252876e+05	1.132967e+06	1.108694e+06	1.055098e+06
std	9.045518e+05	8.697813e+05	8.536700e+05	8.740421e+05	8.777576e+05
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2.849261e+05	1.778221e+05	3.281590e+05	2.773044e+05	2.412286e+05
50%	8.864910e+05	5.692916e+05	9.798336e+05	9.390867e+05	8.290779e+05
75%	2.117460e+06	1.696361e+06	2.045035e+06	2.018223e+06	1.925031e+06
max	2.701884e+06	2.751882e+06	2.572662e+06	2.559644e+06	2.614749e+06

\

	Gharyan	Misurata	Sirte	Magrun	Benghazi
count	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03
mean	8.753849e+05	1.203841e+06	1.231967e+06	1.184942e+06	1.253249e+06
std	8.185537e+05	9.237246e+05	9.045546e+05	8.830059e+05	8.767755e+05
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	1.598462e+05	2.872960e+05	3.781087e+05	3.713953e+05	4.411392e+05
50%	5.717048e+05	1.076485e+06	1.101054e+06	1.008379e+06	1.105333e+06
75%	1.543270e+06	2.226730e+06	2.238574e+06	2.151313e+06	2.225949e+06
max	2.505678e+06	2.750912e+06	2.712657e+06	2.693715e+06	2.702251e+06

\

	Derna	Tobruk	Houn	Gadamis	Sabha
count	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03	8.760000e+03
mean	1.642193e+06	1.290598e+06	1.131815e+06	8.549143e+05	1.113515e+06
std	8.726092e+05	8.703866e+05	7.763619e+05	7.729529e+05	7.957098e+05
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	8.661029e+05	4.672832e+05	4.291030e+05	2.055079e+05	3.891420e+05

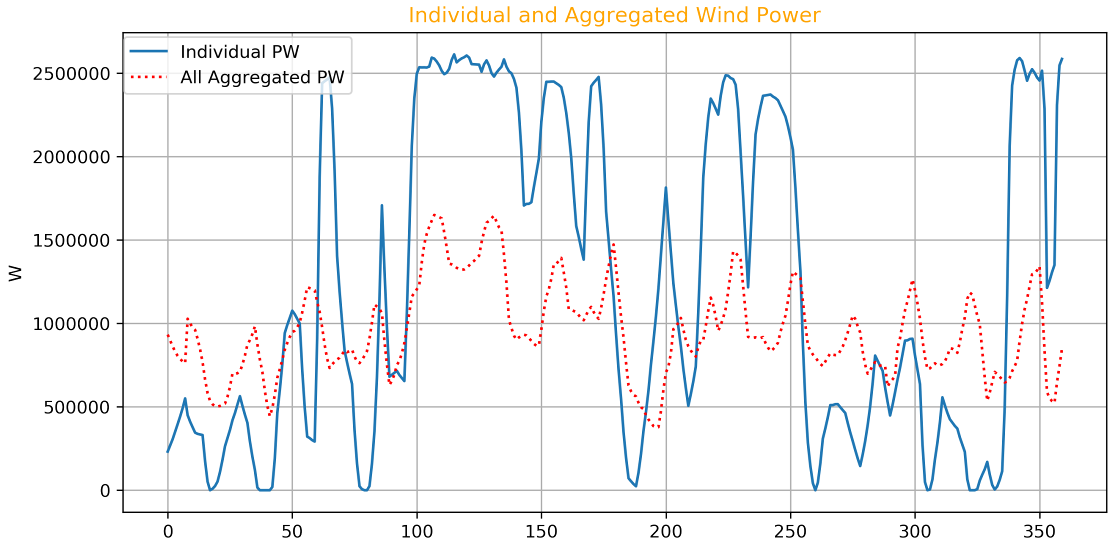
\

```
50%    2.026356e+06  1.222763e+06  1.033785e+06  5.869258e+05  9.608268e+05
75%    2.403194e+06  2.235560e+06  1.920503e+06  1.419236e+06  1.928967e+06
max    2.768783e+06  2.664395e+06  2.501903e+06  2.540151e+06  2.487014e+06

              Kufra       Jaghbub
count  8.760000e+03  8.760000e+03
mean   7.559845e+05  8.087718e+05
std    6.524434e+05  7.946478e+05
min    0.000000e+00  0.000000e+00
25%    2.384865e+05  1.431595e+05
50%    5.465814e+05  5.113383e+05
75%    1.134275e+06  1.324050e+06
max    2.452718e+06  2.631017e+06
```

```
In [91]: Avg_all_agg=df_agg_all_pw/17
         ## print(df_pwi.describe())
         print('\n')
         print('All agg:', Avg_all_agg.describe())
```

```
All agg:                    0
count  8.760000e+03
mean   1.099645e+06
std    3.531031e+05
min    2.788272e+05
25%    8.260719e+05
50%    1.075667e+06
75%    1.356446e+06
max    2.387103e+06
```

```
In [92]: plt.plot(
             df_indiv_PW['2021-01-01':'2021-01-15'].values,'-',
             df_agg_all_PW['2021-01-01':'2021-01-15'].values,'r:',zorder=3)

         plt.legend(['Individual PW', 'All Aggregated PW'],bbox_to_anchor=(-0.008, 1.009),loc=

         plt.ylabel('W')

         plt.title('Individual and Aggregated Wind Power', color='orange')

         plt.grid()
```


Individual and Aggregated Wind Power
Individual PW
All Aggregated PW
W
2500000
2000000
1500000
1000000
500000
0
0
50
100
150
200
250
300
350

In [ ]:

In [ ]:

In [ ]: