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Ideas:

- We will pick up the cleaned meteorological file from the previous exercise. If you missed that exercise, in which I went through step-by-step getting and cleaning files from NOAA, then visit file 2.2 and part 1. The cleaned file is in `data/cleaned_noibai_noaa_isd_2018.csv`
- We will resume to archieved data from `airnow.gov` . This file was cleaned up and reduced to the only $PM_{2.5}$ concentration (and thus all metadata was filtered out). The file is here `data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv` . I did a quick data wrangling in part 2.1
- Correlating meteorological parameters with observed $PM_{2.5}$ is *better than a guessing game* as we try to make some connection between two sets of data (with the same timestamp).

import libraries

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
import seaborn as sns
import datetime
```

In [2]:
```
# use simple style with font and tick setup
plt.style.use('seaborn-white')
```

In [3]:
```
plt.rcParams['figure.figsize'] =  (8,6)
plt.rcParams['font.sans-serif'] = 'Open Sans'
plt.rcParams['font.family'] = 'sans-serif'
plt.rcParams['text.color'] = '#4c4c4c'
plt.rcParams['axes.labelcolor']= '#4c4c4c'
plt.rcParams['xtick.color'] = '#4c4c4c'
plt.rcParams['ytick.color'] = '#4c4c4c'
plt.rcParams['font.size']=12
```

Prepare data

In [4]:
```
# load meteorological data
dfm = pd.read_csv('data/cleaned_noibai_noaa_isd_2018.csv',
                  parse_dates=['DATE'],
                  index_col=['DATE'])
dfm.head()
```

Out[4]:

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
2018-01-01 01:30:00	975.0	7000	17.0	12.0	60	2.1	0.7	975.0
2018-01-01 02:00:00	1006.0	7000	17.0	12.0	80	3.1	0.4	762.0

In [5]:
```
# the interval of file above is 30 minutes each, and PM2.5 is one hou
r a part
dfm = dfm.resample('1H', loffset=datetime.timedelta(hours=1)).mean()
```

In [6]:
```
dfm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2018-01-01 01:00:00 to 2019-01-01 00:00:
00
Freq: H
Data columns (total 8 columns):
CIG      5951 non-null float64
VIS      8524 non-null float64
TMP      8524 non-null float64
DEW      8524 non-null float64
WD       8524 non-null float64
WS       8524 non-null float64
CLDCR    6200 non-null float64
CLDHT    6200 non-null float64
dtypes: float64(8)
memory usage: 615.9 KB
```

In [7]:
```python
# and now is for PM2.5
pm25 = pd.read_csv('data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv',
                   parse_dates=['Date (LT)'],
                   index_col=['Date (LT)'])

pm25.head()
```

Out[7]:

	pm25
Date (LT)	
2018-01-01 01:00:00	69.2
2018-01-01 02:00:00	75.5
2018-01-01 03:00:00	90.2
2018-01-01 04:00:00	97.6
2018-01-01 05:00:00	89.1

In [8]:
```python
# one year has 8760 hours
pm25.shape
```

Out[8]: (8190, 1)

In [9]:
```python
# now we combine to data frame, using the index as the shared key
df = pd.merge(dfm, pm25, left_index=True, right_index=True)
df.head()
```

Out[9]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT	pm25
2018-01-01 01:00:00	1021.0	8000.0	16.0	12.0	70.0	1.50	0.7	1021.0	69.2
2018-01-01 02:00:00	975.0	7000.0	16.5	12.0	70.0	1.80	0.7	975.0	75.5
2018-01-01 03:00:00	1006.0	7000.0	17.0	12.0	80.0	2.85	0.4	762.0	90.2
2018-01-01 04:00:00	1006.0	6000.0	17.0	12.0	40.0	2.10	0.4	762.0	97.6
2018-01-01 05:00:00	1006.0	5000.0	18.5	13.0	65.0	1.50	0.4	762.0	89.1

In [10]:
```python
df.index.rename('DATE', inplace=True)
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8190 entries, 2018-01-01 01:00:00 to 2019-01-01 00:00:
00
Data columns (total 9 columns):
CIG      5604 non-null float64
VIS      7959 non-null float64
TMP      7959 non-null float64
DEW      7959 non-null float64
WD       7959 non-null float64
WS       7959 non-null float64
CLDCR    5815 non-null float64
CLDHT    5815 non-null float64
pm25     8190 non-null float64
dtypes: float64(9)
memory usage: 639.8 KB
```

wait, are we losing data?

- check again with `dfm` , we have over 8500 lines, and now in combined dataframe, the file has 7959 rows
- the combine option by default is **inner**, a **union** of two sets of index, other options also available which are `left` , `right` , `outer` , and assign the option by `pd.merge(df1, df2, how='outer', ...)`

In [12]:
```
# we will calculate RH from approximation from air tempeature and dew
point temperature
df['RH'] = df.apply(lambda row: 100-5*(row['TMP']-row['DEW']), axis=1
)
df.head(3)
```

Out[12]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT	pm25	RH
DATE										
2018-01-01 01:00:00	1021.0	8000.0	16.0	12.0	70.0	1.50	0.7	1021.0	69.2	80.0
2018-01-01 02:00:00	975.0	7000.0	16.5	12.0	70.0	1.80	0.7	975.0	75.5	77.5
2018-01-01 03:00:00	1006.0	7000.0	17.0	12.0	80.0	2.85	0.4	762.0	90.2	75.0

In [13]:
```
# and we save the file
df.to_csv('data/combined_meteo_PM2.5_Hanoi_2018.csv')
```

In [14]:
```
df = pd.read_csv('data/combined_meteo_PM2.5_Hanoi_2018.csv',
                 parse_dates=['DATE'],
                 index_col=['DATE'])
```

In [15]:
```
# let get correlation which generate a dataframe
df.corr()
```

Out[15]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT
CIG	1.000000	0.301060	0.060859	-0.013038	0.130481	-0.032222	-0.195803	0.221168
VIS	0.301060	1.000000	0.038549	-0.242069	0.028815	0.014172	-0.142735	0.150400
TMP	0.060859	0.038549	1.000000	0.819125	0.079949	0.004359	-0.272067	0.142463
DEW	-0.013038	-0.242069	0.819125	1.000000	0.031270	-0.005788	-0.273422	-0.196228
WD	0.130481	0.028815	0.079949	0.031270	1.000000	0.014538	-0.040801	0.088947
WS	-0.032222	0.014172	0.004359	-0.005788	0.014538	1.000000	0.015695	0.013199
CLDCR	-0.195803	-0.142735	-0.272067	-0.273422	-0.040801	0.015695	1.000000	0.125950
CLDHT	0.221168	0.150400	0.142463	-0.196228	0.088947	0.013199	0.125950	1.000000
pm25	0.084939	-0.037716	-0.297633	-0.362755	0.134051	-0.027791	0.139204	0.032396
RH	-0.134297	-0.476898	-0.164482	0.431071	-0.071991	-0.016809	0.005551	-0.570603

- that is easy and **meaningless** as well. One goal of data visualization is to drill down the data and get a simpler, much simpler message from the data. **Meaningless** is for an emphasis. When we are overwhelmed with data, we loss interest of it, and nothing would be retained.

and more note, before we jump in with the analysis, there are plenty reviews the correlation of $PM_{2.5}$ with meterological parameters. The effects are mixed and the change of concentration is both way. The diagram belows are taken from a recent study.

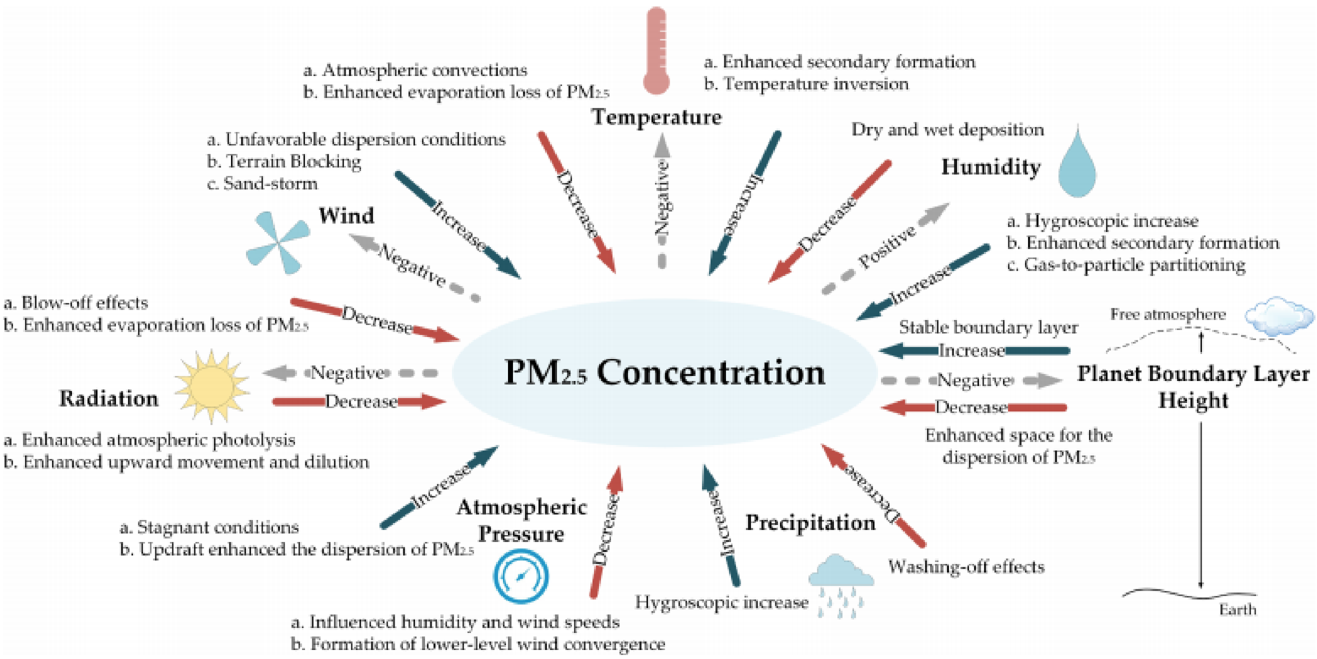


Fig. 11. How major meteorological factors influence $PM_{2.5}$ concentrations through different mechanisms.

Source: [Chen, at el., 2020 (https://doi.org/10.1016/j.envint.2020.105558)](https://doi.org/10.1016/j.envint.2020.105558)

First look at correlation

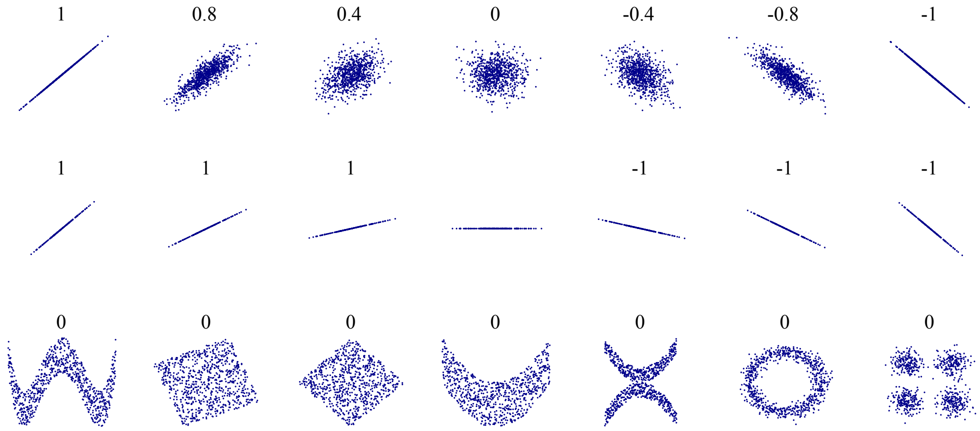
- with `pandas`, getting a bivariate correlation (correlation between two variables) is easy, just call `.corr()` after the DataFrame like this. We can filter out the correlation with one variable such as `pm25`

In [16]:
```
df.corr()['pm25']
```

Out[16]:
```
CIG      0.084939
VIS     -0.037716
TMP     -0.297633
DEW     -0.362755
WD       0.134051
WS      -0.027791
CLDCR    0.139204
CLDHT    0.032396
pm25     1.000000
RH      -0.155600
Name: pm25, dtype: float64
```

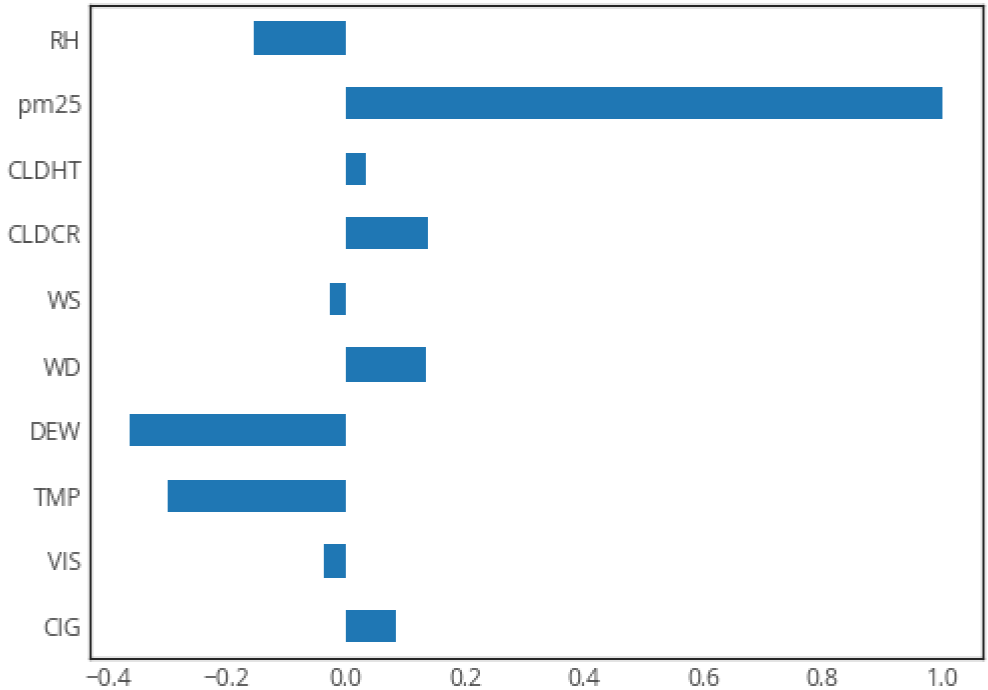
OK, that is quick and easy, but how this number mean?

- First take a look at this diagram about

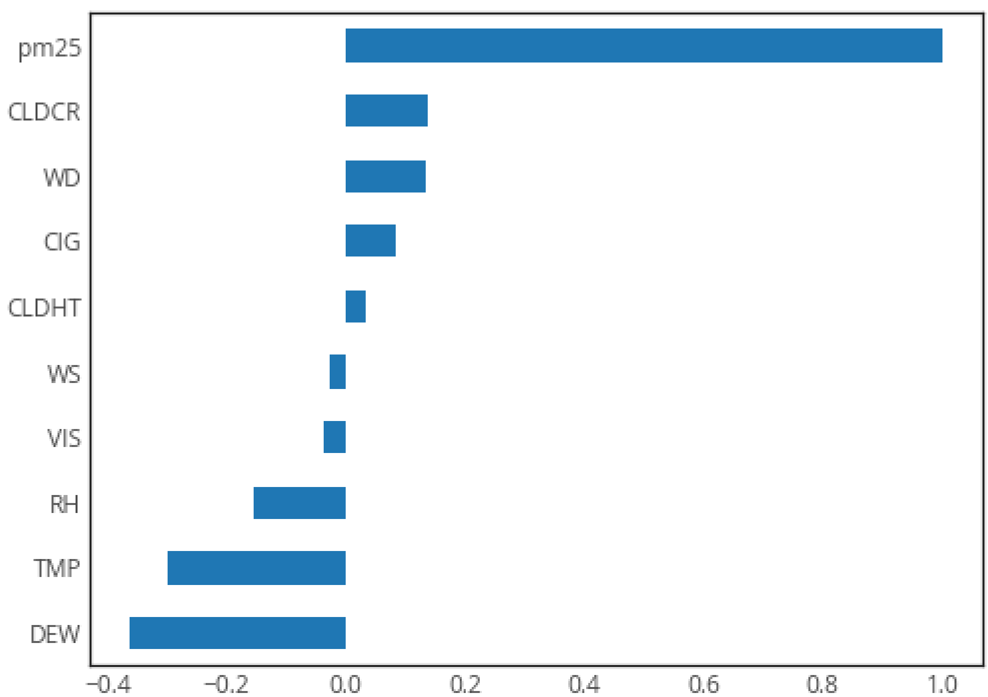


- A value of 1 is show the strongest positive correlation. Positive means when the value of one variable increases, the other also increases. The correlation of `pm25` to `pm25` ($PM_{2.5}$ concentration) is 1, which is always the case.
- A value of -1 show the strongest nagative correlation. Negative means when the value of one variable increases, the other decreases or vice versa.
- A value of 0 show no correlation.
- Anything in between are described as **weak**, **moderate**, **high** correlation. The degree to just is a dependent to the area of study. For the study involves a real environment (as oppose to well-controlled environmnet, simulated environmnet), the correlation is expected the weaker than those in well-defined environment.
- let visualize the table above, using the built-in plot function, we have two options `plot.bar()` and `plot.barh()`

In [17]:
```
df.corr()['pm25'].plot.barh()
```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb91ba72898>



In [18]:
```
# rearange the value
df.corr()['pm25'].sort_values().plot.barh()
```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb9199cc080>



and voila, it is done.

- there is no meteorological parameter in a **strong** correlation with $PM_{2.5}$. To judge a correlation number in **strong** category has to depends on a specific area of investigation but the value usually 0.7 or above.
- and not even in the area of **moderate to highly** band. So if the goal is the find a definitive correlation between observed meteorological inputs with concentration of $PM_{2.5}$, then the journey ended here, unfruitfully.

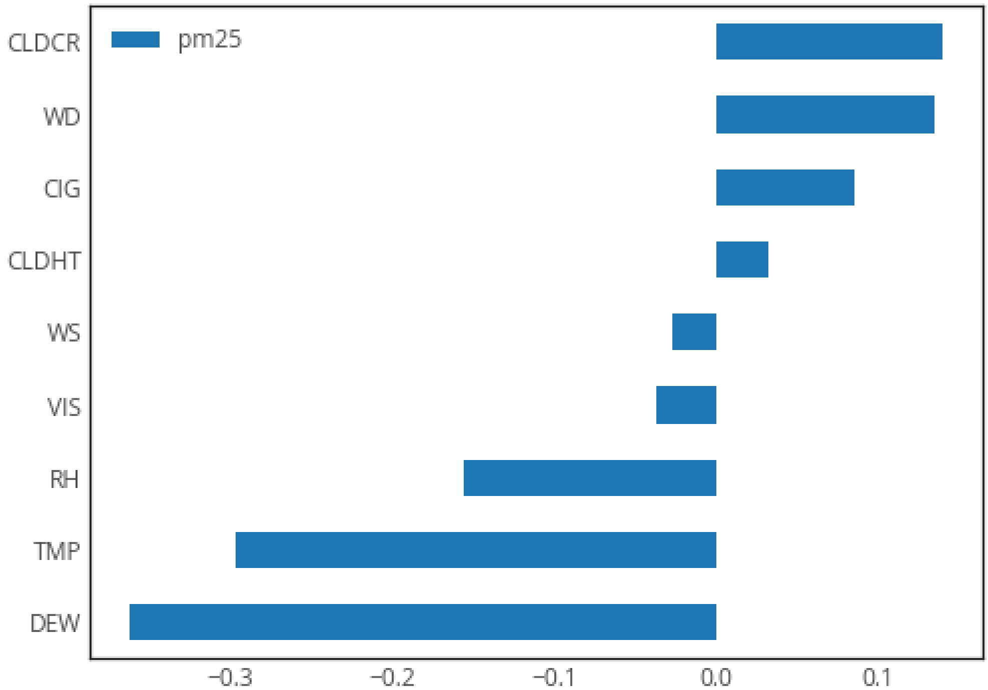
- but if you live in (seasonally) polluted area with aerosol fills the air in the winter, then it becomes something else: curiosity, practical knowledge, and service to others to feather out something interesting
- and on that ground, let move on the figure out what else in this correlation mess

Let refesh what the abbreviation mean?

- RH is relative humidity, the fraction of the current humidity to the saturated humidity that a volume of air can hold at that temperature
- CLDHT: The height of the lower cloud (in meters) relative to a reference point called *VERTICAL-REFERENCE-DATUM*
- CLDCR: Cloud cover in fraction
- WS, WD: windspeed (in meter per second), and degree with zero (or 360) is the wind comming from the north
- DEW: dewpoint temperature
- TMP: air temperature
- VIS: visiblity measured by the horizontal distance at which an object can be identified
- CIG: The height above ground level (AGL) of the lowest cloud

In [19]:
```
# let make a few operation in place
df.corr()['pm25'].sort_values().to_frame().drop(['pm25']).plot.barh()
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb9192ef588>
```



let unpack the operations here

1. take correlation on `DataFrame df`, and filter out the column for `pm25` (or $PM_{2.5}$)
2. sort the value of the correlation coefficients using `sort_values()`
3. turn a `Pandas Series` to a `DataFrame`, so that we can use the `drop()` function to drop the redundancy value of `pm25`
4. finally, the number was plot using horizontal bar chart

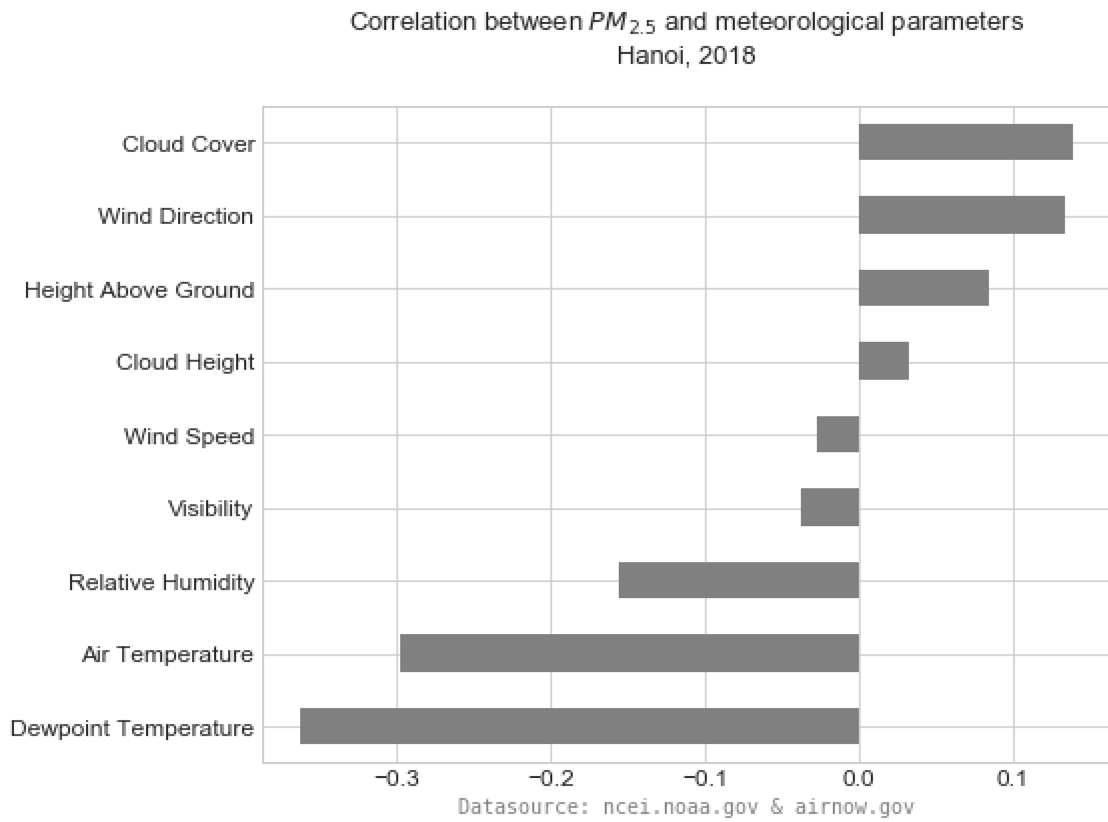
In [20]:
```
label = ['Cloud Cover', 'Wind Direction', 'Height Above Ground',
                    'Cloud Height', 'Wind Speed', 'Visibility', 'Rela
tive Humidity',
         'Air Temperature', 'Dewpoint Temperature']
```

In [21]:
```
label
```

Out[21]:
```
['Cloud Cover',
 'Wind Direction',
 'Height Above Ground',
 'Cloud Height',
 'Wind Speed',
 'Visibility',
 'Relative Humidity',
 'Air Temperature',
 'Dewpoint Temperature']
```

In [22]:
```python
labels = list(reversed(label))
```

In [23]:
```python
# let make the graph with bell and whistle
plt.style.use('seaborn-whitegrid')
fig, ax = plt.subplots()
df.corr()['pm25'].sort_values().to_frame().drop(['pm25']).plot.barh(ax=ax, color='gray')
ax.set_title('Correlation between $PM_{2.5}$ and meteorological parameters\nHanoi, 2018',y=1.05, fontsize=13)
ax.get_legend().remove()
ax.set_yticklabels(labels)
ax.set_xlabel('Datasource: ncei.noaa.gov & airnow.gov',
              fontsize=10, color='gray', fontfamily='monospace')
fig.tight_layout()
fig.savefig('img/2020Jul_corr_pm25.png')
```

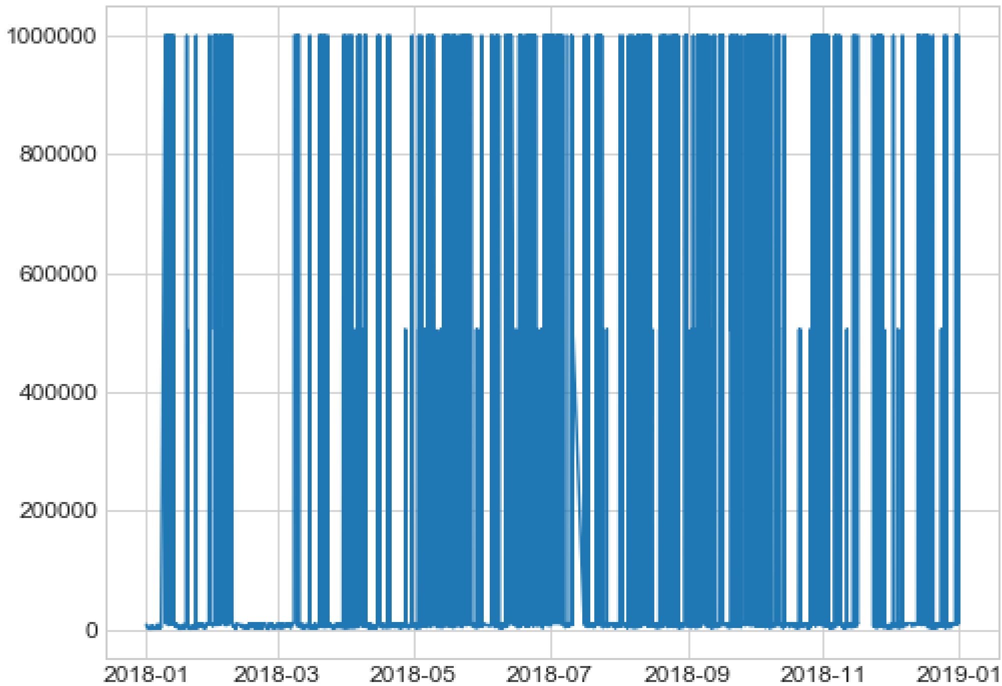


VIS

- Visiblity seems to be a good candidate to start, and it makes sense. Hazy and foggy days in Hanoi are often been observed with a high $PM_{2.5}$ concentration
- Noticed that correlation between visiblity and $PM_{2.5}$ is almost None

In [24]:
```
# pretty noisy
plt.plot(df.index, df.VIS)
```

Out[24]:
```
[<matplotlib.lines.Line2D at 0x7fb9191abcf8>]
```

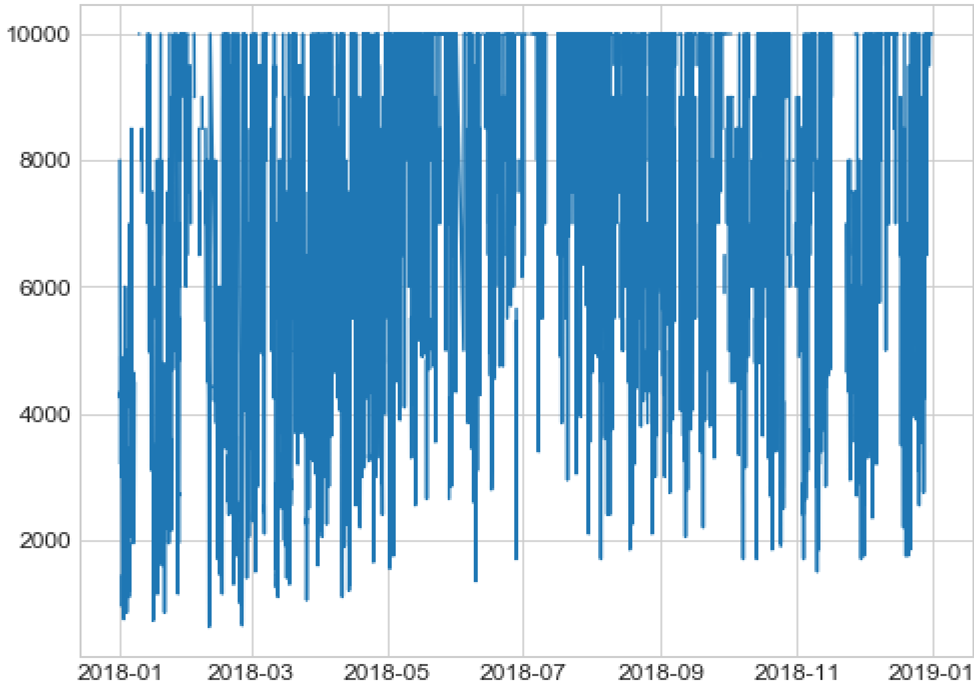


In [25]:
```
# most of data showing a good visibility, but I did not clean up the
 file all the way, the 9999 value for missing still in place
df.VIS.describe()
```

Out[25]:
```
count      7959.000000
mean     179714.442329
std      359655.706573
min         625.000000
25%        5500.000000
50%        9000.000000
75%        9999.000000
max      999999.000000
Name: VIS, dtype: float64
```

In [26]:
```
# setting all missing value, and max value as None
df.loc[df.VIS >=220000, 'VIS'] = None
plt.plot(df.index, df.VIS)
```

Out[26]: [<matplotlib.lines.Line2D at 0x7fb9190c8a20>]

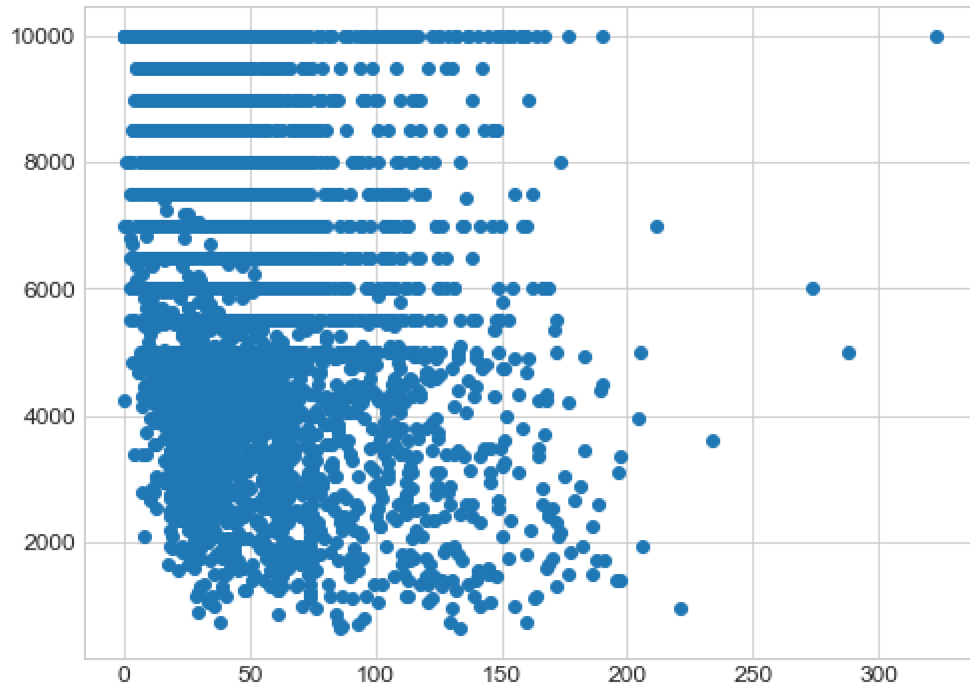


In [27]:
```
df.VIS.describe()
```

Out[27]:
```
count    6380.000000
mean     7216.806740
std      2672.672141
min       625.000000
25%      5000.000000
50%      7500.000000
75%      9999.000000
max      9999.000000
Name: VIS, dtype: float64
```

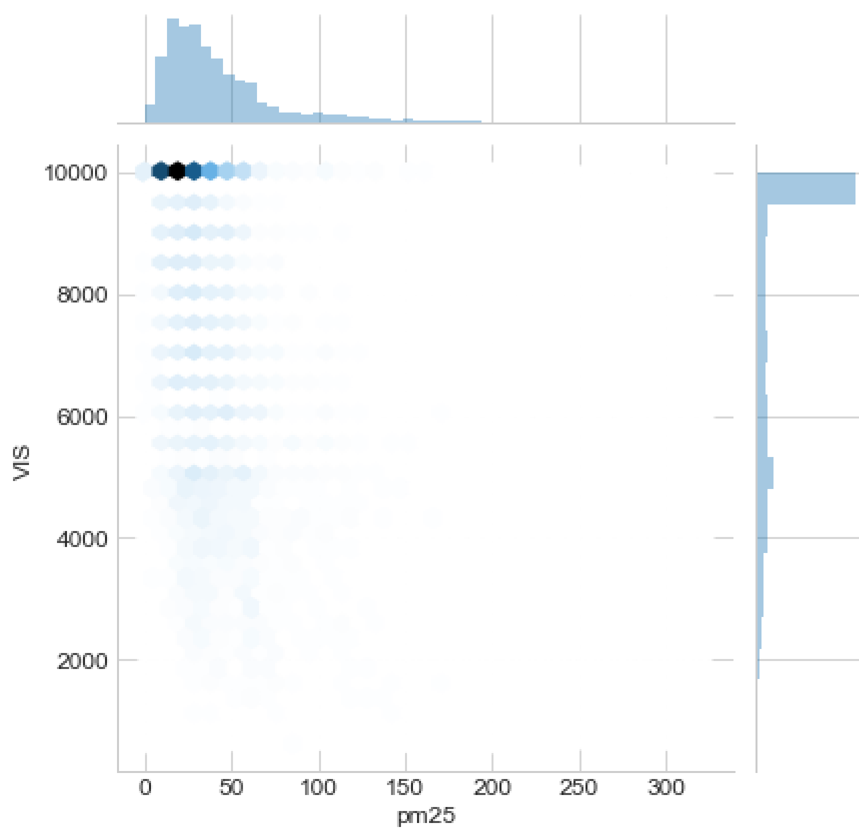
In [28]:
```
# still not clear pattern though we have more point on the lower left corner
plt.scatter(df.pm25, df.VIS)
```

Out[28]: <matplotlib.collections.PathCollection at 0x7fb91909d1d0>



In [29]:
```
sns.jointplot(df.pm25, df.VIS, kind='hex')
```

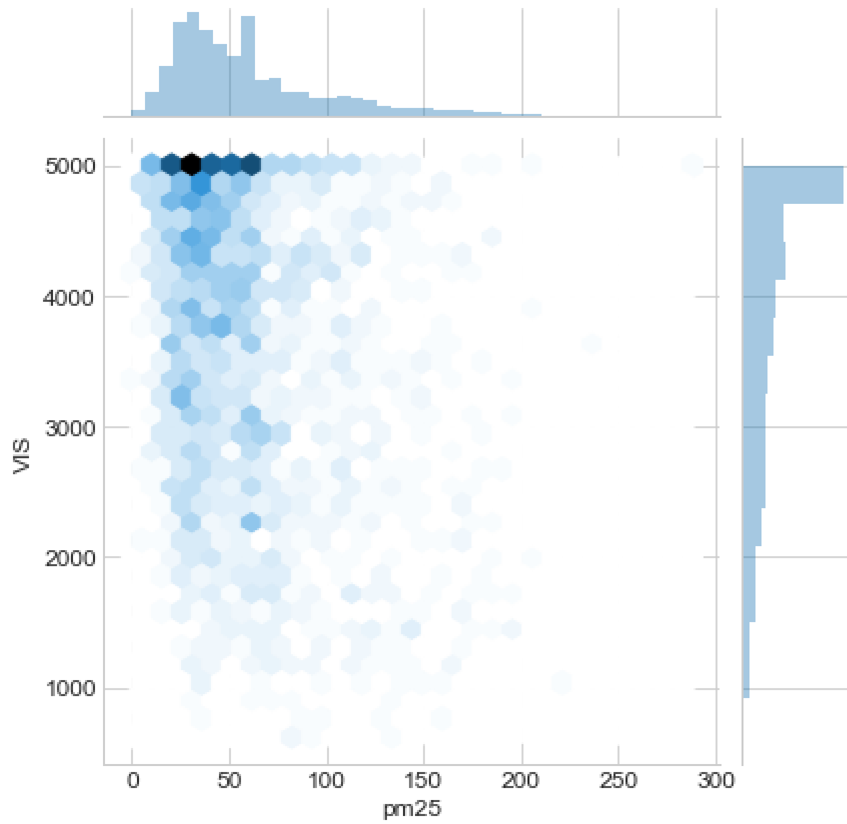
Out[29]: <seaborn.axisgrid.JointGrid at 0x7fb9191fdc18>



In [30]:
```
dft = df.query('VIS <=5000')
```

In [31]:
```
# with even subset data with lower visibility,
sns.jointplot(dft.pm25, dft.VIS, kind='hex')
```

Out[31]: <seaborn.axisgrid.JointGrid at 0x7fb918e50780>



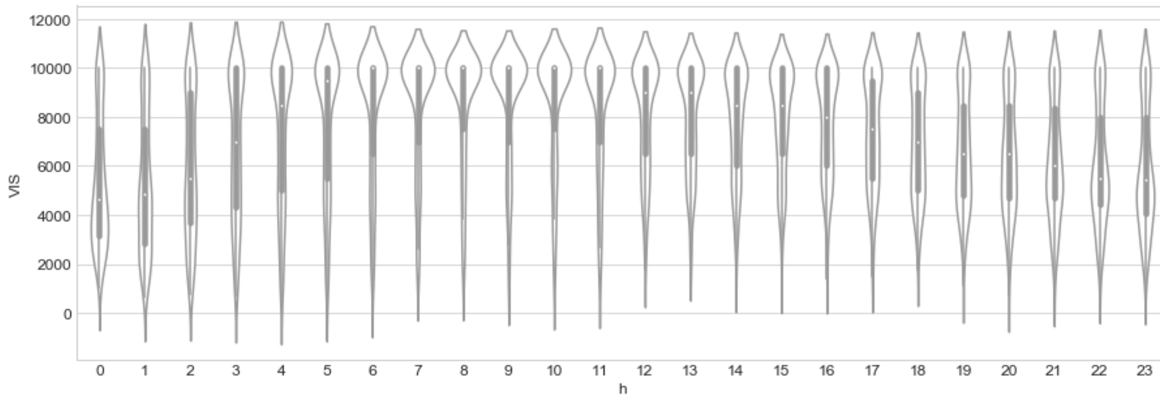
In [32]:
```
df.corr()['pm25']['VIS']
```

Out[32]: -0.4127430609698673

In [33]:
```
df['h'] = df.index.hour
df['m'] = df.index.month
```

In [34]:
```
# ok, VIS seems depended on the hour, lower during the night
plt.figure(figsize=(15,5))
sns.violinplot(data=df, x='h', y='VIS', color='white')
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb918eb5a90>

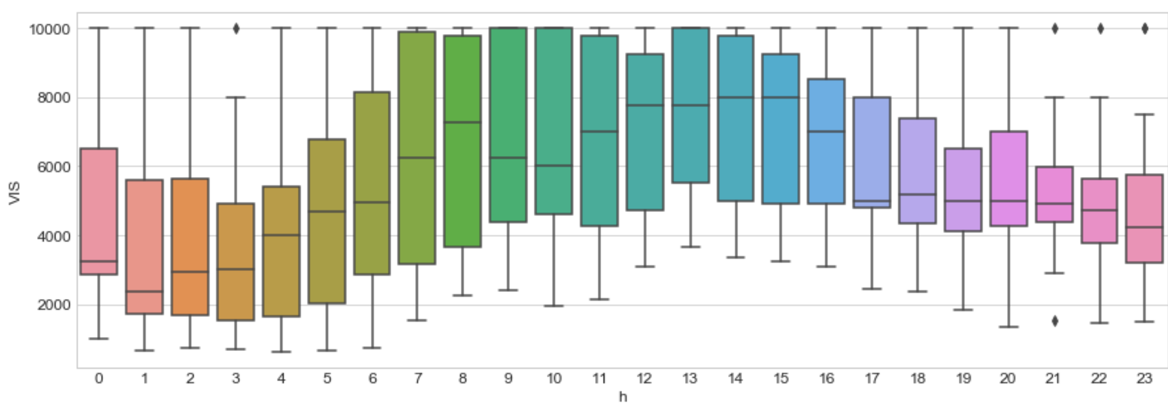


In [35]:
```
# let look for a month
```

In [36]:
```
feb = df.query('m==2')
```

In [37]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=feb, x='h', y='VIS')
```

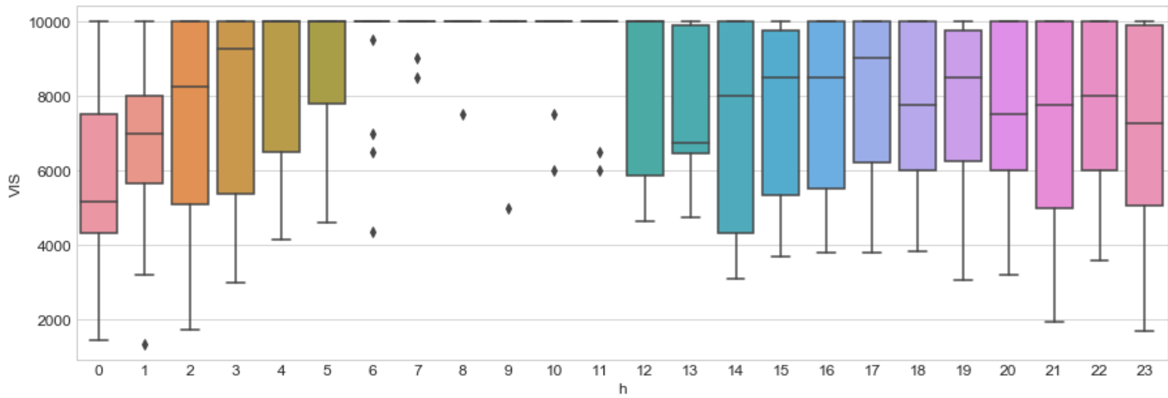
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb914927d68>



In [38]:
```
jun = df.query('m==6')
```

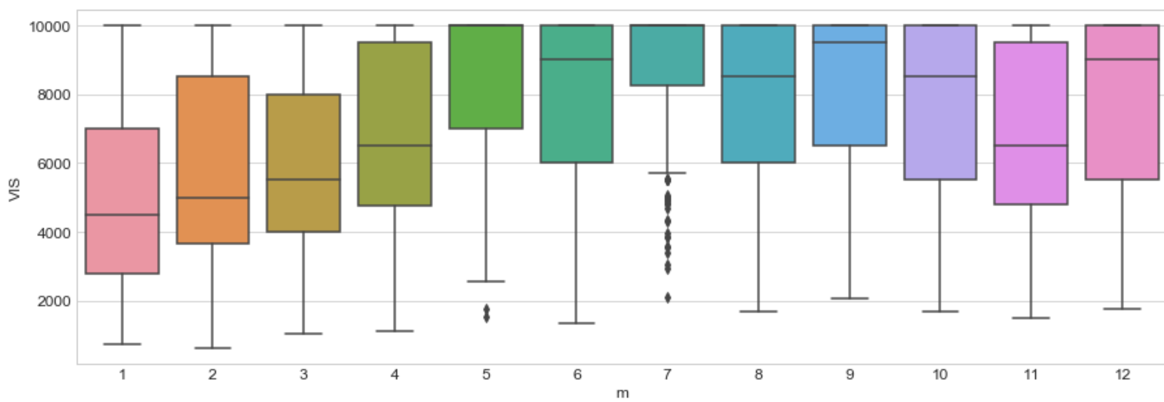
In [39]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=jun, x='h', y='VIS')
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb90ee10550>



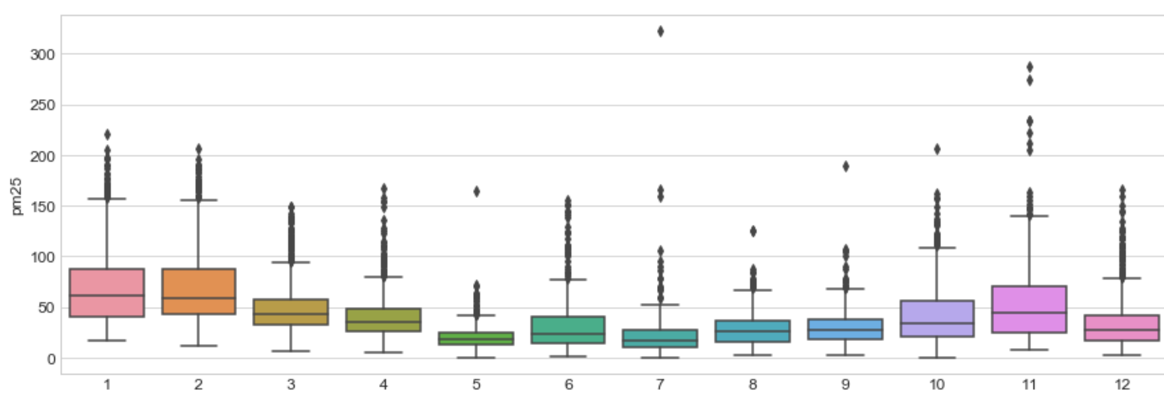
In [40]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=df, x='m', y='VIS')
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb90ec17978>



In [41]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=df, x='m', y='pm25')
```

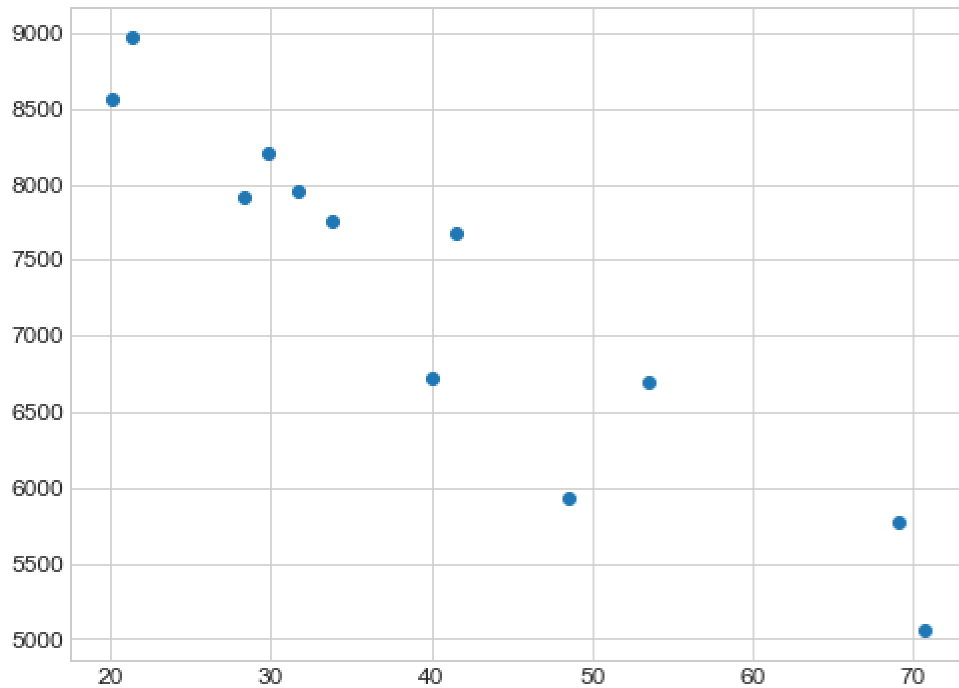
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb90ee105f8>



In [42]:
```
dft = df.groupby('m').mean()
```

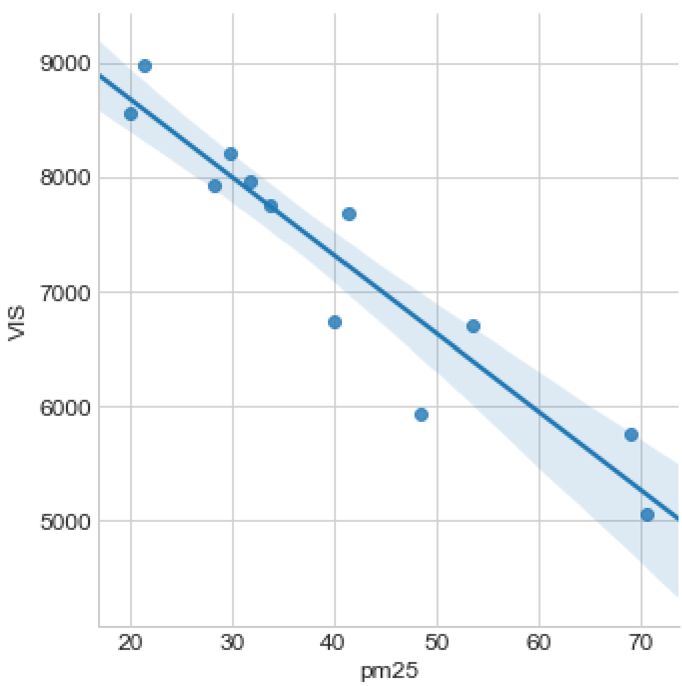
In [43]:
```
plt.scatter(dft.pm25, dft.VIS)
```

Out[43]: <matplotlib.collections.PathCollection at 0x7fb90e912cc0>



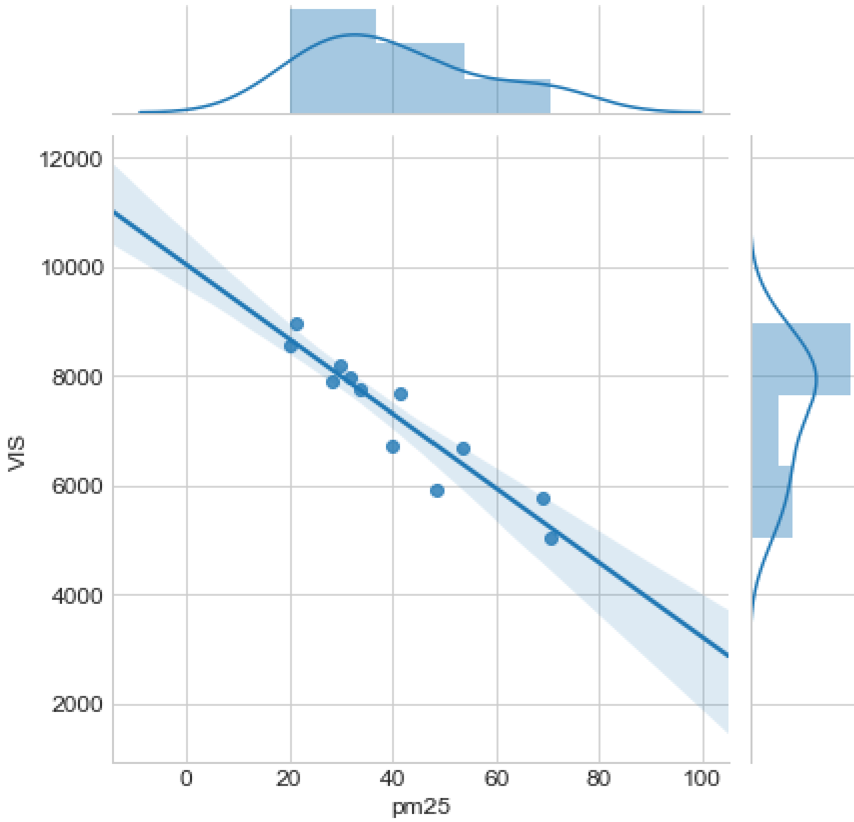
In [44]:
```
sns.lmplot(x='pm25', y='VIS', data=dft)
```

Out[44]: <seaborn.axisgrid.FacetGrid at 0x7fb90e9254a8>



In [45]:
```
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

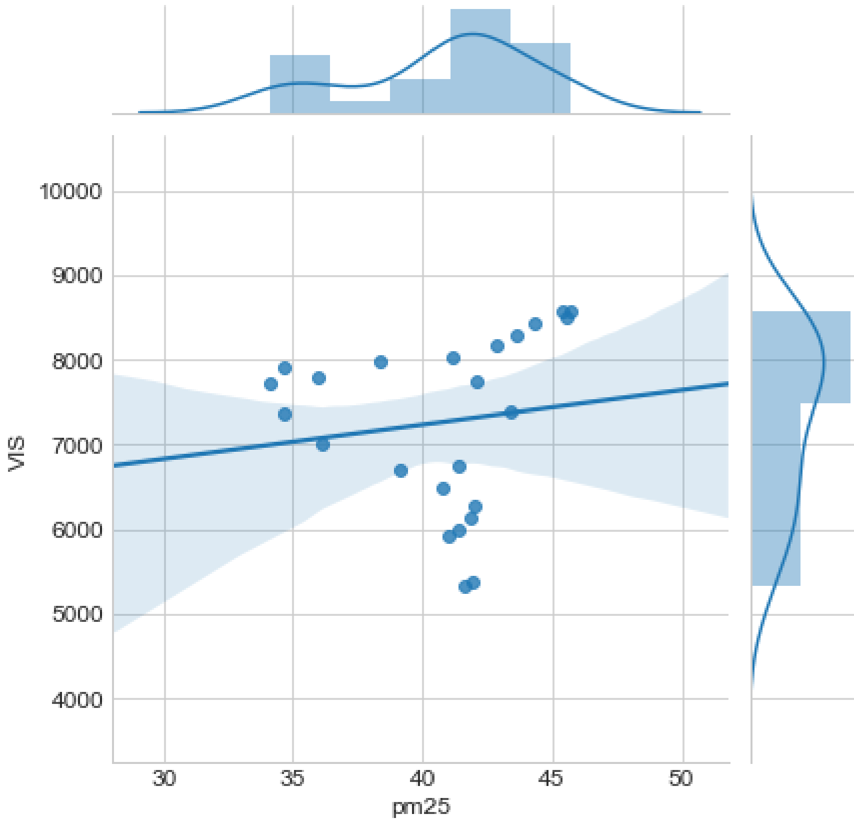
Out[45]:
```
<seaborn.axisgrid.JointGrid at 0x7fb90e8af278>
```



In [46]:
```
# this is impressive, sudently, the correlation of the average concen
tration (by month) is strong, or very strong
dft.corr()['pm25']['VIS']
```

Out[46]:
```
-0.9445724331666244
```

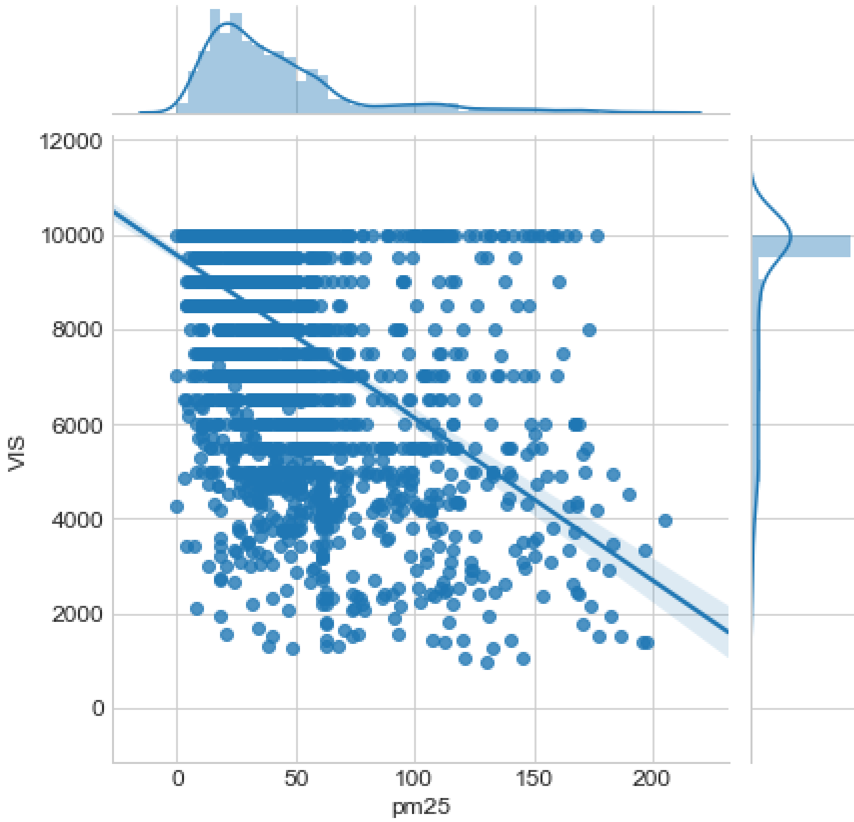
In [47]:
```
dft = df.groupby('h').mean()
```

In [48]:
```python
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```
Out[48]:
```
<seaborn.axisgrid.JointGrid at 0x7fb90e7b6d30>
```


In [49]:
```python
# or not so, if we averaged the input by the hour
dft.corr()['pm25']['VIS']
```
Out[49]:
```
0.13620802167369214
```
In [50]:
```python
# let try to explore more
dft = df[(df['h'] >=7) & (df['h'] <=17)]
```

In [51]:
```
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

Out[51]: <seaborn.axisgrid.JointGrid at 0x7fb90e666550>



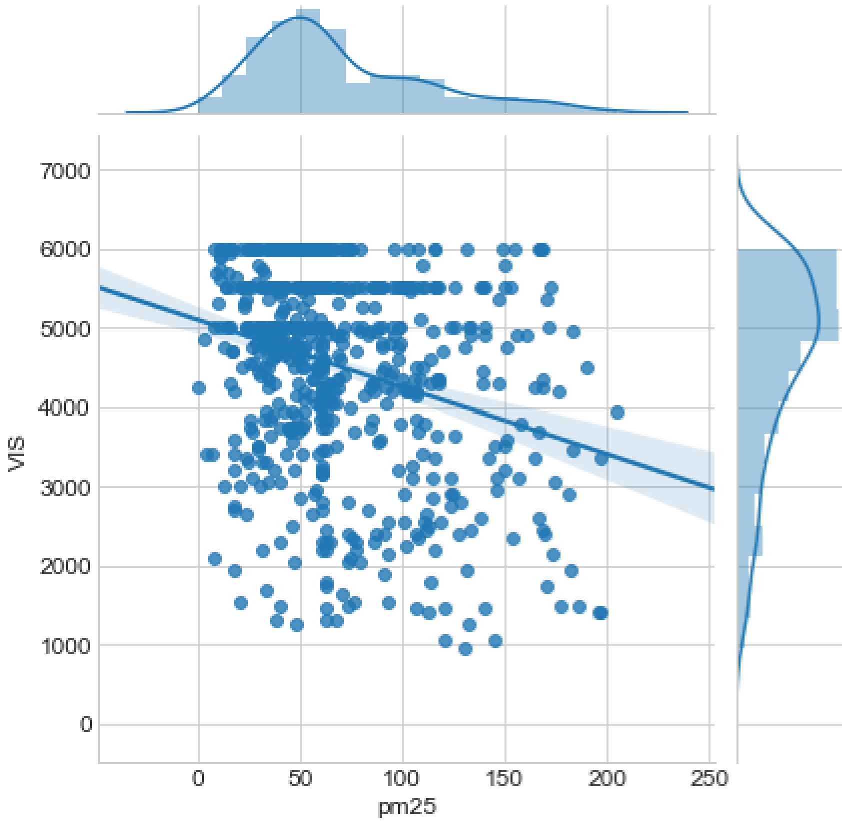
In [52]:
```
dft6 = dft.query('VIS<=6000')
```

In [53]:
```
# this the correlation daily hour
dft.corr()['pm25']['VIS']
```

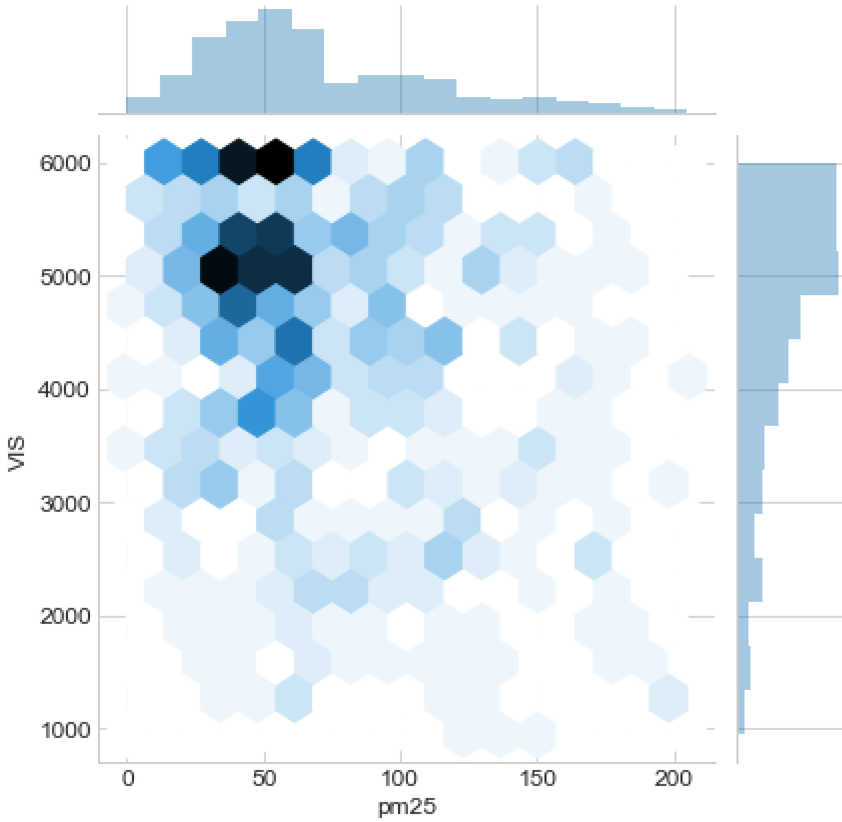
Out[53]: -0.49590702697163747

In [54]:
```
sns.jointplot(x='pm25', y='VIS', data=dft6, kind="reg", )
```

Out[54]:
```
<seaborn.axisgrid.JointGrid at 0x7fb90e5a5748>
```

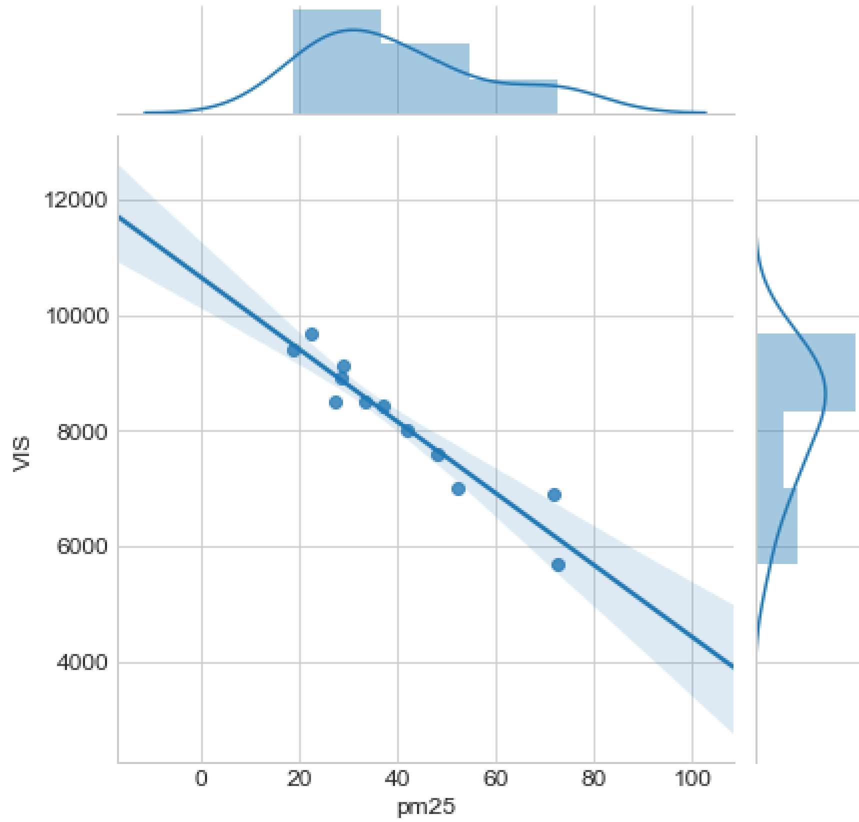


In [55]:
```
sns.jointplot(x='pm25', y='VIS', data=dft6, kind="hex", )
```
Out[55]: <seaborn.axisgrid.JointGrid at 0x7fb90e4977b8>



In [56]:
```
dft = dft.groupby('m').mean()
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

Out[56]: <seaborn.axisgrid.JointGrid at 0x7fb90e666128>

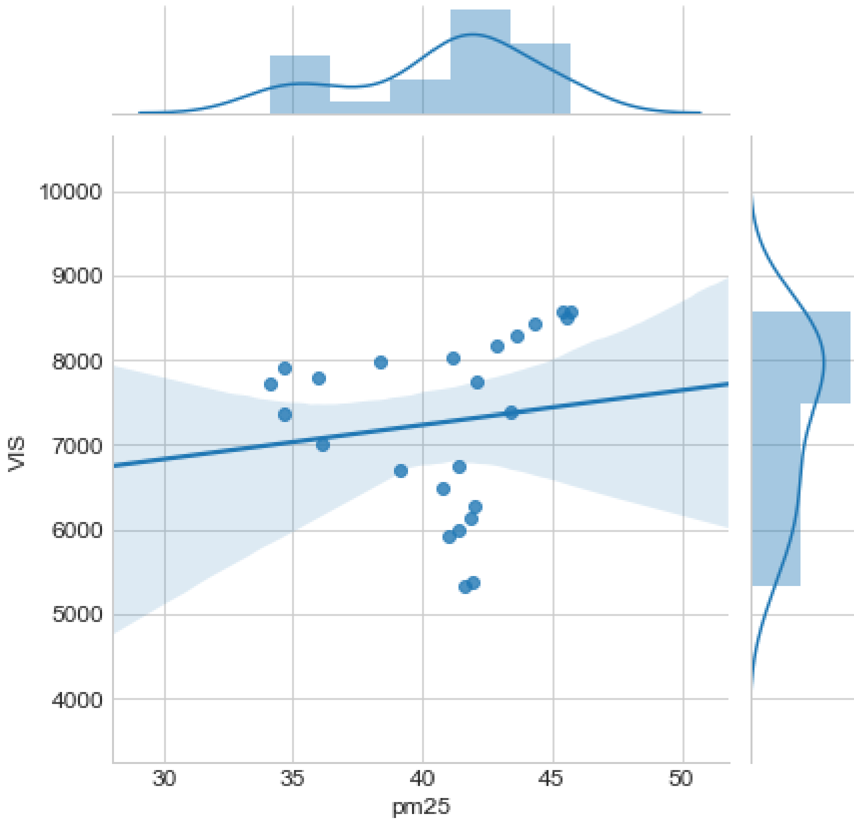


In [57]:
```
# the correlation is strong with daily hours
dft.corr()['pm25']['VIS']
```

Out[57]: -0.9549564104816615

In [58]:
```python
dft1 = df.groupby('h').mean()
sns.jointplot(x='pm25', y='VIS', data=dft1, kind="reg", )
```

Out[58]: <seaborn.axisgrid.JointGrid at 0x7fb90e1322e8>

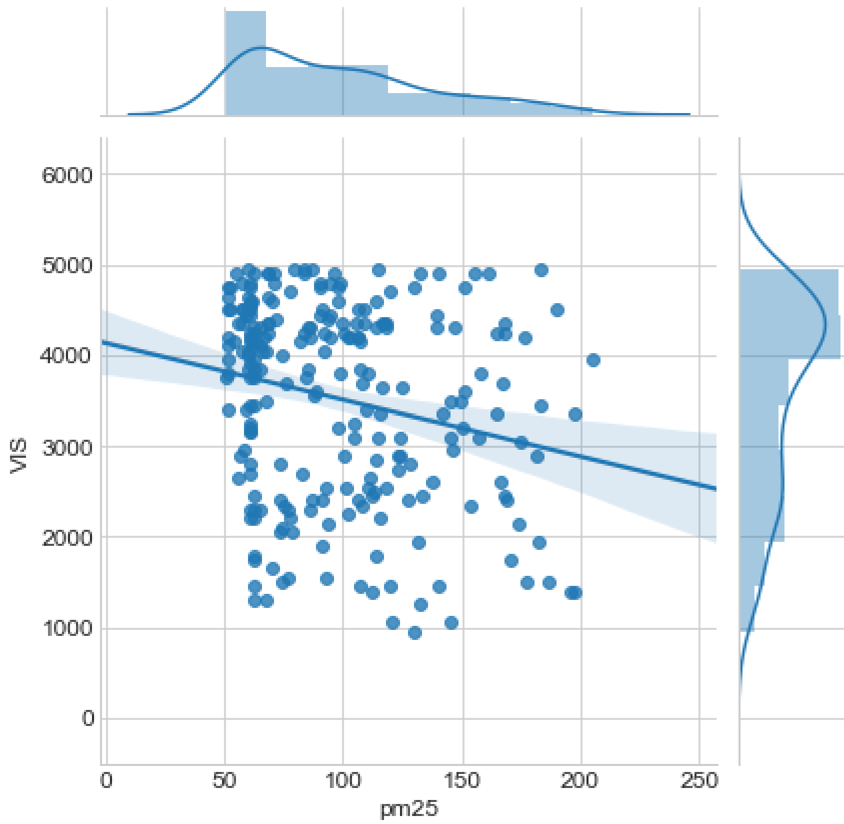


In [59]:
```python
# grouping by the hour with day hour
dft1.corr()['pm25']['VIS']
```

Out[59]: 0.13620802167369214

In [60]:
```
# let try to explore even more
dft = df[(df['h'] >=7) & (df['h'] <=17) & (df['pm25'] > 50) & (df['VIS'] < 5000)]
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
print(dft.corr()['pm25']['VIS'])
```

```
-0.22306622063006426
```



- the analysis can misled by incidently making a gross estimation
- when in doubt, make sure to run through key combination to make sure we know the underlying artifact
- low visiblity is often observed with a high $PM_{2.5}$, but from this set of data, opposite conclusion can be drawn

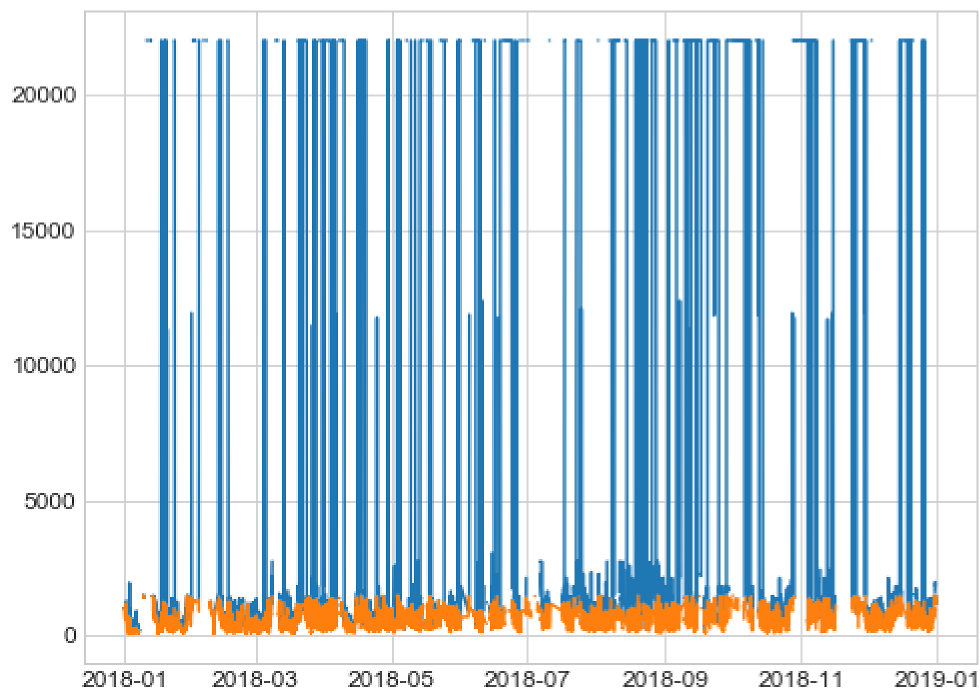
CIG, CLDHT

In [61]:
```python
# we can get correlation to other variable like this
# in the previous section, we look for horizontal direction, now we t
urn to vertical direction
df.corr()['CIG']
```

Out[61]:
```
CIG      1.000000
VIS     -0.085522
TMP      0.060859
DEW     -0.013038
WD       0.130481
WS      -0.032222
CLDCR   -0.195803
CLDHT    0.221168
pm25     0.084939
RH      -0.134297
h        0.143417
m        0.177284
Name: CIG, dtype: float64
```

In [62]:
```python
plt.plot(df.index, df.CIG)
plt.plot(df.index, df.CLDHT)
```

Out[62]:
```
[<matplotlib.lines.Line2D at 0x7fb90e486ac8>]
```



In [63]:
```python
df.CLDHT.describe()
```

Out[63]:
```
count    5815.000000
mean      616.896303
std       345.892369
min        61.000000
25%       305.000000
50%       564.000000
75%       884.000000
max      1494.000000
Name: CLDHT, dtype: float64
```

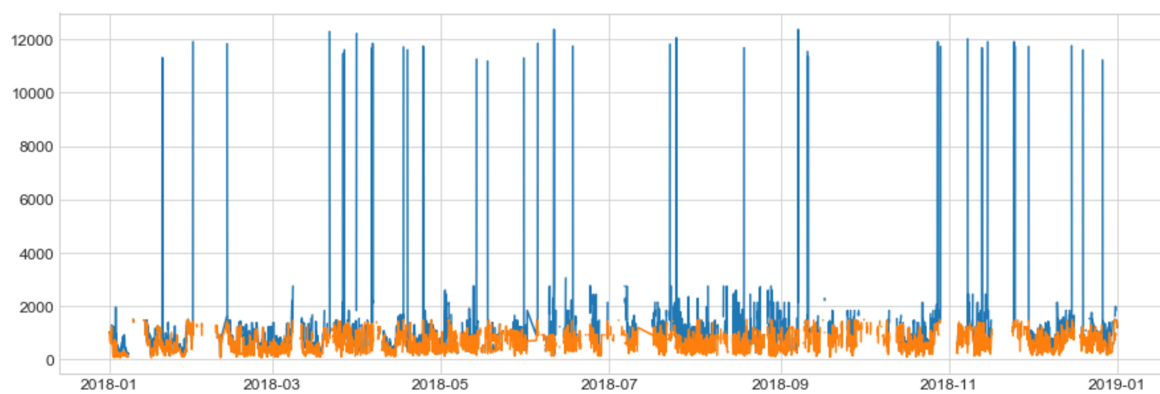
In [64]:
```python
df.CIG.describe()
```

Out[64]:
```
count     5604.000000
mean      5181.372234
std       8437.395829
min         91.000000
25%        610.000000
50%       1006.000000
75%       1676.000000
max      22000.000000
Name: CIG, dtype: float64
```

In [65]:
```python
# 22000 (in meter) is for clear sky, let ignore it by setting to zero
df.loc[df.CIG ==22000, 'CIG'] = None
```

In [66]:
```python
plt.figure(figsize=(15,5))
plt.plot(df.index, df.CIG)
plt.plot(df.index, df.CLDHT)
```

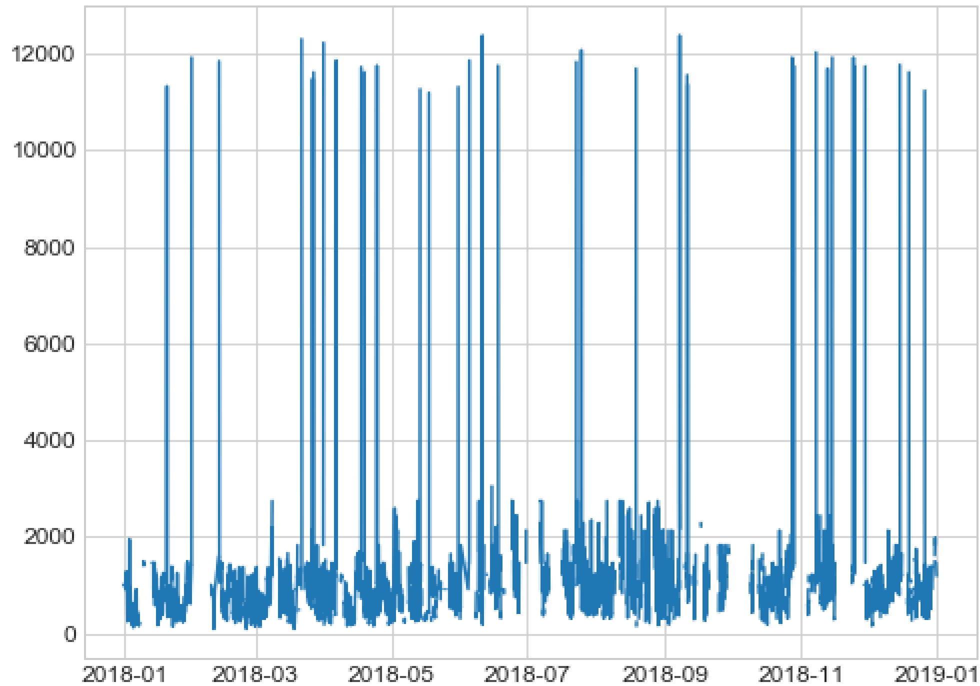
Out[66]:
```
[<matplotlib.lines.Line2D at 0x7fb90de44a20>]
```



- now it look better together, both CIG and CLDHT are to height to the lowest cloud level

In [67]:
```
plt.plot(df.index, df.CIG)
# plt.plot(df.index, df.CLDHT)
```

Out[67]:
```
[<matplotlib.lines.Line2D at 0x7fb90de2a438>]
```

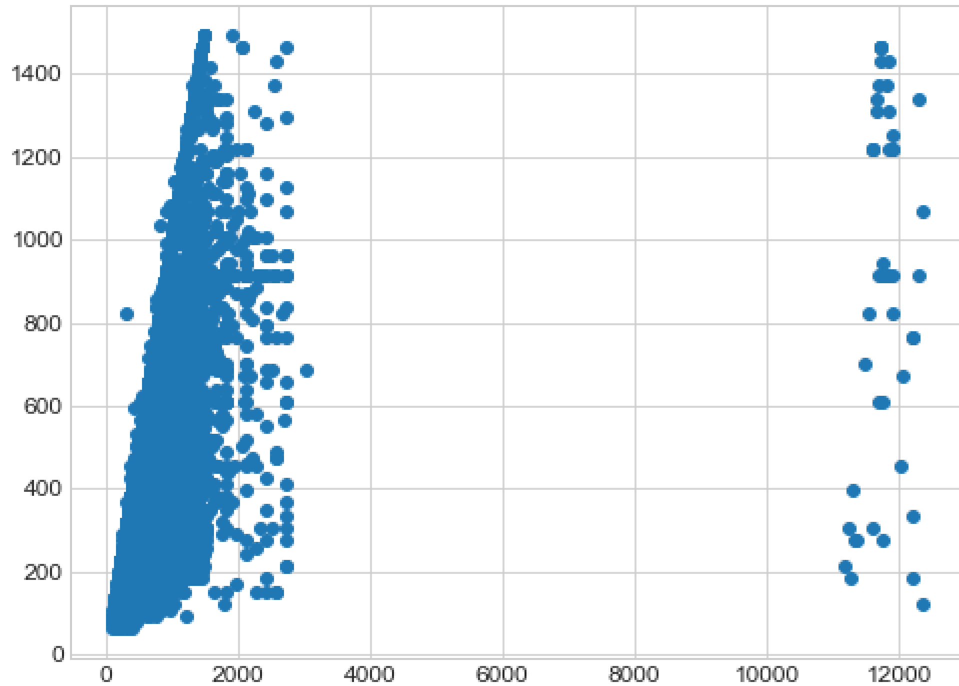


In [68]:
```
df.CIG.describe()
```

Out[68]:
```
count     4492.000000
mean      1017.900712
std       1199.512723
min         91.000000
25%        563.875000
50%        868.500000
75%       1219.000000
max      12371.500000
Name: CIG, dtype: float64
```

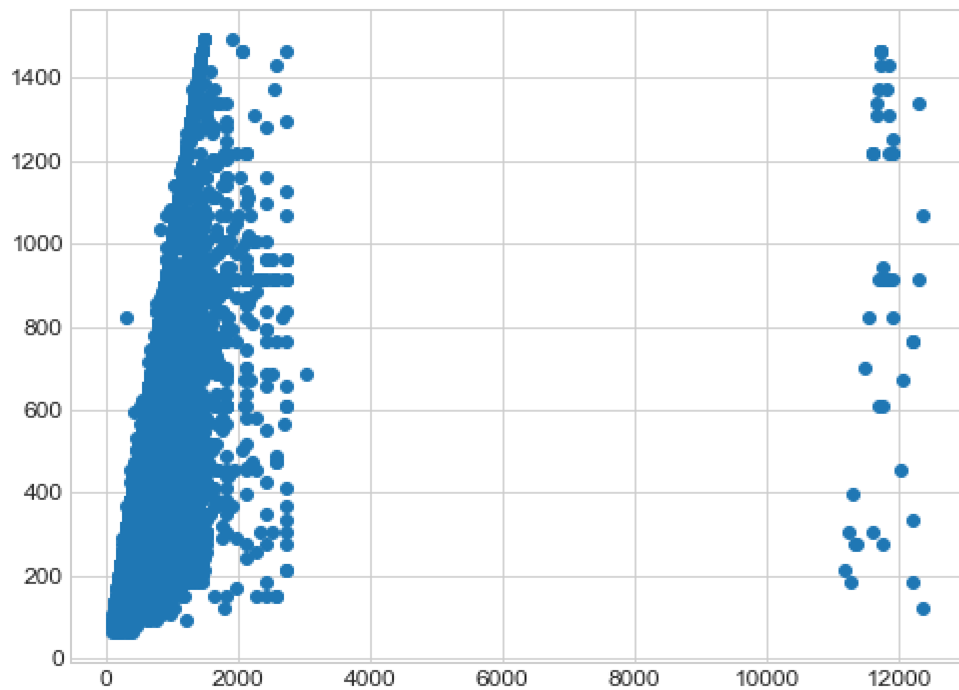
In [69]:
```python
plt.scatter(df.CIG, df.CLDHT)
```

Out[69]: <matplotlib.collections.PathCollection at 0x7fb90dd3f160>

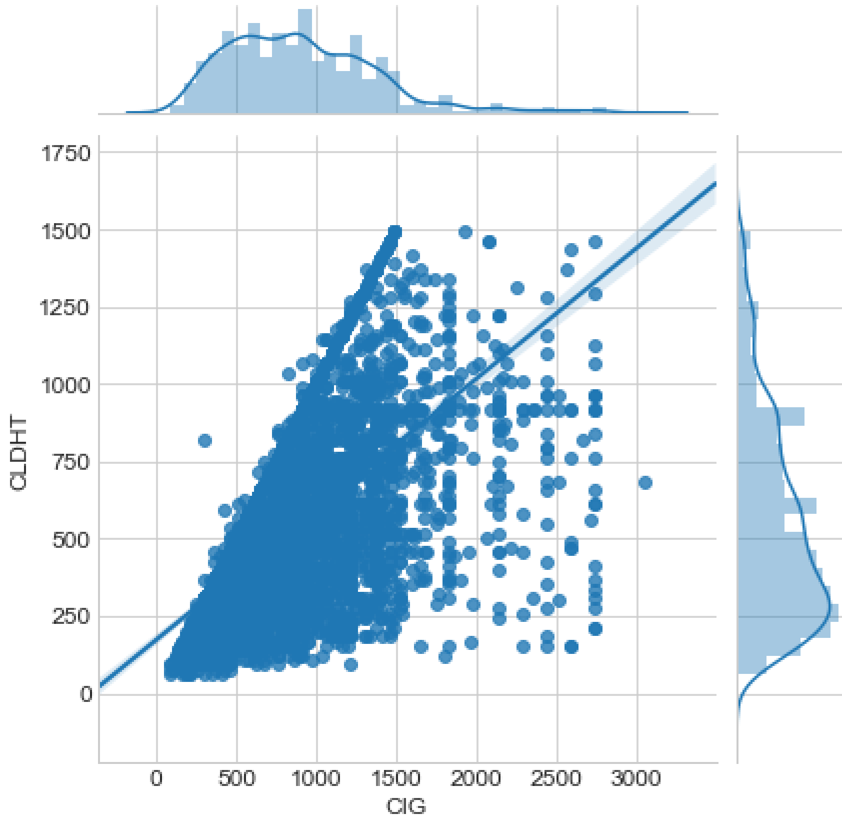


In [70]:
```python
dft = df.query('CIG<=5000')
plt.scatter(df.CIG, df.CLDHT)
```

Out[70]: <matplotlib.collections.PathCollection at 0x7fb90dd1fba8>

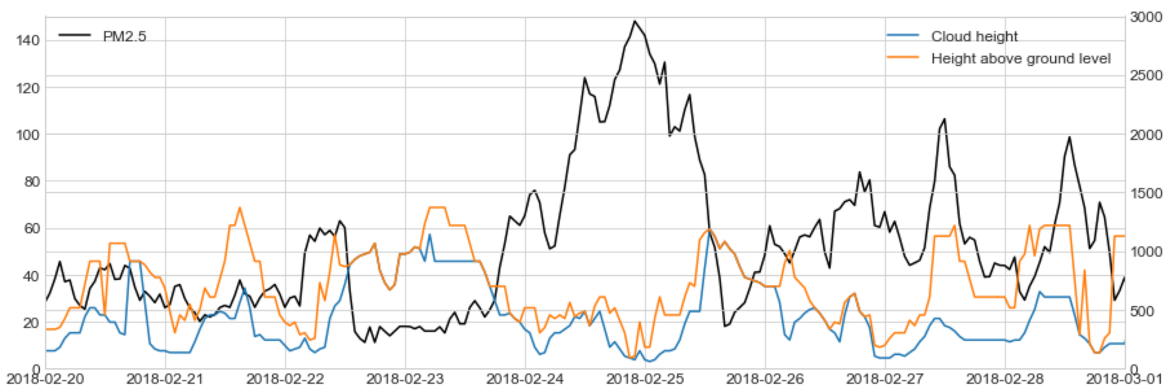


In [71]:
```
sns.jointplot(dft.CIG, dft.CLDHT, kind='reg')
```
Out[71]:
```
<seaborn.axisgrid.JointGrid at 0x7fb90dcc9ac8>
```



In [72]:
```
# VIS is horizontal distance to the identifiable object
# CIG, CLDHT is the height (vertical distance) to ground of a referen
ce point to the lowest cloud
fig, ax = plt.subplots(figsize=(15,5))
ax.set_xlim(datetime.datetime(2018,2,20), datetime.datetime(2018,3,1
))

ax.plot(df.index, df.pm25, color='black', label='PM2.5')
ax.set_ylim(0, 150)

ax.legend(loc='upper left')
ax2 = ax.twinx()
ax2.plot(df.index, df.CLDHT, label='Cloud height')
ax2.plot(df.index, df.CIG, label='Height above ground level')
ax2.set_ylim(0, 3000)
ax2.legend()
```

Out[72]: <matplotlib.legend.Legend at 0x7fb90dfb8828>



let review

- look like we capture a good window showing the reverse relationship between $PM_{2.5}$ concentration with the height of the lowest cloud
- a thin layer between ground and the cloud is one indicator of poor mixing or a stable layer. So in this condition, the $PM_{2.5}$ formed near the ground being kept there
- a consistent high concentration above 50 microgram/cubic meters exceeds the national technical guidance (in Vietnam), for US EPA, that level is 35µg/m^3 for daily average

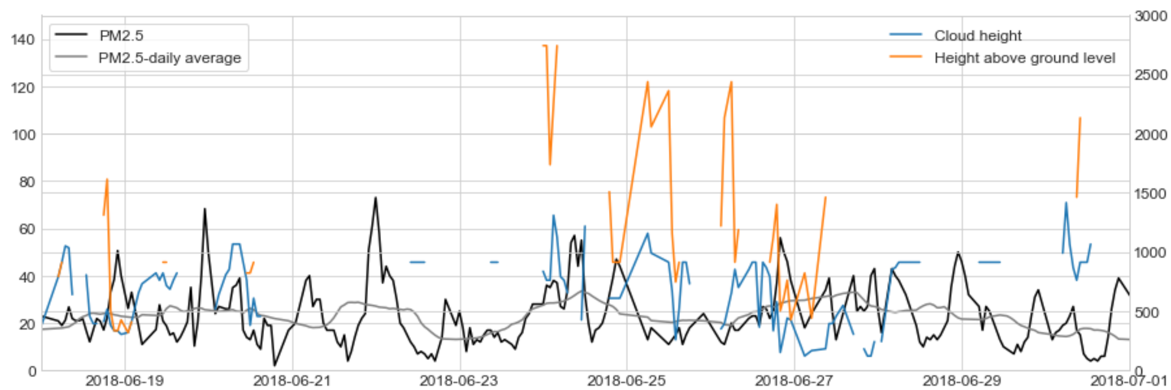
In [73]:
```
# let make a global check to see the whole dataset rather one capture
d moment
df.corr()['pm25'].filter(['CLDHT', 'CIG'])
```

Out[73]:
```
CLDHT    0.032396
CIG     -0.032574
Name: pm25, dtype: float64
```

- this is important to note because one event can be critical to know the relationship (like above) while the global average look no relationship at all

In [74]:
```
# let look another instance
fig, ax = plt.subplots(figsize=(15,5))

ax.plot(df.index, df.pm25, color='black', label='PM2.5')
ax.plot(df.index, df.pm25.rolling(window=24, center=True).mean(), col
or='gray', label='PM2.5-daily average')
ax.set_ylim(0, 150)

ax.legend(loc='upper left', frameon=True)
ax2 = ax.twinx()
ax2.plot(df.index, df.CLDHT, label='Cloud height')
ax2.plot(df.index, df.CIG, label='Height above ground level')
ax2.set_ylim(0, 3000)
ax2.legend()

ax.set_xlim(datetime.datetime(2018,6,18), datetime.datetime(2018,7,1
))
```

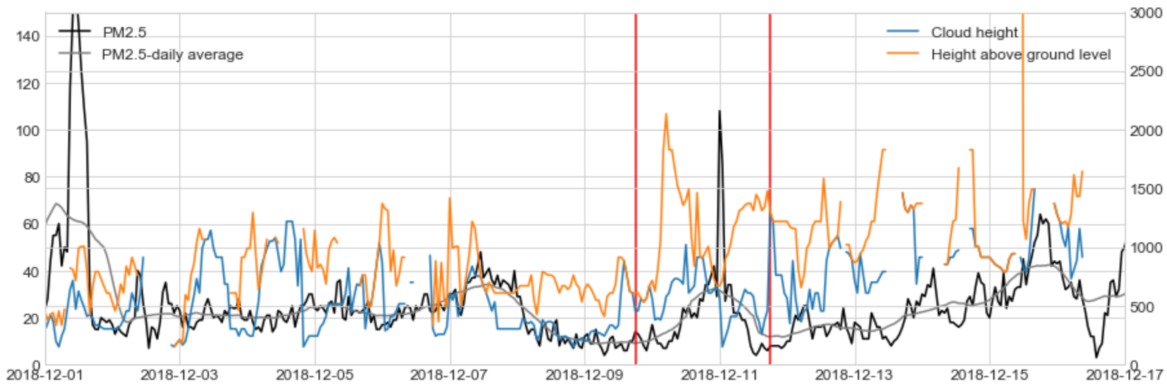
Out[74]:
```
(736863.0, 736876.0)
```



- in the summer, the heights were more sporatic, some was set to `None` with a clear condition, and some of the points are in `missing` tag
- the concentration is also lower, in the range of 20-30 μg/m^3

In [75]:
```
fig, ax = plt.subplots(figsize=(15,5))

ax.plot(df.index, df.pm25, color='black', label='PM2.5')
ax.plot(df.index, df.pm25.rolling(window=24, center=True).mean(), col
or='gray', label='PM2.5-daily average')
ax.set_ylim(0, 150)

ax.legend(loc='upper left')
ax2 = ax.twinx()
ax2.plot(df.index, df.CLDHT, label='Cloud height')
ax2.plot(df.index, df.CIG, label='Height above ground level')
ax2.set_ylim(0, 3000)
ax2.legend(loc='upper right')
ax.set_xlim(datetime.datetime(2018,12,1), datetime.datetime(2018,12,1
7))
ax.axvline(x=datetime.datetime(2018,12,9,18), color='red')
ax.axvline(x=datetime.datetime(2018,12,11,18), color='red')
```

Out[75]: <matplotlib.lines.Line2D at 0x7fb91bb0f4e0>



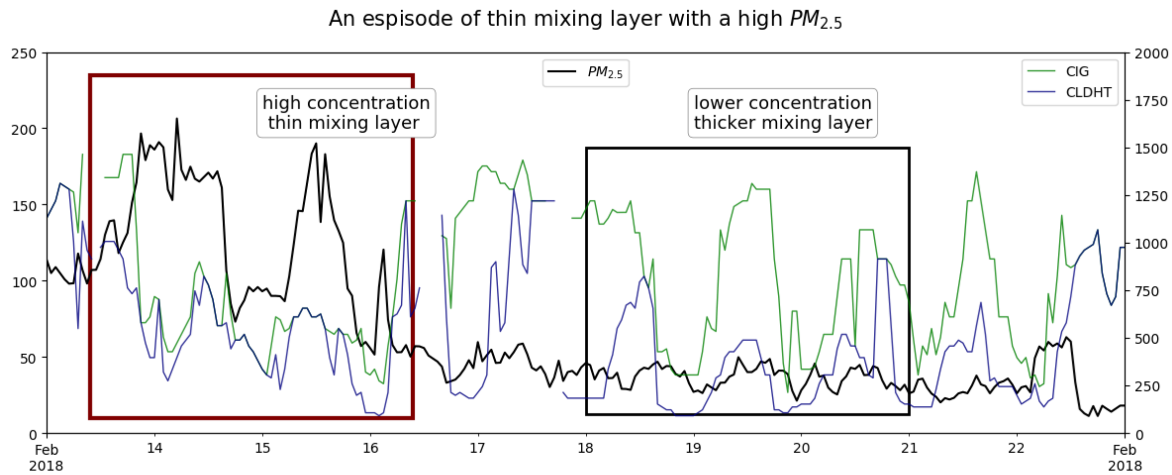
- in this window, another event that capture the inverse correlation of cloud height and $PM_{2.5}$ concentration

In [76]:
```
# import matplotlib.transforms as transforms
```

In [77]:
```
import matplotlib as mpl
```

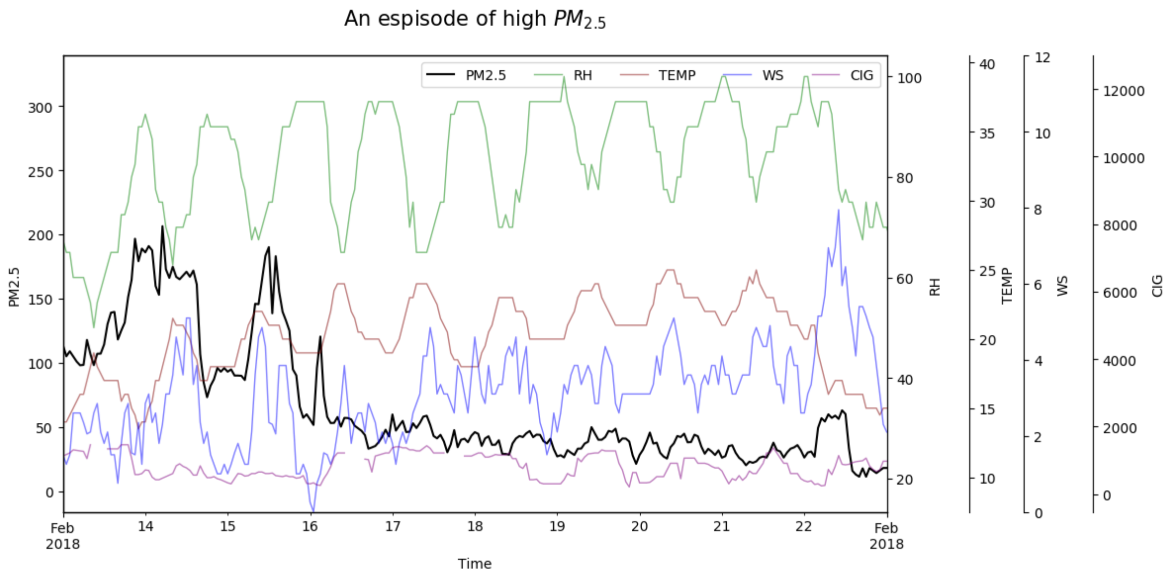
In [78]:

```
plt.style.use('default')
fig, ax = plt.subplots(figsize=(12,5))
ax.plot(df.index, df.pm25, color='black', label=r'$PM_{2.5}$')
ax.set_ylim(0, 250)
ax.legend(loc='upper center')


ax2 = ax.twinx()
ax2.plot(df.index, df.CIG, color='green', label='CIG', lw=1, alpha=0.8)
ax2.plot(df.index, df.CLDHT, color='navy', label='CLDHT', lw=1, alpha=0.8)
ax2.set_xlim(datetime.datetime(2018,2,13), datetime.datetime(2018,2,23))
ax2.set_ylim(0, 2000)
ax2.legend(loc='upper right')

bbox_props = dict(boxstyle="round,pad=0.3", fc="white", ec="gray", lw=0.5)
ax.annotate(s='high concentration\n thin mixing layer', xy=(0.2, 0.8),
            fontsize=13,
            bbox=bbox_props,
             xytext=(0.2,0.80),
            xycoords='axes fraction',
       )
ax.annotate(s='lower concentration\nthicker mixing layer', xy=(0.6, 0.8),
            fontsize=13,
            bbox=bbox_props,
             xytext=(0.6,0.80),
            xycoords='axes fraction',
       )

p = plt.Rectangle((0.04, .04), width=0.3, height=0.9, fill=False, color='maroon', lw=3)
p.set_transform(ax.transAxes)
p1 = plt.Rectangle((0.5, .05), width=0.3, height=0.7, fill=False, color='black', lw=2)
p1.set_transform(ax.transAxes)
p.set_clip_on(False)
ax.add_patch(p)
ax.add_patch(p1)
ax.xaxis.set_major_locator(mpl.dates.MonthLocator())
ax.xaxis.set_minor_locator(mpl.dates.DayLocator())

ax.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%d'));
ax.xaxis.set_major_formatter(mpl.dates.DateFormatter('%h\n%Y'))
ax.set_title('An espisode of thin mixing layer with a high $PM_{2.5}$', y=1.05, fontsize=15)
fig.tight_layout()
fig.savefig('img/2020Jul_mixing_feb.png');
```




```
In [79]: mpl.rcParams.update(mpl.rcParamsDefault)
```

In [80]:
```
fig = plt.figure(figsize=(12,6))
host = fig.add_subplot(111)

par1 = host.twinx()
par2 = host.twinx()
par3 = host.twinx()
par4 = host.twinx()

host.set_xlabel("Time")
host.set_ylabel("PM2.5")
par1.set_ylabel("RH")
par2.set_ylabel("TEMP")
par3.set_ylabel("WS")
par4.set_ylabel("CIG")

p1, = host.plot(df.index, df.pm25, color='black',label="PM2.5")
p2, = par1.plot(df.index, df.RH, color='green', label="RH", alpha=0.5
, lw=1)
p3, = par2.plot(df.index, df.TMP, color='maroon', label="TEMP", alpha
=0.5, lw=1)
p4, = par3.plot(df.index, df.WS, color='blue', label="WS", alpha=0.5,
lw=1)
p5, = par4.plot(df.index, df.CIG, color='purple', label="CIG", alpha=
0.5, lw=1)

lns = [p1, p2, p3,p4, p5]
host.legend(handles=lns, loc='best', ncol=5)

par2.spines['right'].set_position(('outward', 60))

par3.spines['right'].set_position(('outward', 100))
par3.set_ylim(0,12)
par4.spines['right'].set_position(('outward', 150))

host.set_xlim(datetime.datetime(2018,2,13), datetime.datetime(2018,2,
23))

host.xaxis.set_major_locator(mpl.dates.MonthLocator())
host.xaxis.set_minor_locator(mpl.dates.DayLocator())

host.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%d'));
host.xaxis.set_major_formatter(mpl.dates.DateFormatter('%h\n%Y'))
host.set_title('An espisode of high $PM_{2.5}$', y=1.05, fontsize=15)
fig.tight_layout()
fig.savefig('img/2020Jul_all_params.png');
```



Temperature (TMP) and RH

- I have been used `corr()` , often without going to explain what else `cor()` can be used
- with `pandas` we three methods to calculate correlation, those are `pearson (default)` , `kendall` , and `spearman`

In [81]:
```
# using kendall
df.corr(method='kendall')
```

Out[81]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT
CIG	1.000000	0.313360	0.096671	-0.005355	0.043560	-0.033821	-0.184865	0.497624
VIS	0.313360	1.000000	0.308923	0.115910	-0.025996	0.221430	-0.102802	0.351972
TMP	0.096671	0.308923	1.000000	0.601872	0.133937	0.059694	-0.223419	0.162392
DEW	-0.005355	0.115910	0.601872	1.000000	0.057853	-0.001453	-0.218881	-0.081722
WD	0.043560	-0.025996	0.133937	0.057853	1.000000	-0.250307	-0.036673	0.074495
WS	-0.033821	0.221430	0.059694	-0.001453	-0.250307	1.000000	0.006225	-0.034795
CLDCR	-0.184865	-0.102802	-0.223419	-0.218881	-0.036673	0.006225	1.000000	0.018000
CLDHT	0.497624	0.351972	0.162392	-0.081722	0.074495	-0.034795	0.018000	1.000000
pm25	-0.090715	-0.321040	-0.239646	-0.324016	0.072185	-0.158496	0.108613	0.018913
RH	-0.198426	-0.305167	-0.141600	0.294478	-0.087382	-0.087386	-0.008383	-0.432984
h	0.024368	-0.043266	-0.106566	0.012741	-0.041610	-0.046700	0.005592	0.027804
m	0.172048	0.190504	0.172342	0.151405	-0.009270	-0.057510	-0.123790	0.135996

In [82]:
```
# let select a few columns
cols = ['RH', 'TMP', 'VIS']
```

In [83]:
```
spearman = dict()
for col in cols:
    spearman[col] = df.corr(method='spearman')['pm25'][col]
spearman
```

Out[83]:
```
{'RH': -0.17829405965863518,
 'TMP': -0.3386498232001726,
 'VIS': -0.4480579176009144}
```

In [84]:
```
kendall = dict()
for col in cols:
    kendall[col] = df.corr(method='kendall')['pm25'][col]
kendall
```

Out[84]:
```
{'RH': -0.12330443561688877,
 'TMP': -0.23964573988435875,
 'VIS': -0.32103981027468237}
```

In [85]:
```
pearson = dict()
for col in cols:
    pearson[col] = df.corr(method='pearson')['pm25'][col]
pearson
```

Out[85]:
```
{'RH': -0.15560027174497226,
 'TMP': -0.2976330082643488,
 'VIS': -0.412743060969867 3}
```

In [86]:
```
data = pd.DataFrame.from_records([pearson, kendall, spearman], index=
['pearson', 'kendall', 'spearman'])
data
```

Out[86]:

	RH	TMP	VIS
pearson	-0.155600	-0.297633	-0.412743
kendall	-0.123304	-0.239646	-0.321040
spearman	-0.178294	-0.338650	-0.448058

In [87]:
```
pos = np.arange(len(data))
pos
```

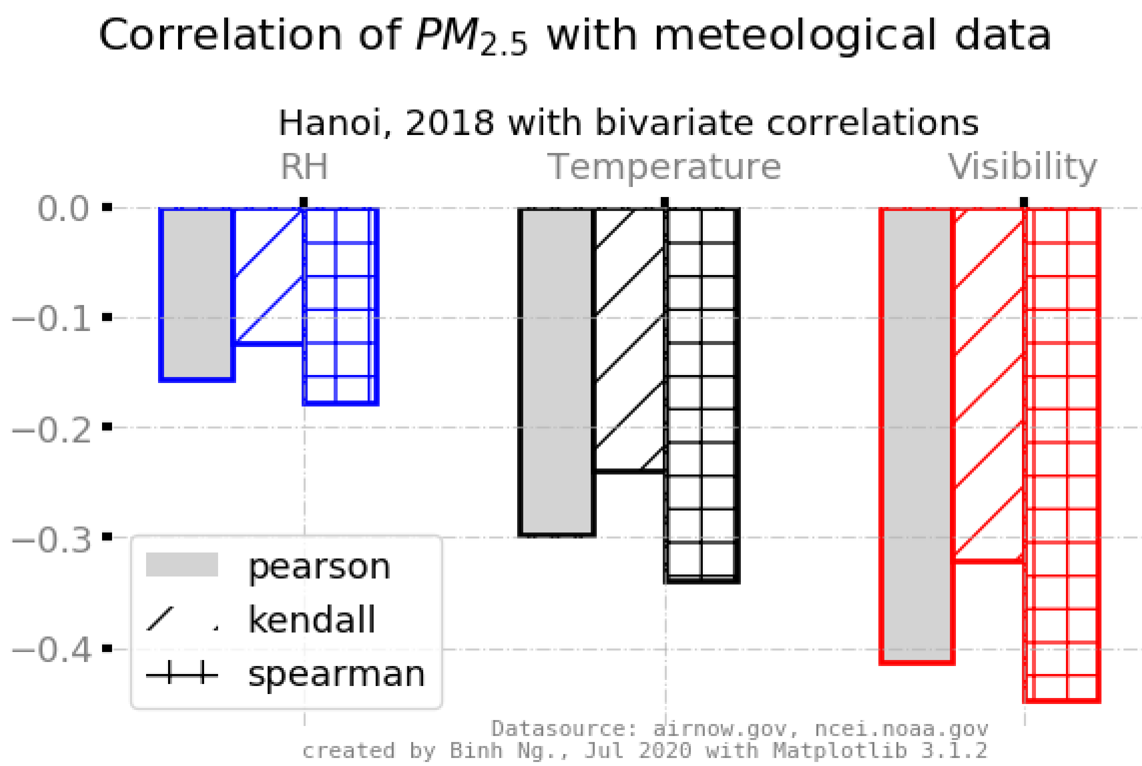
Out[87]:
```
array([0, 1, 2])
```

In [88]:
```
plt.rcParams['hatch.color'] = 'black'
```

In [89]:
```
plt.style.use('seaborn-white')
```

In [90]:
```
import matplotlib as mpl
mpl.rcParams.update(mpl.rcParamsDefault)
```

In [91]:
```
# plt.figure(figsize=(8,8))
fig, ax = plt.subplots(figsize=(6,4))
fig.tight_layout(rect=[0, 0.03, 1, 0.95])
width=0.2
ax.xaxis.tick_top()

ax1 = ax.bar(x=pos-width, height=data.loc['pearson'], width=width, co
lor='lightgray')
ax2 = ax.bar(x=pos, height=data.loc['kendall'], width=width, color='w
hite', hatch='/')
ax3 = ax.bar(x=pos+width, height=data.loc['spearman'], width=width, c
olor='white', hatch='+')
# ax = plt.gca()
ax.set_xticks(pos + width / 2)
ax.set_xticklabels(('RH', 'Temperature', 'Visibility'), fontsize=13)

ax.legend((ax1[0], ax2[0], ax3[0]), ('pearson', 'kendall', 'spearman'
), fontsize=13, frameon=True)
# plt.bar(x=pos+width, height=data.loc['kendall'], width=0.4)
for b in [ax1, ax2, ax3]:
    b[1].set_linewidth(2)
    b[1].set_edgecolor('black')

    b[0].set_linewidth(2)
    b[0].set_edgecolor('blue')

    b[2].set_linewidth(2)
    b[2].set_edgecolor('red')
ax.autoscale_view()
ax.tick_params(labelcolor='gray', labelsize=13, width=3)
ax.grid(True, linestyle='-.', alpha=0.6)

ax.set_frame_on(True)
ax.patch.set_visible(False)
for sp in ax.spines.values():
    sp.set_visible(False)
# plt.ax([.1,.1,.8,.7])
plt.subplots_adjust(top=0.4)
plt.figtext(2,-0.5, 'Datasource: airnow.gov, ncei.noaa.gov\ncreated b
y Binh Ng., Jul 2020 with Matplotlib 3.1.2', transform=ax.transData,
            family='monospace', color='gray', ha='right', fontsize=8)
ax.set_title('Hanoi, 2018 with bivariate correlations', fontsize=13)
plt.subplots_adjust(top=0.4)
plt.suptitle(r'Correlation of $PM_{2.5}$ with meteological data', fon
tsize=16)
plt.tight_layout(rect=(0,0.05,1, 0.9))
plt.savefig('img/2020Jul_corr_method.png')
```

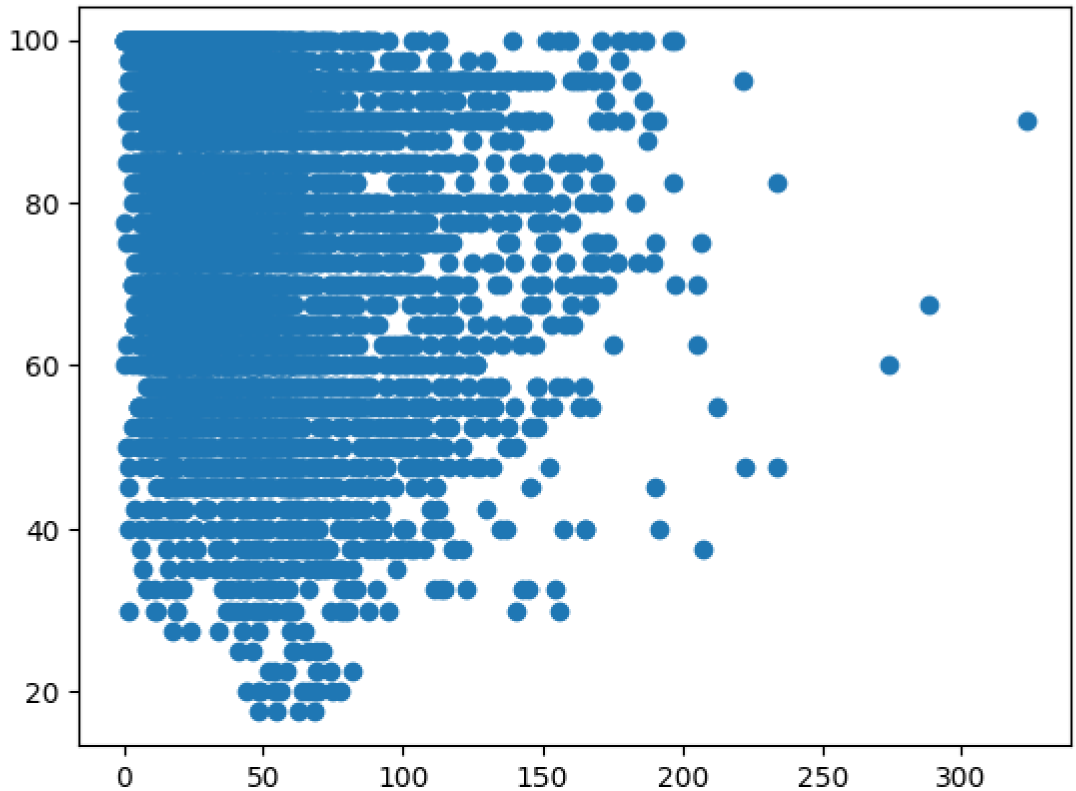


what we have here?

- if you see some correlation, a question you should ask is which method was used? It would be fine if all correlation was carried out with the same method.
- The `pearson` method is a safe choice because it is the average of the two. Knowing with method is used is important when one study indicated the correlation is higher or lower

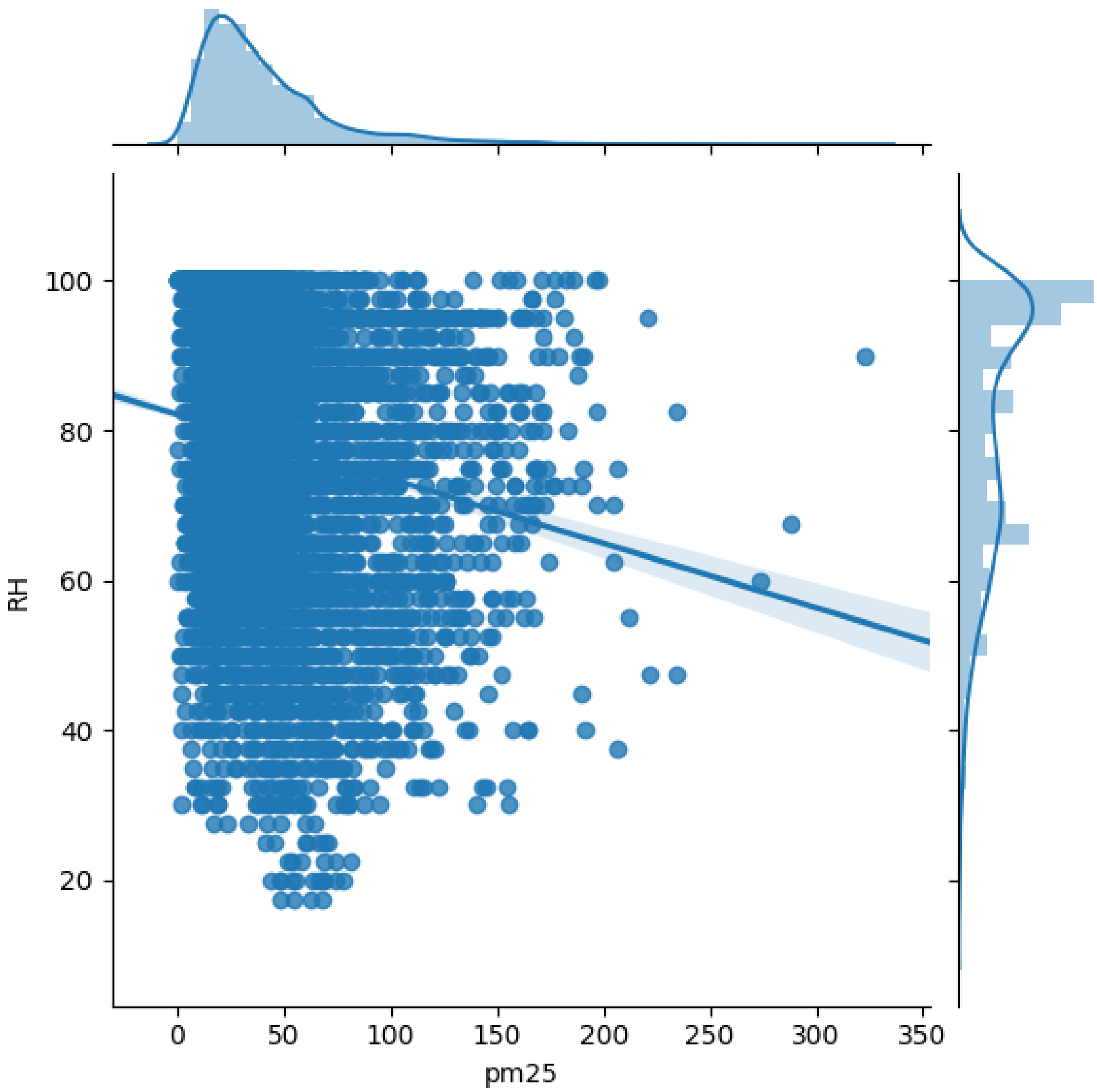
In [92]:
```
plt.scatter(df.pm25, df.RH)
```

Out[92]: <matplotlib.collections.PathCollection at 0x7fb90d7a31d0>



In [93]:
```
sns.jointplot(df.pm25, df.RH, kind='reg')
```

Out[93]: <seaborn.axisgrid.JointGrid at 0x7fb90d74d7b8>



In [94]:
```
rhs = np.linspace(0,100,16)
rhs
```

Out[94]:
```
array([  0.        ,   6.66666667,  13.33333333,  20.        ,
        26.66666667,  33.33333333,  40.        ,  46.66666667,
        53.33333333,  60.        ,  66.66666667,  73.33333333,
        80.        ,  86.66666667,  93.33333333, 100.        ])
```

In [95]:
```
labels = [f'{(rhs[i] + rhs[i+1])/2:.0f}' for i in (range(len(rhs)-1
))]
labels
```

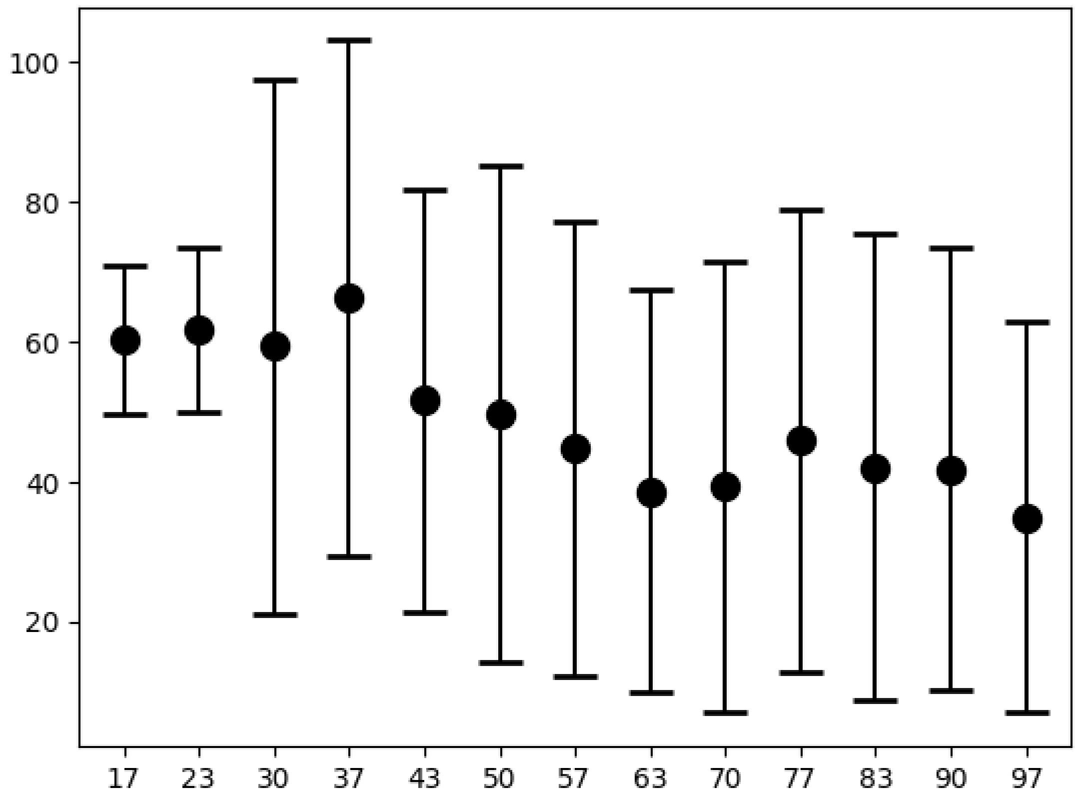
Out[95]:
```
['3',
 '10',
 '17',
 '23',
 '30',
 '37',
 '43',
 '50',
 '57',
 '63',
 '70',
 '77',
 '83',
 '90',
 '97']
```

In [96]:
```
df['RHC'] = pd.cut(df['RH'], bins=rhs, labels=labels).astype('categor
y')
```

In [97]:
```
dfs = df.groupby('RHC')
```

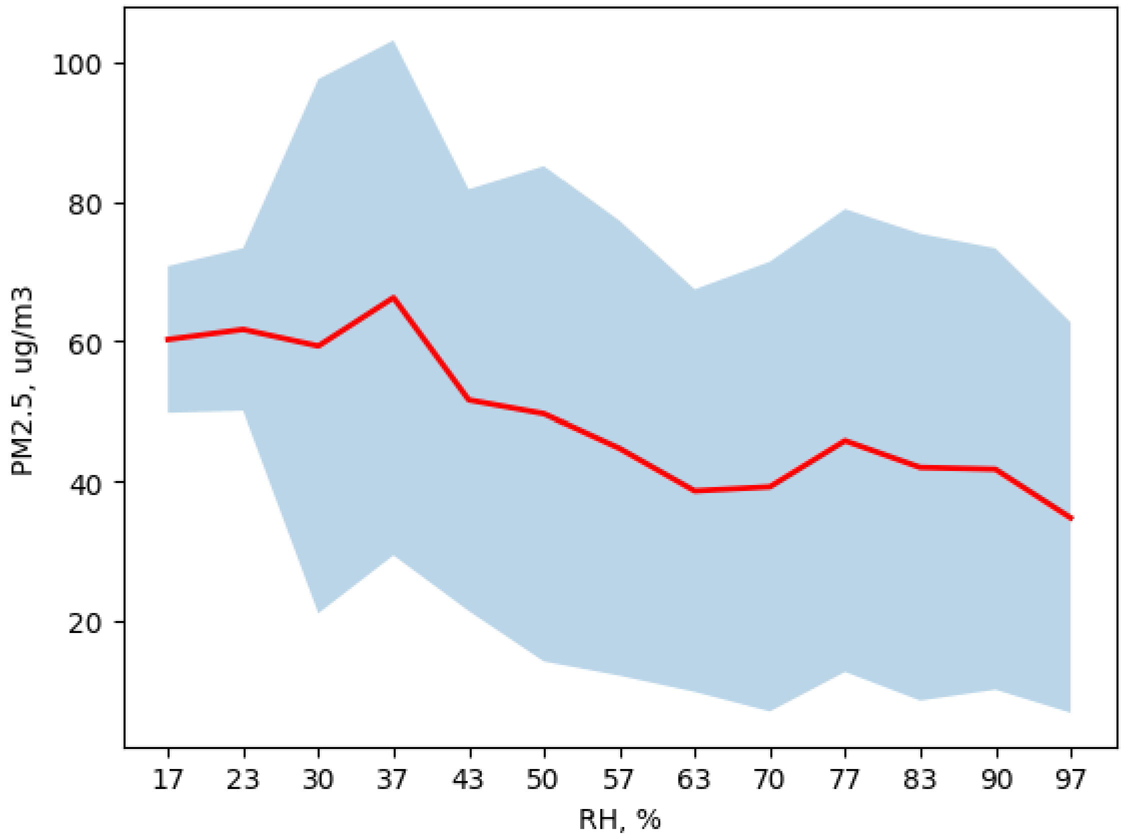
In [98]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.std().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[98]: <ErrorbarContainer object of 3 artists>



In [99]:
```
plt.plot(list(dfs.mean().index), dfs.mean().pm25, lw=2, color='r')
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
plt.ylabel('PM2.5, ug/m3')
plt.xlabel('RH, %')
```

Out[99]:
```
Text(0.5, 0, 'RH, %')
```



In [100]:
```
df.TMP.describe()
```

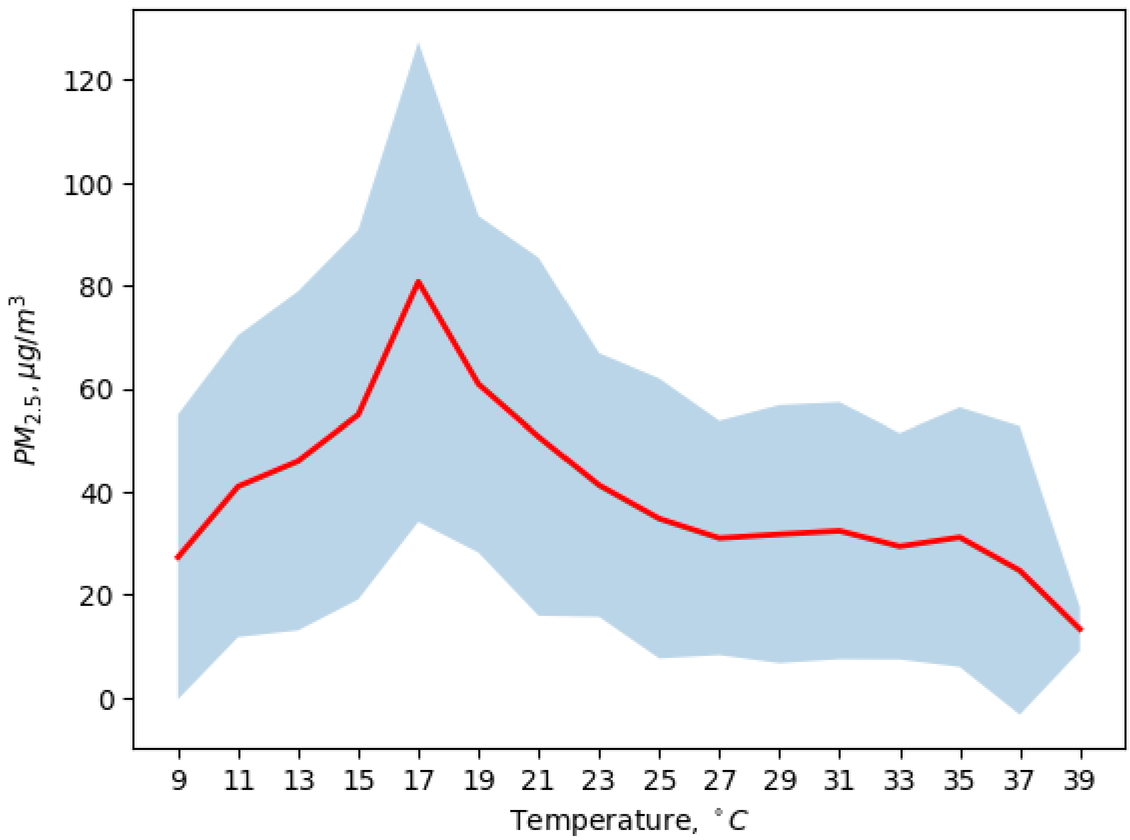
Out[100]:
```
count    7959.000000
mean       24.462935
std         5.519358
min         9.000000
25%        21.000000
50%        25.000000
75%        28.000000
max        39.000000
Name: TMP, dtype: float64
```

In [ ]:

In [122]:
```
# let make a quick run with temperature
tmps = np.linspace(0,40,21)
labels = [f'{(tmps[i] + tmps[i+1])/2:.0f}' for i in (range(len(tmps)-
1))]
df['TMPC'] = pd.cut(df['TMP'], bins=tmps, labels=labels).astype('cate
gory')
```

In [127]:
```
dfs = df.groupby('TMPC')
plt.plot(list(dfs.mean().index), dfs.mean().pm25, lw=2, color='r')
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
plt.ylabel('$PM_{2.5}, \mu g/m^3$')
plt.xlabel('Temperature, $ ^\circ C$')
```

Out[127]:
```
Text(0.5, 0, 'Temperature, $ ^\\circ C$')
```



- the trend is mixed. Higher concentrations of $PM_{2.5}$ were observed during a winter but not when it is at the lowest range. This would suggest the high concentration between the transition between a cold front and a hot front

Wind direction

In [102]:
```
direction = np.linspace(0,360,5)
direction
```

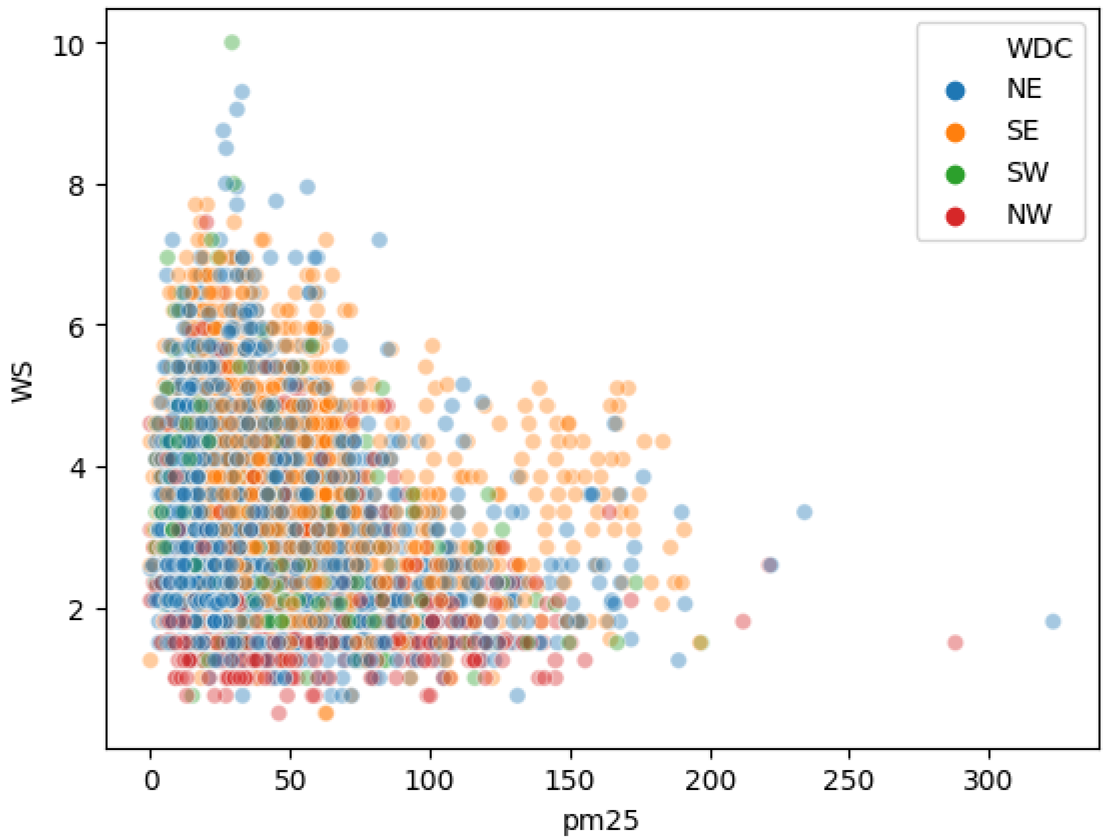
Out[102]:
```
array([  0.,   90., 180., 270., 360.])
```

In [103]:
```
labels = ['NE', 'SE', 'SW', 'NW']
```

```
In [104]: df['WDC'] = pd.cut(df['WD'], bins=direction, labels=labels).astype('category')
```

```
In [105]: sns.scatterplot(data=df, x='pm25', y='WS', hue='WDC', alpha=0.4)
```

```
Out[105]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb90d4a1048>
```




```
In [106]: df.groupby('WDC').std()['pm25']
```

```
Out[106]: WDC
NE    30.924822
SE    28.985036
SW    29.321554
NW    33.651236
Name: pm25, dtype: float64
```

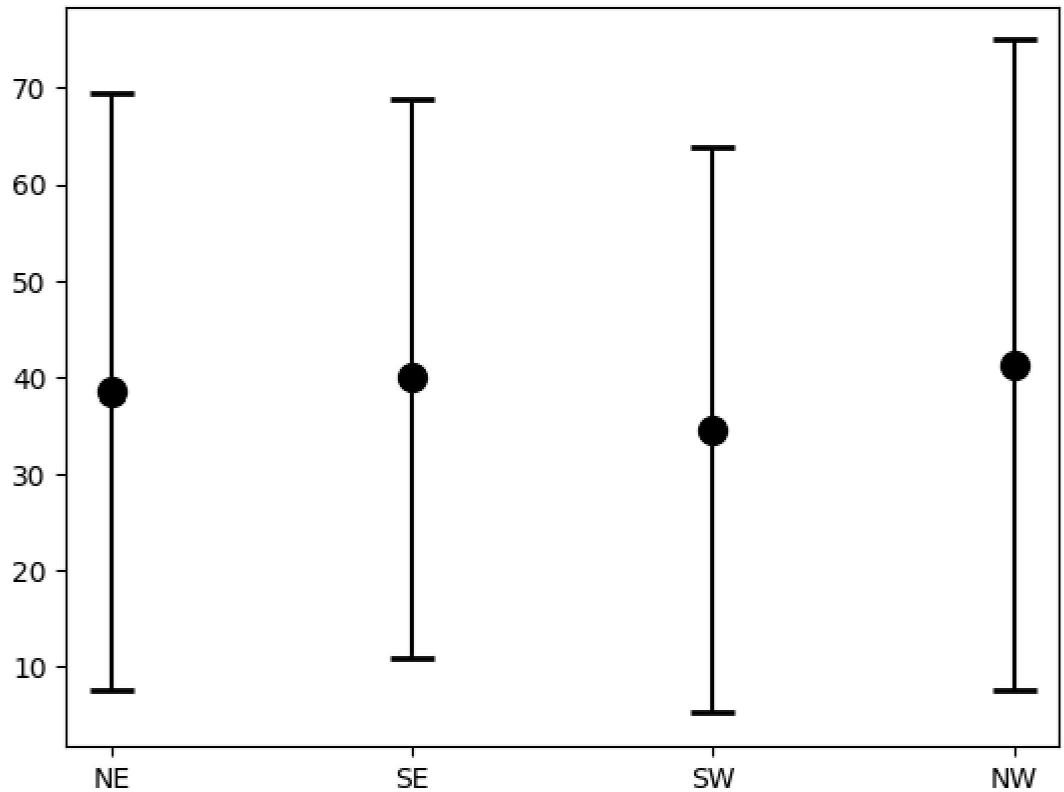
```
In [107]: df.groupby('WDC').mean()['pm25']
```

```
Out[107]: WDC
NE    38.557232
SE    39.893007
SW    34.510490
NW    41.317012
Name: pm25, dtype: float64
```

```
In [108]: dfd = df.groupby('WDC')
```

In [109]:
```
plt.errorbar(x=list(dfd.mean().index), y=dfd.mean().pm25, yerr=dfd.std().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[109]: <ErrorbarContainer object of 3 artists>



Wind speeds

In [110]:
```
speeds = np.linspace(0,12,7)
speeds
```

Out[110]: array([0., 2., 4., 6., 8., 10., 12.])

In [111]:
```
labels = [f'{(speeds[i] + speeds[i+1])/2:.0f}' for i in (range(len(speeds)-1))]
labels
```

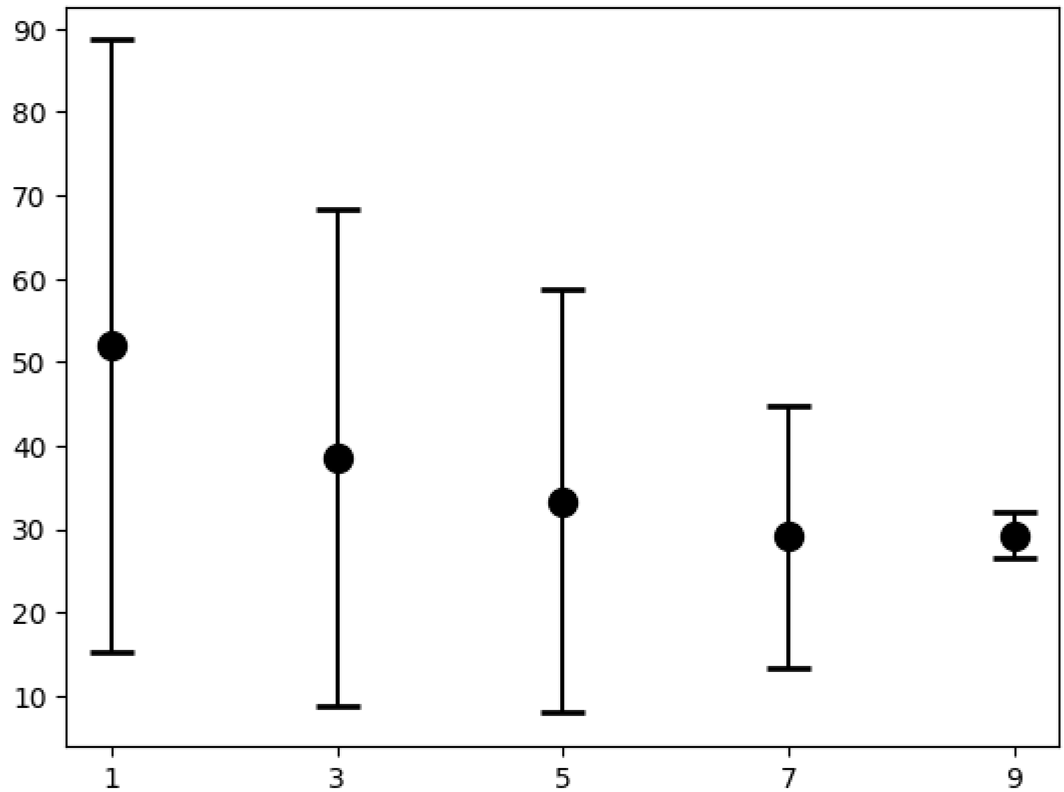
Out[111]: ['1', '3', '5', '7', '9', '11']

In [112]:
```
df['WSC'] = pd.cut(df['WS'], bins=speeds, labels=labels).astype('category')
```

In [113]:
```
dfs = df.groupby('WSC')
```

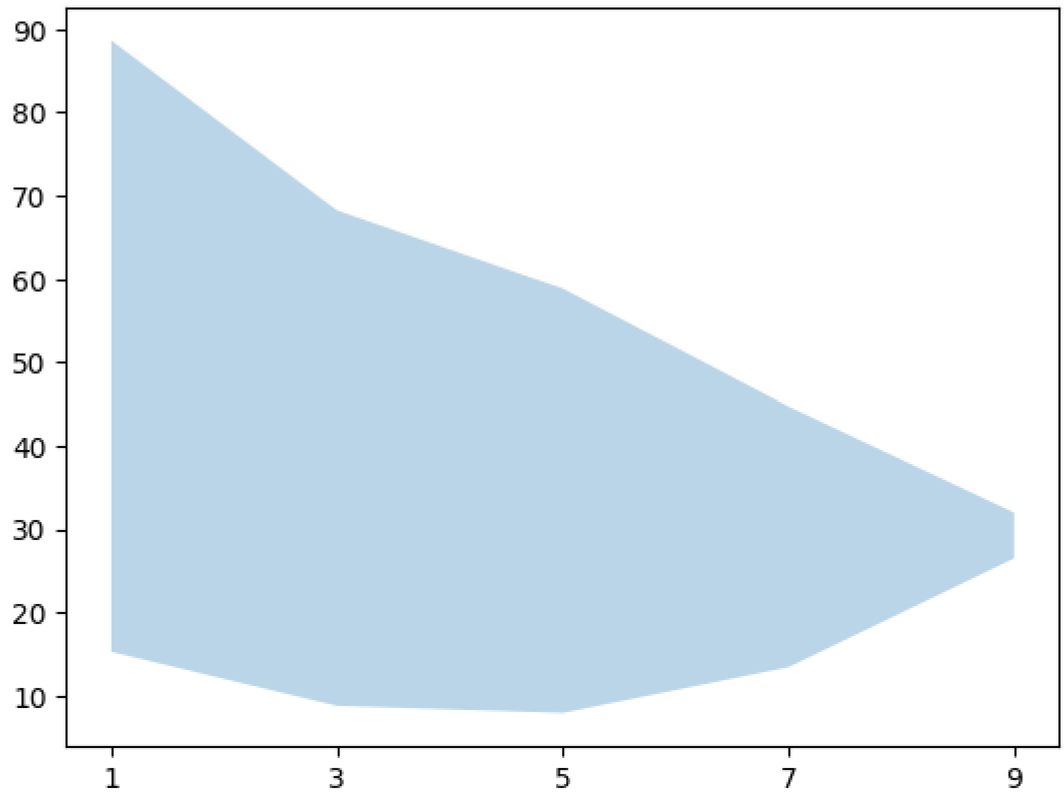
In [114]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.std().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[114]: <ErrorbarContainer object of 3 artists>



In [115]:
```
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
```

Out[115]:
```
<matplotlib.collections.PolyCollection at 0x7fb90d33fbe0>
```

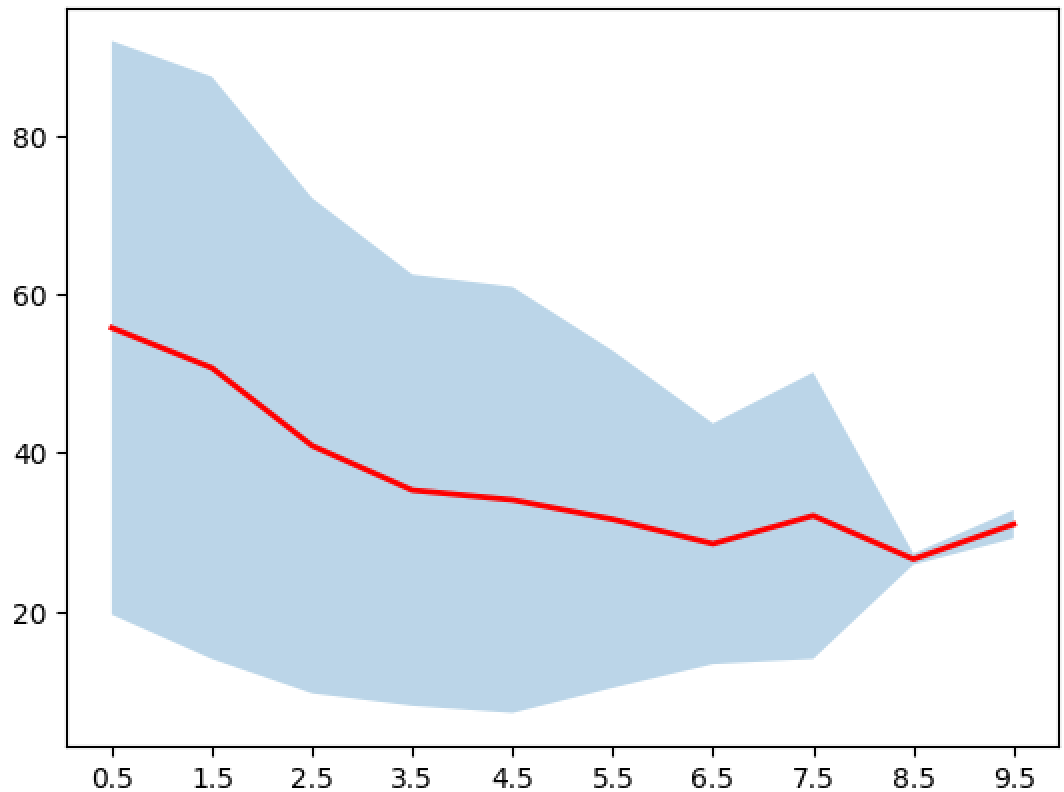


In [116]:
```
speeds = np.linspace(0,12,13)
labels = [f'{(speeds[i] + speeds[i+1])/2:.1f}' for i in (range(len(sp
eeds)-1))]
labels
```

Out[116]:
```
['0.5',
 '1.5',
 '2.5',
 '3.5',
 '4.5',
 '5.5',
 '6.5',
 '7.5',
 '8.5',
 '9.5',
 '10.5',
 '11.5']
```

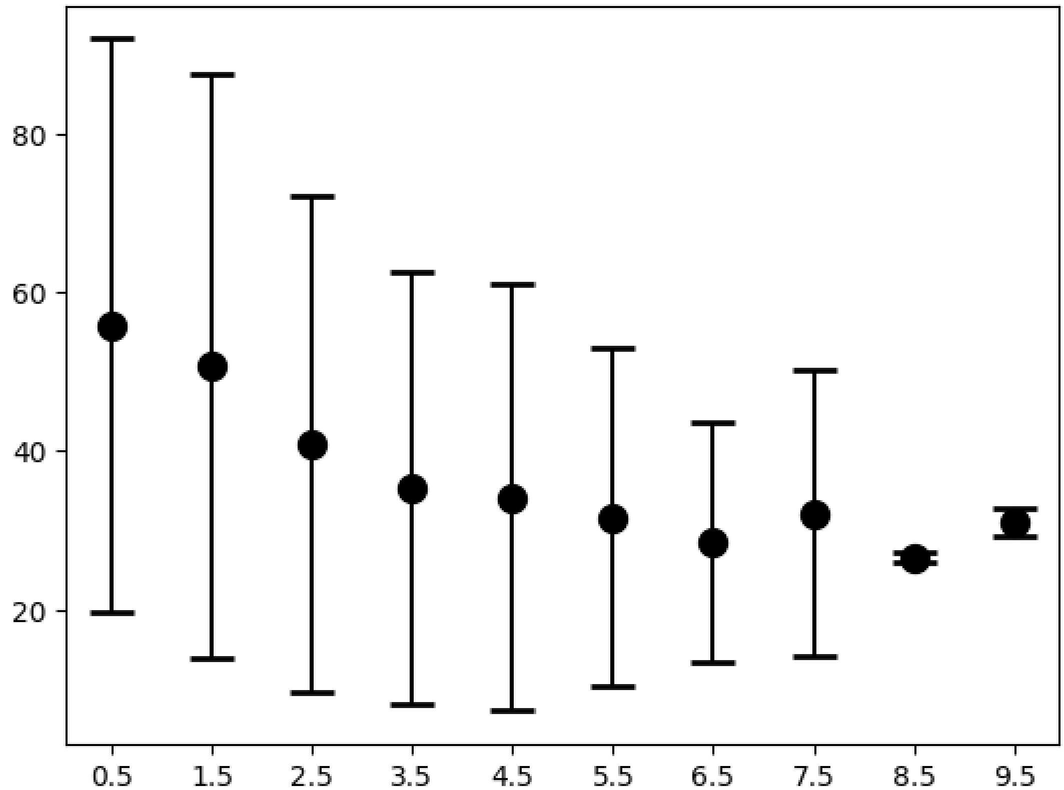
In [117]:
```
df['WSC'] = pd.cut(df['WS'], bins=speeds, labels=labels).astype('cate
gory')
```

In [118]:
```
dfs = df.groupby('WSC')
```

In [119]:
```
df.corr().pm25.WS
```
Out[119]:
```
-0.027791426871811013
```
In [120]:
```
plt.plot(list(dfs.mean().index), dfs.mean().pm25, lw=2, color='r')
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
```
Out[120]:
```
<matplotlib.collections.PolyCollection at 0x7fb90d3519e8>
```


In [121]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.st
d().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[121]: <ErrorbarContainer object of 3 artists>



Concluding notes

- I might introduce the topic more complicated than we started out, but I would take the complexity of $PM_{2.5}$ with meteorological inputs as the matter of fact. We need to do a better job the shed some light (or any light) on it
- I have not mentioned the emission source or the formation rate, which is why the $PM_{2.5}$ is out there in the first place
- Once $PM_{2.5}$ formed and with precussors, wind speed, temperature, the thickness of mixing have a fair share to dictate which how much $PM_{2.5}$ is stored the ground (and so we measured it)
- A higher temperature (such as during the summer month) seems to be dominant factor with a lowerer concentration. This could be explained by a strong turbulent (and unstable mixing layer) so that the polluted air nearby the ground constantly moved upward, and replaced a cooler (and cleaner) air moving downward
- During winter time, with a higher windspeed or with a thicker mixing layer were favored to lower the $PM_{2.5}$ concentration
- Stagnant (or stable) air layer in ground level is a favorable condition to store and accumulate $PM_{2.5}$ which is bad for lung and respiratory tract.

In [ ]:

```

```