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Ideas:

- working on NOAA csv file to clean data from CSV file to numeric field (column)
- Try out some correlation of meteorological paramater with $PM_{2.5}$ concentration
- How wind speed (and direction)?
- Do temperature and relative humidity change $PM_{2.5}$?
- What else do we have?

For this part, we will focus on getting data, and clean data first, the second part will be on analysis

Data exploratory and cleaning (wrangle data)

Data source for meteology

- depend on where you live, the availablity data to the public use differs
- those experienced a higher with $PM_{2.5}$ are in developing countries, and implementation of sharing data is limited
- Open API (Application Program Interface) such as Darksky.net recently acquired by Apple (darksky.net), Openweathermap.org (openweather.org) offers a limited access with free membership. Darksky has been my favorite one to get historical data but recently new registration is no longer open, and a future use is remained to be seen,
- It not always the case, but during search for such data, I often find that research institute in the US like EPA, NOAA are archieved data systematically.
- In this section, we will use meteological data availablity to public use by NCEI (ncei.noaa.gov). We do need to understand the format, and clean the data so that it can be usable for analysism

ref on NCEI.NOAA

- how each data file is formated: https://www.ncei.noaa.gov/data/global-hourly/doc/isd-format-document.pdf (https://www.ncei.noaa.gov/data/global-hourly/doc/isd-format-document.pdf)
- a collection of data: https://www.ncei.noaa.gov/access/search/data-search/global-hourly (https://www.ncei.noaa.gov/access/search/data-search/global-hourly)

Working on Noibai site

In [1]:
```
import pandas as pd
```

In [2]:
```
# we will continue to work with 2018, location is Hanoi
year = 2018
site = 488200 # NOIBAI AIRPORT
base_url = f'https://www.ncei.noaa.gov/data/global-hourly/access/{year}/{site}99999.csv'
```

In [3]:
```
df = pd.read_csv(base_url)
df.head()
```

Out[3]:

	STATION	DATE	SOURCE	LATITUDE	LONGITUDE	ELEVATION	NAME
0	48820099999	2018-01-01T00:00:00	4	21.221192	105.807178	11.88	NOIBAI INTERNATIONAL, VM
1	48820099999	2018-01-01T00:30:00	4	21.221192	105.807178	11.88	NOIBAI INTERNATIONAL, VM
2	48820099999	2018-01-01T01:00:00	4	21.221192	105.807178	11.88	NOIBAI INTERNATIONAL, VM
3	48820099999	2018-01-01T01:30:00	4	21.221192	105.807178	11.88	NOIBAI INTERNATIONAL, VM
4	48820099999	2018-01-01T02:00:00	4	21.221192	105.807178	11.88	NOIBAI INTERNATIONAL, VM

5 rows × 29 columns

In [4]:
```
# or value of one row
df.iloc[0]
```

Out[4]:
```
STATION                                                            48820099999
DATE                                                       2018-01-01T00:00:00
SOURCE                                                                       4
LATITUDE                                                               21.2212
LONGITUDE                                                              105.807
ELEVATION                                                                11.88
NAME                                                NOIBAI INTERNATIONAL, VM
REPORT_TYPE                                                             FM-15
CALL_SIGN                                                               99999
QUALITY_CONTROL                                                          V020
WND                                                          080,1,N,0015,1
CIG                                                             01067,1,C,N
VIS                                                           008000,1,9,9
TMP                                                               +0160,1
DEW                                                               +0120,1
SLP                                                               99999,9
GA1                                                    07,1,+01067,1,99,9
GA2                                                                   NaN
GA3                                                                   NaN
GA4                                                                   NaN
GE1                                                  9,MSL   ,+99999,+99999
GF1                                      99,99,9,07,1,99,9,01067,1,99,9,99,9
MA1                                                        10190,1,99999,9
MW1                                                                   NaN
MW2                                                                   NaN
MW3                                                                   NaN
OC1                                                                   NaN
REM                  MET057METAR VVNB 010000Z 08003KT 8000 BKN035 1...
EQD                                                                   NaN
Name: 0, dtype: object
```

What in here?

- columns from `Station` to `Quality_control` is metadata (or data about data)
- we have wind, tempeature, and few other

In [5]:
```
# let save the raw file, so if you want to work on it directly,
df.to_csv('data/noibai_noaa_isd_2018.csv', index=False)
```

In [6]:
```
# and read again, this time from local file
df = pd.read_csv('data/noibai_noaa_isd_2018.csv')
```

In [7]:
```
# a few exploratory functions
df.columns
```

Out[7]:
```
Index(['STATION', 'DATE', 'SOURCE', 'LATITUDE', 'LONGITUDE', 'ELEVATI
ON',
       'NAME', 'REPORT_TYPE', 'CALL_SIGN', 'QUALITY_CONTROL', 'WND',
'CIG',
       'VIS', 'TMP', 'DEW', 'SLP', 'GA1', 'GA2', 'GA3', 'GA4', 'GE1',
'GF1',
       'MA1', 'MW1', 'MW2', 'MW3', 'OC1', 'REM', 'EQD'],
      dtype='object')
```

In [8]:
```
df.shape
```

Out[8]:
```
(16911, 29)
```

In [9]:
```
df.describe()
```

Out[9]:

	STATION	SOURCE	LATITUDE	LONGITUDE	ELEVATION	CALL_SIGN
count	1.691100e+04	16911.0	1.691100e+04	1.691100e+04	1.691100e+04	16911.0
mean	4.882010e+10	4.0	2.122119e+01	1.058072e+02	1.188000e+01	99999.0
std	0.000000e+00	0.0	5.403837e-12	1.078636e-11	2.762317e-12	0.0
min	4.882010e+10	4.0	2.122119e+01	1.058072e+02	1.188000e+01	99999.0
25%	4.882010e+10	4.0	2.122119e+01	1.058072e+02	1.188000e+01	99999.0
50%	4.882010e+10	4.0	2.122119e+01	1.058072e+02	1.188000e+01	99999.0
75%	4.882010e+10	4.0	2.122119e+01	1.058072e+02	1.188000e+01	99999.0
max	4.882010e+10	4.0	2.122119e+01	1.058072e+02	1.188000e+01	99999.0

In [10]:
```
# now will want to create a list of columns that contain Wind, Temper
ature and relevant data
cols = ['DATE', 'WND', 'CIG', 'VIS', 'TMP', 'DEW', 'GA1']
```

In [11]:
```
# and select those columns, reassign to the df name
df = df[cols]
```

In [12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16911 entries, 0 to 16910
Data columns (total 7 columns):
DATE    16911 non-null object
WND     16911 non-null object
CIG     16911 non-null object
VIS     16911 non-null object
TMP     16911 non-null object
DEW     16911 non-null object
GA1     11853 non-null object
dtypes: object(7)
memory usage: 924.9+ KB
```

In [13]:
```
df.head(3)
```

Out[13]:

	DATE	WND	CIG	VIS	TMP	DEW	GA1
0	2018-01-01T00:00:00	080,1,N,0015,1	01067,1,C,N	008000,1,9,9	+0160,1	+0120,1	07,1,+01067,1,99,9
1	2018-01-01T00:30:00	060,1,N,0015,1	00975,1,C,N	008000,1,9,9	+0160,1	+0120,1	07,1,+00975,1,99,9
2	2018-01-01T01:00:00	080,1,N,0015,1	00975,1,C,N	007000,1,9,9	+0160,1	+0120,1	07,1,+00975,1,99,9

In [14]:
```
# again a smaller file, just in case you need it later
df.to_csv('data/reduced_noibai_noaa_isd_2018.csv', index=False)
```

Wait, each column contains other types of data rather numeric values!!

- yes, they are formatted with a QA/QC inplace
- let take sometime to read through a description for one parameter, in this case `TMP` or air temperature

Time to read some manual, here is what I found for **TMP** term, more on [ncei.noaa.gov] (https://www.ncei.noaa.gov/data/global-hourly/doc/isd-format-document.pdf (https://www.ncei.noaa.gov/data/global-hourly/doc/isd-format-document.pdf))

POS: 88-92 AIR-TEMPERATURE-OBSERVATION air temperature

```
 The temperature of the air.
 MIN: -0932 MAX: +0618 UNITS: Degrees Celsius
 SCALING FACTOR: 10
 DOM: A general domain comprised of the numeric characters (0-9), a plus sign (+), and a minus sign (-). +9999 = Missing.
```

POS: 93-93 AIR-TEMPERATURE-OBSERVATION air temperature quality code

```
 The code that denotes a quality status of an AIR-TEMPERATURE-OBSERVATION.
 DOM: A specific domain comprised of the characters in the ASCII character set.

 0 = Passed gross limits check
 1 = Passed all quality control checks
 2 = Suspect
 3 = Erroneous
 4 = Passed gross limits check, data originate from an NCEI data source
 5 = Passed all quality control checks, data originate from an NCEI data source
 6 = Suspect, data originate from an NCEI data source
 7 = Erroneous, data originate from an NCEI data source
 9 = Passed gross limits check if element is present
 A = Data value flagged as suspect, but accepted as a good value
 C = Temperature and dew point received from Automated Weather Observing System (AWOS) are reported in
    whole degrees Celsius. Automated QC flags these values, but they are accepted as valid.
 I = Data value not originally in data, but inserted by validator
 M = Manual changes made to value based on information provided by NWS or FAA
 P = Data value not originally flagged as suspect, but replaced by validator
 R = Data value replaced with value computed by NCEI software
 U = Data value replaced with edited value
```

*so if the value code is **3**, or **7**, the data should not be used*, let see what the distribution of the quality code on **TMP**

In [15]:
```python
# let work on TMP by first splitting each column by the comma, the op
tion expand=True, as the name implies
# expand each field to a columns
df['TMP'].str.split(pat=',', expand=True).sample(5)
```

Out[15]:

	0	1
14248	+0240	1
12056	+0270	1
16490	+0240	1
7297	+0320	1
2569	+0160	1

In [16]:
```python
df['TMP'].str.split(pat=',', expand=True)[1].value_counts(normalize=T
rue)
# for the file I were working on, only a few instance with code 5, so
the TMP will be processed as it is
```

Out[16]:
```
1    0.999113
5    0.000532
2    0.000355
Name: 1, dtype: float64
```

In [17]:
```
# the scaling factor is 10, to take temperature,
# 1. take the first element
# 2. cast type is int(eger)
# 3. deviding to 10
df['TMP'].str.split(pat=',', expand=True)[0].astype(int)/10
```

Out[17]:
```
0        16.0
1        16.0
2        16.0
3        17.0
4        17.0
         ...
16906    11.0
16907    11.0
16908    11.0
16909    11.0
16910    11.0
Name: 0, Length: 16911, dtype: float64
```

In [18]:
```
# and assign processed value back to the columns
df['TMP'] = df['TMP'].str.split(pat=',', expand=True)[0].astype(int)/
10
df.head(3)
```

Out[18]:

	DATE	WND	CIG	VIS	TMP	DEW	GA1
0	2018-01-01T00:00:00	080,1,N,0015,1	01067,1,C,N	008000,1,9,9	16.0	+0120,1	07,1,+01067,1,99,9
1	2018-01-01T00:30:00	060,1,N,0015,1	00975,1,C,N	008000,1,9,9	16.0	+0120,1	07,1,+00975,1,99,9
2	2018-01-01T01:00:00	080,1,N,0015,1	00975,1,C,N	007000,1,9,9	16.0	+0120,1	07,1,+00975,1,99,9

In [19]:
```
# Dewpoint temperature is processed the same way
df['DEW'] = df['DEW'].str.split(pat=',', expand=True)[0].astype(int)/
10
df.head(3)
```

Out[19]:

	DATE	WND	CIG	VIS	TMP	DEW	GA1
0	2018-01-01T00:00:00	080,1,N,0015,1	01067,1,C,N	008000,1,9,9	16.0	12.0	07,1,+01067,1,99,9
1	2018-01-01T00:30:00	060,1,N,0015,1	00975,1,C,N	008000,1,9,9	16.0	12.0	07,1,+00975,1,99,9
2	2018-01-01T01:00:00	080,1,N,0015,1	00975,1,C,N	007000,1,9,9	16.0	12.0	07,1,+00975,1,99,9

In [20]:
```python
# What is this parameter?
df['CIG']
```

Out[20]:
```
0        01067,1,C,N
1        00975,1,C,N
2        00975,1,C,N
3        00975,1,C,N
4        01006,1,9,N
            ...
16906    01250,1,C,N
16907    01250,1,C,N
16908    01219,1,C,N
16909    01219,1,C,N
16910    01158,1,C,N
Name: CIG, Length: 16911, dtype: object
```

here is the definition from [weather.gove (https://forecast.weather.gov/glossary.php?word=cig)](https://forecast.weather.gov/glossary.php?word=cig)

> CIG: Ceiling- The height of the lowest layer of clouds, when the sky is broken or overcast.

POS: 71-75 SKY-CONDITION-OBSERVATION ceiling height dimension

```
The height above ground level (AGL) of the lowest cloud or obscuring phenome
na layer aloft with 5/8 or more summation total skycover, which may be predo
minantly opaque, or the vertical visibility into a surface-based obstructio
n.
Unlimited = 22000. MIN: 00000 MAX: 22000 UNITS: Meters
SCALING FACTOR: 1
DOM: A general domain comprised of the numeric characters (0-9).
99999 = Missing.
```

In [21]:
```python
# we have 2/3 data is passed with confident, and 1/3 is take-it-as-it
-is
df['CIG'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[21]:
```
1    10942
9     5969
Name: 1, dtype: int64
```

```
In [22]: df['CIG'].str.split(pat=',', expand=True)[0].astype(int)
```

```
Out[22]: 0        1067
         1         975
         2         975
         3         975
         4        1006
                  ...
         16906    1250
         16907    1250
         16908    1219
         16909    1219
         16910    1158
         Name: 0, Length: 16911, dtype: int64
```

```
In [23]: df['CIG'] =  df['CIG'].str.split(pat=',', expand=True)[0].astype(int
         )
```

```
In [24]: df.query('CIG==99999')
```

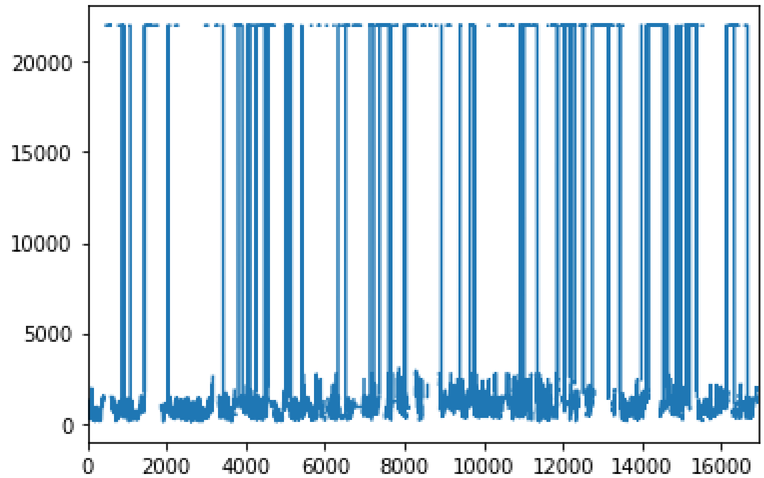
Out[24]:

	DATE	WND	CIG	VIS	TMP	DEW	GA1
330	2018-01-07T21:30:00	100,1,N,0026,1	99999	001500,1,9,9	21.0	20.0	04,1,+00091,1,99,9
405	2018-01-09T11:00:00	020,1,N,0015,1	99999	999999,9,9,9	13.0	5.0	NaN
406	2018-01-09T11:30:00	020,1,N,0015,1	99999	999999,9,9,9	13.0	6.0	NaN
407	2018-01-09T12:00:00	999,9,V,0010,1	99999	999999,9,9,9	13.0	6.0	NaN
408	2018-01-09T12:30:00	080,1,N,0015,1	99999	999999,9,9,9	13.0	6.0	NaN
...	...	...	...	...	...	...	...
16893	2018-12-31T15:00:00	060,1,N,0026,1	99999	999999,9,9,9	12.0	5.0	NaN
16894	2018-12-31T15:30:00	070,1,N,0026,1	99999	999999,9,9,9	12.0	5.0	NaN
16895	2018-12-31T16:00:00	060,1,V,0015,1	99999	999999,9,9,9	12.0	6.0	NaN
16896	2018-12-31T16:30:00	030,1,N,0026,1	99999	999999,9,9,9	12.0	6.0	NaN
16897	2018-12-31T17:00:00	050,1,V,0021,1	99999	999999,9,9,9	12.0	6.0	NaN

5969 rows × 7 columns

```
In [25]: # and assign any value with 99999 (missing) as None (or null)
         df.loc[df['CIG'] == 99999, 'CIG'] = None
```

In [26]:
```
df['CIG'].plot(kind='line')
```
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd4df3a550>



- we see many place with above 20000 (meter). Those are from 22000 value with a clear sky

next is **VIS** (visiblity)

POS: 79-84 VISIBILITY-OBSERVATION distance dimension

```
The horizontal distance at which an object can be seen and identified.
MIN: 000000 MAX: 160000 UNITS: Meters
DOM: A general domain comprised of the numeric characters (0-9).
Missing = 999999
NOTE: Values greater than 160000 are entered as 160000
```

In [27]:
```
 df['VIS'] =  df['VIS'].str.split(pat=',', expand=True)[0].astype(int
)
```

In [28]:
```
df.head()
```
Out[28]:

	DATE	WND	CIG	VIS	TMP	DEW	GA1
0	2018-01-01T00:00:00	080,1,N,0015,1	1067.0	8000	16.0	12.0	07,1,+01067,1,99,9
1	2018-01-01T00:30:00	060,1,N,0015,1	975.0	8000	16.0	12.0	07,1,+00975,1,99,9
2	2018-01-01T01:00:00	080,1,N,0015,1	975.0	7000	16.0	12.0	07,1,+00975,1,99,9
3	2018-01-01T01:30:00	060,1,V,0021,1	975.0	7000	17.0	12.0	07,1,+00975,1,99,9
4	2018-01-01T02:00:00	080,1,N,0031,1	1006.0	7000	17.0	12.0	04,1,+00762,1,99,9

In [29]:
```
# and wind
df['WND'].str.split(pat=',', expand=True)
```

Out[29]:

	0	1	2	3	4
0	080	1	N	0015	1
1	060	1	N	0015	1
2	080	1	N	0015	1
3	060	1	V	0021	1
4	080	1	N	0031	1
...	...	...	...	...	...
16906	020	1	N	0031	1
16907	030	1	N	0036	1
16908	020	1	N	0031	1
16909	030	1	N	0031	1
16910	030	1	V	0036	1

16911 rows × 5 columns

format
0 - the angle 1 - quality code for the wind direction
2 - characters of this observation (N for Normal, V for Variable, C: Calm)
3 - Wind speed (m/s), scaling factor of 10
4 - Quality code for windspeed

In [30]:
```
df['WND'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[30]:
```
1    15202
9     1709
Name: 1, dtype: int64
```

In [31]:
```
df['WND'].str.split(pat=',', expand=True)[2].value_counts()
```

Out[31]:
```
N    8805
V    7988
C     118
Name: 2, dtype: int64
```

In [32]:
```
df['WND'].str.split(pat=',', expand=True)[4].value_counts()
```

Out[32]:
```
1    16904
9        6
2        1
Name: 4, dtype: int64
```

In [33]:
```
# look data is good quality
df['WD'] =  df['WND'].str.split(pat=',', expand=True)[0].astype(int)
```

In [34]:
```
df['WS'] = df['WND'].str.split(pat=',', expand=True)[3].astype(int)/10
```

In [35]:
```
df.head()
```

Out[35]:

	DATE	WND	CIG	VIS	TMP	DEW	GA1	WD	WS
0	2018-01-01T00:00:00	080,1,N,0015,1	1067.0	8000	16.0	12.0	07,1,+01067,1,99,9	80	1.5
1	2018-01-01T00:30:00	060,1,N,0015,1	975.0	8000	16.0	12.0	07,1,+00975,1,99,9	60	1.5
2	2018-01-01T01:00:00	080,1,N,0015,1	975.0	7000	16.0	12.0	07,1,+00975,1,99,9	80	1.5
3	2018-01-01T01:30:00	060,1,V,0021,1	975.0	7000	17.0	12.0	07,1,+00975,1,99,9	60	2.1
4	2018-01-01T02:00:00	080,1,N,0031,1	1006.0	7000	17.0	12.0	04,1,+00762,1,99,9	80	3.1

In [36]:
```
df.drop(columns=['WND'], inplace=True)
df.head(3)
```

Out[36]:

	DATE	CIG	VIS	TMP	DEW	GA1	WD	WS
0	2018-01-01T00:00:00	1067.0	8000	16.0	12.0	07,1,+01067,1,99,9	80	1.5
1	2018-01-01T00:30:00	975.0	8000	16.0	12.0	07,1,+00975,1,99,9	60	1.5
2	2018-01-01T01:00:00	975.0	7000	16.0	12.0	07,1,+00975,1,99,9	80	1.5

FLD LEN: 3 SKY-COVER-LAYER identifier

```
 The identifier that represents a SKY-COVER-LAYER.
 DOM: A specific domain comprised of the characters in the ASCII character s
et.
 GA1-GA6 An indicator of up to 6 repeating fields of the following items:
 SKY-COVER-LAYER coverage code
 SKY-COVER-LAYER coverage quality code
 SKY-COVER-LAYER base height dimension
 SKY-COVER-LAYER base height quality code
 SKY-COVER-LAYER cloud type code
 SKY-COVER-LAYER cloud type quality code
```

SKY-COVER-LAYER coverage code

```
 The code that denotes the fraction of the total celestial dome covered by a
SKY-COVER-LAYER.
 Note: This is for a discrete cloud layer, as opposed to the cloud later sum
mation data in the GD1-GD6 section.
```

SKY-COVER-LAYER base height dimension

```
 The height relative to a VERTICAL-REFERENCE-DATUM of the lowest surface of
 a cloud.
 MIN: -00400 MAX: +35000 UNITS: Meters
 SCALING FACTOR: 1
 DOM: A general domain comprised of the numeric characters (0-9), a plus sig
n (+), and a minus sign (-).
 +99999 = Missing
```

https://www.ngs.noaa.gov/datums/vertical/#:~:text=A%20vertical%20datum%20is%20a,the%20surface%20of%20t
(https://www.ngs.noaa.gov/datums/vertical/#:~:text=A%20vertical%20datum%20is%20a,the%20surface%20of%20

In [37]:
```
# let split out GA columns
df['GA1'].str.split(pat=',', expand=True)[4].value_counts()
```

Out[37]:
```
99    11390
08      250
09      213
Name: 4, dtype: int64
```

In [38]:
```
df['GA1'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[38]:
```
1    11853
Name: 1, dtype: int64
```

In [39]:
```
df['CLDCR'] = df['GA1'].str.split(pat=',', expand=True)[0].astype(flo
at)/10
```

In [40]:
```
df['CLDHT'] = df['GA1'].str.split(pat=',', expand=True)[2].astype(flo
at)
```

In [41]:
```
# and convert DATE column to proper data type
df['DATE'] = pd.to_datetime(df['DATE'])
df.set_index('DATE', inplace=True)
```

In [42]:
```
df.drop(columns=['GA1'], inplace=True)
```

In [43]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 16911 entries, 2018-01-01 00:00:00 to 2018-12-31 23:3
0:00
Data columns (total 8 columns):
CIG      10942 non-null float64
VIS      16911 non-null int64
TMP      16911 non-null float64
DEW      16911 non-null float64
WD       16911 non-null int64
WS       16911 non-null float64
CLDCR    11853 non-null float64
CLDHT    11853 non-null float64
dtypes: float64(6), int64(2)
memory usage: 1.2 MB
```

In [44]:
```
# and save to file
df.to_csv('data/cleaned_noibai_noaa_isd_2018.csv')
```

In [45]:
```
# assume that you return to work the file, then this may help
df = pd.read_csv('data/cleaned_noibai_noaa_isd_2018.csv',
                parse_dates=['DATE'],
                index_col=['DATE'])
```

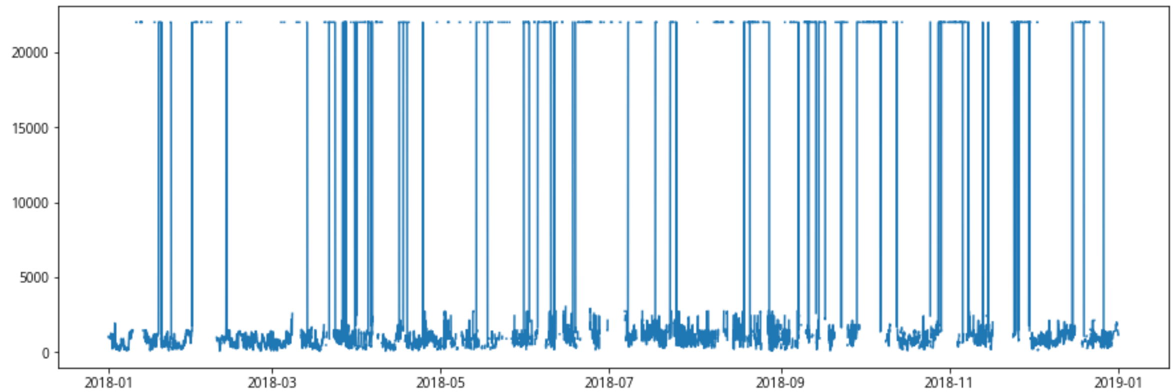
In [46]:
```
# sweet, you got the same information as before saving
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 16911 entries, 2018-01-01 00:00:00 to 2018-12-31 23:3
0:00
Data columns (total 8 columns):
CIG      10942 non-null float64
VIS      16911 non-null int64
TMP      16911 non-null float64
DEW      16911 non-null float64
WD       16911 non-null int64
WS       16911 non-null float64
CLDCR    11853 non-null float64
CLDHT    11853 non-null float64
dtypes: float64(6), int64(2)
memory usage: 1.2 MB
```

In [47]:
```
# let bring a big tool,
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] =  (15,5)
plt.rcParams['font.sans-serif'] = 'Open Sans'
```

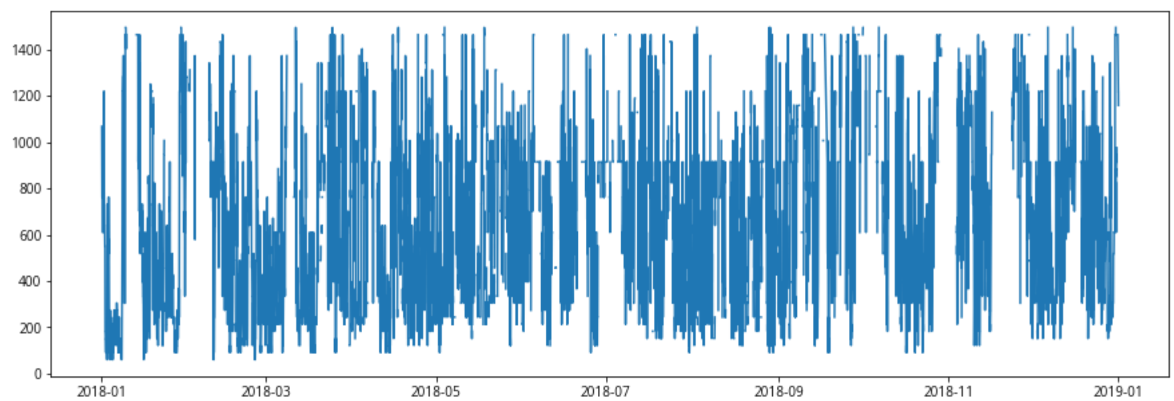
In [48]:
```python
# not easy to see the pattern
plt.plot(df.index, df['CIG'])
```

Out[48]: [<matplotlib.lines.Line2D at 0x7fbd41988ba8>]



In [49]:
```python
# let try out with cloud height, both CIG and CLDHT supposed to be si
milar (in a ball part)
plt.plot(df.index, df['CLDHT'])
```

Out[49]: [<matplotlib.lines.Line2D at 0x7fbd4d0e8828>]

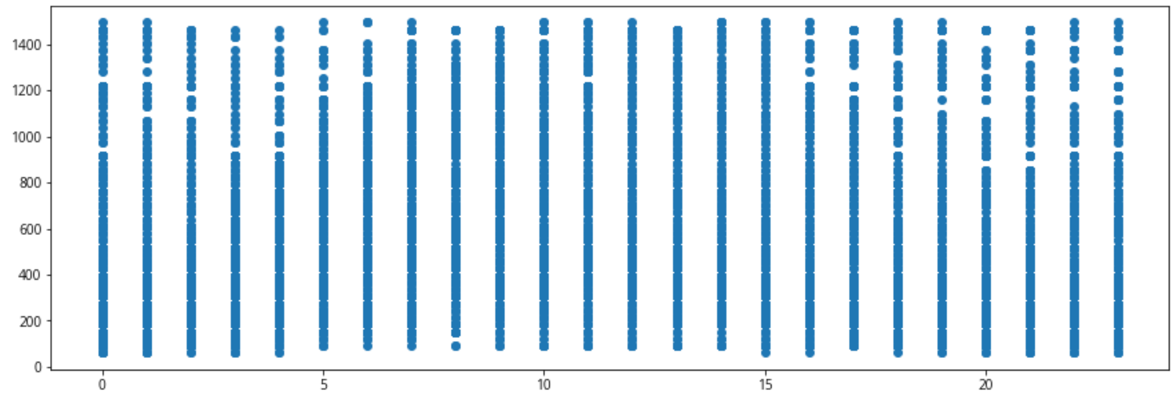


In [50]:
```python
df['CLDHT'].describe()
```

Out[50]:
```
count    11853.000000
mean       612.704379
std        351.049698
min         61.000000
25%        305.000000
50%        549.000000
75%        914.000000
max       1494.000000
Name: CLDHT, dtype: float64
```

In [51]:
```python
# let see the distribution by hour
plt.scatter(df.index.hour, df['CLDHT'])
```

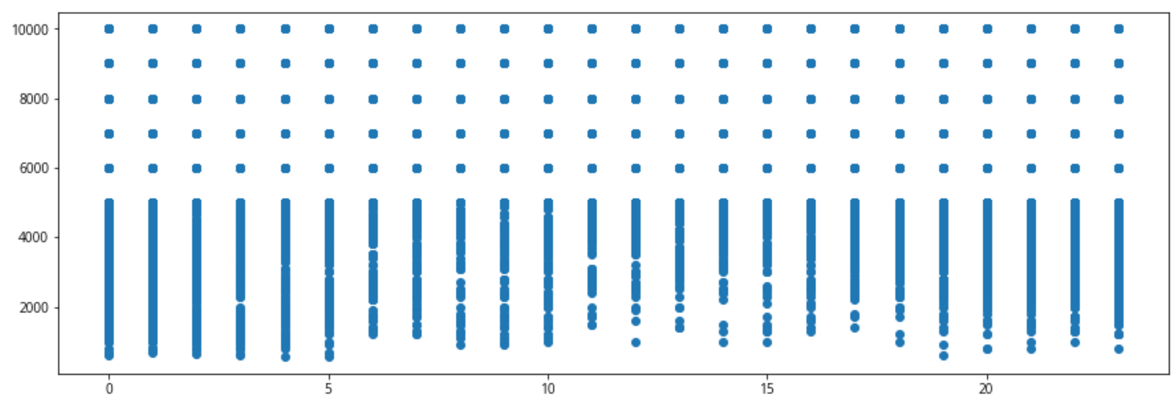
Out[51]: <matplotlib.collections.PathCollection at 0x7fbd41d2ffd0>



In [52]:
```python
# cleaning with VIS
df.loc[df['VIS'] == 999999, 'VIS'] = None
```

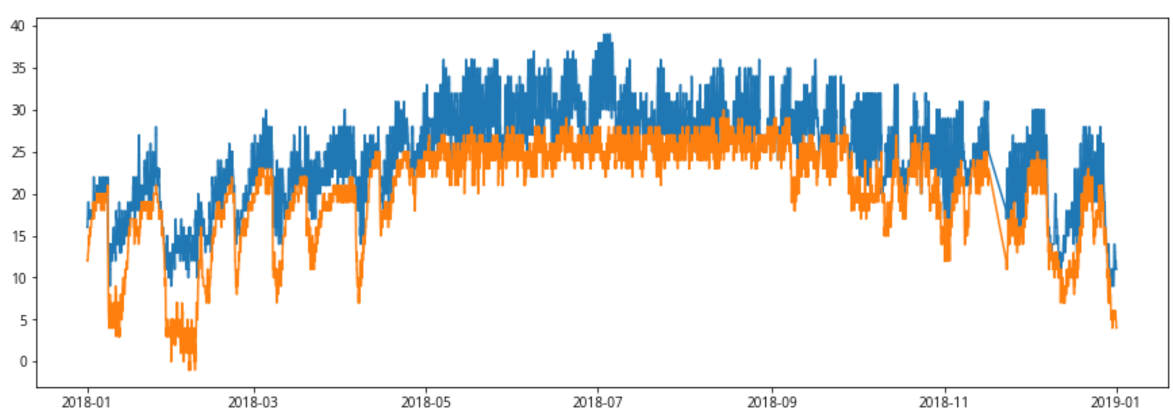
In [53]:
```python
plt.scatter(df.index.hour, df['VIS'])
```

Out[53]: <matplotlib.collections.PathCollection at 0x7fbd41d88828>



In [54]:
```python
# let check out temperature
plt.plot(df.index, df.TMP)
plt.plot(df.index, df.DEW)
```

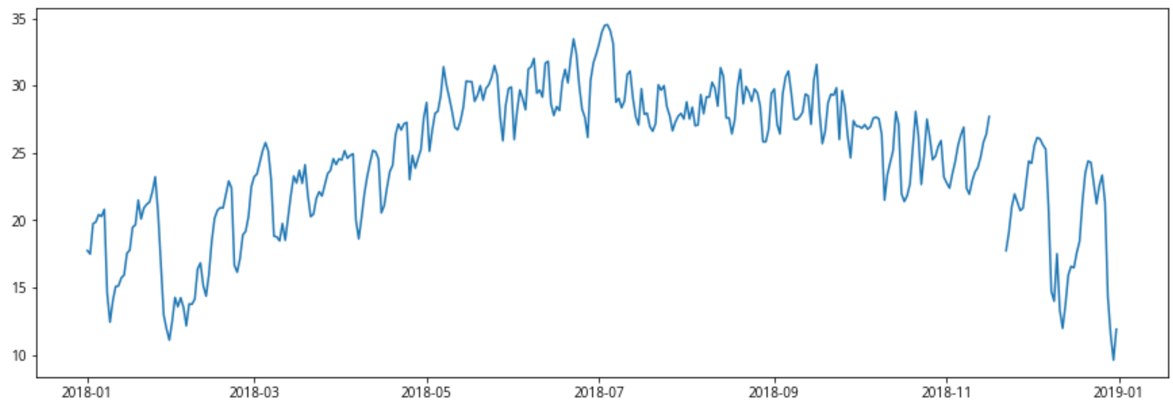
Out[54]: [<matplotlib.lines.Line2D at 0x7fbd4d05f7f0>]



In [55]:
```
# if you want to zoom in certain part, use the command below
# plt.close()
# %matplotlib notebook
# plt.figure(figsize=(12,5))
# plt.plot(df.index, df.TMP)
```

In [56]:
```
# %matplotlib inline
plt.figure(figsize=(15,5))
plt.plot(df['TMP'].resample('1D').mean())
# yeah, the change of tempeature during the year is looking fine
```

Out[56]:
```
[<matplotlib.lines.Line2D at 0x7fbd41c32320>]
```



Working with Hadong site

In [57]:
```
# dfm.to_csv('handong_noaa_isd_2018.csv', index=False)
```

In [58]:
```
# In Hanoi, we have several locations that have data archieved on NCE
I. here is another one
hadong = 488250# Ha dong
year = 2018
base_url = f'https://www.ncei.noaa.gov/data/global-hourly/access/{yea
r}/{hadong}99999.csv'
base_url
```

Out[58]:
```
'https://www.ncei.noaa.gov/data/global-hourly/access/2018/4882509999
9.csv'
```

In [59]:
```
dfm = pd.read_csv(base_url)
dfm.columns
```

Out[59]:
```
Index(['STATION', 'DATE', 'SOURCE', 'LATITUDE', 'LONGITUDE', 'ELEVATI
ON',
       'NAME', 'REPORT_TYPE', 'CALL_SIGN', 'QUALITY_CONTROL', 'WND',
'CIG',
       'VIS', 'TMP', 'DEW', 'SLP', 'AA1', 'AA2', 'AA3', 'AY1', 'AY2',
'GA1',
       'GA2', 'GA3', 'GE1', 'GF1', 'IA1', 'IA2', 'KA1', 'KA2', 'MA1',
'MD1',
       'MW1', 'REM', 'EQD'],
      dtype='object')
```

In [60]:
```
dfm.iloc[0]
```

Out[60]:
```
STATION                                           48825099999
DATE                                      2018-01-01T00:00:00
SOURCE                                                      4
LATITUDE                                              20.9667
LONGITUDE                                             105.767
ELEVATION                                                7.91
NAME                                              HA DONG, VM
REPORT_TYPE                                             FM-12
CALL_SIGN                                               99999
QUALITY_CONTROL                                          V020
WND                                            140,1,N,0010,1
CIG                                              01250,1,9,9
VIS                                             004000,1,9,9
TMP                                                  +0157,1
DEW                                                  +0145,1
SLP                                                  10189,1
AA1                                                      NaN
AA2                                                      NaN
AA3                                                      NaN
AY1                                                1,1,06,1
AY2                                                      NaN
GA1                                     02,1,+00450,1,08,1
GA2                                     08,1,+01250,1,06,1
GA3                                                      NaN
GE1                                  9,MSL    ,+99999,+99999
GF1                  08,99,1,02,1,99,9,00450,1,99,9,99,9
IA1                                                     08,9
IA2                                              999,+0140,9
KA1                                            120,N,+0140,1
KA2                                                      NaN
MA1                                          99999,9,10180,1
MD1                                         3,1,006,1,-053,1
MW1                                                     10,1
REM                                               SYN004BUFR
EQD                                                      NaN
Name: 0, dtype: object
```

In [61]:
```
# For Ha dong, we have "GF1", so we will have a look
```

In [62]:
```
# filter
cols = ['DATE', 'WND', 'CIG', 'VIS', 'TMP', 'DEW', 'SLP', 'GA1', 'GF
1']
dfm = dfm[cols]
```

In [63]:
```
dfm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2805 entries, 0 to 2804
Data columns (total 9 columns):
DATE    2805 non-null object
WND     2805 non-null object
CIG     2805 non-null object
VIS     2805 non-null object
TMP     2805 non-null object
DEW     2805 non-null object
SLP     2805 non-null object
GA1     2456 non-null object
GF1     2759 non-null object
dtypes: object(9)
memory usage: 197.4+ KB
```

In [64]:
```
dfm.to_csv('data/hadong_noaa_isd_2018.csv', index=False)
```

In [65]:
```
! ls data/*
```

```
data/cleaned_hadong_noaa_isd_2018.csv
data/cleaned_hadong_noaa_isd_2018_withRH.csv
data/cleaned_Hanoi_PM2.5_2018_YTD.csv
data/cleaned_noibai_noaa_isd_2018.csv
data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv
data/hadong_noaa_isd_2018.csv
data/Hanoi_PM2.5_2018_YTD.csv
data/noibai_noaa_isd_2018.csv
data/reduced_noibai_noaa_isd_2018.csv
```

- we have a number of files, depend on on which stage this writing go, you seeing could be different

In [66]:
```
# let load the file again, I use df name for this one
df = pd.read_csv('data/hadong_noaa_isd_2018.csv',
                 parse_dates=['DATE'],
                 index_col=['DATE'])
df.head(3)
```

Out[66]:

	WND	CIG	VIS	TMP	DEW	SLP	GA1
DATE							
2018-01-01 00:00:00	140,1,N,0010,1	01250,1,9,9	004000,1,9,9	+0157,1	+0145,1	10189,1	02,1,+00450,1,08,1
2018-01-01 03:00:00	140,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0177,1	+0133,1	10202,1	02,1,+00450,1,08,1
2018-01-01 06:00:00	090,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0196,1	+0140,1	10174,1	02,1,+00450,1,08,1

In [67]:
```
# let go through cleaning one more time
df.WND.str.split(pat=',', expand=True)
```

Out[67]:

	0	1	2	3	4
DATE					
2018-01-01 00:00:00	140	1	N	0010	1
2018-01-01 03:00:00	140	1	N	0010	1
2018-01-01 06:00:00	090	1	N	0010	1
2018-01-01 09:00:00	140	1	N	0010	1
2018-01-01 12:00:00	360	1	N	0000	1
...	...	...	...	...	...
2018-12-31 09:00:00	340	1	N	0020	1
2018-12-31 12:00:00	360	1	N	0010	1
2018-12-31 15:00:00	360	1	N	0020	1
2018-12-31 18:00:00	340	1	N	0030	1
2018-12-31 21:00:00	360	1	N	0030	1

2805 rows × 5 columns

In [68]:
```
df.WND.str.split(pat=',', expand=True)[1].value_counts() # look goood
```

Out[68]:
```
1    2736
9      69
Name: 1, dtype: int64
```

In [69]:
```
df['WD'] = df.WND.str.split(pat=',', expand=True)[0].astype(int)
```

In [70]:
```
df.head()
```
Out[70]:

	WND	CIG	VIS	TMP	DEW	SLP	GA1
DATE							
2018-01-01 00:00:00	140,1,N,0010,1	01250,1,9,9	004000,1,9,9	+0157,1	+0145,1	10189,1	02,1,+00450,1,08,1
2018-01-01 03:00:00	140,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0177,1	+0133,1	10202,1	02,1,+00450,1,08,1
2018-01-01 06:00:00	090,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0196,1	+0140,1	10174,1	02,1,+00450,1,08,1
2018-01-01 09:00:00	140,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0192,1	+0143,1	10164,1	03,1,+00450,1,08,1
2018-01-01 12:00:00	360,1,N,0000,1	01250,1,9,9	010000,1,9,9	+0187,1	+0153,1	10178,1	03,1,+00450,1,08,1

In [71]:
```
df.WND.str.split(pat=',', expand=True)[4].value_counts() # look goood
```
Out[71]:
```
1    2736
9      69
Name: 4, dtype: int64
```

In [72]:
```
df['WS'] = df.WND.str.split(pat=',', expand=True)[3].astype(int)/10
```

In [73]:
```
df.head()
```
Out[73]:

	WND	CIG	VIS	TMP	DEW	SLP	GA1
DATE							
2018-01-01 00:00:00	140,1,N,0010,1	01250,1,9,9	004000,1,9,9	+0157,1	+0145,1	10189,1	02,1,+00450,1,08,1
2018-01-01 03:00:00	140,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0177,1	+0133,1	10202,1	02,1,+00450,1,08,1
2018-01-01 06:00:00	090,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0196,1	+0140,1	10174,1	02,1,+00450,1,08,1
2018-01-01 09:00:00	140,1,N,0010,1	01250,1,9,9	010000,1,9,9	+0192,1	+0143,1	10164,1	03,1,+00450,1,08,1
2018-01-01 12:00:00	360,1,N,0000,1	01250,1,9,9	010000,1,9,9	+0187,1	+0153,1	10178,1	03,1,+00450,1,08,1

In [74]:
```
df.CIG.str.split(pat=',', expand=True)[1].value_counts()
```

Out[74]:
```
1    2154
9     651
Name: 1, dtype: int64
```

In [75]:
```
 df['CIG'] =  df['CIG'].str.split(pat=',', expand=True)[0].astype(int
)
```

In [76]:
```
df.CIG.value_counts()
```

Out[76]:
```
1250     1102
99999     651
22000     502
2750      372
800       163
450        12
3000        2
1500        1
Name: CIG, dtype: int64
```

In [77]:
```
df.loc[df['CIG'] == 99999, 'CIG'] = None
```

In [78]:
```
df.CIG.value_counts()
```

Out[78]:
```
1250.0     1102
22000.0     502
2750.0      372
800.0       163
450.0        12
3000.0        2
1500.0        1
Name: CIG, dtype: int64
```

In [79]:
```
df['TMP'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[79]:
```
1    2803
2       2
Name: 1, dtype: int64
```

In [80]:
```
df['TMP'] = df['TMP'].str.split(pat=',', expand=True)[0].astype(int)/
10
```

In [81]:
```
df['DEW'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[81]:
```
1    2804
2       1
Name: 1, dtype: int64
```

In [82]:
```
df['DEW'] = df['DEW'].str.split(pat=',', expand=True)[0].astype(int)/
10
```

In [83]:
```
df.head()
```

Out[83]:

	WND	CIG	VIS	TMP	DEW	SLP	GA1	
DATE								
2018-01-01 00:00:00	140,1,N,0010,1	1250.0	004000,1,9,9	15.7	14.5	10189,1	02,1,+00450,1,08,1	08,99,1,0
2018-01-01 03:00:00	140,1,N,0010,1	1250.0	010000,1,9,9	17.7	13.3	10202,1	02,1,+00450,1,08,1	08,99,1,0
2018-01-01 06:00:00	090,1,N,0010,1	1250.0	010000,1,9,9	19.6	14.0	10174,1	02,1,+00450,1,08,1	07,99,1,0
2018-01-01 09:00:00	140,1,N,0010,1	1250.0	010000,1,9,9	19.2	14.3	10164,1	03,1,+00450,1,08,1	08,99,1,0
2018-01-01 12:00:00	360,1,N,0000,1	1250.0	010000,1,9,9	18.7	15.3	10178,1	03,1,+00450,1,08,1	08,99,1,0

In [84]:
```
df['SLP'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[84]:
```
1    2803
9       2
Name: 1, dtype: int64
```

new term

FLD LEN: 5 ATMOSPHERIC-PRESSURE-OBSERVATION (STP/SLP) average station pressure for the day

```
 The average pressure at the observed point for the day derived computationa
lly from other QC’ed elements
 MIN: 04500 MAX: 10900 UNITS: hectopascals
 SCALING FACTOR: 10
 DOM: A general domain comprised of the numeric characters (0-9).
 99999 = Missing.
```

In [85]:
```
df['SLP'].str.split(pat=',', expand=True)[0].value_counts()
```

Out[85]:
```
10140    28
10137    22
10121    22
10113    22
10136    21
         ..
10287     1
10210     1
10269     1
10288     1
09966     1
Name: 0, Length: 342, dtype: int64
```

In [86]:
```
df['SLP'] = df['SLP'].str.split(pat=',', expand=True)[0].astype(int)/
10
```

In [87]:
```
df.head()
```

Out[87]:

	WND	CIG	VIS	TMP	DEW	SLP	GA1	
DATE								
2018-01-01 00:00:00	140,1,N,0010,1	1250.0	004000,1,9,9	15.7	14.5	1018.9	02,1,+00450,1,08,1	08,99,1,02
2018-01-01 03:00:00	140,1,N,0010,1	1250.0	010000,1,9,9	17.7	13.3	1020.2	02,1,+00450,1,08,1	08,99,1,02
2018-01-01 06:00:00	090,1,N,0010,1	1250.0	010000,1,9,9	19.6	14.0	1017.4	02,1,+00450,1,08,1	07,99,1,02
2018-01-01 09:00:00	140,1,N,0010,1	1250.0	010000,1,9,9	19.2	14.3	1016.4	03,1,+00450,1,08,1	08,99,1,03
2018-01-01 12:00:00	360,1,N,0000,1	1250.0	010000,1,9,9	18.7	15.3	1017.8	03,1,+00450,1,08,1	08,99,1,03

In [88]:
```
df['GA1'].str.split(pat=',', expand=True)[1].value_counts()
```

Out[88]:
```
1    2452
9       3
2       1
Name: 1, dtype: int64
```

In [89]:
```
df['CLDCR'] = df['GA1'].str.split(pat=',', expand=True)[0].astype(flo
at)/10
```

In [90]:
```
df['GA1'].str.split(pat=',', expand=True)[3].value_counts()
```

Out[90]:
```
1    2455
9       1
Name: 3, dtype: int64
```

In [91]:
```
df['CLDHT'] = df['GA1'].str.split(pat=',', expand=True)[2].astype(float) # some NaN values
```

In [92]:
```
df.drop(columns=['WND', 'GA1', 'GF1'], inplace=True)
```

In [93]:
```
df.VIS.str.split(pat=',', expand=True)
```

Out[93]:

	0	1	2	3
DATE				
2018-01-01 00:00:00	004000	1	9	9
2018-01-01 03:00:00	010000	1	9	9
2018-01-01 06:00:00	010000	1	9	9
2018-01-01 09:00:00	010000	1	9	9
2018-01-01 12:00:00	010000	1	9	9
...	...	...	...	...
2018-12-31 09:00:00	010000	1	9	9
2018-12-31 12:00:00	010000	1	9	9
2018-12-31 15:00:00	010000	1	9	9
2018-12-31 18:00:00	010000	1	9	9
2018-12-31 21:00:00	010000	1	9	9

2805 rows × 4 columns

In [94]:
```
df.VIS.str.split(pat=',', expand=True)[1].value_counts()
```

Out[94]:
```
1    2805
Name: 1, dtype: int64
```

In [95]:
```
df.VIS.str.split(pat=',', expand=True)[1]
```

Out[95]:
```
DATE
2018-01-01 00:00:00    1
2018-01-01 03:00:00    1
2018-01-01 06:00:00    1
2018-01-01 09:00:00    1
2018-01-01 12:00:00    1
                      ..
2018-12-31 09:00:00    1
2018-12-31 12:00:00    1
2018-12-31 15:00:00    1
2018-12-31 18:00:00    1
2018-12-31 21:00:00    1
Name: 1, Length: 2805, dtype: object
```

In [96]:
```
df['VIS'] = df.VIS.str.split(pat=',', expand=True)[0].astype(int)
```

In [97]:
```
df.to_csv('data/cleaned_hadong_noaa_isd_2018.csv')
```

In [98]:
```
df.head()
```

Out[98]:

	CIG	VIS	TMP	DEW	SLP	WD	WS	CLDCR	CLDHT
DATE									
2018-01-01 00:00:00	1250.0	4000	15.7	14.5	1018.9	140	1.0	0.2	450.0
2018-01-01 03:00:00	1250.0	10000	17.7	13.3	1020.2	140	1.0	0.2	450.0
2018-01-01 06:00:00	1250.0	10000	19.6	14.0	1017.4	90	1.0	0.2	450.0
2018-01-01 09:00:00	1250.0	10000	19.2	14.3	1016.4	140	1.0	0.3	450.0
2018-01-01 12:00:00	1250.0	10000	18.7	15.3	1017.8	360	0.0	0.3	450.0

Relative humidity is not exist, could we somehow calculate them?

In [99]:
```
# ref: https://iridl.ldeo.columbia.edu/dochelp/QA/Basic/dewpoint.html
# the most simple way to to get RH if we know TMP and DEW is using th
is equation RH = 100 - 5(TMP-DEW)
# https://journals.ametsoc.org/bams/article-pdf/86/2/225/3931558/bams
-86-2-225.pdf
```

https://en.wikipedia.org/wiki/Pearson_correlation_coefficient (https://en.wikipedia.org/wiki/Pearson_correlation_coefficient) https://doi.org/10.1175/BAMS-86-2-225 (https://doi.org/10.1175/BAMS-86-2-225) The Relationship between Relative Humidity and the Dewpoint Temperature in Moist Air A Simple Conversion and Applications

In [100]:
```
df['RH'] = df.apply(lambda row: 100 - 5*(row['TMP']-row['DEW']), axis
=1)
```

what is happening here?

- `.apply()` is a very power function, and it takes another function called `lambda` as the input
- first `lambda` function calculate RH value for each row (`axis=1` specifies that the calculation is carried out on row)
- the `.apply()` take the calculation from `lambda` and apply to every row. If you specify, `axis=0` , the `.apply()` is carried out on column

In [101]:
```
df.to_csv('data/cleaned_hadong_noaa_isd_2018_withRH.csv')
```

In [102]:
```
df.head()
```

Out[102]:

DATE	CIG	VIS	TMP	DEW	SLP	WD	WS	CLDCR	CLDHT	RH
2018-01-01 00:00:00	1250.0	4000	15.7	14.5	1018.9	140	1.0	0.2	450.0	94.0
2018-01-01 03:00:00	1250.0	10000	17.7	13.3	1020.2	140	1.0	0.2	450.0	78.0
2018-01-01 06:00:00	1250.0	10000	19.6	14.0	1017.4	90	1.0	0.2	450.0	72.0
2018-01-01 09:00:00	1250.0	10000	19.2	14.3	1016.4	140	1.0	0.3	450.0	75.5
2018-01-01 12:00:00	1250.0	10000	18.7	15.3	1017.8	360	0.0	0.3	450.0	83.0

let compare two sites and see anything interesting?

In [103]:
```
nb = pd.read_csv('data/cleaned_noibai_noaa_isd_2018.csv', parse_dates
=['DATE'], index_col=['DATE'])
nb.head(3)
```

Out[103]:

DATE	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT
2018-01-01 00:00:00	1067.0	8000	16.0	12.0	80	1.5	0.7	1067.0
2018-01-01 00:30:00	975.0	8000	16.0	12.0	60	1.5	0.7	975.0
2018-01-01 01:00:00	975.0	7000	16.0	12.0	80	1.5	0.7	975.0

In [104]:
```
nb['RH'] = nb.apply(lambda x: 100 - 5*(x['TMP']-x['DEW']), axis=1)
```

In [105]:
```
# to make graph pretty
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
plt.style.use('seaborn-whitegrid')
plt.rcParams['figure.figsize'] =  (15,5)
plt.rcParams['font.sans-serif'] = 'Open Sans'
```

In [106]:
```
hd = pd.read_csv('data/cleaned_hadong_noaa_isd_2018_withRH.csv', pars
e_dates=['DATE'], index_col=['DATE'])
hd.head(3)
```

Out[106]:

DATE	CIG	VIS	TMP	DEW	SLP	WD	WS	CLDCR	CLDHT	RH
2018-01-01 00:00:00	1250.0	4000	15.7	14.5	1018.9	140	1.0	0.2	450.0	94.0
2018-01-01 03:00:00	1250.0	10000	17.7	13.3	1020.2	140	1.0	0.2	450.0	78.0
2018-01-01 06:00:00	1250.0	10000	19.6	14.0	1017.4	90	1.0	0.2	450.0	72.0

let check on the size of data

In [107]:
```
# Noibai has 16k line a year
nb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 16911 entries, 2018-01-01 00:00:00 to 2018-12-31 23:3
0:00
Data columns (total 9 columns):
CIG      10942 non-null float64
VIS      16911 non-null int64
TMP      16911 non-null float64
DEW      16911 non-null float64
WD       16911 non-null int64
WS       16911 non-null float64
CLDCR    11853 non-null float64
CLDHT    11853 non-null float64
RH       16911 non-null float64
dtypes: float64(7), int64(2)
memory usage: 1.3 MB
```

In [108]:
```
# and indeed, the measurement interval is 30 minutes each
nb.head()
```

Out[108]:

DATE	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT	RH
2018-01-01 00:00:00	1067.0	8000	16.0	12.0	80	1.5	0.7	1067.0	80.0
2018-01-01 00:30:00	975.0	8000	16.0	12.0	60	1.5	0.7	975.0	80.0
2018-01-01 01:00:00	975.0	7000	16.0	12.0	80	1.5	0.7	975.0	80.0
2018-01-01 01:30:00	975.0	7000	17.0	12.0	60	2.1	0.7	975.0	75.0
2018-01-01 02:00:00	1006.0	7000	17.0	12.0	80	3.1	0.4	762.0	75.0

In [109]:
```
# for Ha Dong site
hd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2805 entries, 2018-01-01 00:00:00 to 2018-12-31 21:00:
00
Data columns (total 10 columns):
CIG      2154 non-null float64
VIS      2805 non-null int64
TMP      2805 non-null float64
DEW      2805 non-null float64
SLP      2805 non-null float64
WD       2805 non-null int64
WS       2805 non-null float64
CLDCR    2456 non-null float64
CLDHT    2456 non-null float64
RH       2805 non-null float64
dtypes: float64(8), int64(2)
memory usage: 241.1 KB
```

In [110]:
```
hd.head()
```

Out[110]:

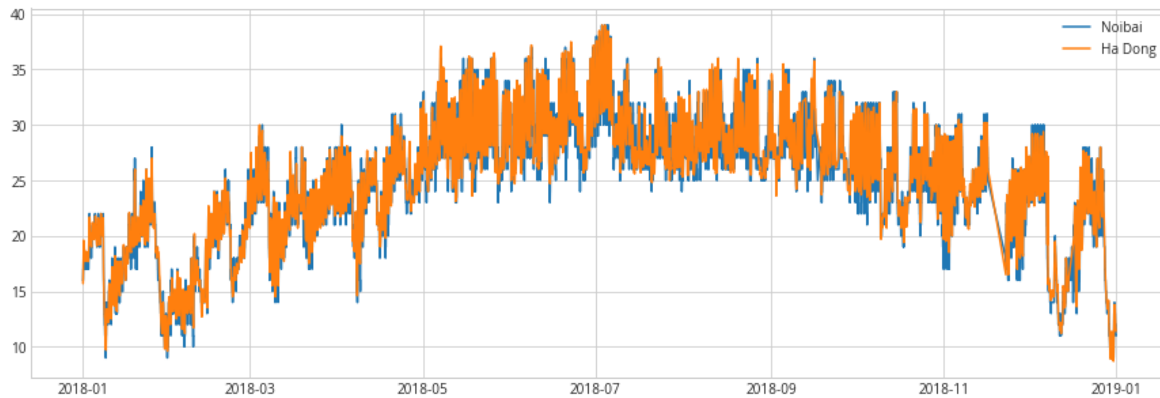
DATE	CIG	VIS	TMP	DEW	SLP	WD	WS	CLDCR	CLDHT	RH
2018-01-01 00:00:00	1250.0	4000	15.7	14.5	1018.9	140	1.0	0.2	450.0	94.0
2018-01-01 03:00:00	1250.0	10000	17.7	13.3	1020.2	140	1.0	0.2	450.0	78.0
2018-01-01 06:00:00	1250.0	10000	19.6	14.0	1017.4	90	1.0	0.2	450.0	72.0
2018-01-01 09:00:00	1250.0	10000	19.2	14.3	1016.4	140	1.0	0.3	450.0	75.5
2018-01-01 12:00:00	1250.0	10000	18.7	15.3	1017.8	360	0.0	0.3	450.0	83.0

- so even two sites with recent data, the interval measurement can be different. Ha Dong site has data read for every 3 hours,
- I prefer meteorological data that as close the observation of $PM_{2.5}$ as possible, but in this case, also means as the cost of data richness

Temperature

In [111]:
```
# first let have a look at data in 2018 (whole year)
plt.plot(nb.index, nb.TMP, label='Noibai', )
plt.plot(hd.index, hd.TMP, label='Ha Dong')
plt.legend()
```

Out[111]: `<matplotlib.legend.Legend at 0x7fbd32816160>`



In [112]:

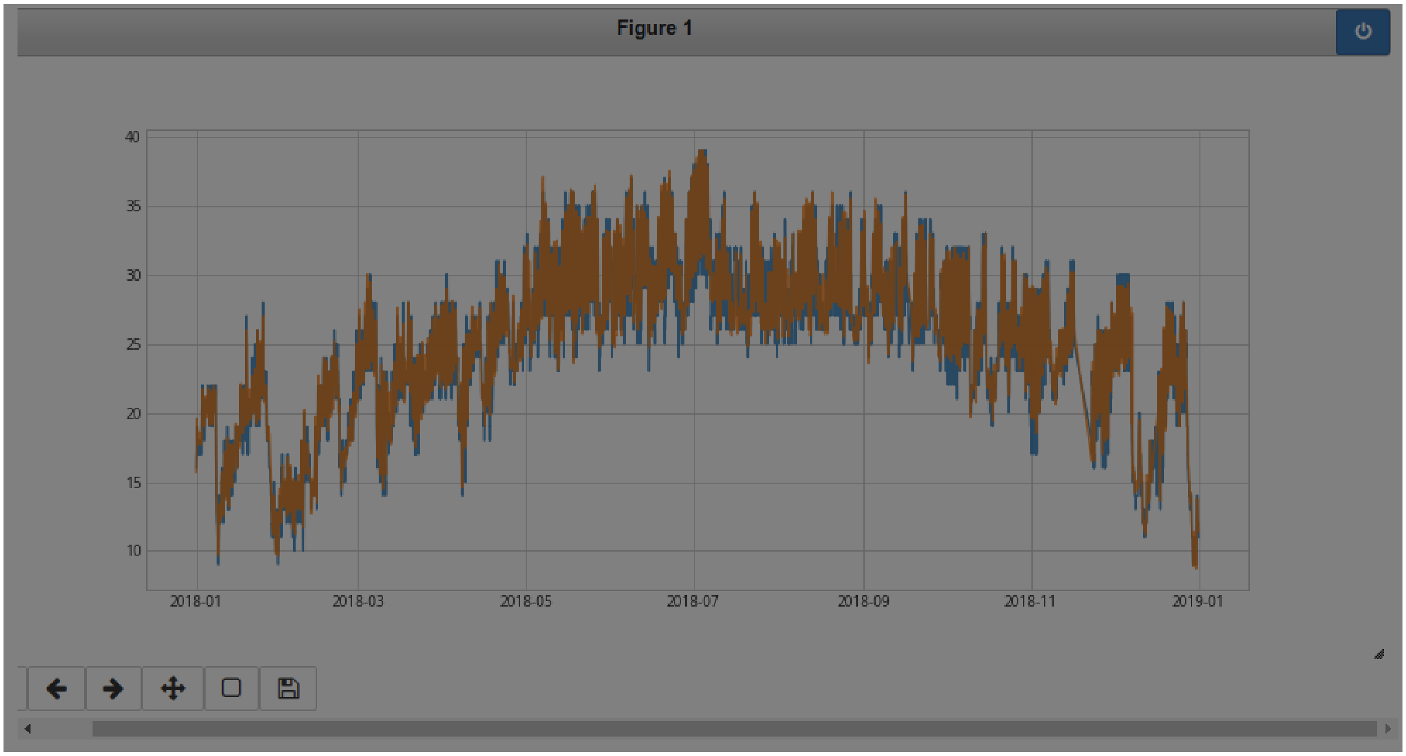
```
# you may need to run twice so the the interaction mode kicked in
plt.close()
%matplotlib notebook
plt.figure(figsize=(14,6))
plt.plot(nb.index, nb.TMP, label='Noibai', alpha=0.8)
plt.plot(hd.index, hd.TMP, label='Ha Dong', alpha=0.8)
# plt.legend()
```

Out[112]:

```
[<matplotlib.lines.Line2D at 0x7fbd3277b160>]
```

with this mode, you can zoom in and move the chart around the explore data

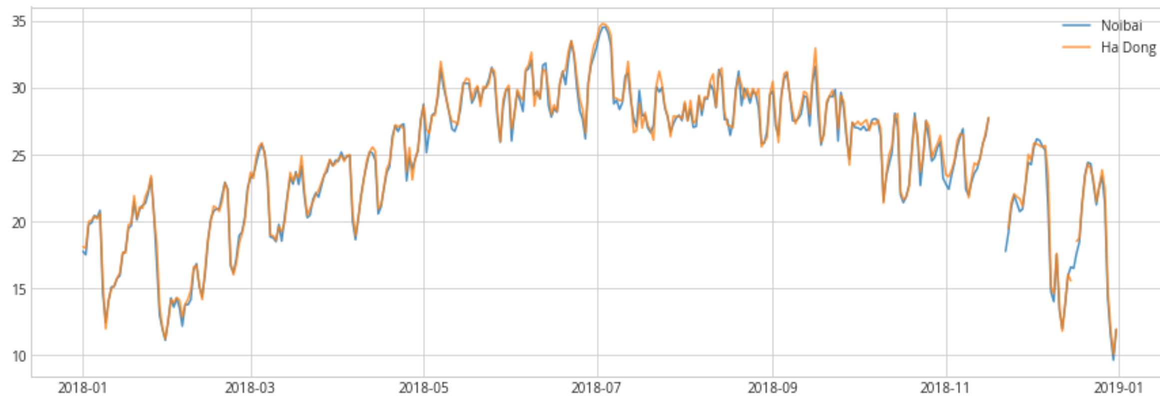
in case, the *interactive mode* is not familar to you, here is how it look



In [113]:
```
# back to normal mode
%matplotlib inline
plt.style.use('seaborn-whitegrid')
plt.rcParams['figure.figsize'] =  (15,5)
plt.rcParams['font.sans-serif'] = 'Open Sans'
```

In [114]:
```python
# they look similar in a ball part let see them daily
nbd = nb.resample('1D').mean()
hdd = hd.resample('1D').mean()
plt.plot(nbd.index, nbd.TMP, label='Noibai', alpha=0.8)
plt.plot(hdd.index, hdd.TMP, label='Ha Dong', alpha=0.8)
plt.legend()
```

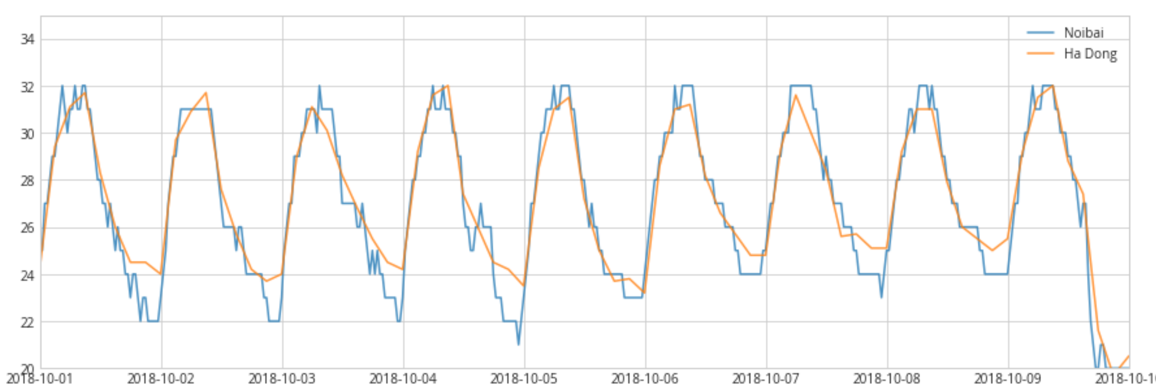
Out[114]: <matplotlib.legend.Legend at 0x7fbd32714048>



In [115]:
```python
# let have a closer look, first we need to precisely define timestime
import datetime
```

In [116]:
```python
# late fall
left = datetime.datetime(2018,10,1)
right = datetime.datetime(2018,10,10)
plt.plot(nb.index, nb.TMP, label='Noibai', alpha=0.8)
plt.plot(hd.index, hd.TMP, label='Ha Dong', alpha=0.8)
plt.xlim(left, right)
plt.ylim(20,35)
plt.legend()
```

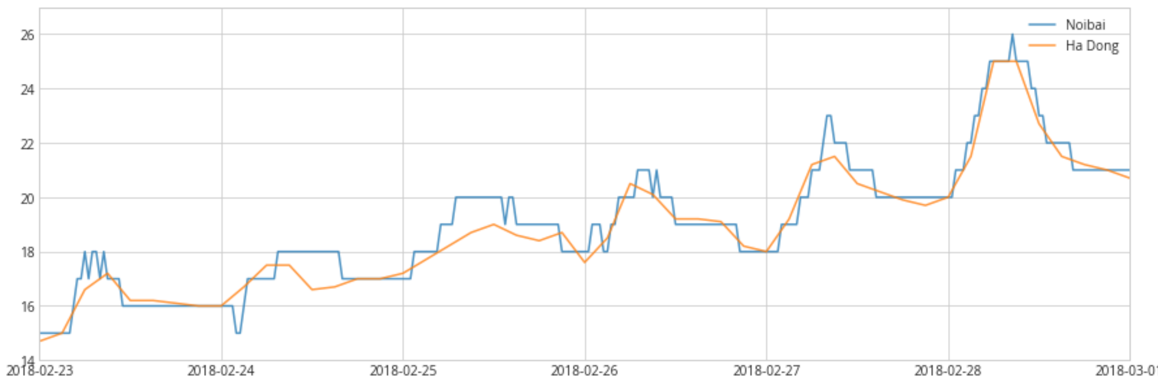
Out[116]: <matplotlib.legend.Legend at 0x7fbd3280ef60>



- it is expected, the station in the urban area has some heat retension. It is clear that the temperature in Ha Dong site is higher right before the sunrise than the suburban site (Noibai Airport)
- sparse interval of Ha dong already show missing trends
- let examine some more

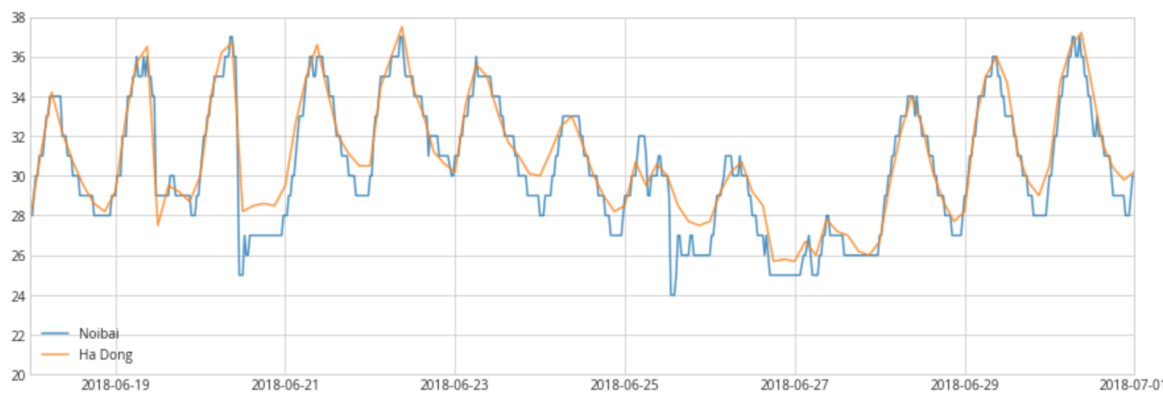
In [117]:
```
# late spring
left = datetime.datetime(2018,2,23)
right = datetime.datetime(2018,3,1)
plt.plot(nb.index, nb.TMP, label='Noibai', alpha=0.8)
plt.plot(hd.index, hd.TMP, label='Ha Dong', alpha=0.8)
plt.xlim(left, right)
plt.ylim(14,27)
plt.legend()
```

Out[117]:
```
<matplotlib.legend.Legend at 0x7fbd3266fb38>
```



In [118]:
```
# right in the middle of summer
left = datetime.datetime(2018,6,18)
right = datetime.datetime(2018,7,1)
plt.plot(nb.index, nb.TMP, label='Noibai', alpha=0.8)
plt.plot(hd.index, hd.TMP, label='Ha Dong', alpha=0.8)
plt.xlim(left, right)
plt.ylim(20,38)
plt.legend()
```

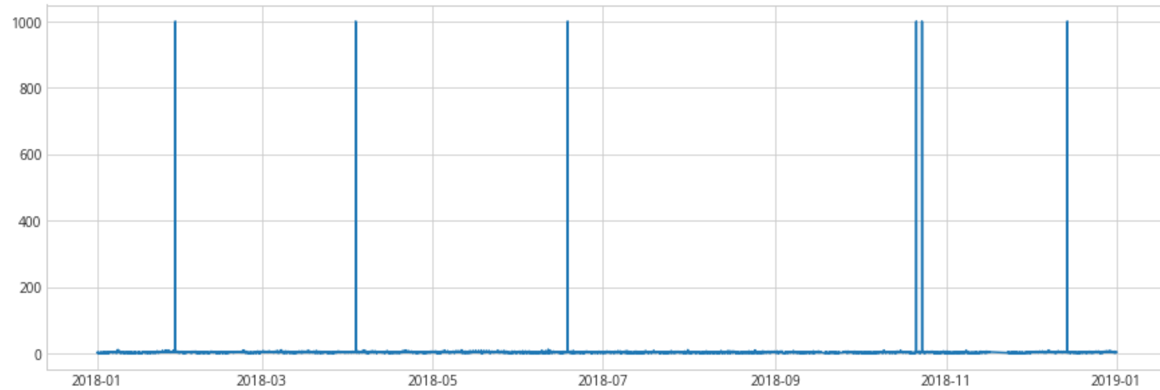
Out[118]:
```
<matplotlib.legend.Legend at 0x7fbd325ea4a8>
```



Wind

In [119]:
```
plt.plot(nb.index, nb.WS)
```

Out[119]:
```
[<matplotlib.lines.Line2D at 0x7fbd32601f98>]
```



oh no, I forgot the remove 999 value, which marked for missing entry, let check it out

In [120]:
```
nb.query('WS>999')
```

Out[120]:

DATE	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT	RH
2018-01-28 22:30:00	1219.0	9999	11.0	4.0	999	999.9	0.7	1219.0	65.0
2018-04-03 13:30:00	NaN	999999	25.0	19.0	999	999.9	NaN	NaN	70.0
2018-06-18 11:00:00	NaN	999999	31.0	26.0	999	999.9	NaN	NaN	75.0
2018-10-21 07:30:00	NaN	999999	32.0	22.0	999	999.9	NaN	NaN	50.0
2018-10-23 08:00:00	1372.0	9999	27.0	25.0	999	999.9	0.4	518.0	90.0
2018-12-14 09:30:00	1219.0	9999	18.0	11.0	999	999.9	0.4	914.0	65.0

In [121]:
```
nb.loc[nb['WD']==999, 'WD'] = None
```

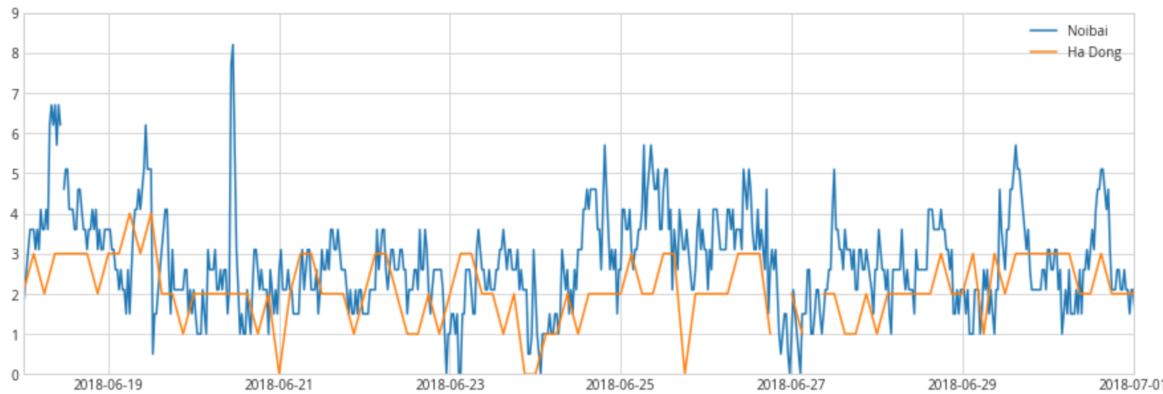
In [122]:
```
hd.loc[hd['WD']==999, 'WD'] = None
```

In [123]:
```
# and wind direction of 9999, (also for missing value)
nb.loc[nb['WS']==999.9, 'WS'] = None
```

In [124]:
```
hd.loc[hd['WS']==999.9, 'WS'] = None
```

In [125]:
```
left = datetime.datetime(2018,6,18)
right = datetime.datetime(2018,7,1)
plt.plot(nb.index, nb.WS, label='Noibai')
plt.plot(hd.index, hd.WS, label='Ha Dong')
plt.xlim(left, right)
plt.ylim(0,9)
plt.legend()
```

Out[125]: <matplotlib.legend.Legend at 0x7fbd3252e518>



In [126]:
```
nb.WS.mean(), hd.WS.mean()
```

Out[126]: (2.852913339248087, 2.000730994152047)

- in compare to temperature, the wind speed data is **very different** between two sites
- wind speed in Ha Dong is much lower than in Noibai, which make sense
- the average of mean value is about 1/3 difference

visualize wind speed and direction is not easy as the data point, we need to resource to a special package called windrose

- check out the [windrose package (https://windrose.readthedocs.io/en/latest/usage.html#script-example)](https://windrose.readthedocs.io/en/latest/usage.html#script-example)

In [127]:
```
! pip install windrose --upgrade
```

```
WARNING: The directory '/home/uno/.cache/pip' or its parent directory
is not owned or is not writable by the current user. The cache has be
en disabled. Check the permissions and owner of that directory. If ex
ecuting pip with sudo, you may want sudo's -H flag.
Defaulting to user installation because normal site-packages is not w
riteable
Requirement already up-to-date: windrose in /usr/local/lib/python3.6/
dist-packages (1.6.7)
Requirement already satisfied, skipping upgrade: numpy in /usr/local/
lib/python3.6/dist-packages (from windrose) (1.18.1)
Requirement already satisfied, skipping upgrade: matplotlib in /usr/l
ocal/lib/python3.6/dist-packages (from windrose) (3.1.2)
Requirement already satisfied, skipping upgrade: cycler>=0.10 in /us
r/local/lib/python3.6/dist-packages (from matplotlib->windrose) (0.1
0.0)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.1
in /usr/lib/python3/dist-packages (from matplotlib->windrose) (2.6.1)
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in
/usr/local/lib/python3.6/dist-packages (from matplotlib->windrose)
 (1.1.0)
Requirement already satisfied, skipping upgrade: pyparsing!=2.0.4,!=
2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from
matplotlib->windrose) (2.4.6)
Requirement already satisfied, skipping upgrade: six in /home/uno/.lo
cal/lib/python3.6/site-packages (from cycler>=0.10->matplotlib->windr
ose) (1.14.0)
Requirement already satisfied, skipping upgrade: setuptools in /usr/l
ocal/lib/python3.6/dist-packages (from kiwisolver>=1.0.1->matplotlib-
>windrose) (44.0.0)
```

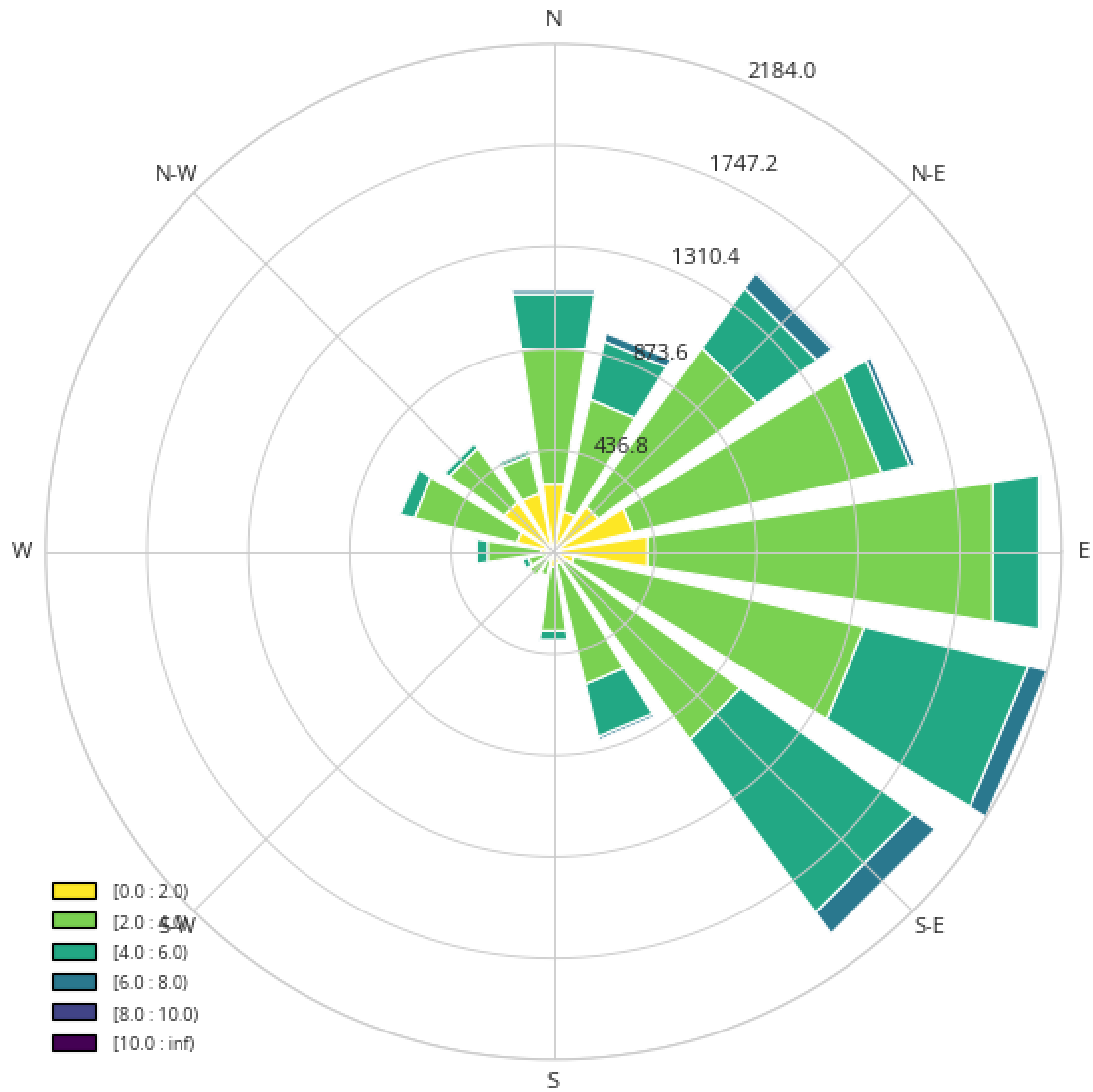
In [128]:

```python
from windrose import WindroseAxes
# from matplotlib import pyplot as plt
import matplotlib.cm as cm
import numpy as np
```

```
/usr/local/lib/python3.6/dist-packages/windrose/windrose.py:29: Matpl
otlibDeprecationWarning:
The Appender class was deprecated in Matplotlib 3.1 and will be remov
ed in 3.3.
  addendum = docstring.Appender(msg, "\n\n")
/usr/local/lib/python3.6/dist-packages/windrose/windrose.py:30: Matpl
otlibDeprecationWarning:
The copy_dedent function was deprecated in Matplotlib 3.1 and will be
removed in 3.3. Use docstring.copy() and cbook.dedent() instead.
  return lambda func: addendum(docstring.copy_dedent(base)(func))
/usr/local/lib/python3.6/dist-packages/windrose/windrose.py:30: Matpl
otlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be remo
ved in 3.3. Use inspect.getdoc() instead.
  return lambda func: addendum(docstring.copy_dedent(base)(func))
/usr/local/lib/python3.6/dist-packages/windrose/windrose.py:30: Matpl
otlibDeprecationWarning:
The dedent function was deprecated in Matplotlib 3.1 and will be remo
ved in 3.3. Use inspect.cleandoc instead.
  return lambda func: addendum(docstring.copy_dedent(base)(func))
```

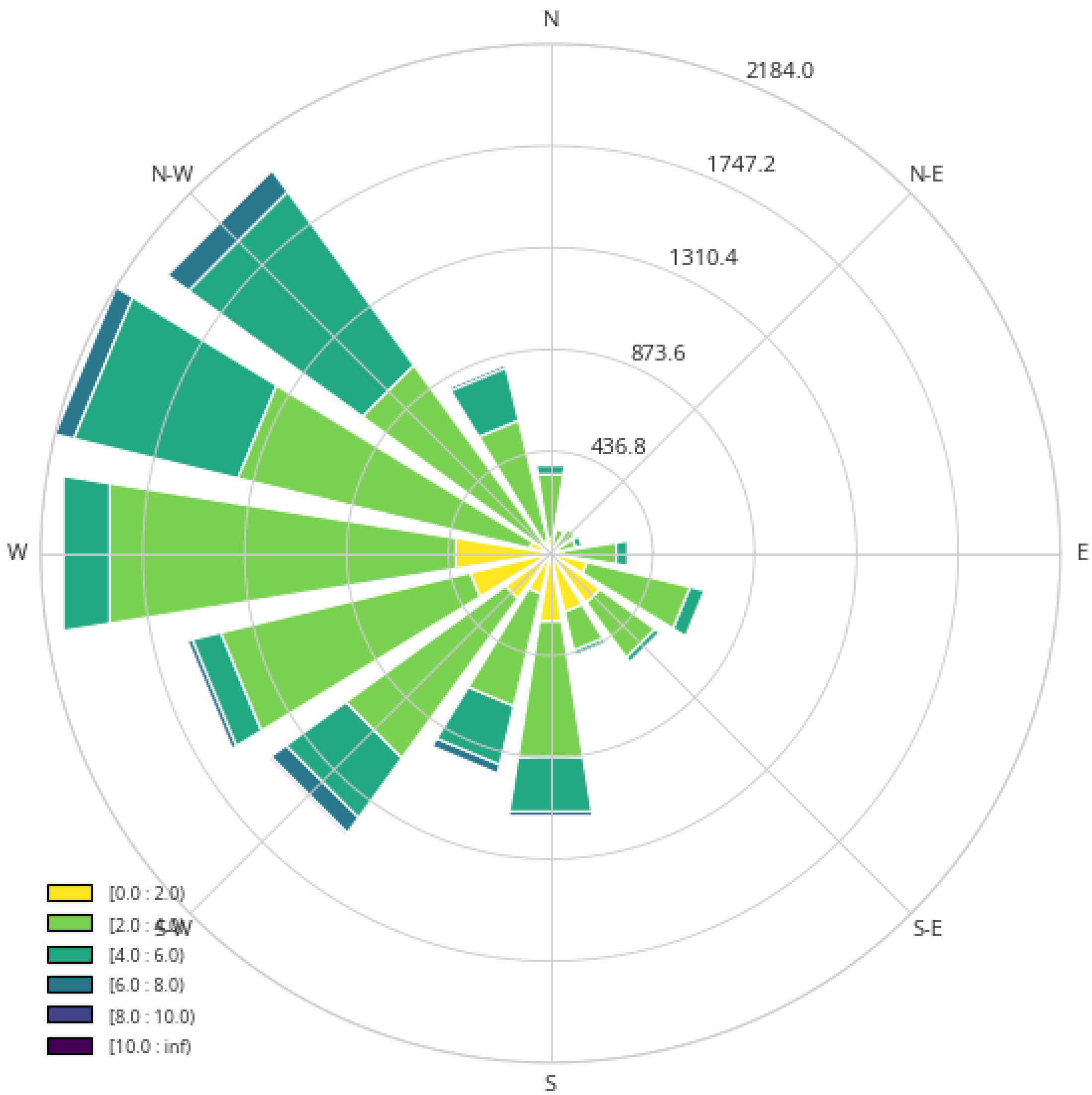
In [129]:
```
# let visualize wind speed and wind direction of Noibai
wd = nb.WD
ws = nb.WS
ax = WindroseAxes.from_ax()
bins = np.arange(0,12,2)
ax.bar(wd, ws, normed=False, edgecolor='white', bins=bins,  cmap=cm.v
iridis_r)
ax.set_legend()
```

Out[129]: <matplotlib.legend.Legend at 0x7fbd3249a358>



In [130]:
```
# and the same site with blowto=True option
wd = nb.WD
ws = nb.WS
ax = WindroseAxes.from_ax()
bins = np.arange(0,12,2)
ax.bar(wd, ws, normed=False, blowto=True, edgecolor='white', bins=bin
s,  cmap=cm.viridis_r)
ax.set_legend()
```

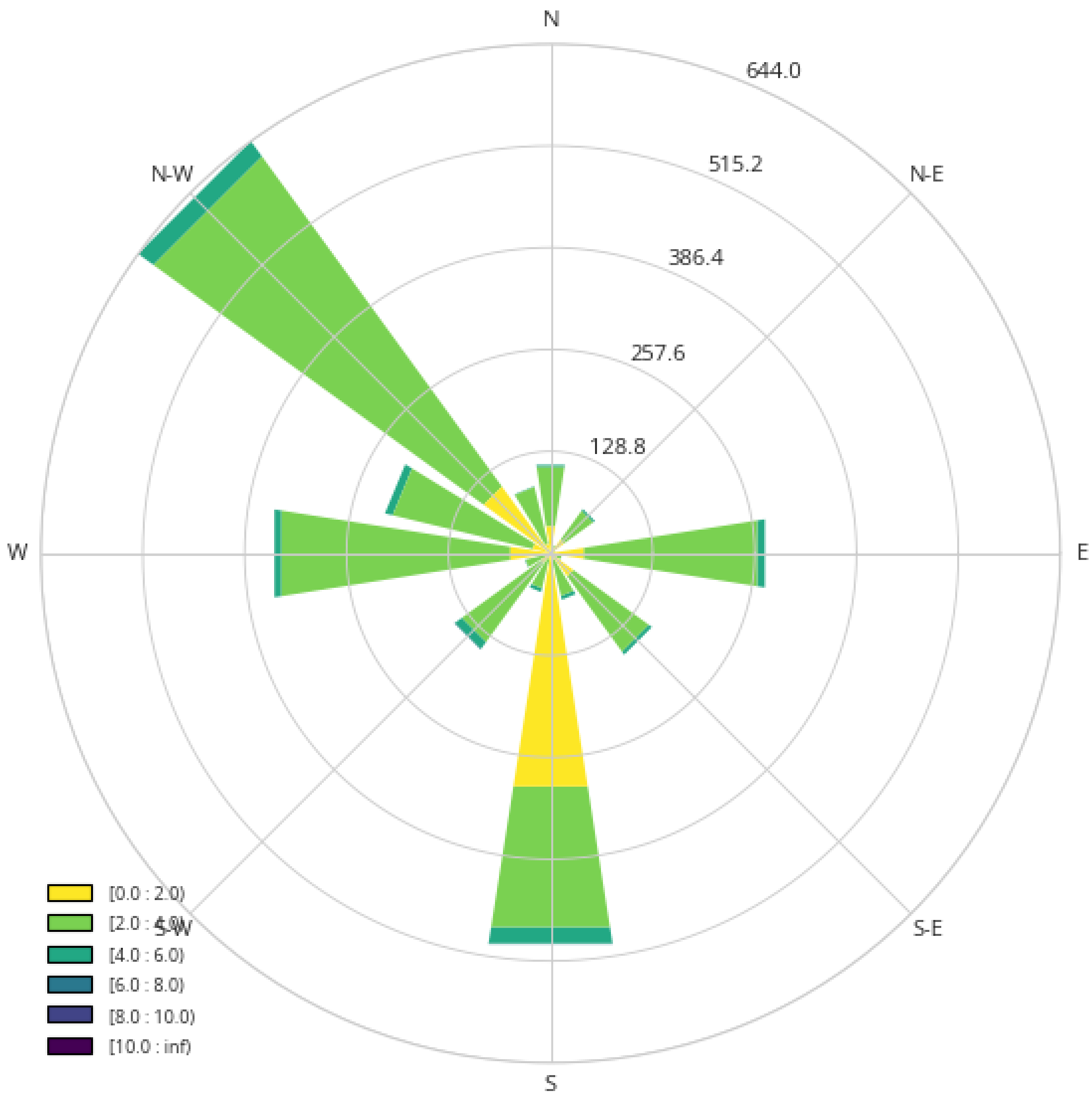
Out[130]: <matplotlib.legend.Legend at 0x7fbd323d9c50>



- yes, the *blowto* change direction of the wind but how to what does this mean to connect with the outside
- the graph above (with major colors in South-East cornor) is to show where the wind comes from. So if you stand outside and facing to the South-East, you should feel to wind blows on your face
- the graph with **blowto=True** is suitable when showing the disperse of pollutants. For example, if you have a chimney at the origin, in next hours, you should see the smoke blows to the North-East direction

In [131]:
```
# how about Ha dong site
wd = hd.WD
ws = hd.WS
ax = WindroseAxes.from_ax()
bins = np.arange(0,12,2)
ax.bar(wd, ws, normed=False, bins=bins, blowto=True, cmap=cm.viridis_
r)
ax.set_legend()
```

Out[131]: <matplotlib.legend.Legend at 0x7fbd32363da0>

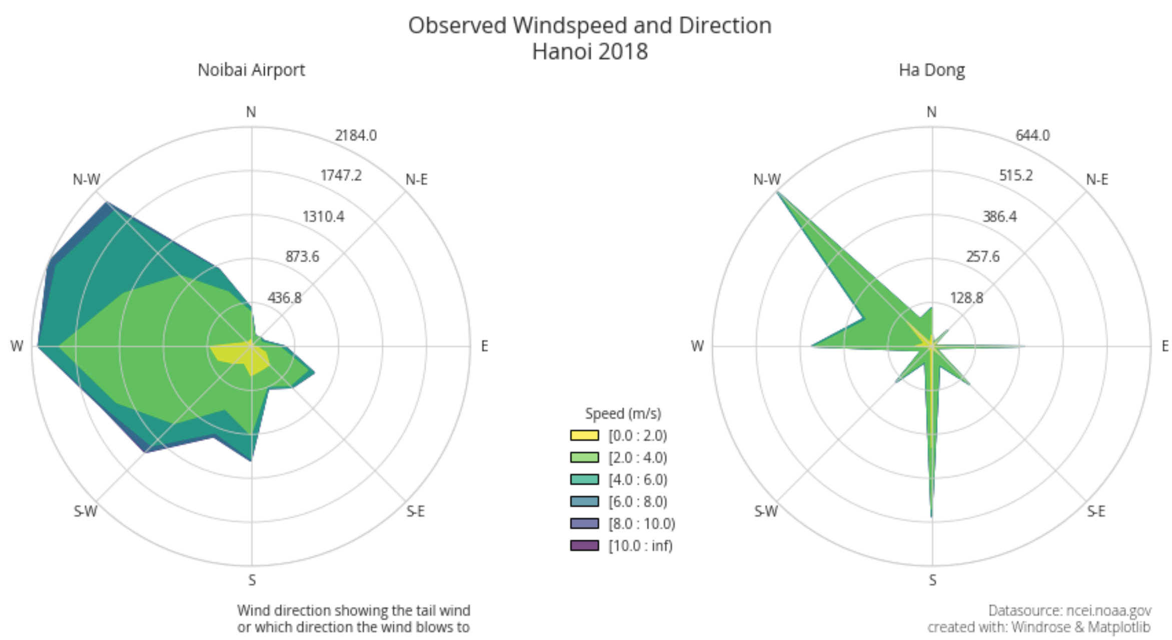


In [132]:
```
# and ofcourse, you want to present side-by-site
fig = plt.figure(figsize=(12,6.5))
ax = fig.add_subplot(121, projection="windrose", )

ax.contourf(nb.WD, nb.WS, bins=np.arange(0, 12, 2), cmap=cm.viridis_r
, alpha=0.7, blowto=True)

ax.legend(bbox_to_anchor=(1.2, 0), title='Speed (m/s)')
ax.set_title('Noibai Airport', y=1.1)
ax1 = fig.add_subplot(122, projection="windrose")
ax1.contourf(hd.WD, hd.WS, bins=np.arange(0, 12, 2), cmap=cm.viridis_
r, alpha=0.7, blowto=True)
ax1.set_title('Ha Dong', y=1.1)
fig.suptitle('Observed Windspeed and Direction\nHanoi 2018', fontsize
=16)
fig.subplots_adjust(bottom=0.2)
fig.text(1,-0.15, 'Datasource: ncei.noaa.gov\ncreated with: Windrose
 & Matplotlib',
         transform=ax1.transAxes, ha='right', weight='light')
fig.text(1,-0.15, 'Wind direction showing the tail wind\nor which dir
ection the wind blows to',
         transform=ax.transAxes, ha='right', weight='book')

fig.tight_layout()
fig.savefig('img/2020Jul_windrose_noibai_hadong.png', dpi=120)
```



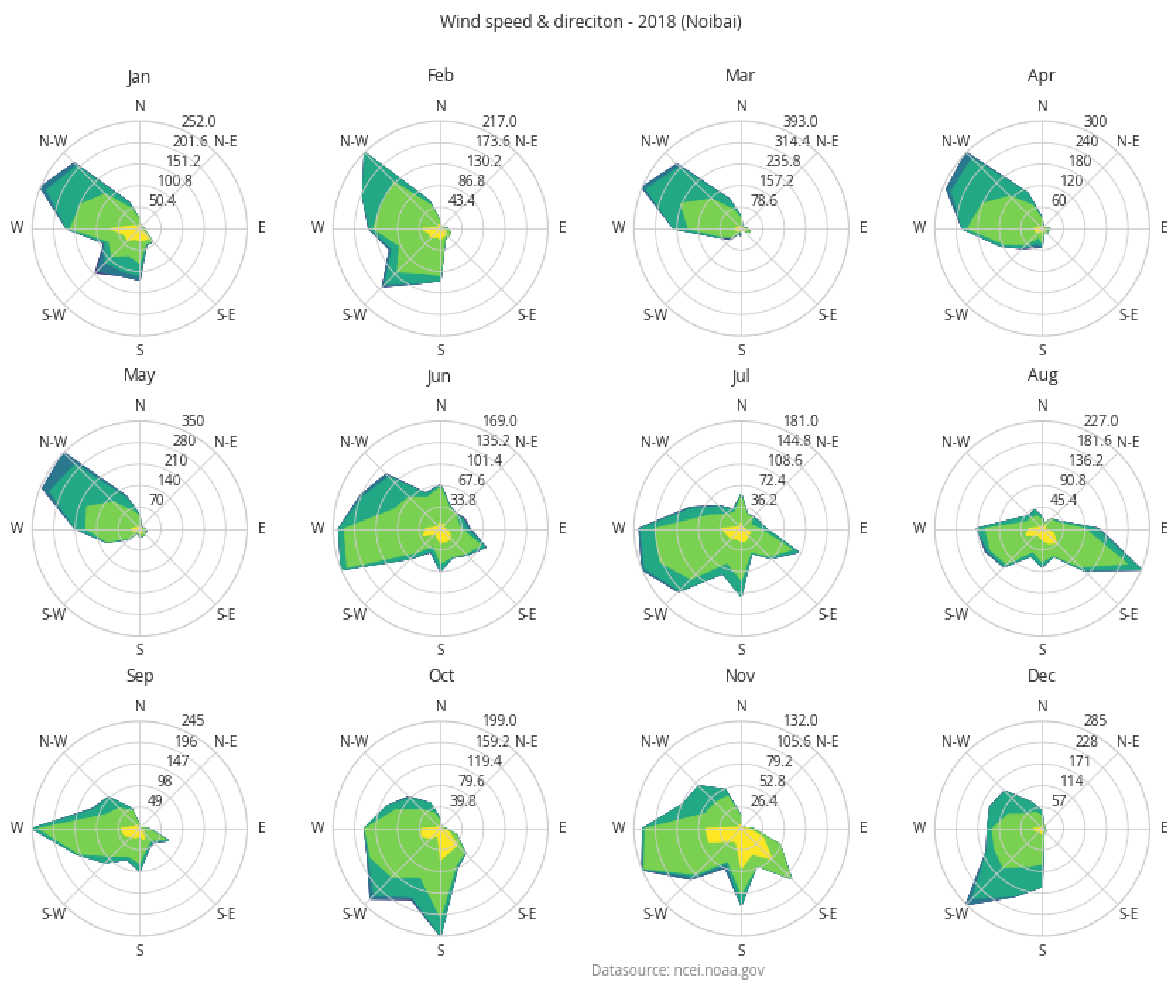
- the graph above is a sort of deal-breaker, a closer and more representative to urban area is not very rich in data
- we will work with `Noibai` site, since $PM_{2.5}$ is a regional pollutant, so a location like in a nearby airport would be a fine choice to see the overall wind pattern

In [133]:
```
# can we do more with wind
nb['m'] = nb.index.month
```

In [134]:
```
nrows, ncols = 3, 4
year = 2018
fig = plt.figure(figsize=(12,9))
bins = np.arange(0.01, 12, 2)

fig.suptitle("Wind speed & direciton - %d (Noibai)" % year,y=1.05)
for month in range(1, 13):
    ax = fig.add_subplot(nrows, ncols, month, projection="windrose")
    title = datetime.datetime(year, month, 1).strftime("%b")
    ax.set_title(title,y=1.15)
    try:
        dft = nb[['WS', 'WD', 'm']].query(f'm=={month}')
    except KeyError:
        continue
    direction = dft['WD']
    var = dft['WS']

    ax.contourf(direction, var, bins=bins, cmap=cm.viridis_r, blowto=
True)
    fig.subplots_adjust(hspace=0.6)
fig.text(0.5,0,'Datasource: ncei.noaa.gov', color='gray')
fig.tight_layout()
fig.savefig('img/2020Jul_subplot_windrose.png', dpi=120)
```



- and now you can see the wind direction, and wind speed differ on each month.
- For

Relative Humidity

In [135]:
```
# and here the paper to convert RH from air temperature and dewpoint
 temperature
# https://pdfs.semanticscholar.org/e873/a898ba9373af4e12907841411f3e9
d83cb9a.pdf
```

In [136]:
```
nb['RH'] = nb.apply(lambda row: 100-5*(row['TMP']-row['DEW']), axis=1
)
```

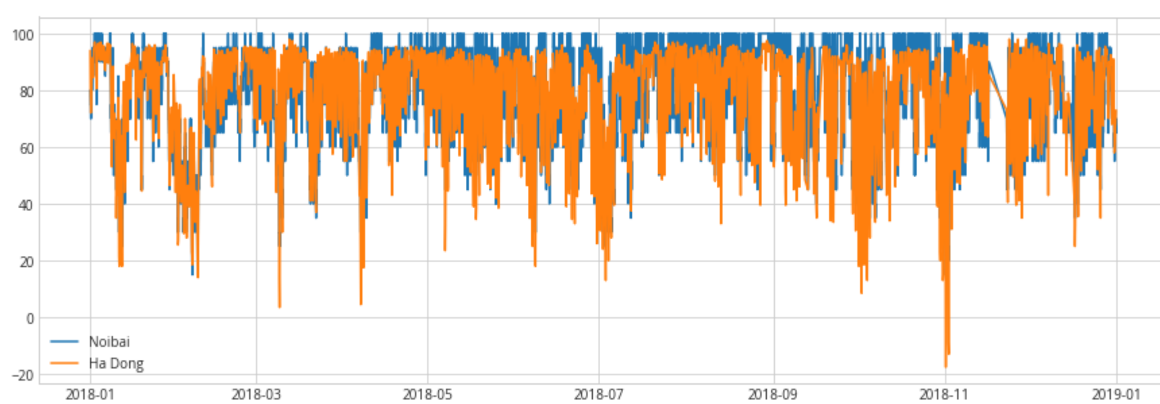
In [137]:
```
nb.head()
```

Out[137]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT	RH	m
DATE										
2018-01-01 00:00:00	1067.0	8000	16.0	12.0	80.0	1.5	0.7	1067.0	80.0	1
2018-01-01 00:30:00	975.0	8000	16.0	12.0	60.0	1.5	0.7	975.0	80.0	1
2018-01-01 01:00:00	975.0	7000	16.0	12.0	80.0	1.5	0.7	975.0	80.0	1
2018-01-01 01:30:00	975.0	7000	17.0	12.0	60.0	2.1	0.7	975.0	75.0	1
2018-01-01 02:00:00	1006.0	7000	17.0	12.0	80.0	3.1	0.4	762.0	75.0	1

In [138]:
```
plt.plot(nb.index, nb.RH , label='Noibai',)
plt.plot(hd.index, hd.RH, label='Ha Dong')
plt.legend()
```

Out[138]: <matplotlib.legend.Legend at 0x7fbd28521e80>



- look like in Ha dong site, the RH is lower than in Noibai,
- and around November, a minus RH (which is not possible)

In [139]:
```
hd[hd['RH'] < 0]
```

Out[139]:

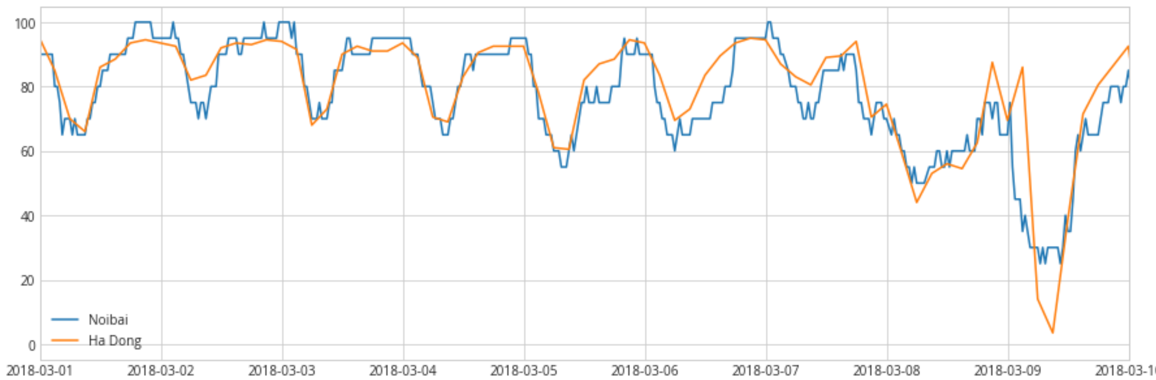
DATE	CIG	VIS	TMP	DEW	SLP	WD	WS	CLDCR	CLDHT	RH
2018-11-01 06:00:00	22000.0	10000	29.0	5.5	1015.3	360.0	3.0	NaN	NaN	-17.5
2018-11-01 09:00:00	22000.0	10000	29.2	5.7	1014.3	320.0	2.0	NaN	NaN	-17.5
2018-11-02 06:00:00	22000.0	20000	28.5	6.7	1016.0	360.0	2.0	NaN	NaN	-9.0
2018-11-02 09:00:00	22000.0	20000	29.0	6.4	1014.3	270.0	3.0	NaN	NaN	-13.0

- wow, the air is really dry, but the RH is between 0 and 100%, so we will fix it using `loc`

In [140]:
```
hd.loc[hd['RH']<0, 'RH'] = 0
```

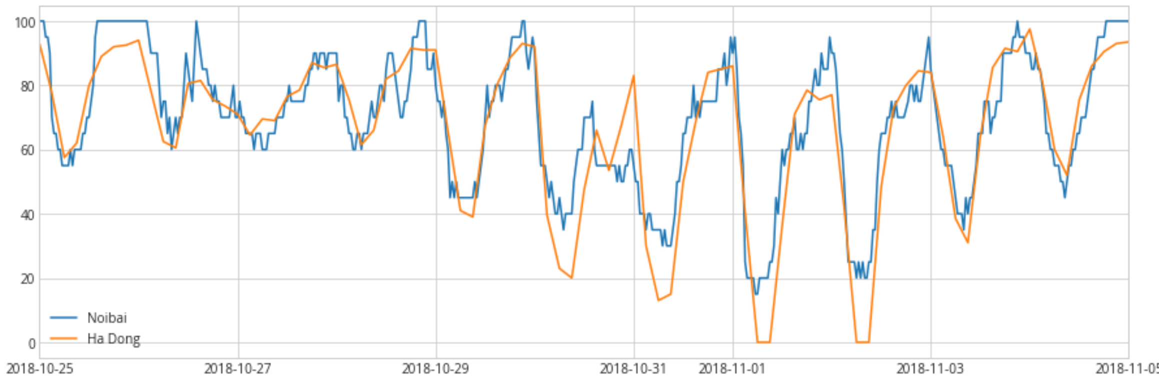
In [141]:
```
left = datetime.datetime(2018,3,1)
right = datetime.datetime(2018, 3,10)
plt.plot(nb.index, nb.RH , label='Noibai',)
plt.plot(hd.index, hd.RH, label='Ha Dong')
plt.xlim(left, right)
plt.legend()
```

Out[141]: `<matplotlib.legend.Legend at 0x7fbd2865ff60>`



In [142]:
```
left = datetime.datetime(2018,10,25)
right = datetime.datetime(2018, 11,5)
plt.plot(nb.index, nb.RH , label='Noibai',)
plt.plot(hd.index, hd.RH, label='Ha Dong')
plt.xlim(left, right)
plt.legend()
```

Out[142]: <matplotlib.legend.Legend at 0x7fbd28478630>

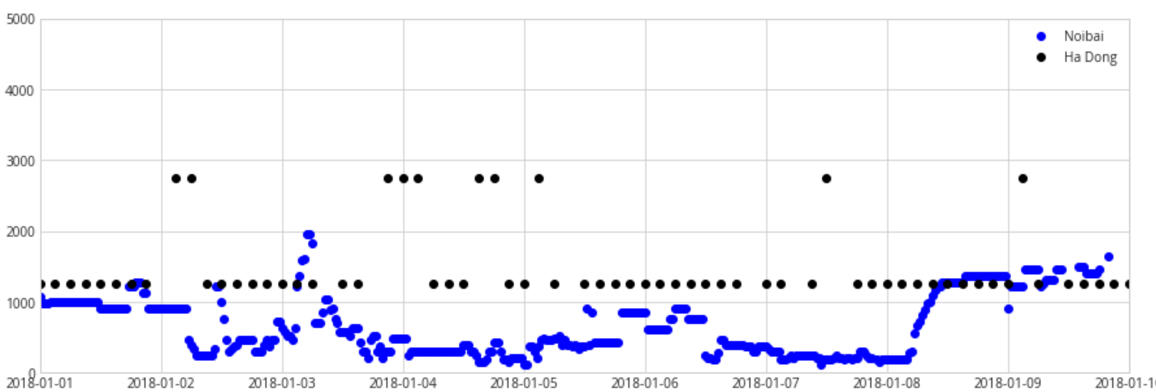


Ceiling height

- this is important parameter to indicate how thick the mixing layer near the ground

In [143]:
```
left = datetime.datetime(2018,1,1)
right = datetime.datetime(2018,1,10)
plt.plot(nb.index, nb.CIG,  'bo', label='Noibai',)
plt.plot(hd.index, hd.CIG, 'ko', label='Ha Dong')
plt.xlim(left, right)
plt.ylim(0,5000)
plt.legend()
```

Out[143]: <matplotlib.legend.Legend at 0x7fbd283c5da0>



- the data from Ha Dong is not so informative, so I have enough reason to take Noibai data for the next analysis

Concluding notes

So we have go through several step in this exercise

- First, we explore the possiblity to acquire meteorological data. For historical one, data on `ncei.noaa.gov` is an excellent stop
- The data from this site requires rather extensive data wrangle and cleaning. We've gone through using `str.split` , `loc` to take the relevant data, and settling data with `None` with missing value
- We can calculate `RH` by using the simple approximation using `air temperature and dewpoint temperature`
- Data from two sites near Hanoi were explored by main parameters
- We use `windrose` package to visualize wind speed and wind direction

```
In [ ]:
```