2.4 MERRA-2_wind_RH

August 14, 2020

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1 Ideas

- in the previous post (correlation of data in MERRA-2 reanalysis and observed PM2.5 concentration on the ground), the focus on the a quick correlation on available data in the original format

- wind data, one of the key meteorological paramters influences on the PM2.5 transport is in U,V vectors (not in speed and angle direction), so that is not very useful to make any correlation. In this exercise, I will calculate wind speed and direction from MERRA-2 format manually, and with a new Python package called `MetPy`
- **MetPy** provides a collection of function to work with atmospheric data
- we will calculate *relative humidity* using `MetPy` and compared with a quick approximation using in the previous post
- the overarching goal is to feather out the important meteorological and atmospheric parameters to predict PM2.5. By the end of this exercise, I will bring together three sources of data:
  - the observed data from NCEI,
  - the reanalsysis from MERRA-2
  - the forecast data from Darksky

2 import libraries

[1]:
```
# first let import library, and ignore some of the warnings
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import pandas as pd
import numpy as np
import datetime
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('default')
plt.rcParams['figure.figsize'] = (10,6)
```

3 Import PM2.5 data

[3]:
```
# load PM2.5 data and combine 3 operations at once
pm25 = pd.read_csv('data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv',
                   parse_dates=['Date (LT)'],
                  index_col=['Date (LT)'])
pm25.head()
```

[3]:
```
                     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
```

4 SLV (Single Level Diagnosis - MERRA-2)

[4]:
```
# similar with single level data
df = pd.read_csv('data/merra2_slv_hanoi_2018.csv',
                 parse_dates=['time'],
                 index_col=['time'])
df.head()
```

[4]:
```
                          U2M       V250      TROPT      TROPPB        T2M  \
time
2018-01-01 00:00:00  0.023183  10.807207  192.34645  10051.0290  287.10890
2018-01-01 01:00:00  0.189619  11.351880  192.50723  10052.2750  286.79376
2018-01-01 02:00:00  0.243190  11.913273  192.63431  10051.5625  286.48932
2018-01-01 03:00:00  0.195083  12.295908  192.71167  10052.2780  286.24753
2018-01-01 04:00:00  0.132475  12.672207  192.72789  10050.9120  285.96360

                          TQL       T500      U850         PS       V850  …  \
time                                                                    …
2018-01-01 00:00:00  0.008423  267.34950 -0.678858  100905.08  6.310610  …
2018-01-01 01:00:00  0.009235  267.07660 -0.398818  100865.09  6.162886  …
2018-01-01 02:00:00  0.006260  266.77542 -0.217877  100819.56  5.993750  …
2018-01-01 03:00:00  0.003489  266.50415 -0.217092  100793.71  5.911840  …
2018-01-01 04:00:00  0.002314  266.30140 -0.108732  100791.80  5.884082  …

                          H850       T850      U50M      U10M    TROPPV  \
time
2018-01-01 00:00:00  1527.0985  283.53122  0.030755  0.031674  7564.037
2018-01-01 01:00:00  1522.4517  283.64413  0.424628  0.304242  7369.791
2018-01-01 02:00:00  1518.0483  283.75928  0.544786  0.386887  7256.081
2018-01-01 03:00:00  1515.4990  283.86768  0.383533  0.283328  7255.750
2018-01-01 04:00:00  1514.8696  283.87558  0.213028  0.169195  7256.080

                          H500      V500     T2MWET       U500     QV10M
time
2018-01-01 00:00:00  5840.2160 -1.304574  284.03730  11.181688  0.007823
2018-01-01 01:00:00  5835.2650 -2.038413  283.94345  11.029030  0.007823
2018-01-01 02:00:00  5830.6333 -2.332026  283.87656  10.573646  0.007822
2018-01-01 03:00:00  5828.6885 -2.251715  283.76090  10.046288  0.007807
2018-01-01 04:00:00  5828.3154 -1.790147  283.66614   9.330713  0.007804

[5 rows x 39 columns]
```

[5]:
```
df.columns
```

[5]:
```
Index(['U2M', 'V250', 'TROPT', 'TROPPB', 'T2M', 'TQL', 'T500', 'U850', 'PS',
       'V850', 'H250', 'Q250', 'T2MDEW', 'V50M', 'Q500', 'DISPH', 'H1000',
```

```
       'TS', 'T10M', 'TROPPT', 'SLP', 'U250', 'Q850', 'ZLCL', 'TQV', 'V2M',
       'T250', 'TROPQ', 'V10M', 'H850', 'T850', 'U50M', 'U10M', 'TROPPV',
       'H500', 'V500', 'T2MWET', 'U500', 'QV10M'],
      dtype='object')
```

[6]:
```
df.describe()
```

[6]:
```
              U2M         V250       TROPT        TROPPB          T2M  \
count  8483.000000  8483.000000  8483.000000   8483.000000  8483.000000
mean     -0.661194     0.911338   192.983228   9874.836900   296.432677
std       1.022452     7.235232     2.459432   1055.276131     6.134071
min      -5.820403   -24.197369   184.202580   7255.293000   275.719970
25%      -1.263075    -3.923812   191.382130   8735.479000   292.590985
50%      -0.678653     0.018114   192.955900  10051.172000   297.864900
75%      -0.086650     5.154851   194.554450  10052.314000   300.669405
max       3.647237    28.693241   207.632840  14726.783000   309.323800

              TQL         T500        U850             PS         V850  …  \
count  8483.000000  8483.000000  8483.000000    8483.000000  8483.000000  …
mean      0.080424   268.319280     0.650805  100073.794543     1.204573  …
std       0.083286     2.165962     4.702194     734.635678     4.222000  …
min       0.000000   258.809420   -22.636606   98338.780000   -17.767721  …
25%       0.012516   266.953430    -2.512539   99431.925000    -1.230508  …
50%       0.055450   268.411380     0.655021  100131.125000     1.752397  …
75%       0.121292   270.076035     3.664199  100565.390000     3.917061  …
max       0.451294   272.917000    21.900370  102189.990000    14.195785  …

             H850         T850        U50M        U10M        TROPPV  \
count  8483.000000  8483.000000  8483.000000  8483.000000   8483.000000
mean   1498.307756   289.649016    -1.421893   -0.978380   8695.439796
std      39.089350     4.745890     2.253938    1.502244   1091.511613
min    1367.254400   271.759030   -11.224982   -8.524143   6149.086000
25%    1470.055150   287.306015    -2.895601   -1.876319   8104.948150
50%    1504.329500   290.681700    -1.665551   -1.138683   8544.076000
75%    1527.514700   293.126145    -0.180966   -0.146952   9564.690750
max    1588.751800   297.514160     7.377525    5.157908  14727.668000

             H500         V500       T2MWET        U500        QV10M
count  8483.000000  8483.000000  8483.000000  8483.000000  8483.000000
mean   5853.869860     1.205586   293.377792     7.558238     0.015139
std      26.150734     4.703001     5.855006     8.829429     0.004645
min    5744.518000   -16.558525   271.761080   -22.920101     0.002889
25%    5836.291500    -1.708599   290.466200     1.127894     0.011993
50%    5853.969000     1.083833   295.096560     7.797653     0.016063
75%    5873.187500     4.363369   298.027035    13.789646     0.019173
max    5925.305700    19.502840   301.152130    31.799278     0.022890
```

```
[8 rows x 39 columns]
```

4.1 reading netCDF4

- let see the standard name by reading metadata using netCDF

```
[7]: import netCDF4 as nc
```

```
[8]: ds = nc.Dataset('data/nc4/MERRA2_400.tavg1_2d_slv_Nx.20180722.nc4')
```

```
[9]: name_ = dict()
for k in ds.variables.keys():
    name_[k] = f'{ds.variables[k].standard_name}, {ds.variables[k].units}'
name_
```

```
[9]: {'U2M': '2-meter_eastward_wind, m s-1',
 'V250': 'northward_wind_at_250_hPa, m s-1',
 'TROPT': 'tropopause_temperature_using_blended_TROPP_estimate, K',
 'TROPPB': 'tropopause_pressure_based_on_blended_estimate, Pa',
 'T2M': '2-meter_air_temperature, K',
 'TQL': 'total_precipitable_liquid_water, kg m-2',
 'T500': 'air_temperature_at_500_hPa, K',
 'U850': 'eastward_wind_at_850_hPa, m s-1',
 'PS': 'surface_pressure, Pa',
 'V850': 'northward_wind_at_850_hPa, m s-1',
 'H250': 'height_at_250_hPa, m',
 'Q250': 'specific_humidity_at_250_hPa, kg kg-1',
 'T2MDEW': 'dew_point_temperature_at_2_m, K',
 'V50M': 'northward_wind_at_50_meters, m s-1',
 'Q500': 'specific_humidity_at_500_hPa, kg kg-1',
 'DISPH': 'zero_plane_displacement_height, m',
 'H1000': 'height_at_1000_mb, m',
 'TS': 'surface_skin_temperature, K',
 'T10M': '10-meter_air_temperature, K',
 'TROPPT': 'tropopause_pressure_based_on_thermal_estimate, Pa',
 'SLP': 'sea_level_pressure, Pa',
 'U250': 'eastward_wind_at_250_hPa, m s-1',
 'Q850': 'specific_humidity_at_850_hPa, kg kg-1',
 'ZLCL': 'lifting_condensation_level, m',
 'TQV': 'total_precipitable_water_vapor, kg m-2',
 'V2M': '2-meter_northward_wind, m s-1',
 'T250': 'air_temperature_at_250_hPa, K',
 'TROPQ': 'tropopause_specific_humidity_using_blended_TROPP_estimate, kg kg-1',
 'V10M': '10-meter_northward_wind, m s-1',
 'H850': 'height_at_850_hPa, m',
 'T850': 'air_temperature_at_850_hPa, K',
```

```
 'U50M': 'eastward_wind_at_50_meters, m s-1',
 'U10M': '10-meter_eastward_wind, m s-1',
 'TROPPV': 'tropopause_pressure_based_on_EPV_estimate, Pa',
 'H500': 'height_at_500_hPa, m',
 'V500': 'northward_wind_at_500_hPa, m s-1',
 'T2MWET': 'wet_bulb_temperature_at_2_m, K',
 'U500': 'eastward_wind_at_500_hPa, m s-1',
 'QV10M': '10-meter_specific_humidity, kg kg-1'}
```

[10]:
```
# select data of wind only
wind_cols = list()
for k, v in name_.items():
    if 'wind' in v:
        print(k,v)
        wind_cols.append(k)
wind_cols
```

```
U2M 2-meter_eastward_wind, m s-1
V250 northward_wind_at_250_hPa, m s-1
U850 eastward_wind_at_850_hPa, m s-1
V850 northward_wind_at_850_hPa, m s-1
V50M northward_wind_at_50_meters, m s-1
U250 eastward_wind_at_250_hPa, m s-1
V2M 2-meter_northward_wind, m s-1
V10M 10-meter_northward_wind, m s-1
U50M eastward_wind_at_50_meters, m s-1
U10M 10-meter_eastward_wind, m s-1
V500 northward_wind_at_500_hPa, m s-1
U500 eastward_wind_at_500_hPa, m s-1
```

[10]:
```
['U2M',
 'V250',
 'U850',
 'V850',
 'V50M',
 'U250',
 'V2M',
 'V10M',
 'U50M',
 'U10M',
 'V500',
 'U500']
```

[11]:
```
# all columns to wind
# let hold off question about what is this wind data, a short answer is that is␣
↪winds in different altitudes
df[wind_cols].describe()
```

[11]:
```
              U2M         V250         U850         V850         V50M  \
count  8483.000000  8483.000000  8483.000000  8483.000000  8483.000000
mean     -0.661194     0.911338     0.650805     1.204573     0.827948
std       1.022452     7.235232     4.702194     4.222000     3.357065
min      -5.820403   -24.197369   -22.636606   -17.767721   -10.803814
25%      -1.263075    -3.923812    -2.512539    -1.230508    -1.804140
50%      -0.678653     0.018114     0.655021     1.752397     1.389059
75%      -0.086650     5.154851     3.664199     3.917061     3.515750
max       3.647237    28.693241    21.900370    14.195785     8.654327

             U250          V2M         V10M         U50M         U10M  \
count  8483.000000  8483.000000  8483.000000  8483.000000  8483.000000
mean     12.517031     0.278457     0.455033    -1.421893    -0.978380
std      16.789135     1.555940     2.270334     2.253938     1.502244
min     -25.246635    -5.911692    -8.217997   -11.224982    -8.524143
25%      -3.606235    -0.749631    -1.253041    -2.895601    -1.876319
50%      13.254944     0.520839     0.915810    -1.665551    -1.138683
75%      27.017761     1.236187     2.029492    -0.180966    -0.146952
max      54.048200     5.089890     6.895058     7.377525     5.157908

             V500         U500
count  8483.000000  8483.000000
mean      1.205586     7.558238
std       4.703001     8.829429
min     -16.558525   -22.920101
25%      -1.708599     1.127894
50%       1.083833     7.797653
75%       4.363369    13.789646
max      19.502840    31.799278
```

[12]:
```python
# let start more, 2M wind with V and U components (wind at 2m from the ground)
dfw = df[['V2M', 'U2M']]
dfw.head()
```

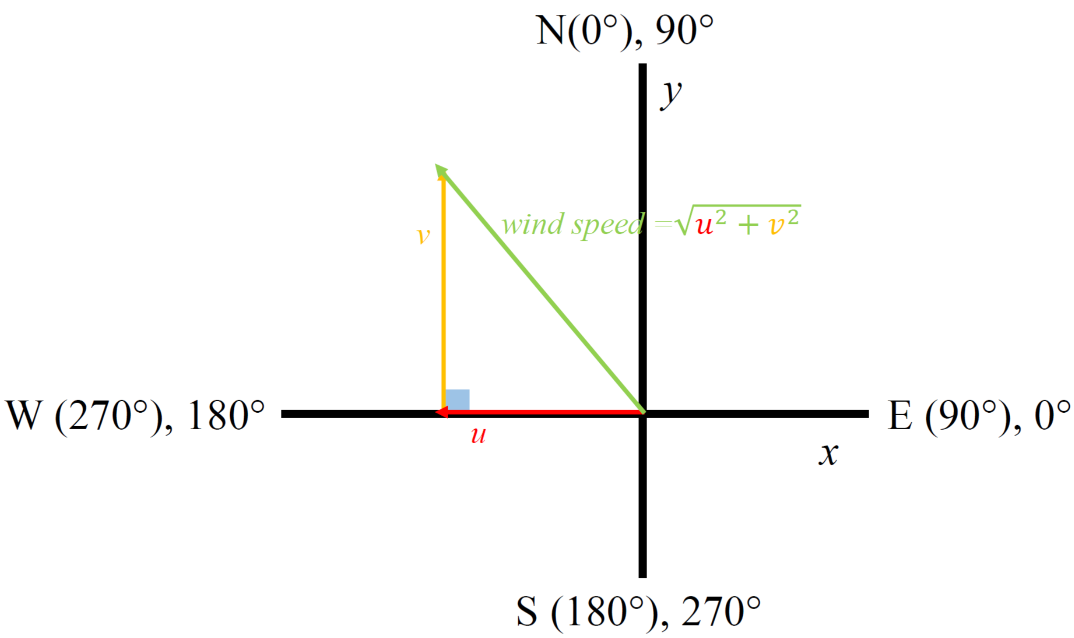
[12]:
```
                          V2M       U2M
time
2018-01-01 00:00:00  0.507052  0.023183
2018-01-01 01:00:00  0.384886  0.189619
2018-01-01 02:00:00  0.296402  0.243190
2018-01-01 03:00:00  0.277474  0.195083
2018-01-01 04:00:00  0.275675  0.132475
```

4.2 Working with wind data

- a good place to start with wind data in MERRA-2 is from this post on MERRA-2 wind
- in short, instead of giving wind data in speed (m/s) and angle (in degree with zero to 360,

or main directiton such as North-East), in which zero degree is northerly wind or the wind blows from north to the south

- report wind data in degree due North is called azimuth degrees or cardinal directions. If you look back at SLV data, in original format, wind data is with U,V components



conversion

- wind speed is simple from U, V vectors

$$ws = \sqrt{u^2 + v^2}$$

- angle is more complex:

$$wd = arctan(v/u)$$

  except when v = 0, luckily in numpy package, the `arctan2` will take care of zero values. The output is in radian, not in degree

- and also, if wind data is presented in speed (m/s) and angle (in degree due North), then
  - U = -ws*sin(direction in radians)
  - and V = -ws.cost(direction in radians)
  - more about equation is in ucar.edu

4.3 Manual calculate

[13]:
```
# wind speed is easy
dfw['ws'] = dfw.apply(lambda row: np.sqrt(row['V2M']**2 + row['U2M']**2),␣
 ↪axis=1)
dfw.head()
```

[13]:

	V2M	U2M	ws
time			
2018-01-01 00:00:00	0.507052	0.023183	0.507582
2018-01-01 01:00:00	0.384886	0.189619	0.429060
2018-01-01 02:00:00	0.296402	0.243190	0.383400
2018-01-01 03:00:00	0.277474	0.195083	0.339189
2018-01-01 04:00:00	0.275675	0.132475	0.305853

[14]:
```
# to convert to direction (in degree), it is more complext
dfw['deg'] = dfw.apply(lambda row: ((180/np.pi)*np.arctan2(row['U2M'],␣
↪row['V2M']))%360, axis=1)
dfw.head()
```

[14]:

	V2M	U2M	ws	deg
time				
2018-01-01 00:00:00	0.507052	0.023183	0.507582	2.617815
2018-01-01 01:00:00	0.384886	0.189619	0.429060	26.227729
2018-01-01 02:00:00	0.296402	0.243190	0.383400	39.367919
2018-01-01 03:00:00	0.277474	0.195083	0.339189	35.109724
2018-01-01 04:00:00	0.275675	0.132475	0.305853	25.666509

[15]:
```
dfw.describe()
```

[15]:

	V2M	U2M	ws	deg
count	8483.000000	8483.000000	8483.000000	8483.000000
mean	0.278457	-0.661194	1.722973	242.907187
std	1.555940	1.022452	1.006058	98.782262
min	-5.911692	-5.820403	0.005149	0.188730
25%	-0.749631	-1.263075	0.947313	190.805811
50%	0.520839	-0.678653	1.476474	272.368924
75%	1.236187	-0.086650	2.316369	325.353762
max	5.089890	3.647237	6.811332	359.985100

[16]:
```
# let reverse to to U, V component
```

[17]:
```
dfw['V_re'] = dfw.apply(lambda row: row['ws']*np.cos(np.radians(row['deg'])),␣
↪axis=1)
dfw.head()
```

[17]:

	V2M	U2M	ws	deg	V_re
time					
2018-01-01 00:00:00	0.507052	0.023183	0.507582	2.617815	0.507052
2018-01-01 01:00:00	0.384886	0.189619	0.429060	26.227729	0.384886
2018-01-01 02:00:00	0.296402	0.243190	0.383400	39.367919	0.296402
2018-01-01 03:00:00	0.277474	0.195083	0.339189	35.109724	0.277474
2018-01-01 04:00:00	0.275675	0.132475	0.305853	25.666509	0.275675

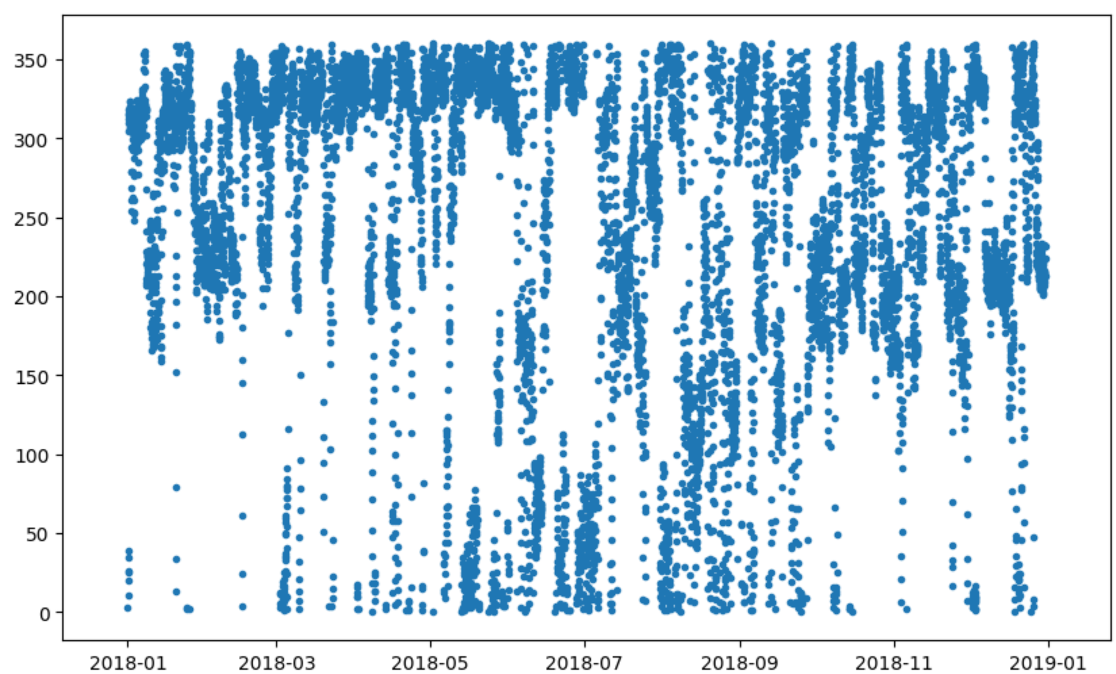
[18]:
```
dfw['U_re'] = dfw.apply(lambda row: row['ws']*np.sin(np.radians(row['deg'])),␣
↪axis=1)
dfw.head()
```

[18]:
```
                          V2M       U2M        ws        deg      V_re  \
time
2018-01-01 00:00:00  0.507052  0.023183  0.507582   2.617815  0.507052
2018-01-01 01:00:00  0.384886  0.189619  0.429060  26.227729  0.384886
2018-01-01 02:00:00  0.296402  0.243190  0.383400  39.367919  0.296402
2018-01-01 03:00:00  0.277474  0.195083  0.339189  35.109724  0.277474
2018-01-01 04:00:00  0.275675  0.132475  0.305853  25.666509  0.275675

                         U_re
time
2018-01-01 00:00:00  0.023183
2018-01-01 01:00:00  0.189619
2018-01-01 02:00:00  0.243190
2018-01-01 03:00:00  0.195083
2018-01-01 04:00:00  0.132475
```

- noted that I did put a minus in front of U, V vectors

[19]:
```
plt.scatter(dfw.index, dfw['deg'], marker='.')
```

[19]: <matplotlib.collections.PathCollection at 0x7f14fb47a0b8>



- so we can manually calculate back and foward between vectors (U,V) components and in speed and direction,
- do we have a better way to convert using some prepared package, you yes, you bet, there are such package

4.4 Welcome to MetPy

- comprehensive package to work with atmospheric data

[20]:
```
# https://unidata.github.io/MetPy/latest/api/generated/metpy.calc.html
try:
    import metpy.calc as mpcalc
except Exception as e:
    print(e)
    !pip install metpy --user
```

[21]:
```
# you could have all conversion function, and many of them are
# wind speed and component in the end of Dynamic/Kinematic session
# to use the metpy function, you need to attach the units.
# to do that we will import
from metpy.units import pandas_dataframe_to_unit_arrays, units
```

[22]:
```
print(len(dir(units)))
# almost one thoudsand types of units
```

```
963
```

[23]:
```
wind_cols
```

[23]:
```
['U2M',
 'V250',
 'U850',
 'V850',
 'V50M',
 'U250',
 'V2M',
 'V10M',
 'U50M',
 'U10M',
 'V500',
 'U500']
```

[24]:
```
# make a dictionary to map each parameter with the unit
w_units = dict()
for col in wind_cols:
    w_units[col] = 'meter_per_second'
```

```
w_units
```

[24]:
```
{'U2M': 'meter_per_second',
 'V250': 'meter_per_second',
 'U850': 'meter_per_second',
 'V850': 'meter_per_second',
 'V50M': 'meter_per_second',
 'U250': 'meter_per_second',
 'V2M': 'meter_per_second',
 'V10M': 'meter_per_second',
 'U50M': 'meter_per_second',
 'U10M': 'meter_per_second',
 'V500': 'meter_per_second',
 'U500': 'meter_per_second'}
```

[25]:
```
select_cols = ['V2M', 'U2M']
```

[26]:
```
df[select_cols].head()
```

[26]:
```
                          V2M       U2M
time
2018-01-01 00:00:00  0.507052  0.023183
2018-01-01 01:00:00  0.384886  0.189619
2018-01-01 02:00:00  0.296402  0.243190
2018-01-01 03:00:00  0.277474  0.195083
2018-01-01 04:00:00  0.275675  0.132475
```

[27]:
```
# convert a pandas column to an array, this approach is much faster than␣
↪row-wise with apply() function
wind = pandas_dataframe_to_unit_arrays(df[select_cols], w_units)
```

[28]:
```
wind
```

[28]:
```
{'V2M': array([ 0.507052  ,  0.38488576,  0.29640204, …, -1.092206   ,
        -1.2885575 , -1.7575915 ]) <Unit('meter_per_second')>,
 'U2M': array([ 0.02318308,  0.1896187 ,  0.24318957, …,  0.09979065,
        -0.01472685, -0.12540904]) <Unit('meter_per_second')>}
```

[29]:
```
# and to calculate speed and direction, we call them directly from the package
wind['v_2m'] = mpcalc.wind_speed(wind['U2M'], wind['V2M'])
wind['d_2m']  = mpcalc.wind_direction(wind['U2M'], wind['V2M'])
```

[30]:
```
# make a dataframe with shared timestamps as the index
dft = pd.DataFrame({
        'v_2m': wind['v_2m'],
        'd_2m': wind['d_2m']}, index=df.index.to_list(),)
dft.dtypes
```

[30]:
```
v_2m    float64
d_2m    float64
dtype: object
```

[31]:
```
dft.head()
```

[31]:
```
                         v_2m        d_2m
2018-01-01 00:00:00  0.507582  182.617815
2018-01-01 01:00:00  0.429060  206.227729
2018-01-01 02:00:00  0.383400  219.367919
2018-01-01 03:00:00  0.339189  215.109724
2018-01-01 04:00:00  0.305853  205.666509
```

[32]:
```
# let merge dataframe with manual calculate and through MetPy package
dfw = pd.merge(dfw, dft, right_index=True, left_index=True)
```

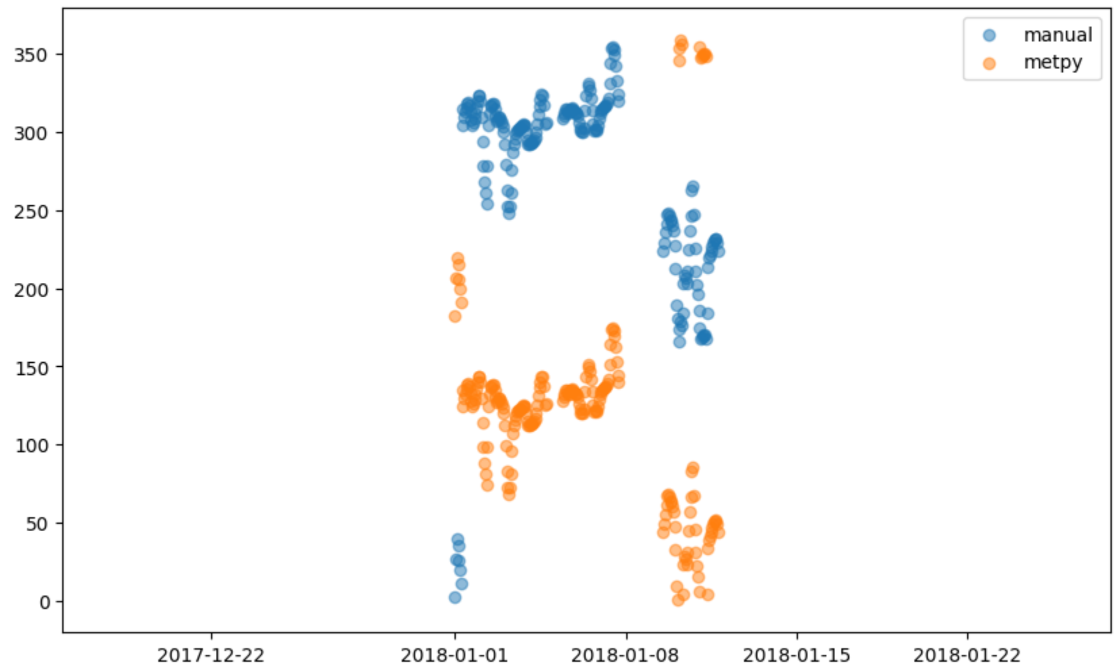
[33]:
```
dfw.index.rename('time', inplace=True)
dfw.head()
```

[33]:
```
                          V2M       U2M        ws        deg      V_re  \
time
2018-01-01 00:00:00  0.507052  0.023183  0.507582   2.617815  0.507052
2018-01-01 01:00:00  0.384886  0.189619  0.429060  26.227729  0.384886
2018-01-01 02:00:00  0.296402  0.243190  0.383400  39.367919  0.296402
2018-01-01 03:00:00  0.277474  0.195083  0.339189  35.109724  0.277474
2018-01-01 04:00:00  0.275675  0.132475  0.305853  25.666509  0.275675

                         U_re      v_2m        d_2m
time
2018-01-01 00:00:00  0.023183  0.507582  182.617815
2018-01-01 01:00:00  0.189619  0.429060  206.227729
2018-01-01 02:00:00  0.243190  0.383400  219.367919
2018-01-01 03:00:00  0.195083  0.339189  215.109724
2018-01-01 04:00:00  0.132475  0.305853  205.666509
```

a few interesting point, - `deg` and `d_2m` seems have some different

[34]:
```
# let visualize data
dft = dfw[0:200]
plt.scatter(dft.index, dft['deg'], label='manual', alpha=0.5)
plt.scatter(dft.index, dft['d_2m'], label='metpy', alpha=0.5)
plt.legend()
```

[34]:
```
<matplotlib.legend.Legend at 0x7f15277de438>
```



- there is something wrong, since the direction in angle is not consistent, in fact they are different with 180 degree

[35]:
```
# let redo manual calculation, and add 180 degree to equation:
dfw['deg2'] = dfw.apply(lambda row: ((180/np.pi)*np.arctan2(row['U2M'],␣
↪row['V2M'])+180)%360, axis=1)
dfw.head()
```

[35]:
```
                          V2M       U2M        ws        deg      V_re  \
time
2018-01-01 00:00:00  0.507052  0.023183  0.507582   2.617815  0.507052
2018-01-01 01:00:00  0.384886  0.189619  0.429060  26.227729  0.384886
2018-01-01 02:00:00  0.296402  0.243190  0.383400  39.367919  0.296402
2018-01-01 03:00:00  0.277474  0.195083  0.339189  35.109724  0.277474
2018-01-01 04:00:00  0.275675  0.132475  0.305853  25.666509  0.275675

                         U_re      v_2m         d_2m        deg2
time
2018-01-01 00:00:00  0.023183  0.507582  182.617815  182.617815
2018-01-01 01:00:00  0.189619  0.429060  206.227729  206.227729
2018-01-01 02:00:00  0.243190  0.383400  219.367919  219.367919
2018-01-01 03:00:00  0.195083  0.339189  215.109724  215.109724
2018-01-01 04:00:00  0.132475  0.305853  205.666509  205.666509
```

- now the degree match, but then the U, V component will be different

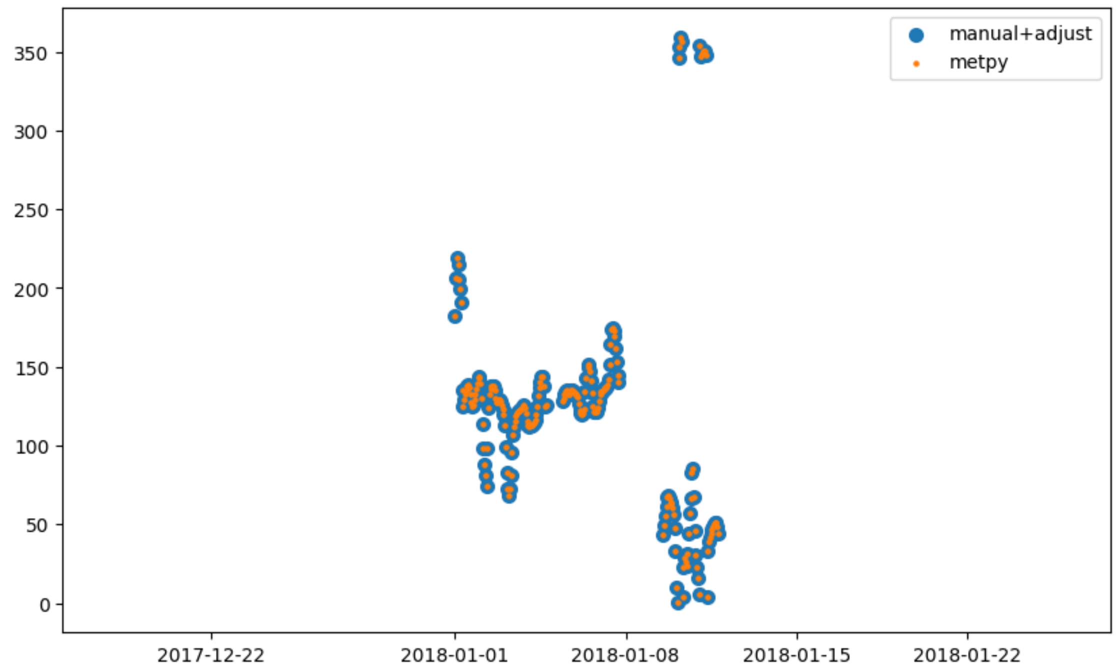
[36]:
```
dfw['U_re2'] = dfw.apply(lambda row: -row['ws']*np.sin(np.
↪radians(row['deg2'])), axis=1)
dfw['V_re2'] = dfw.apply(lambda row: -row['ws']*np.cos(np.
↪radians(row['deg2'])), axis=1)
dfw.head()
```

[36]:
```
                          V2M       U2M        ws        deg      V_re  \
time
2018-01-01 00:00:00  0.507052  0.023183  0.507582   2.617815  0.507052
2018-01-01 01:00:00  0.384886  0.189619  0.429060  26.227729  0.384886
2018-01-01 02:00:00  0.296402  0.243190  0.383400  39.367919  0.296402
2018-01-01 03:00:00  0.277474  0.195083  0.339189  35.109724  0.277474
2018-01-01 04:00:00  0.275675  0.132475  0.305853  25.666509  0.275675

                         U_re      v_2m         d_2m        deg2     U_re2  \
time
2018-01-01 00:00:00  0.023183  0.507582  182.617815  182.617815  0.023183
2018-01-01 01:00:00  0.189619  0.429060  206.227729  206.227729  0.189619
2018-01-01 02:00:00  0.243190  0.383400  219.367919  219.367919  0.243190
2018-01-01 03:00:00  0.195083  0.339189  215.109724  215.109724  0.195083
2018-01-01 04:00:00  0.132475  0.305853  205.666509  205.666509  0.132475

                        V_re2
time
2018-01-01 00:00:00  0.507052
2018-01-01 01:00:00  0.384886
2018-01-01 02:00:00  0.296402
2018-01-01 03:00:00  0.277474
2018-01-01 04:00:00  0.275675
```

- that it, we can now properly and manually calculate wind components between U, V components to speed and angle due north

[37]:
```
dft = dfw[0:200]
plt.scatter(dft.index, dft['deg2'], label='manual+adjust',  lw=2)
plt.scatter(dft.index, dft['d_2m'], marker='o', s=5, label='metpy')
plt.legend()
# and the degrees should matched (perfectly)
```

[37]:
```
<matplotlib.legend.Legend at 0x7f15277b31d0>
```



5 Working with winds with different altitude

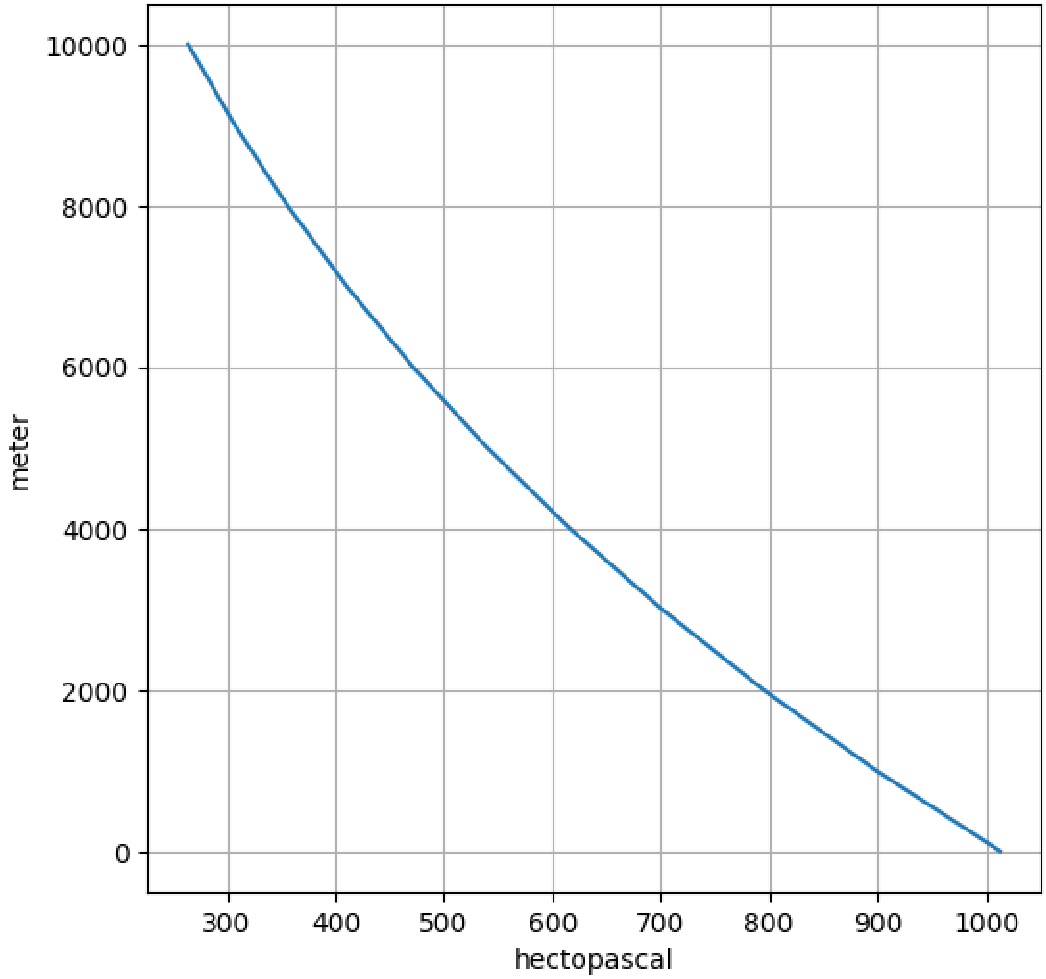
5.1 Pressure and height

- the higher from the ground, the lesser the pressure of air is (and air is thinner)

$$p = p_0 e^{\frac{g}{R\Gamma}\ln(1-\frac{Z\Gamma}{T_0})}$$

[38]:
```
# let make a chart for that
height = np.linspace(0, 10000, num=11)* units.m
press = mpcalc.height_to_pressure_std(height)
```

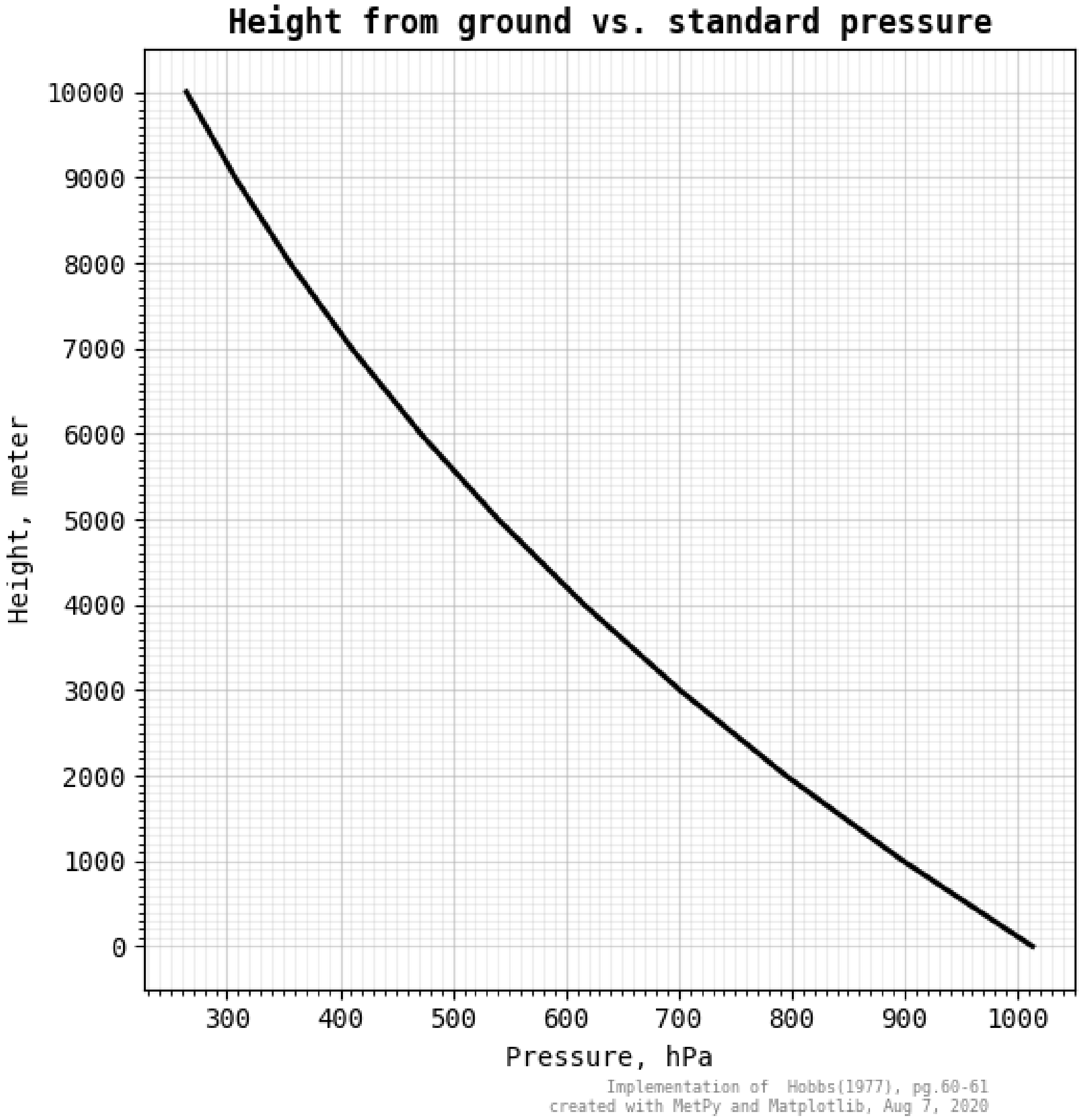
[39]:
```
minory = np.linspace(0, 10000, num=101)
minorx = np.linspace(0, 1000, num=101)
fig, ax = plt.subplots(figsize=(6,6))
ax.plot(press, height)
ax.grid(which='both')
```



- so now you can see wind at 250 (hPa) is almost at the top of the troposhere (10km)

[40]:
```
# let make a good graph to display this relationship
plt.rcParams['font.family'] ='monospace'
fig = plt.figure(figsize=(6,6))

ax = fig.add_subplot(1, 1, 1)

x_major_ticks = np.linspace(0, 1100, 12 )
x_minor_ticks = np.linspace(0, 1100, 111)
y_major_ticks = np.linspace(0, 10_000, 11 )
y_minor_ticks = np.linspace(0, 10_000, 101)



ax.set_xticks(x_major_ticks)
```

```python
ax.set_xticks(x_minor_ticks , minor=True)
ax.set_yticks(y_major_ticks)
ax.set_yticks(y_minor_ticks, minor=True)

ax.grid(which='both')

ax.grid(which='minor', alpha=0.2)
ax.grid(which='major', alpha=0.5)
ax.plot(press, height, color='black', lw=2)
ax.set_ylabel('Height, meter')
ax.set_xlabel('Pressure, hPa')
ax.set_title('Height from ground vs. standard pressure', weight='bold')
fig.text(0.9,0.01, 'Implementation of  Hobbs(1977), pg.60-61\ncreated with␣
↪MetPy and Matplotlib, Aug 7, 2020',
         color='gray', fontsize=6, ha='right')
fig.tight_layout(rect=(0.02,0.02, 1, 1))
fig.savefig('img/height.vs.pressure.png', dpi=120, optimize=True)
```



Resources: what is the atmosphere level again: - https://scied.ucar.edu/atmosphere-layers - https://niwa.co.nz/education-and-training/schools/students/layers - https://scied.ucar.edu/shortcontent/troposphere-overview

5.2 Convert wind (U,V) to speed (m/s)

[41]:
```
# let first convert wind speed and wind direction for all data related to wind␣
↪MERRA-2
wind = pandas_dataframe_to_unit_arrays(df[wind_cols], w_units)
```

[42]:
```python
wind['v_2m'] = mpcalc.wind_speed(wind['U2M'], wind['V2M'])
wind['d_2m']  = mpcalc.wind_direction(wind['U2M'], wind['V2M'])

wind['v_10m'] = mpcalc.wind_speed(wind['U10M'], wind['V10M'])
wind['d_10m']  = mpcalc.wind_direction(wind['U10M'], wind['V10M'])

wind['v_50m'] = mpcalc.wind_speed(wind['U50M'], wind['V50M'])
wind['d_50m']  = mpcalc.wind_direction(wind['U50M'], wind['V50M'])

wind['v_850'] = mpcalc.wind_speed(wind['U850'], wind['V850'])
wind['d_850']  = mpcalc.wind_direction(wind['U850'], wind['V850'])

wind['v_500'] = mpcalc.wind_speed(wind['U500'], wind['V500'])
wind['d_500']  = mpcalc.wind_direction(wind['U500'], wind['V500'])

wind['v_250'] = mpcalc.wind_speed(wind['U250'], wind['V250'])
wind['d_250']  = mpcalc.wind_direction(wind['U250'], wind['V250'])
```

[43]:
```python
dft = pd.DataFrame({
        'v_2m': wind['v_2m'],
        'd_2m': wind['d_2m'],
        'v_10m': wind['v_10m'],
        'd_10m': wind['d_10m'],
        'v_50m': wind['v_50m'],
        'd_50m': wind['d_50m'],
        'v_850': wind['v_850'],
        'd_850': wind['d_850'],
        'v_500': wind['v_500'],
        'd_500': wind['d_500'],
        'v_250': wind['v_250'],
        'd_250': wind['d_250'],
        }, index=df.index.to_list(),)
dft.head()
```

[43]:
```
                         v_2m        d_2m     v_10m       d_10m     v_50m  \
2018-01-01 00:00:00  0.507582  182.617815  0.820326  182.212835  1.167523
2018-01-01 01:00:00  0.429060  206.227729  0.691324  206.109338  0.979452
2018-01-01 02:00:00  0.383400  219.367919  0.617108  218.824390  0.872296
2018-01-01 03:00:00  0.339189  215.109724  0.525337  212.637784  0.729687
2018-01-01 04:00:00  0.305853  205.666509  0.477588  200.748694  0.666341

                          d_50m     v_850       d_850      v_500       d_500  \
2018-01-01 00:00:00  181.509485  6.347019  173.860069  11.257534  276.654649
2018-01-01 01:00:00  205.692157  6.175777  176.297386  11.215821  280.471385
2018-01-01 02:00:00  218.648565  5.997708  177.918171  10.827758  282.437516
2018-01-01 03:00:00  211.709574  5.915825  177.896957  10.295540  282.633150
2018-01-01 04:00:00  198.644717  5.885087  178.941354   9.500886  280.860531
```

```
                          v_250       d_250
2018-01-01 00:00:00  23.196986  242.232266
2018-01-01 01:00:00  23.475563  241.081727
2018-01-01 02:00:00  23.842929  240.022727
2018-01-01 03:00:00  24.137831  239.375860
2018-01-01 04:00:00  24.453376  238.787131
```

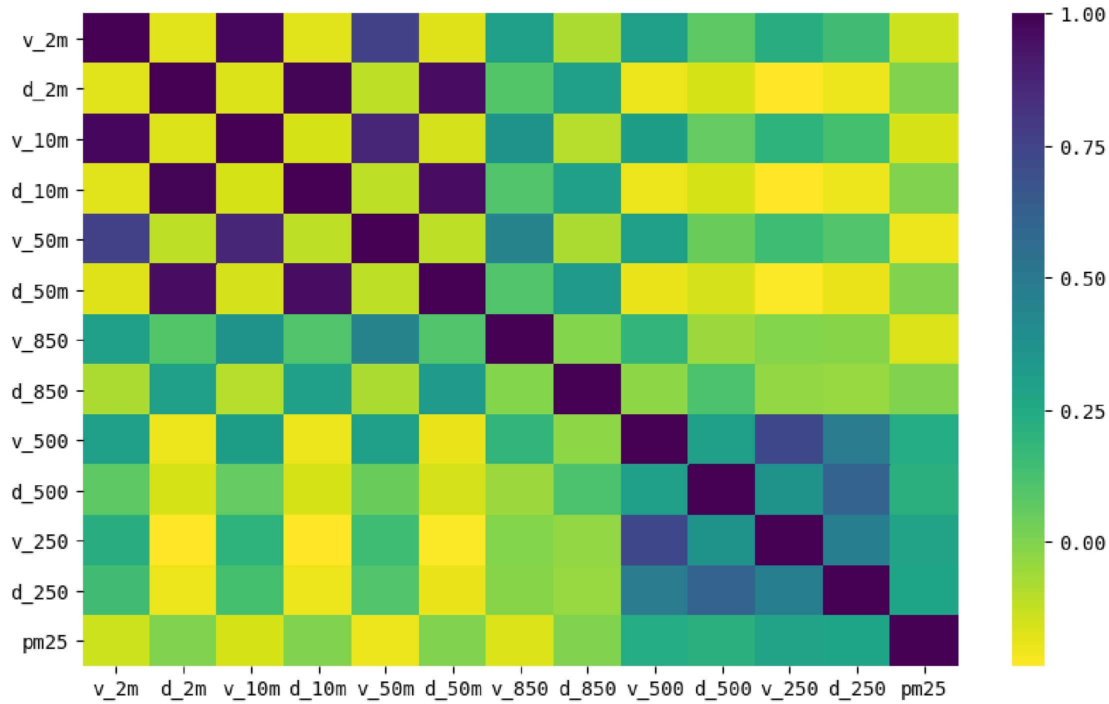
[44]:
```python
# and save data to work later
# dft.to_csv('data/merra2_hanoi_2018_wind_converted.csv')
```

5.3 merge data of wind with pm25

[45]:
```python
df = pd.merge(dft, pm25, right_index=True, left_index=True)
```

[46]:
```python
sns.heatmap(df.corr(), cmap='viridis_r')
```

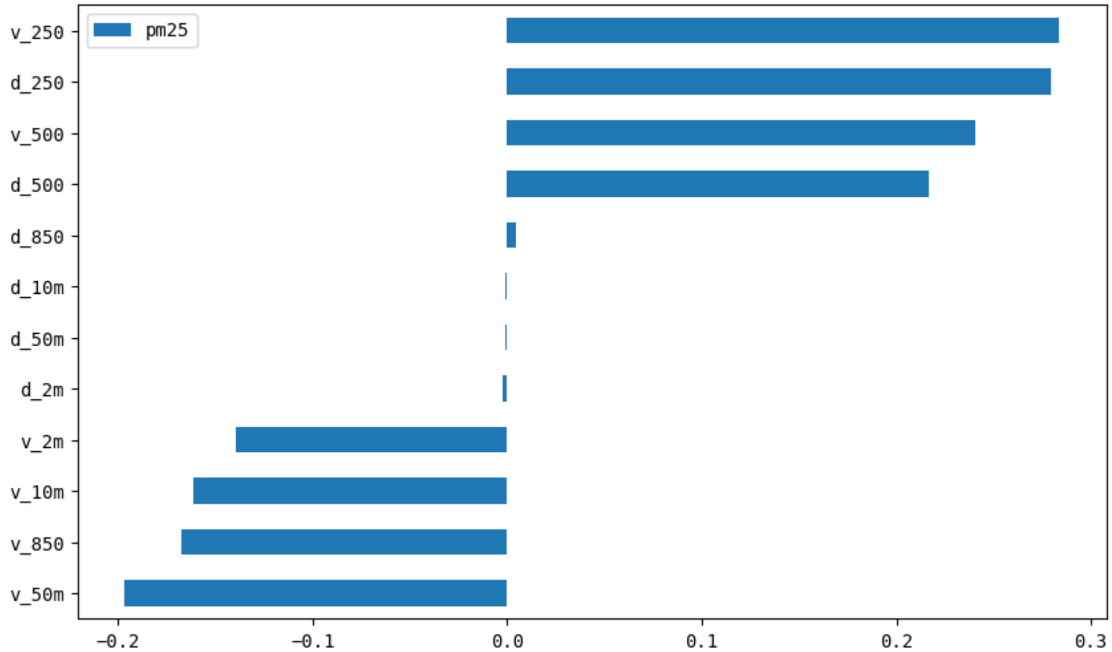
[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7f15276e8f28>



- pretty colorful, and heatmap was useful to see pattern from a large datashet,
- in this case, the correlation of winds to PM2.5 is light green and yellowish - which is weak

[47]:
```
# let try to plot by horizonal bars
df.corr()['pm25'].sort_values().to_frame().drop('pm25').plot.barh()
```

[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7f152712a828>



[48]:
```
# direction seems important (in agreement with the previous analysis)
# let drill more on speed and direction
# all columns related to speed
vs = [v for v in list(df.columns) if 'v' in v]
```

[49]:
```
# and direction
ds = [v for v in list(df.columns) if 'd' in v]
```

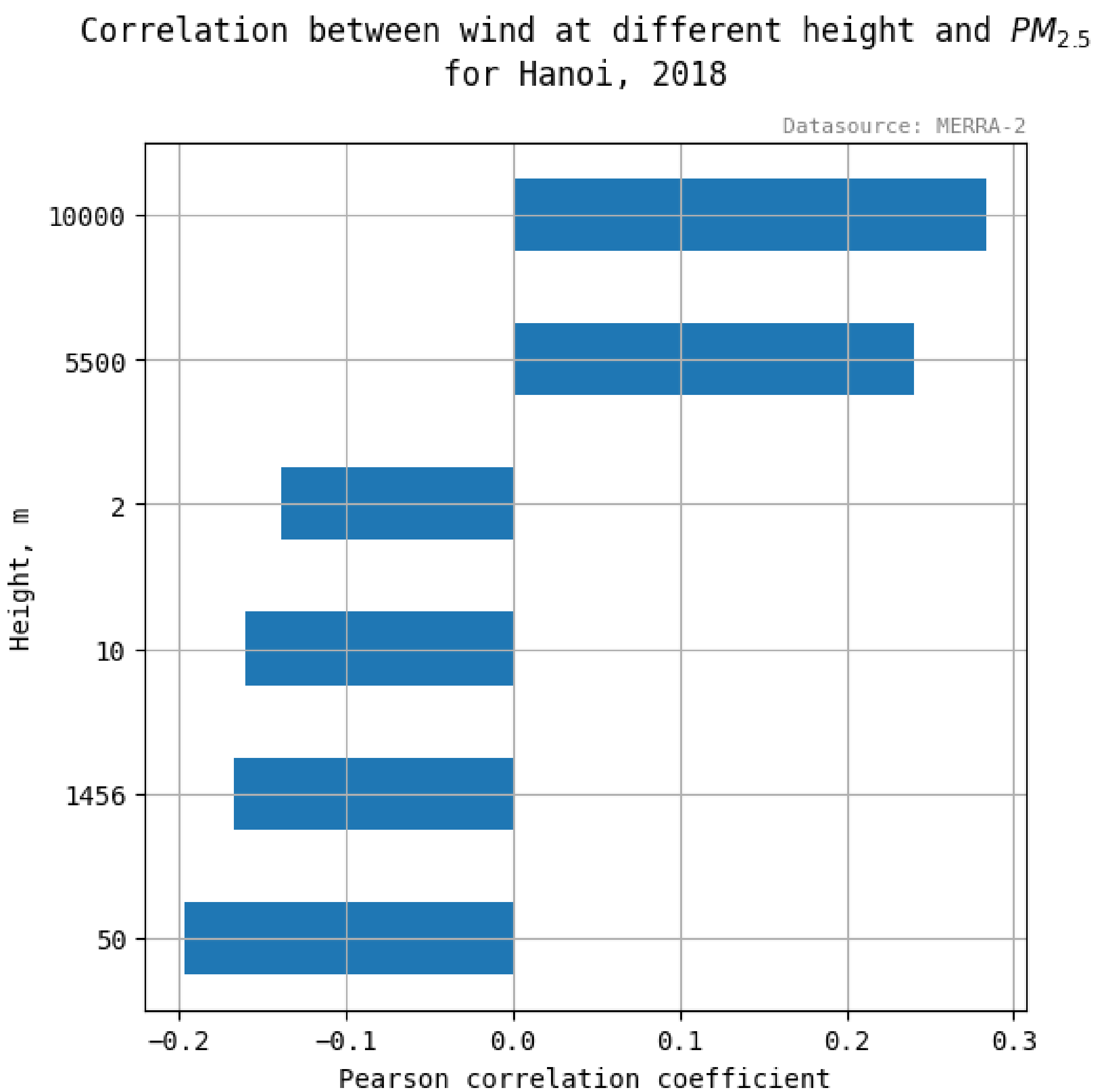
[50]:
```
# and PM2.5 columns
vs.append('pm25')
ds.append('pm25')
```

[51]:
```
# we can also find out what would the height (to the ground) if we know the␣
 ↪standard pressure (in hectopascal)
mpcalc.pressure_to_height_std([850, 500, 250]*units.hectopascal)
```

[51]: $\begin{pmatrix}1.456566413934906 & 5.571624925427431 & 10.357705969899126\end{pmatrix}$ kilometer

[52]:
```
# just for proximation
ylabelsz = [50, 1456, 10, 2, 5500, 10000]
```

[53]:
```
fig, ax = plt.subplots(figsize=(6,6))
df[vs].corr()['pm25'].sort_values().to_frame().drop('pm25').plot.barh(ax=ax)
ax.set_yticklabels(ylabelsz)
ax.set_ylabel('Height, m')
ax.set_xlabel('Pearson correlation coefficient')
ax.set_title('Correlation between wind at different height and $PM_{2.5}$\nfor␣
↪Hanoi, 2018', y=1.05)
ax.text(1.0,1.02, s='Datasource: MERRA-2', va='center', ha='right',␣
↪transform=ax.transAxes,
       fontsize=8, color='gray')
ax.get_legend().remove()
ax.grid()
fig.tight_layout()
fig.savefig('img/2020Aug_wind_corr_heights.png', optimize=True)
```

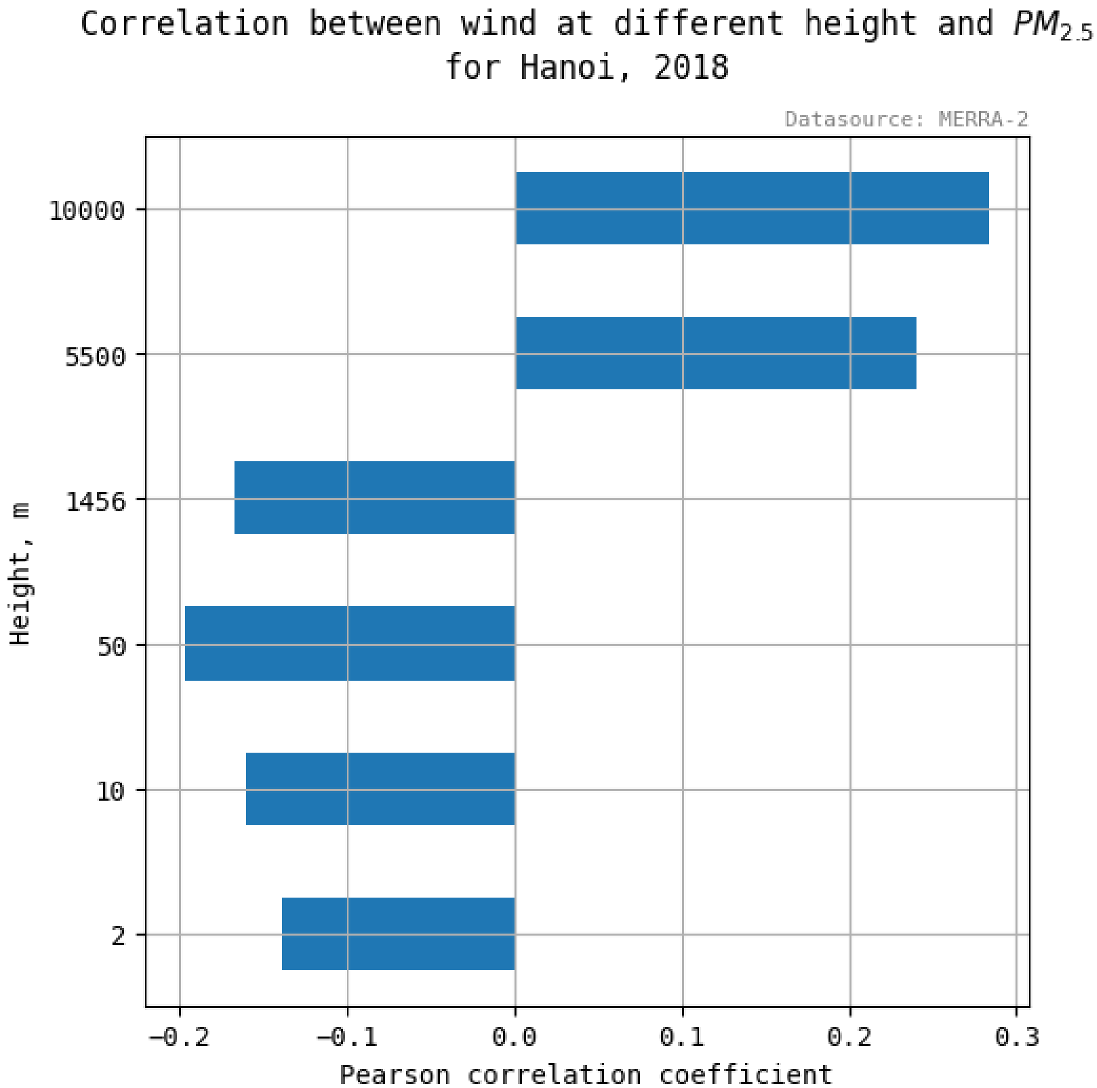


[54]:
```
df[vs].corr()['pm25']
```

[54]:
```
v_2m    -0.139372
v_10m   -0.160878
v_50m   -0.196811
v_850   -0.167242
v_500    0.240385
v_250    0.283819
pm25     1.000000
Name: pm25, dtype: float64
```

[ ]:
```

```

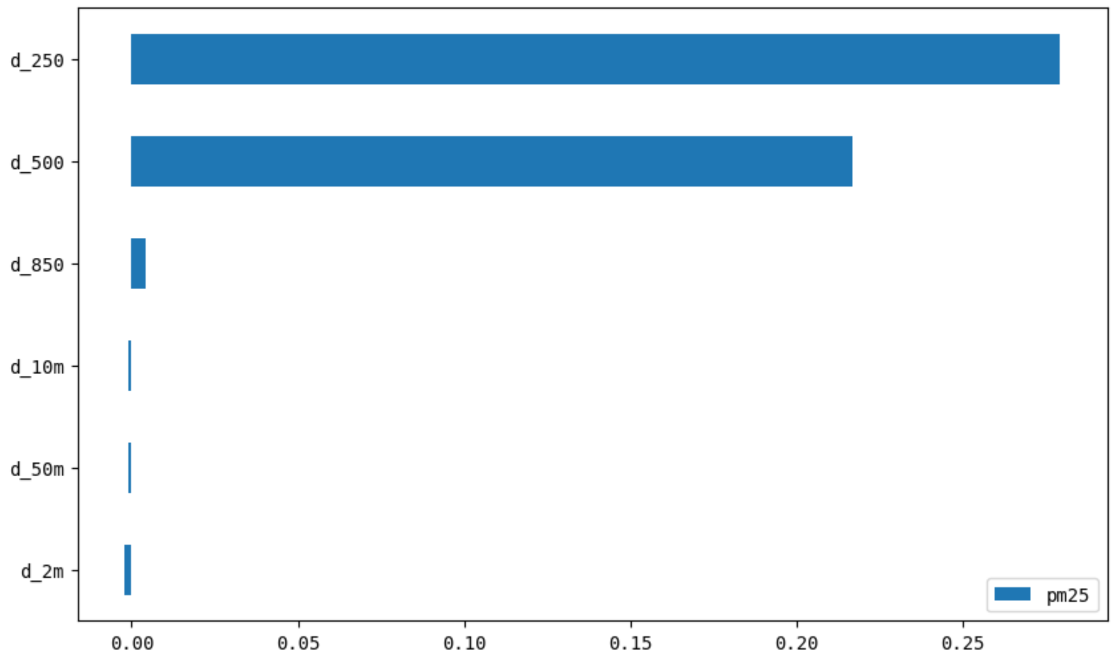
[55]:
```
fig, ax = plt.subplots(figsize=(6,6))
df[vs].corr()['pm25'].to_frame().drop('pm25').plot.barh(ax=ax)
ax.set_yticklabels(sorted(ylabelsz))
ax.set_ylabel('Height, m')
ax.set_xlabel('Pearson correlation coefficient')
ax.set_title('Correlation between wind at different height and $PM_{2.5}$\nfor␣
↪Hanoi, 2018', y=1.05)
ax.text(1.0,1.02, s='Datasource: MERRA-2', va='center', ha='right',␣
↪transform=ax.transAxes,
       fontsize=8, color='gray')
ax.get_legend().remove()
ax.grid()
fig.tight_layout()
fig.savefig('img/2020Aug_wind_corr_heights_inc.png', optimize=True)
```



- wind speed near ground (<1000m) is inversely correlated with PM2.5 concentration,
- wind speed on the top of atmosphere (>5000m) is possively correlated with PM2.5

[56]:
```
# with direction
df[ds].corr()['pm25'].sort_values().to_frame().drop('pm25').plot.barh()
```

[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14f6e1d240>

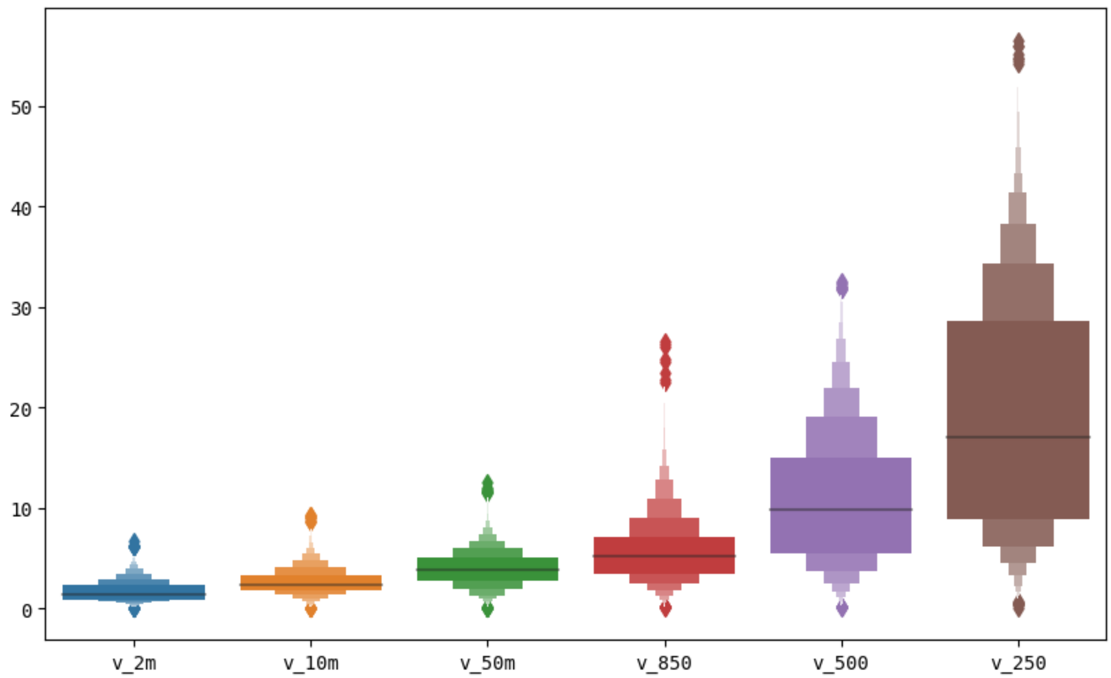


- noted that wind direction is the degree due North, so a large degree (or really close to zero) is the northerly wind (wind blows from the North). We may have look at this in a later time

[57]:
```
# filter only wind columns
vs0 = ['v_2m', 'v_10m', 'v_50m', 'v_850', 'v_500', 'v_250']
```

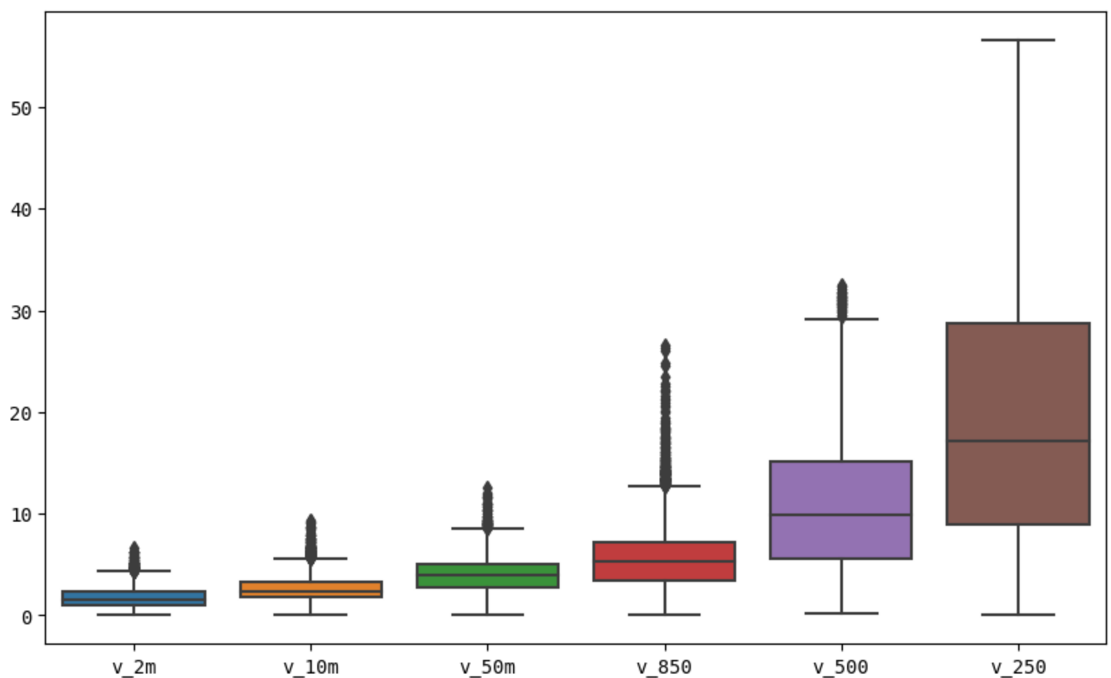
[58]:
```
sns.boxenplot(data=df[vs0])
```

[58]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14f6db4ac8>



[59]:
```
fig, ax = plt.subplots()
sns.boxplot(data=df[vs0], ax=ax)
```

[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14f6cc9c88>



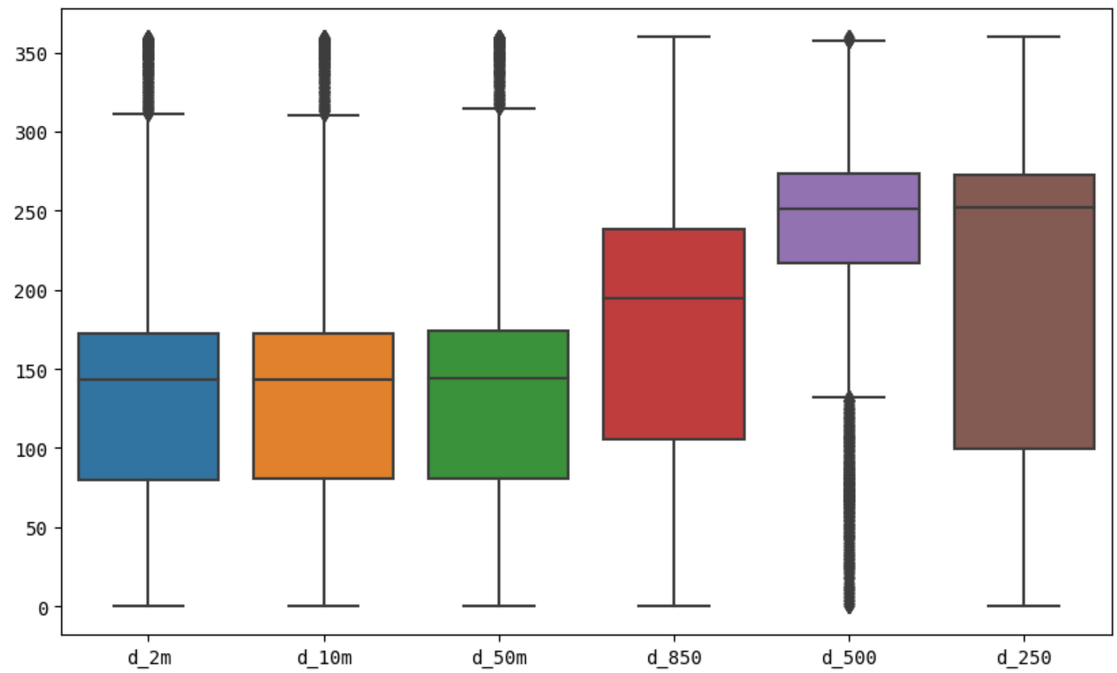
[60]:
```
ds
```

[60]: ['d_2m', 'd_10m', 'd_50m', 'd_850', 'd_500', 'd_250', 'pm25']

[61]:
```
ds0 = ['d_2m', 'd_10m', 'd_50m', 'd_850', 'd_500', 'd_250']
```

[62]:
```
sns.boxplot(data=df[ds0])
```

[62]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14f461c358>



- nothing much to comment on

6 Convert specific humdity to relative humdity

The formula used is that from [Bolton1980]_ for T in degrees Celsius:

$$6.112e^{\frac{17.67T}{T+243.5}}$$

[63]:
```
# let load the data file from MERRA-2
df = pd.read_csv('data/merra2_slv_hanoi_2018.csv',
                 parse_dates=['time'],
                 index_col=['time'])
```

```
df.head()
```

[63]:
```
                          U2M       V250      TROPT      TROPPB        T2M  \
time
2018-01-01 00:00:00  0.023183  10.807207  192.34645  10051.0290  287.10890
2018-01-01 01:00:00  0.189619  11.351880  192.50723  10052.2750  286.79376
2018-01-01 02:00:00  0.243190  11.913273  192.63431  10051.5625  286.48932
2018-01-01 03:00:00  0.195083  12.295908  192.71167  10052.2780  286.24753
2018-01-01 04:00:00  0.132475  12.672207  192.72789  10050.9120  285.96360

                          TQL       T500      U850         PS      V850  …  \
time                                                                     …
2018-01-01 00:00:00  0.008423  267.34950 -0.678858  100905.08  6.310610  …
2018-01-01 01:00:00  0.009235  267.07660 -0.398818  100865.09  6.162886  …
2018-01-01 02:00:00  0.006260  266.77542 -0.217877  100819.56  5.993750  …
2018-01-01 03:00:00  0.003489  266.50415 -0.217092  100793.71  5.911840  …
2018-01-01 04:00:00  0.002314  266.30140 -0.108732  100791.80  5.884082  …

                          H850       T850      U50M      U10M    TROPPV  \
time
2018-01-01 00:00:00  1527.0985  283.53122  0.030755  0.031674  7564.037
2018-01-01 01:00:00  1522.4517  283.64413  0.424628  0.304242  7369.791
2018-01-01 02:00:00  1518.0483  283.75928  0.544786  0.386887  7256.081
2018-01-01 03:00:00  1515.4990  283.86768  0.383533  0.283328  7255.750
2018-01-01 04:00:00  1514.8696  283.87558  0.213028  0.169195  7256.080

                          H500      V500     T2MWET       U500     QV10M
time
2018-01-01 00:00:00  5840.2160 -1.304574  284.03730  11.181688  0.007823
2018-01-01 01:00:00  5835.2650 -2.038413  283.94345  11.029030  0.007823
2018-01-01 02:00:00  5830.6333 -2.332026  283.87656  10.573646  0.007822
2018-01-01 03:00:00  5828.6885 -2.251715  283.76090  10.046288  0.007807
2018-01-01 04:00:00  5828.3154 -1.790147  283.66614   9.330713  0.007804

[5 rows x 39 columns]
```

[64]:
```
df.columns
```

[64]:
```
Index(['U2M', 'V250', 'TROPT', 'TROPPB', 'T2M', 'TQL', 'T500', 'U850', 'PS',
       'V850', 'H250', 'Q250', 'T2MDEW', 'V50M', 'Q500', 'DISPH', 'H1000',
       'TS', 'T10M', 'TROPPT', 'SLP', 'U250', 'Q850', 'ZLCL', 'TQV', 'V2M',
       'T250', 'TROPQ', 'V10M', 'H850', 'T850', 'U50M', 'U10M', 'TROPPV',
       'H500', 'V500', 'T2MWET', 'U500', 'QV10M'],
      dtype='object')
```

[65]:
```
# we will need air temperature and dewpoint temperature
cols = ['T2M', 'T2MDEW']
```

[66]:
```python
# standard name
name_
```

[66]:
```
{'U2M': '2-meter_eastward_wind, m s-1',
 'V250': 'northward_wind_at_250_hPa, m s-1',
 'TROPT': 'tropopause_temperature_using_blended_TROPP_estimate, K',
 'TROPPB': 'tropopause_pressure_based_on_blended_estimate, Pa',
 'T2M': '2-meter_air_temperature, K',
 'TQL': 'total_precipitable_liquid_water, kg m-2',
 'T500': 'air_temperature_at_500_hPa, K',
 'U850': 'eastward_wind_at_850_hPa, m s-1',
 'PS': 'surface_pressure, Pa',
 'V850': 'northward_wind_at_850_hPa, m s-1',
 'H250': 'height_at_250_hPa, m',
 'Q250': 'specific_humidity_at_250_hPa, kg kg-1',
 'T2MDEW': 'dew_point_temperature_at_2_m, K',
 'V50M': 'northward_wind_at_50_meters, m s-1',
 'Q500': 'specific_humidity_at_500_hPa, kg kg-1',
 'DISPH': 'zero_plane_displacement_height, m',
 'H1000': 'height_at_1000_mb, m',
 'TS': 'surface_skin_temperature, K',
 'T10M': '10-meter_air_temperature, K',
 'TROPPT': 'tropopause_pressure_based_on_thermal_estimate, Pa',
 'SLP': 'sea_level_pressure, Pa',
 'U250': 'eastward_wind_at_250_hPa, m s-1',
 'Q850': 'specific_humidity_at_850_hPa, kg kg-1',
 'ZLCL': 'lifting_condensation_level, m',
 'TQV': 'total_precipitable_water_vapor, kg m-2',
 'V2M': '2-meter_northward_wind, m s-1',
 'T250': 'air_temperature_at_250_hPa, K',
 'TROPQ': 'tropopause_specific_humidity_using_blended_TROPP_estimate, kg kg-1',
 'V10M': '10-meter_northward_wind, m s-1',
 'H850': 'height_at_850_hPa, m',
 'T850': 'air_temperature_at_850_hPa, K',
 'U50M': 'eastward_wind_at_50_meters, m s-1',
 'U10M': '10-meter_eastward_wind, m s-1',
 'TROPPV': 'tropopause_pressure_based_on_EPV_estimate, Pa',
 'H500': 'height_at_500_hPa, m',
 'V500': 'northward_wind_at_500_hPa, m s-1',
 'T2MWET': 'wet_bulb_temperature_at_2_m, K',
 'U500': 'eastward_wind_at_500_hPa, m s-1',
 'QV10M': '10-meter_specific_humidity, kg kg-1'}
```

[67]:
```python
dft = df[cols]
```

6.1 Approximation

[68]:
```python
dft.columns
```

[68]:
```
Index(['T2M', 'T2MDEW'], dtype='object')
```

[69]:
```python
# this use *C degree, but since but of T2M and T2MDEW in Kelvin degree, we␣
↪don't have convert
dft['RH_est'] = dft.apply(lambda row: 100-5*(row['T2M']-row['T2MDEW']), axis=1)
dft.head()
```

[69]:

time	T2M	T2MDEW	RH_est
2018-01-01 00:00:00	287.10890	284.03317	84.62135
2018-01-01 01:00:00	286.79376	283.94443	85.75335
2018-01-01 02:00:00	286.48932	283.87836	86.94520
2018-01-01 03:00:00	286.24753	283.75630	87.54385
2018-01-01 04:00:00	285.96360	283.65967	88.48035

6.2 Use MetPy package

ref https://unidata.github.io/MetPy/latest/api/generated/metpy.calc.relative_humidity_from_dewp

[70]:
```python
# inline method not work
dft['RH_mp'] = dft.apply(lambda row: mpcalc.
↪relative_humidity_from_dewpoint(row['T2M']*units.K, row['T2MDEW']*units.K).
↪magnitude*100, axis=1)
```

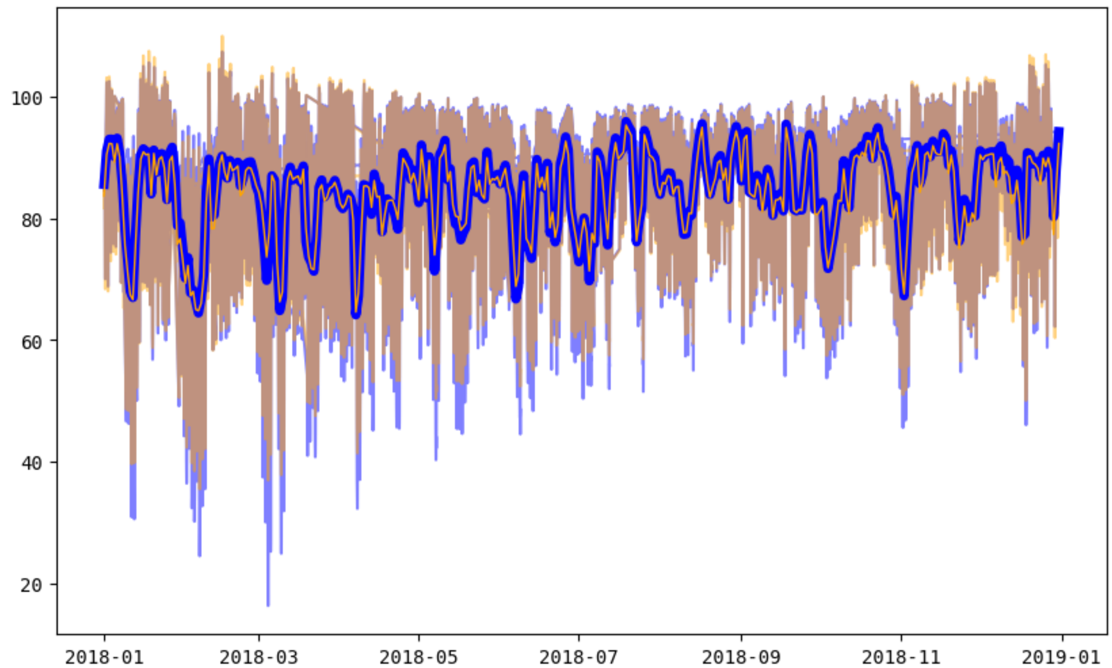
[71]:
```python
dft.head()
```

[71]:

time	T2M	T2MDEW	RH_est	RH_mp
2018-01-01 00:00:00	287.10890	284.03317	84.62135	81.704321
2018-01-01 01:00:00	286.79376	283.94443	85.75335	82.904195
2018-01-01 02:00:00	286.48932	283.87836	86.94520	84.193856
2018-01-01 03:00:00	286.24753	283.75630	87.54385	84.840914
2018-01-01 04:00:00	285.96360	283.65967	88.48035	85.876586

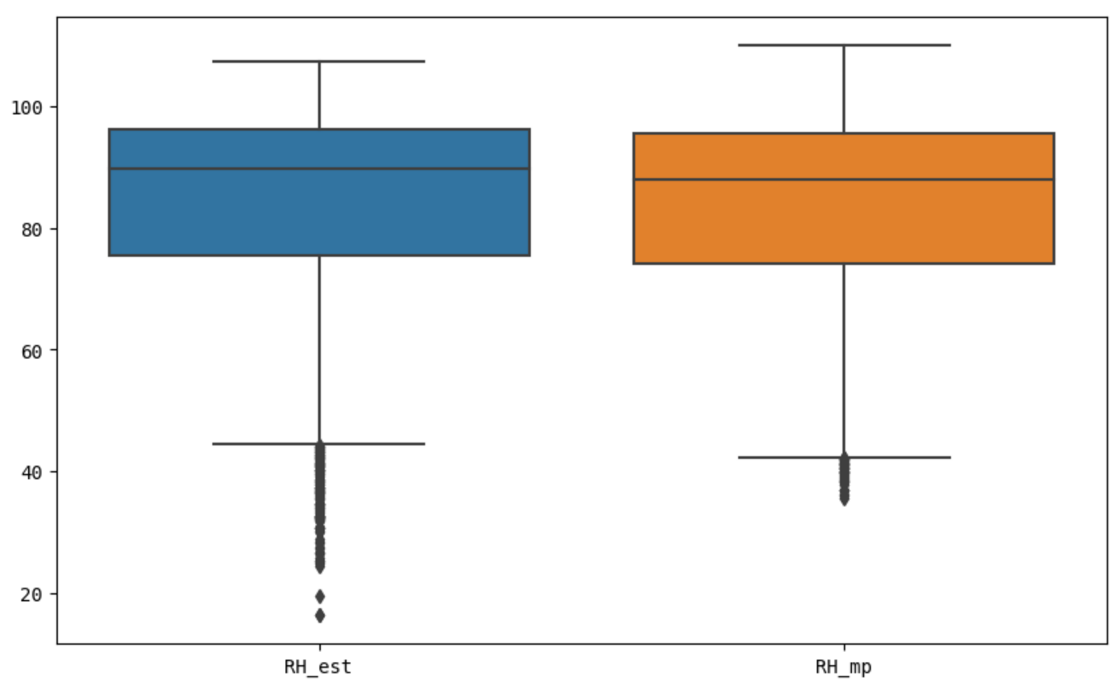
[72]:
```python
plt.plot(dft.index, dft['RH_est'], color='blue', alpha=0.5)
plt.plot(dft.index, dft['RH_mp'], color='orange', alpha=0.5)
dftd = dft.resample('1D').mean()
plt.plot(dftd.index, dftd['RH_est'], color='blue', lw=5)
plt.plot(dftd.index, dftd['RH_mp'], color='orange', lw=1)
```

[72]:
```
[<matplotlib.lines.Line2D at 0x7f14f6ee8e80>]
```



[73]:
```
sns.boxplot(data=dft[['RH_est', 'RH_mp']])
```

[73]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14f73ee128>



- they are quite similar, so either go with more accurate method (MetPy) or quick and simple (approxiation)

7 Darksky (forecast and historical API) vs. observed data (Noiba via NOAA)

7.1 DarkSky

[74]:
```
import datetime
```

[75]:
```
dk = pd.read_csv('data/darksky_hanoi_2018.csv',
                parse_dates=['time'],
                index_col=['time'])
```

[76]:
```
dk.head()
```

[76]:
```
                     apparenttemperature  cloudcover  dewpoint  humidity  \
time
2017-12-31 00:00:00                16.98         NaN     10.99      0.68
2017-12-31 01:00:00                16.97         1.0     10.47      0.66
2017-12-31 02:00:00                16.98         NaN      9.99      0.63
2017-12-31 03:00:00                16.98         NaN      9.99      0.63
2017-12-31 04:00:00                16.79         1.0     10.41      0.66

                            icon  ozone  precipintensity  precipprobability  \
time
2017-12-31 00:00:00  clear-night    NaN              0.0                0.0
2017-12-31 01:00:00       cloudy    NaN              0.0                0.0
2017-12-31 02:00:00  clear-night    NaN              0.0                0.0
2017-12-31 03:00:00  clear-night    NaN              0.0                0.0
2017-12-31 04:00:00       cloudy    NaN              0.0                0.0

                    preciptype  pressure   summary  temperature  uvindex  \
time
2017-12-31 00:00:00        NaN       NaN     Clear        16.98      0.0
2017-12-31 01:00:00        NaN   1023.82  Overcast        16.97      0.0
2017-12-31 02:00:00        NaN       NaN     Clear        16.98      0.0
2017-12-31 03:00:00        NaN       NaN     Clear        16.98      0.0
2017-12-31 04:00:00        NaN   1023.19  Overcast        16.79      0.0

                     visibility  windbearing  windgust  windspeed
time
2017-12-31 00:00:00       10.01         11.0       NaN       4.60
2017-12-31 01:00:00       10.01          9.0       NaN       3.20
2017-12-31 02:00:00       10.01         11.0       NaN       4.10
```

```
2017-12-31 03:00:00       10.01          11.0        NaN        3.60
2017-12-31 04:00:00       10.01           0.0        NaN        3.04
```

[77]:
```
# dk['time'] = dk['utctime'].apply(dt.fromtimestamp)
# dk.to_csv('data/darksky_hanoi_2018.csv')
```

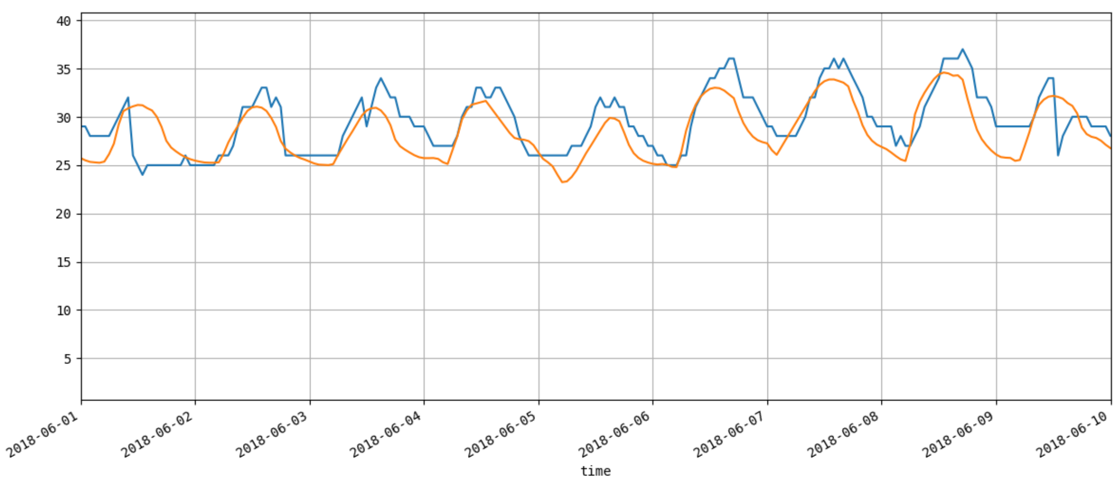
[78]:
```
import matplotlib as mpl
```

[79]:
```
# plt.style.use('seaborn-paper')
```

[80]:
```
df.sort_index(inplace=True)
```

[81]:
```
df['T2M_C'] = df['T2M'] - 273.15
```

[82]:
```
fig, ax = plt.subplots(figsize=[14,6])
dk['temperature'].plot(ax=ax)
ax.plot(df.index, df['T2M_C'])
# ax.xaxis.set_major_locator(mpl.dates.DayLocator())
ax.xaxis.set_minor_locator(mpl.dates.AutoDateLocator())
ax.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%h'));
# ax.xaxis.set_major_formatter(mpl.dates.DateFormatter('%h\n%Y'))
ax.set_xlim(datetime.datetime(2018,6,1), datetime.datetime(2018,6,10))
plt.grid(which='both', axis='both')
```



[83]:
```
dk.columns
```

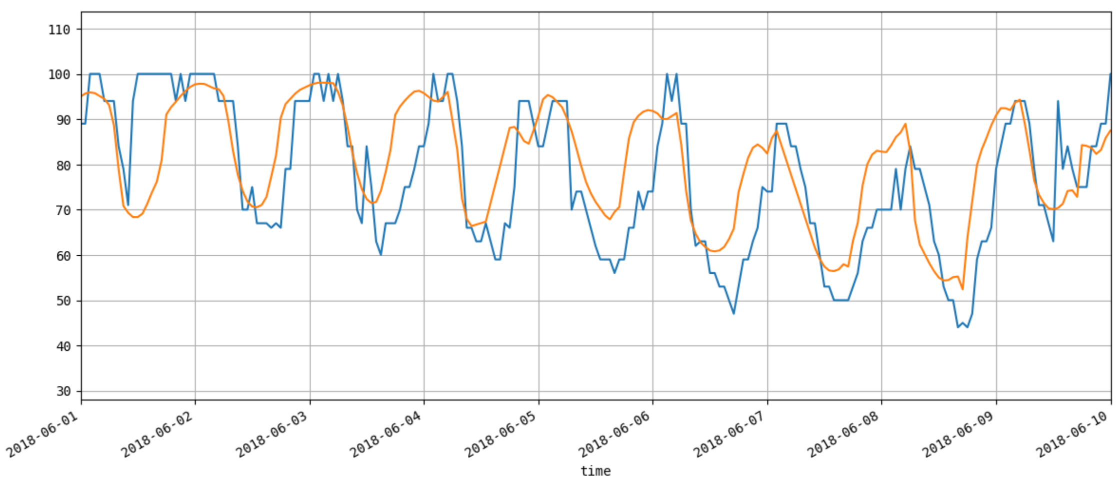
[83]:
```
Index(['apparenttemperature', 'cloudcover', 'dewpoint', 'humidity', 'icon',
       'ozone', 'precipintensity', 'precipprobability', 'preciptype',
       'pressure', 'summary', 'temperature', 'uvindex', 'visibility',
       'windbearing', 'windgust', 'windspeed'],
```

```
dtype='object')
```

[84]:
```python
dft.sort_index(inplace=True)
```

[85]:
```python
dk.humidity = dk.humidity*100
```

[86]:
```python
fig, ax = plt.subplots(figsize=[14,6])
dk['humidity'].plot(ax=ax)
ax.plot(dft.index, dft['RH_mp'])
# ax.xaxis.set_major_locator(mpl.dates.DayLocator())
ax.xaxis.set_minor_locator(mpl.dates.AutoDateLocator())
ax.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%h'));
# ax.xaxis.set_major_formatter(mpl.dates.DateFormatter('%h\n%Y'))
ax.set_xlim(datetime.datetime(2018,6,1), datetime.datetime(2018,6,10))
plt.grid(which='both', axis='both')
```



7.2 Noibai meteorological data

[87]:
```python
nb = pd.read_csv('data/cleaned_noibai_noaa_isd_2018.csv',
                 parse_dates=['DATE'],
                 index_col=['DATE'])
```

[88]:
```python
nb.head()
```

[88]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT
DATE								
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
```

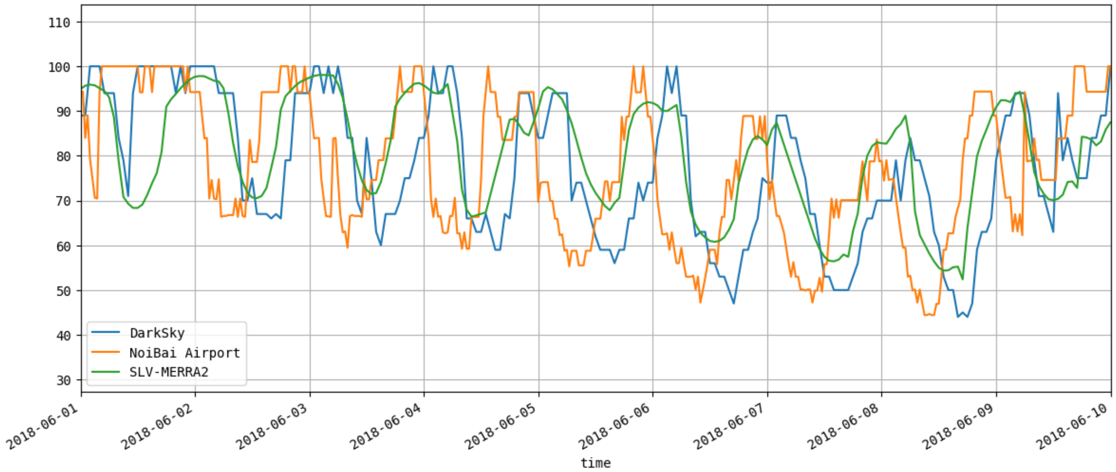
[89]:
```
nb['RH_mp'] = nb.apply(lambda row: mpcalc.relative_humidity_from_dewpoint(
    (row['TMP']+273.15)*units.K, (row['DEW']+273.15)*units.K).magnitude*100,␣
 ↪axis=1)
```

[90]:
```
nb.head()
```

[90]:
```
                        CIG   VIS   TMP   DEW  WD   WS  CLDCR   CLDHT  \
DATE
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

                         RH_mp
DATE
2018-01-01 00:00:00  77.137733
2018-01-01 00:30:00  77.137733
2018-01-01 01:00:00  77.137733
2018-01-01 01:30:00  72.380993
2018-01-01 02:00:00  72.380993
```

[91]:
```
fig, ax = plt.subplots(figsize=[14,6])
dk['humidity'].plot(ax=ax, label='DarkSky')
ax.plot(nb.index, nb['RH_mp'], label='NoiBai Airport')
ax.plot(dft.index, dft['RH_mp'], label='SLV-MERRA2')
ax.set_xlim(datetime.datetime(2018,6,1), datetime.datetime(2018,6,10))
plt.grid(which='both', axis='both')
plt.legend()
```

[91]:
```
<matplotlib.legend.Legend at 0x7f1527635630>
```



- the data from Darksky and from NOAA not quite match, they are about 7 hours different by the pitches
- let add 7 hours to the Noibai set and that the timezone different between UTC time (GMT+0), and local time (GMT+&)

[92]:
```
dft.columns
```

[92]: Index(['T2M', 'T2MDEW', 'RH_est', 'RH_mp'], dtype='object')

[93]:
```
dft['T2M_C'] = dft['T2M'] - 273.15
```

[94]:
```
nb.head()
```

[94]:

	CIG	VIS	TMP	DEW	WD	WS	CLDCR	CLDHT	\
DATE									
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	

	RH_mp
DATE	
2018-01-01 00:00:00	77.137733
2018-01-01 00:30:00	77.137733
2018-01-01 01:00:00	77.137733
2018-01-01 01:30:00	72.380993
2018-01-01 02:00:00	72.380993

[95]:
```
nb.index = nb.index + datetime.timedelta(hours=7)
```

[97]:
```python
import random
```

[98]:
```python
random.randint(1, 355)
```

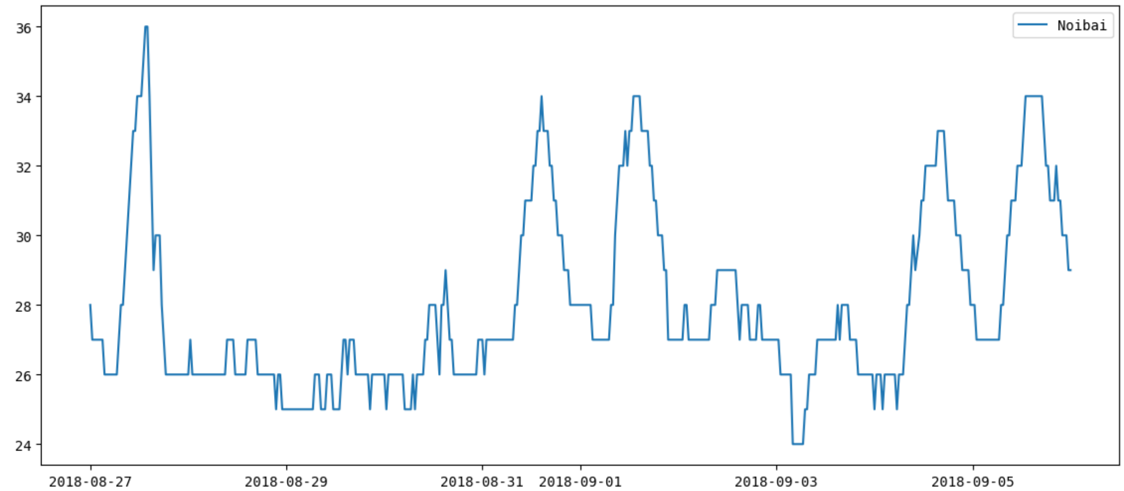
[98]: 3

[99]:
```python
ylabels = [item.get_text() for item in ax.get_xticklabels()]
ylabels
```

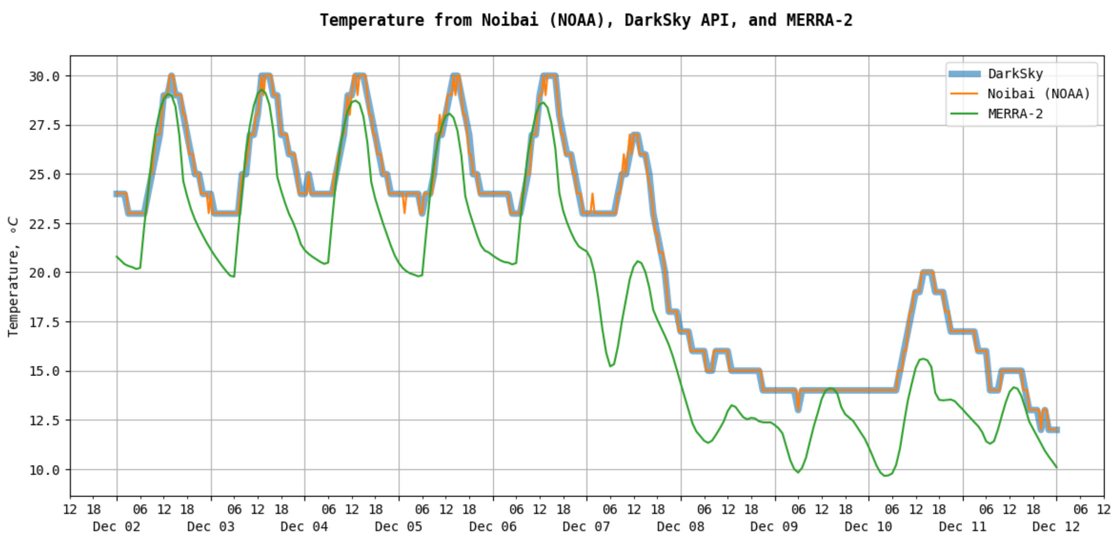
[99]:
```
['2018-06-01',
 '2018-06-02',
 '2018-06-03',
 '2018-06-04',
 '2018-06-05',
 '2018-06-06',
 '2018-06-07',
 '2018-06-08',
 '2018-06-09',
 '2018-06-10']
```

[100]:
```python
def select_peridod(df=None, start=None, days=10):
    end = start+datetime.timedelta(days=days)
    return df[(df.index >=start) & (df.index <= end)]
```

[102]:
```python
days=10
start = datetime.datetime(2018, 1, 1) + datetime.timedelta(random.randint(1,␣
↪365-days))

fig, ax = plt.subplots(figsize=[14,6])
nbt = select_peridod(df=nb, start=start, days=days)
ax.plot(nbt.index, nbt['TMP'], label='Noibai')
plt.legend();
```



[113]:
```
days=10
start = datetime.datetime(2018, 1, 1) + datetime.timedelta(random.randint(1,␣
↪365-days))

fig, ax = plt.subplots(figsize=[14,6])

dkt = select_peridod(df=dk, start=start, days=days)
ax.plot(dkt.index, dkt.temperature, label='DarkSky', lw=5, alpha=0.6)

nbt = select_peridod(df=nb, start=start, days=days)
ax.plot(nbt.index, nbt['TMP'], label='Noibai (NOAA)', lw=1.5)

mrt = select_peridod(df=dft, start=start, days=days)
ax.plot(mrt.index, mrt['T2M_C'], label='MERRA-2')



ax.xaxis.set_major_locator(mpl.dates.DayLocator())
ax.xaxis.set_minor_locator(mpl.dates.HourLocator(interval=6))
ax.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%H'))
ax.xaxis.set_major_formatter(mpl.dates.DateFormatter('\n%b %d'))

ax.set_ylabel('Temperature, $\circ C$')
ax.set_title('Temperature from Noibai (NOAA), DarkSky API, and MERRA-2', y=1.
↪05, weight='bold')

plt.grid(axis='both')
plt.legend();
plt.savefig('img/2020Aug-Temp-sources.png', optimize=True)
```



8 explore

[114]:
```
dk.head()
```

[114]:
```
                     apparenttemperature  cloudcover  dewpoint  humidity  \
time
2017-12-31 00:00:00                16.98         NaN     10.99      68.0
2017-12-31 01:00:00                16.97         1.0     10.47      66.0
2017-12-31 02:00:00                16.98         NaN      9.99      63.0
2017-12-31 03:00:00                16.98         NaN      9.99      63.0
2017-12-31 04:00:00                16.79         1.0     10.41      66.0

                            icon  ozone  precipintensity  precipprobability  \
time
2017-12-31 00:00:00  clear-night    NaN              0.0                0.0
2017-12-31 01:00:00       cloudy    NaN              0.0                0.0
2017-12-31 02:00:00  clear-night    NaN              0.0                0.0
2017-12-31 03:00:00  clear-night    NaN              0.0                0.0
2017-12-31 04:00:00       cloudy    NaN              0.0                0.0

                    preciptype  pressure   summary  temperature  uvindex  \
time
2017-12-31 00:00:00        NaN       NaN     Clear        16.98      0.0
2017-12-31 01:00:00        NaN   1023.82  Overcast        16.97      0.0
2017-12-31 02:00:00        NaN       NaN     Clear        16.98      0.0
2017-12-31 03:00:00        NaN       NaN     Clear        16.98      0.0
2017-12-31 04:00:00        NaN   1023.19  Overcast        16.79      0.0

                     visibility  windbearing  windgust  windspeed
time
2017-12-31 00:00:00       10.01         11.0       NaN       4.60
2017-12-31 01:00:00       10.01          9.0       NaN       3.20
2017-12-31 02:00:00       10.01         11.0       NaN       4.10
2017-12-31 03:00:00       10.01         11.0       NaN       3.60
2017-12-31 04:00:00       10.01          0.0       NaN       3.04
```

[115]:
```
dk.dtypes
```

[115]:
```
apparenttemperature    float64
cloudcover             float64
dewpoint               float64
humidity               float64
icon                    object
```

```
ozone                     float64
precipintensity           float64
precipprobability         float64
preciptype                 object
pressure                  float64
summary                    object
temperature               float64
uvindex                   float64
visibility                float64
windbearing               float64
windgust                  float64
windspeed                 float64
dtype: object
```

[116]:
```
dk.columns
```

[116]:
```
Index(['apparenttemperature', 'cloudcover', 'dewpoint', 'humidity', 'icon',
       'ozone', 'precipintensity', 'precipprobability', 'preciptype',
       'pressure', 'summary', 'temperature', 'uvindex', 'visibility',
       'windbearing', 'windgust', 'windspeed'],
      dtype='object')
```

[117]:
```
cols = ['cloudcover', 'dewpoint', 'humidity', 'precipintensity', 'pressure',␣
 ↪'temperature', 'visibility', 'windbearing', 'windspeed']
```

[118]:
```
del dkt
dkt = dk[cols]
```

[119]:
```
dkt.tail()
```

[119]:
```
                     cloudcover  dewpoint  humidity  precipintensity  \
time
2018-12-31 20:00:00         NaN       5.0      58.0              NaN
2018-12-31 21:00:00         NaN       6.0      67.0              NaN
2018-12-31 22:00:00         NaN       5.0      62.0              NaN
2018-12-31 23:00:00         NaN       6.0      67.0              NaN
2019-01-01 00:00:00         NaN       6.0      67.0              NaN

                     pressure  temperature  visibility  windbearing  windspeed
time
2018-12-31 20:00:00       NaN        12.99       10.01         60.0        2.1
2018-12-31 21:00:00       NaN        11.98       10.01         80.0        1.5
2018-12-31 22:00:00       NaN        11.98       10.01         60.0        2.6
2018-12-31 23:00:00       NaN        11.98       10.01         60.0        1.5
2019-01-01 00:00:00       NaN        11.98       10.01         50.0        2.1
```

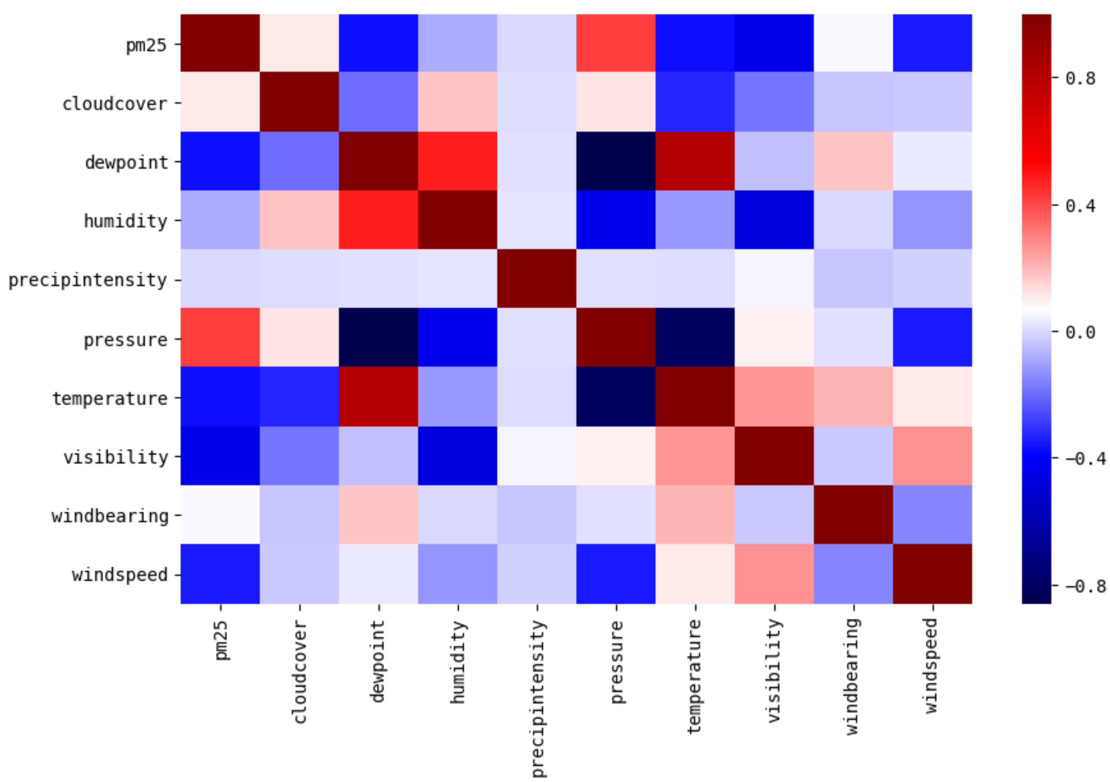
[120]:
```
dkt = pd.merge(pm25, dkt, right_index=True, left_index=True)
```

[121]:
```
dkt.head()
```

[121]:
```
                     pm25  cloudcover  dewpoint  humidity  precipintensity  \
2018-01-01 01:00:00  69.2        0.82     13.24      81.0              0.0
2018-01-01 02:00:00  75.5        0.75     10.99      72.0              0.0
2018-01-01 03:00:00  90.2        0.75     11.99      77.0              0.0
2018-01-01 04:00:00  97.6        0.00     12.48      86.0              0.0
2018-01-01 05:00:00  89.1        0.00     10.99      77.0              0.0

                     pressure  temperature  visibility  windbearing  windspeed
2018-01-01 01:00:00   1019.69        16.44         9.0        330.0        1.5
2018-01-01 02:00:00       NaN        15.99         9.0         90.0        1.5
2018-01-01 03:00:00       NaN        15.99         8.0         80.0        1.5
2018-01-01 04:00:00   1018.30        14.73         8.0         71.0        1.5
2018-01-01 05:00:00       NaN        14.99         8.0         71.0        1.0
```

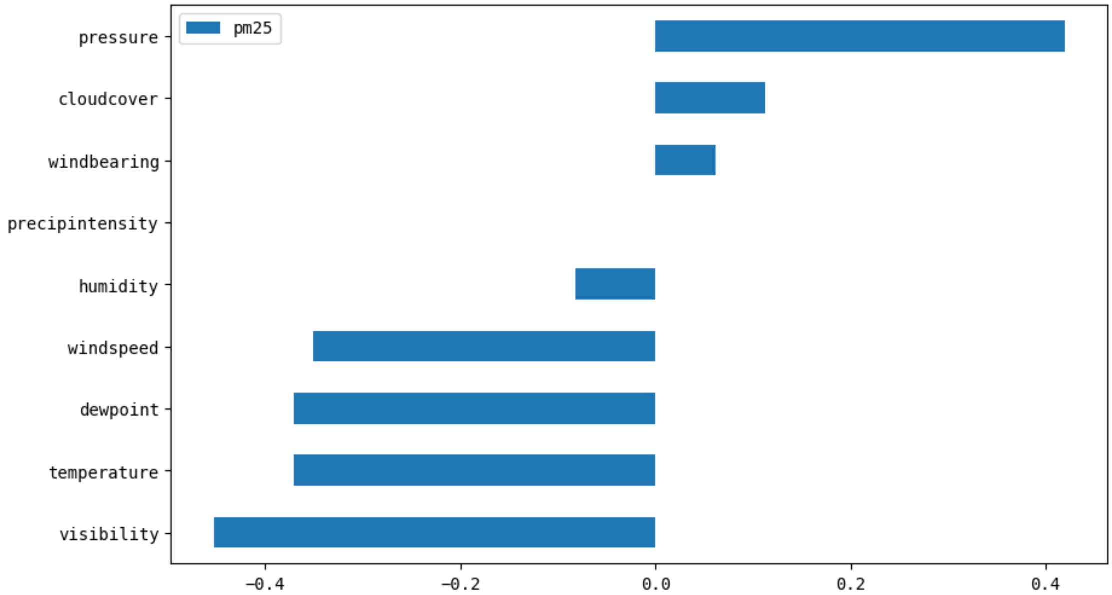
[122]:
```
sns.heatmap(dkt.corr(), cmap='seismic')
```

[122]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14e67a7080>



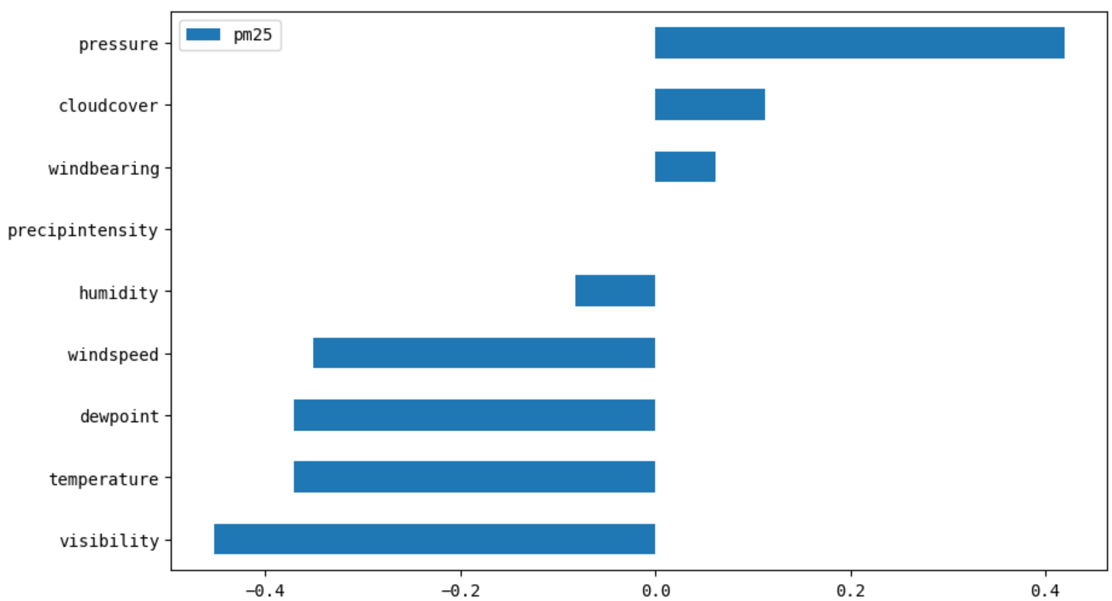
[123]:
```
dkt.corr()['pm25'].sort_values().to_frame().drop('pm25').plot.barh()
```

[123]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14e610c908>



[124]:
```
dkt.corr()['pm25'].sort_values().to_frame().drop('pm25').plot.barh()
```

[124]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14e6531390>



[125]:
```
dkt.count()
```

[125]:

```
pm25                8153
cloudcover          6441
dewpoint            8150
humidity            8150
precipintensity     3220
pressure            1079
temperature         8150
visibility          8119
windbearing         7939
windspeed           8020
dtype: int64
```

- interesting enough, the relative humidity is in very weak correlation with PM2.5
- the data from DarkSky API was basic in 2018, and the missing data of pressure shows

[126]:

```
df['H500'].mean()
```

[126]:

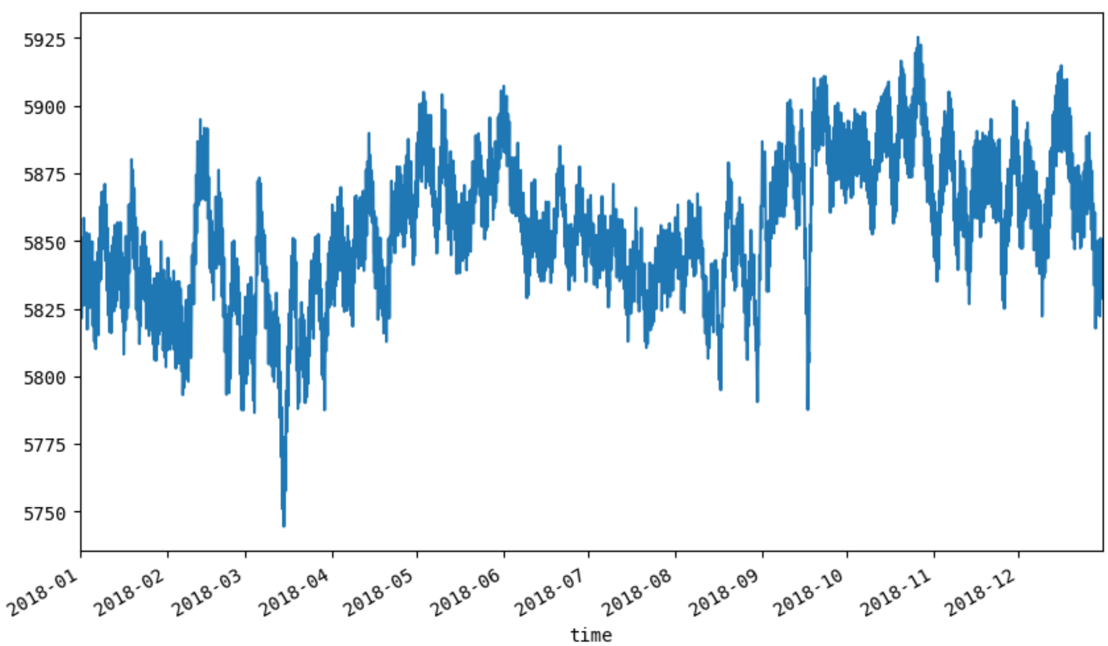
```
5853.869860132034
```

[127]:

```
df['H500'].plot()
```

[127]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14e63b0a20>
```



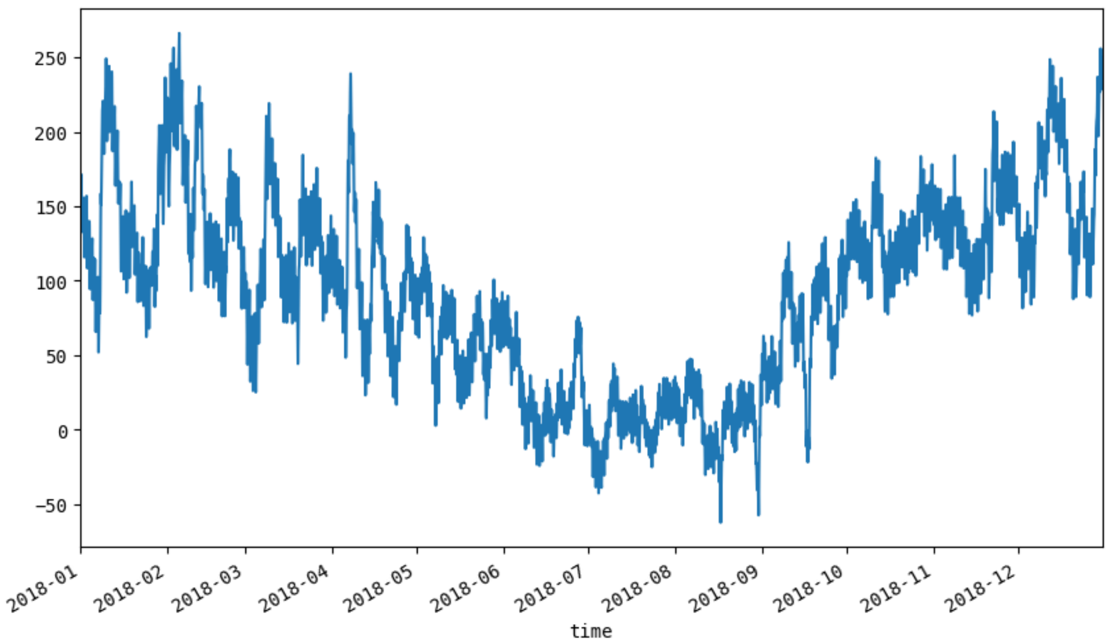
[128]:

```
df.columns
```

[128]: Index(['U2M', 'V250', 'TROPT', 'TROPPB', 'T2M', 'TQL', 'T500', 'U850', 'PS',
        'V850', 'H250', 'Q250', 'T2MDEW', 'V50M', 'Q500', 'DISPH', 'H1000',
        'TS', 'T10M', 'TROPPT', 'SLP', 'U250', 'Q850', 'ZLCL', 'TQV', 'V2M',
        'T250', 'TROPQ', 'V10M', 'H850', 'T850', 'U50M', 'U10M', 'TROPPV',
        'H500', 'V500', 'T2MWET', 'U500', 'QV10M', 'T2M_C'],
       dtype='object')

[129]:
```
df['H1000'].plot()
```

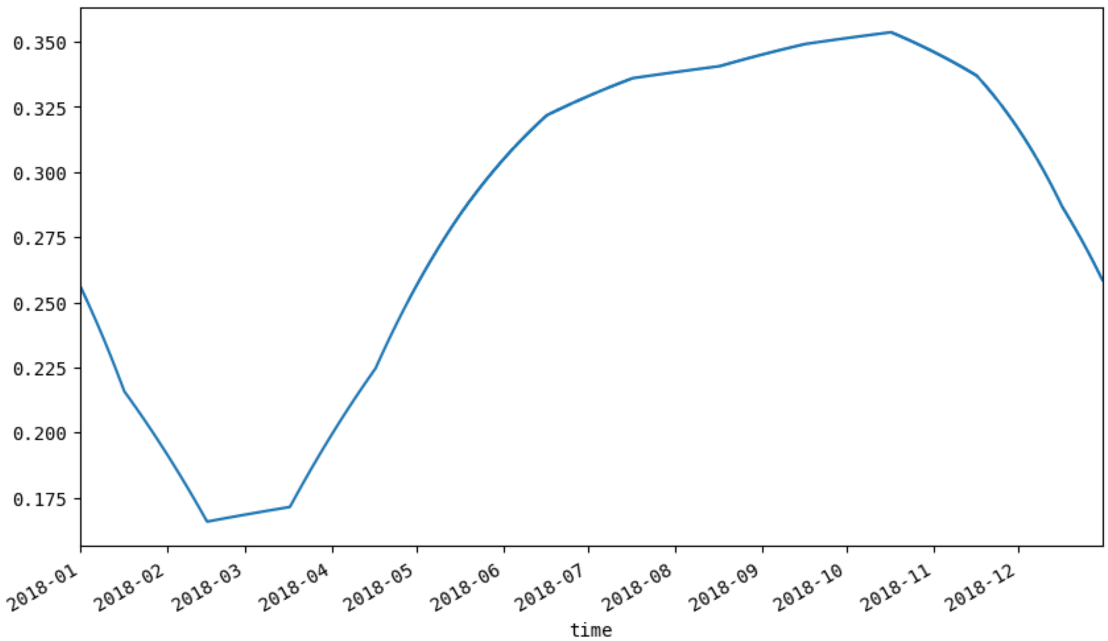
[129]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14e618f898>



- interesting, during the summer (in which the ground temperature is higher), a thinkness of 1000hPa pressure is much lower than in the winter. Why is this important for PM2.5 because PM2.5 concentration during hot months is lower than in colder months

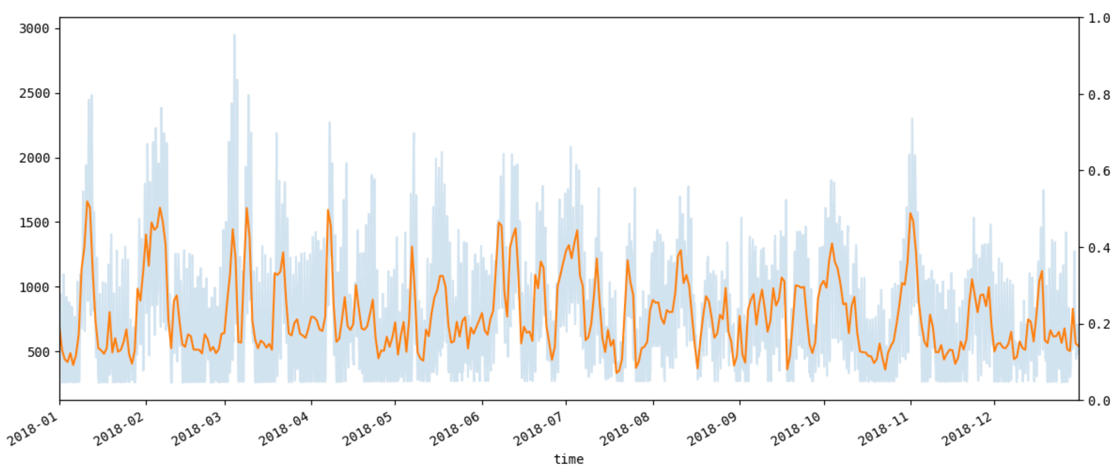
[130]:
```
df['DISPH'].plot()
```

[130]: <matplotlib.axes._subplots.AxesSubplot at 0x7f14e6139a20>



[131]:

```
fig, ax = plt.subplots(figsize=[14,6])
df['ZLCL'].plot(ax=ax, alpha=0.2)
df['ZLCL'].resample('1D').mean().plot(ax=ax)
ax2 = ax.twinx()
# pm25[['pm25']].resample('1D').mean().plot(ax=ax2, color='red')
# dft = pm25[['pm25']].resample('1D').mean()
# ax2.plot(dft, color='red')
```



9 select important columns to be included in a final df for ML

- the limitation of forecast data, or any data we know in advance that influence PM2.5 is a key obstacle
- all the parameters we have looked at so far is in weak or at best low-moderate correlation with PM2.5. That emphasis the nature of PM2.5 as a mixed-bag collector of pollutants in the ground atmosphere. In addition, since I forgone the emission sources and formation pathway, in a plain language, we are guessing what we can guess.
- as the interest of forecast PM2.5, we can try two approaches:
  1. Comb all relevant parameters from MERRA-2, observed data (NOAA), Open Forecast weather (Darksky), to make a comprehensive set of data. From this exercise, the observed data archieved in NCEI (NOAA) surfice the need to get data from forecast API. This is helpful to diagnosis the past events and understand what might have been the causess
  2. Select only available forecast data. This approach is simplistic but practical to building some forecast for PM2.5