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Ideas

- in the previous excercise (2.2), we started with a raw data from a ground station, then went cleaning data, and analyzed correlation between inputs like wind speed, temperature with $PM_{2.5}$ concentration.
- data ground station is an important resource, but it is limited in quantity, and depends on the location, will be hard to find
- data generated in the model presents a large-scale data, available to almost (all) location in the world, but the resolution is coarse. Extract data from the digital product also requires more hardware and software than a single CSV file in the previous excercise
- in this exercise, we are going to investigate the data from MERRA-2 and how to use the data to understand the correlation with $PM_{2.5}$ concentration

MERRA-2

or The Modern-Era Retrospective for Research and Applications, Version 2 published by NASA (https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/)

- it is a massive digital product under reanalysis category, the most accurate and well-curated product in the world of numerical dataset
- data is generated in a scalar format, with latitude, longtitude, timestamp and with interested parameters such as skin temperature, windpseed at 2m above the grond, and many others

Getting data (introduction)

- depend on the resources you have, my guess is (since you found this post) don't have the access and resources like those in big insitutes with a direct share with NASA
- if so, getting the whole set of data in regular basis is not an option
- this is true for me, I was lucky to found out that the MERRA-2 can be acquired by sub-set approach, that is only get data from the area of interest, a single point of interest actually
  - For example, you can manually down interest data wia OpeNDAP Access (https://goldsmr4.gesdisc.eosdis.nasa.gov/opendap/MERRA2)
  - and here is a longer version about OPeNDAP (https://earthdata.nasa.gov/collaborate/open-data-services-and-software/api/opendap/opendap-user-guide)
- however, before you are able to download file in .nc4 (or NetCDF-4 (https://goldsmr4.gesdisc.eosdis.nasa.gov/opendap/MERRA2/M2T1NXFLX.5.12.4/2020/05/MERRA2_400.tav format
  - register user (https://urs.earthdata.nasa.gov/users/new)
  - Under Applications/Authorized Apps, then Approve more application, select NASA GESDISC DATA ARCHIVE
  - and basically, go through this notebook to understand how to get the data https://github.com/Open-Power-System-Data/weather_data/blob/ace842004fd2cc018673085f77e4d91bb30da3d9/download_merra2.ipynb (https://github.com/Open-Power-System-Data/weather_data/blob/ace842004fd2cc018673085f77e4d91bb30da3d9/download_merra2.ipynb)
- to work with specific tags, check out this document: https://gmao.gsfc.nasa.gov/pubs/docs/Bosilovich785.pdf (https://gmao.gsfc.nasa.gov/pubs/docs/Bosilovich785.pdf)

- In this exercise, we will data with three groups (tags):

1. SLV = single level
2. FLX = surface turbulent fluxes and related quantities
3. AER = aerosol mixing ratio

- There are more than 20 groups in MERRA-2

What did I get the data?

1. Customzied a url link the server for a single location (Hanoi in this case). The link addresses Hyrax server that support sub-setting, so I can freely choose the group and parameters in the group to download.
2. Download the files. Each file contains data for the location for each day. Depends on the group (tag), each file is about 300kB in .nc4 file
3. Read the raw .nc4 file using xarray and pandas and concatinate the data of each day into a dataframe. The data then is saved to a CSV file

Working with files

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
plt.style.use('default')
plt.rcParams['font.family'] = 'monospace'
```

In [3]:
```
# in addition we need netCDF package to read raw .nc4 file
# try to install this package by
try:
    import netCDF4 as nc
except Exception:
    !pip install netCDF4 --user
```

$PM_{2.5}$

In [4]:
```
# first let load PM2.5 data into a dataframe
pm25 = pd.read_csv('data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv',
                   parse_dates=['Date (LT)'],
                   index_col=['Date (LT)'])
```

In [5]:
```
pm25.head()
```

Out[5]:

	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

SLV

Single Level Diagnosis

In [6]:
```
# load the preprocessed file, noted that the raw format from MERRA-2
 is in .nc4
df = pd.read_csv('data/merra2_slv_hanoi_2018.csv',
                 parse_dates=['time'],
                 index_col=['time'])
df.head(3)
```

Out[6]:

	U2M	V250	TROPT	TROPPB	T2M	TQL	T500	U85
time								
2018-01-01 00:00:00	0.023183	10.807207	192.34645	10051.0290	287.10890	0.008423	267.34950	-0.67885
2018-01-01 01:00:00	0.189619	11.351880	192.50723	10052.2750	286.79376	0.009235	267.07660	-0.39881
2018-01-01 02:00:00	0.243190	11.913273	192.63431	10051.5625	286.48932	0.006260	266.77542	-0.21787

3 rows × 39 columns

In [7]:
```
df.index.rename('DATE', inplace=True)
```

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

Out[8]:
```
Index(['U2M', 'V250', 'TROPT', 'TROPPB', 'T2M', 'TQL', 'T500', 'U85
0', 'PS',
       'V850', 'H250', 'Q250', 'T2MDEW', 'V50M', 'Q500', 'DISPH', 'H1
000',
       'TS', 'T10M', 'TROPPT', 'SLP', 'U250', 'Q850', 'ZLCL', 'TQV',
'V2M',
       'T250', 'TROPQ', 'V10M', 'H850', 'T850', 'U50M', 'U10M', 'TROP
PV',
       'H500', 'V500', 'T2MWET', 'U500', 'QV10M'],
      dtype='object')
```

In [9]:
```
# merge data with PM2.5 based on timestamp
df = pd.merge(df, pm25, right_index=True, left_index=True)
```

In [10]:
```
# correlation
df.corr()
```

Out[10]:

	U2M	V250	TROPT	TROPPB	T2M	TQL	T500	U850
U2M	1.000000	-0.168647	0.127118	0.103545	0.204930	-0.214273	0.217229	0.271165
V250	-0.168647	1.000000	-0.105805	-0.143095	-0.173800	0.055265	-0.346683	0.099452
TROPT	0.127118	-0.105805	1.000000	0.710519	0.315999	0.113366	0.084146	-0.048513
TROPPB	0.103545	-0.143095	0.710519	1.000000	0.241940	0.192804	0.208752	-0.155499
T2M	0.204930	-0.173800	0.315999	0.241940	1.000000	0.167113	0.379661	0.187251
TQL	-0.214273	0.055265	0.113366	0.192804	0.167113	1.000000	0.176738	-0.212809
T500	0.217229	-0.346683	0.084146	0.208752	0.379661	0.176738	1.000000	-0.034795
U850	0.271165	0.099452	-0.048513	-0.155499	0.187251	-0.212809	-0.034795	1.000000
PS	-0.335614	0.163366	-0.268950	-0.221896	-0.800861	-0.220019	-0.536012	-0.270052
V850	-0.312188	0.220298	-0.044988	-0.076772	0.043098	0.090908	-0.166849	0.322359
H250	0.307683	-0.330496	0.205358	0.362908	0.532656	0.206638	0.760916	-0.089342
Q250	0.284000	-0.187080	0.311729	0.293736	0.562340	0.366423	0.598024	-0.026072
T2MDEW	0.252522	-0.121195	0.330871	0.297066	0.881810	0.234983	0.399133	0.197757
V50M	-0.052309	0.143110	0.039430	-0.083421	0.284063	-0.195008	-0.085953	0.573711
Q500	0.251268	-0.180645	0.296136	0.278538	0.487455	0.414046	0.428289	-0.057321
DISPH	0.309657	-0.326269	0.352388	0.447360	0.456001	0.204244	0.534780	-0.251756
H1000	-0.339236	0.168014	-0.266953	-0.220505	-0.791838	-0.223211	-0.544481	-0.267324
TS	0.152840	-0.150674	0.290673	0.216660	0.979687	0.172689	0.329715	0.188984
T10M	0.237887	-0.186387	0.322596	0.248458	0.995631	0.148431	0.397767	0.187460
TROPPT	0.098688	-0.138952	0.621385	0.959286	0.218696	0.177579	0.206119	-0.156447
SLP	-0.335630	0.161301	-0.270024	-0.222850	-0.803458	-0.219853	-0.532607	-0.272208
U250	-0.349872	0.334070	-0.270363	-0.330989	-0.590143	-0.195609	-0.754873	0.072297
Q850	0.159805	-0.083300	0.264918	0.283338	0.752515	0.403688	0.409837	0.165815
ZLCL	0.061855	-0.219796	0.019520	-0.068382	0.284674	-0.215289	0.095869	-0.027212
TQV	0.216785	-0.185137	0.338259	0.328528	0.700037	0.483621	0.477523	0.039222
V2M	-0.043367	0.130550	0.027889	-0.097585	0.311341	-0.176413	-0.106078	0.534604
T250	0.352099	-0.289509	0.225112	0.292160	0.568895	0.291312	0.540392	-0.027707
TROPQ	0.156627	-0.219427	0.768931	0.566553	0.403356	0.205404	0.298724	-0.046710
V10M	-0.041583	0.132761	0.034189	-0.091241	0.307853	-0.185323	-0.095578	0.557411
H850	-0.286488	0.158475	-0.193460	-0.171207	-0.610742	-0.267564	-0.567753	-0.223194
T850	0.335203	-0.060771	0.274756	0.213358	0.787170	0.134607	0.332949	0.346789
U50M	0.920096	-0.165804	0.115386	0.090211	0.282559	-0.174081	0.200402	0.268449
U10M	0.988198	-0.169402	0.121791	0.097291	0.229919	-0.202633	0.212091	0.269970
TROPPV	0.167138	-0.176518	0.560634	0.537686	0.429204	0.209282	0.288657	-0.094457
H500	0.063282	-0.079082	0.072506	0.161373	0.172058	-0.083714	0.197303	-0.073197

	U2M	V250	TROPT	TROPPB	T2M	TQL	T500	U850
V500	-0.244479	0.532668	0.002238	-0.034919	-0.029962	0.134465	-0.280775	0.100878
T2MWET	0.252473	-0.121347	0.330952	0.297063	0.881913	0.234983	0.399307	0.197762
U500	-0.307177	0.244796	-0.339504	-0.380916	-0.564566	-0.202340	-0.576094	0.269002
QV10M	0.248954	-0.156424	0.343560	0.300166	0.840431	0.273304	0.473378	0.183711
pm25	-0.028249	0.123757	-0.263994	-0.239577	-0.332513	-0.290687	-0.216435	0.028578

40 rows × 40 columns

In [11]:
```python
# not very useful, let select correlation with PM2.5 only
df.corr()['pm25']
```

Out[11]:
```
U2M      -0.028249
V250      0.123757
TROPT    -0.263994
TROPPB   -0.239577
T2M      -0.332513
TQL      -0.290687
T500     -0.216435
U850      0.028578
PS        0.357018
V850     -0.009497
H250     -0.308451
Q250     -0.363976
T2MDEW   -0.377794
V50M     -0.004372
Q500     -0.333410
DISPH    -0.298620
H1000     0.359755
TS       -0.299172
T10M     -0.333160
TROPPT   -0.217568
SLP       0.358491
U250      0.315245
Q850     -0.408753
ZLCL      0.055482
TQV      -0.468133
V2M       0.036243
T250     -0.321817
TROPQ    -0.308604
V10M      0.019581
H850      0.314116
T850     -0.369821
U50M     -0.024330
U10M     -0.028514
TROPPV   -0.296435
H500     -0.080740
V500      0.006930
T2MWET   -0.377879
U500      0.292795
QV10M    -0.418552
pm25      1.000000
Name: pm25, dtype: float64
```

In [12]:

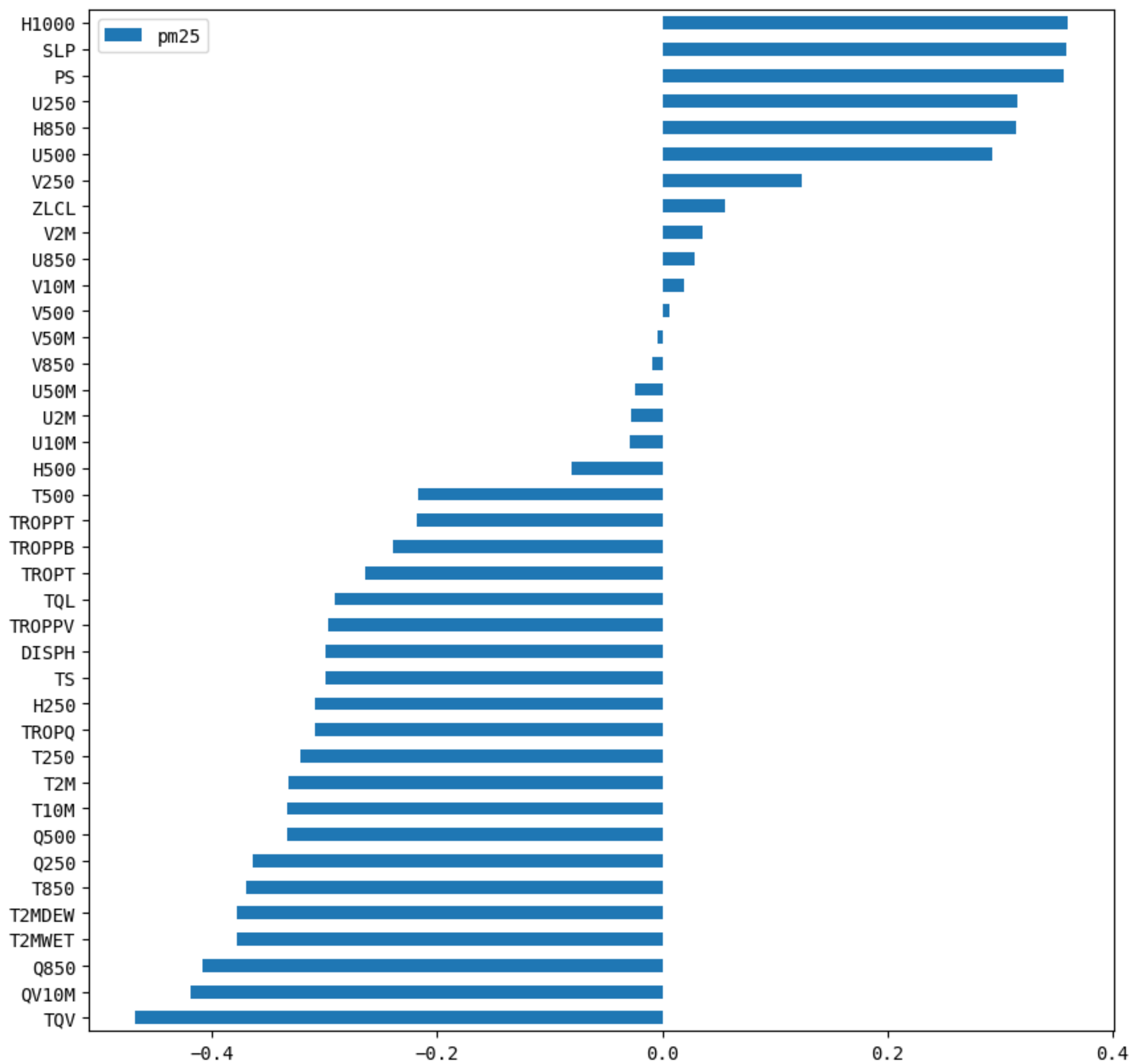
```
# still quit many paramters, and if you link me, these abbreviation i
s quite foreign,
# let first try to sort out the value first
df.corr()['pm25'].sort_values()
```

Out[12]:

```
TQV      -0.468133
QV10M    -0.418552
Q850     -0.408753
T2MWET   -0.377879
T2MDEW   -0.377794
T850     -0.369821
Q250     -0.363976
Q500     -0.333410
T10M     -0.333160
T2M      -0.332513
T250     -0.321817
TROPQ    -0.308604
H250     -0.308451
TS       -0.299172
DISPH    -0.298620
TROPPV   -0.296435
TQL      -0.290687
TROPT    -0.263994
TROPPB   -0.239577
TROPPT   -0.217568
T500     -0.216435
H500     -0.080740
U10M     -0.028514
U2M      -0.028249
U50M     -0.024330
V850     -0.009497
V50M     -0.004372
V500      0.006930
V10M      0.019581
U850      0.028578
V2M       0.036243
ZLCL      0.055482
V250      0.123757
U500      0.292795
H850      0.314116
U250      0.315245
PS        0.357018
SLP       0.358491
H1000     0.359755
pm25      1.000000
Name: pm25, dtype: float64
```

In [13]:
```
# how about to visualize in a bar graph
fig, ax = plt.subplots(figsize=(10,10))
df.corr()['pm25'].sort_values().to_frame().dropna().drop('pm25').plot
.barh(ax=ax)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fec2e7cac88>



In [14]:
```
# it look better, and we can now refer to the manual to figure out ea
ch abbr. to know what the name
# or we can try to read the .nc4 file and see if any metadata for suc
h
ds = nc.Dataset('data/nc4/MERRA2_400.tavg1_2d_slv_Nx.20180722.nc4')
type(ds)
# here is an extensive post about netCDF https://www.unidata.ucar.ed
u/software/netcdf/docs/netcdf_introduction.html
```

Out[14]: netCDF4._netCDF4.Dataset

In [15]:
```
# let see the variables in the file
list(ds.variables)[:5]
```

Out[15]: ['U2M', 'V250', 'TROPT', 'TROPPB', 'T2M']

In [16]:
```python
# attributes for one variable
ds['T2M']
```

Out[16]:
```
<class 'netCDF4._netCDF4.Variable'>
float32 T2M(time, lat, lon)
    long_name: 2-meter_air_temperature
    units: K
    _FillValue: 1000000000000000.0
    missing_value: 1000000000000000.0
    fmissing_value: 1000000000000000.0
    scale_factor: 1.0
    add_offset: 0.0
    standard_name: 2-meter_air_temperature
    vmax: 1000000000000000.0
    vmin: -1000000000000000.0
    valid_range: [-1.e+15  1.e+15]
    origname: T2M
    fullnamepath: /T2M
unlimited dimensions:
current shape = (24, 1, 1)
filling on
```

In [17]:
```
# data of one variable
ds['T2M'][:]
```

Out[17]:
```
masked_array(
  data=[[[299.71216]],

        [[300.8526 ]],

        [[301.99396]],

        [[302.95706]],

        [[303.83118]],

        [[304.4854 ]],

        [[304.7953 ]],

        [[304.90894]],

        [[304.77728]],

        [[304.73157]],

        [[304.043  ]],

        [[302.65665]],

        [[302.12634]],

        [[301.88544]],

        [[301.65826]],

        [[301.3927 ]],

        [[301.118  ]],

        [[300.71042]],

        [[300.1887 ]],

        [[299.79138]],

        [[299.47867]],

        [[299.27167]],

        [[299.28024]],

        [[300.38   ]]],
  mask=False,
  fill_value=1e+20,
  dtype=float32)
```

In [18]:
```
# and sure enough, we can check back the unit
ds['T2M'].units
```

Out[18]:
```
'K'
```

In [19]:
```
# what is T2M stand for exactly?
ds['T2M'].standard_name
```

Out[19]:
```
'2-meter_air_temperature'
```

In [20]:
```
# now we can find the standard name, and the unit based on the abbrev
iation like above
name_ = dict()
for k in ds.variables.keys():
#     print(k)
#     name_[k] = 'None'
    name_[k] = f'{ds.variables[k].standard_name}, {ds.variables[k].un
its}'
name_
```

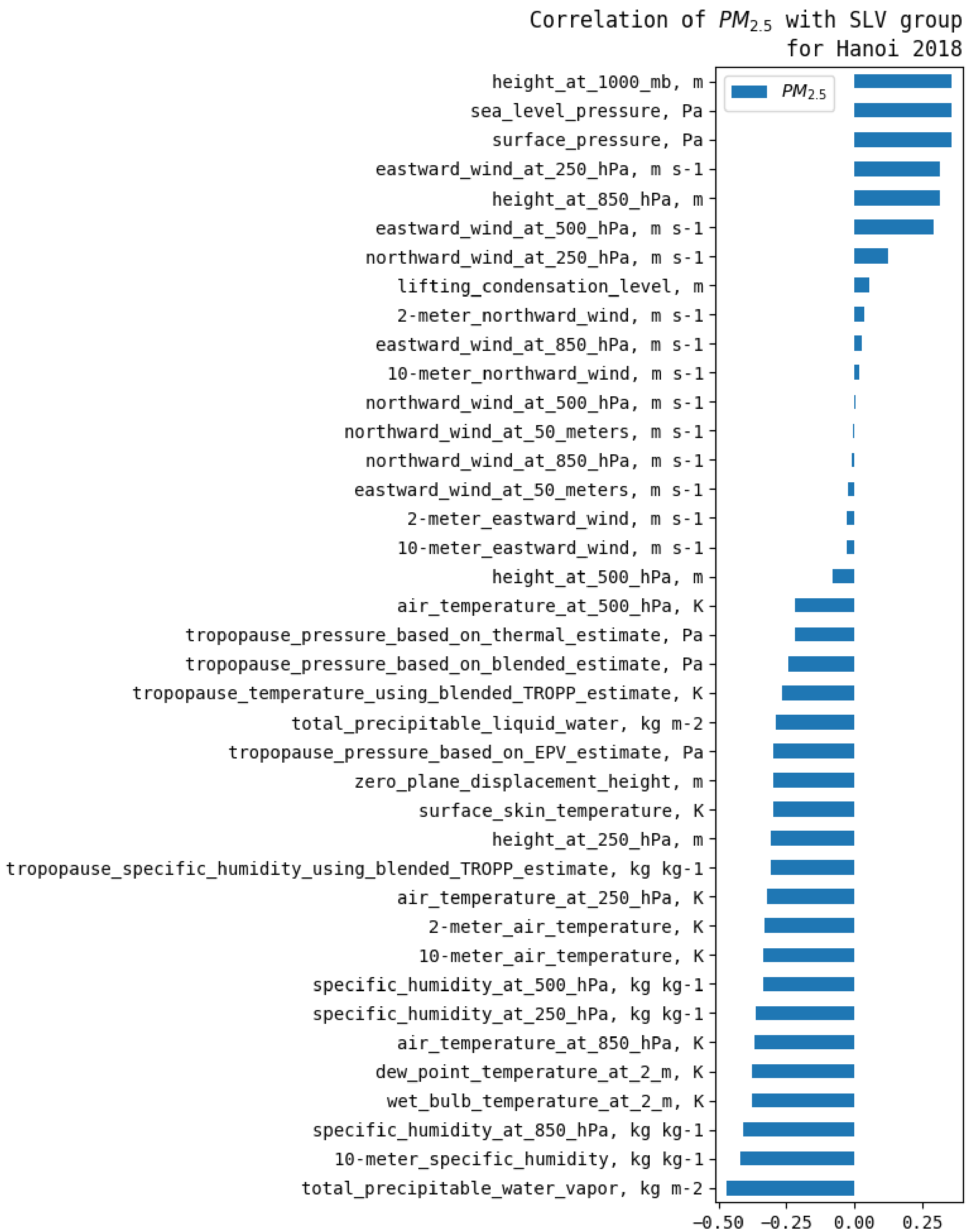
Out[20]:
```
{'U2M': '2-meter_eastward_wind, m s-1',
 'V250': 'northward_wind_at_250_hPa, m s-1',
 'TROPT': 'tropopause_temperature_using_blended_TROPP_estimate, K',
 'TROPPB': 'tropopause_pressure_based_on_blended_estimate, Pa',
 'T2M': '2-meter_air_temperature, K',
 'TQL': 'total_precipitable_liquid_water, 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'}
```

In [21]:
```python
# and sort out the standard name
new_label = dict()
labels = list(df.columns)
for label in labels:
    if label in list(name_.keys()):
        new_label[label] = name_[label]
    else:
        new_label[label] = label
new_label
```

Out[21]:
```
{'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',
 'pm25': 'pm25'}
```

In [22]:

```
# and recreate the figure above with the standard name
fig, ax = plt.subplots(figsize=(8,10))
df.corr()['pm25'].sort_values().to_frame().dropna().drop('pm25').plot
.barh(ax=ax)
ax.legend(['$PM_{2.5}$'], frameon=True)
labels = [item.get_text() for item in ax.get_yticklabels()]

# looking for a standard name for each abbreviation
new_label = dict()
for label in labels:
    if label in list(name_.keys()):
        new_label[label] = name_[label]
    else:
        new_label[label] = label
ax.set_yticklabels(new_label.values())
plt.title('Correlation of $PM_{2.5}$ with SLV group\nfor Hanoi 2018',
loc='right')
plt.tight_layout()
plt.savefig('img/2020Aug-SLV-PM25.png', dpi=120, optimize=True)
```



What are the strongest parameters correalation with $PM_{2.5}$?

- vapor and specific humidity
- near-ground (10m) temperature
- height at 1000mb
- surface pressure
- noted wind (eastward and northward) but not in speed and angle, the correlation in this format is almost none

In [23]:
```
# better, but there are many parameter, let figure out how to see the
m in topic
# from above graph, there are 5 main keywords: temperature, humidity,
wind, height, pressure
kw='temperature'
cols = list()
for k,v in name_.items():
    if kw in v:
        cols.append(k)
cols
```

Out[23]:
```
['TROPT', 'T2M', 'T500', 'T2MDEW', 'TS', 'T10M', 'T250', 'T850', 'T2M
WET']
```

In [24]:
```
# and append 'pm25' to the list
cols.append('pm25')
df[cols].head(3)
```

Out[24]:

	TROPT	T2M	T500	T2MDEW	TS	T10M	T250	T8
2018-01-01 01:00:00	192.50723	286.79376	267.07660	283.94443	284.81787	287.64883	231.87766	283.644
2018-01-01 02:00:00	192.63431	286.48932	266.77542	283.87836	284.58258	287.32483	231.85870	283.759
2018-01-01 03:00:00	192.71167	286.24753	266.50415	283.75630	284.24567	287.03120	231.80463	283.867

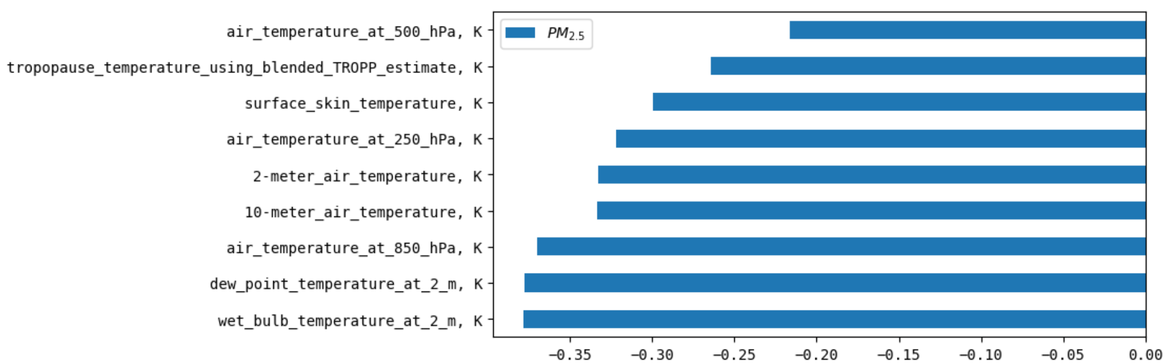
In [25]:
```
df[cols].corr()
```

Out[25]:

	TROPT	T2M	T500	T2MDEW	TS	T10M	T250	T850
TROPT	1.000000	0.315999	0.084146	0.330871	0.290673	0.322596	0.225112	0.274756
T2M	0.315999	1.000000	0.379661	0.881810	0.979687	0.995631	0.568895	0.787170
T500	0.084146	0.379661	1.000000	0.399133	0.329715	0.397767	0.540392	0.332949
T2MDEW	0.330871	0.881810	0.399133	1.000000	0.814180	0.898560	0.613574	0.927069
TS	0.290673	0.979687	0.329715	0.814180	1.000000	0.958857	0.506865	0.712200
T10M	0.322596	0.995631	0.397767	0.898560	0.958857	1.000000	0.588949	0.810002
T250	0.225112	0.568895	0.540392	0.613574	0.506865	0.588949	1.000000	0.583293
T850	0.274756	0.787170	0.332949	0.927069	0.712200	0.810002	0.583293	1.000000
T2MWET	0.330952	0.881913	0.399307	0.999999	0.814307	0.898652	0.613656	0.927037
pm25	-0.263994	-0.332513	-0.216435	-0.377794	-0.299172	-0.333160	-0.321817	-0.369821

In [26]:

```
# now we can sub-set only interested columns with temperature topic
# let try again with correlation and sorting
# and recreate the figure above with the standard name
fig, ax = plt.subplots(figsize=(8,4))
df[cols].corr()['pm25'].sort_values().to_frame().dropna().drop('pm25'
).plot.barh(ax=ax)
ax.legend(['$PM_{2.5}$'], frameon=True)
labels = [item.get_text() for item in ax.get_yticklabels()]

new_label = dict()
for label in labels:
    if label in list(name_.keys()):
        new_label[label] = name_[label]
    else:
        new_label[label] = label

ax.set_yticklabels(new_label.values());
```



- the all paramaters related to **temperature** is inversely correlated with $PM_{2.5}$ concentration, with a temperature increases, then $PM_{2.5.}$ concentration decreases
- the correlation is wea
- could we apply this approach to similar topic

In [27]:

```
# filter out topics that not in list of keyword
kws = ['temperature', 'wind', 'pressure']
ignore_cols = dict()
for word in kws:
        for k, v in name_.items():
            if word in v:
                ignore_cols[k] = v
all_cols = name_.keys()
cols = [col for col in all_cols if col not in ignore_cols.keys()]
print(cols)
```

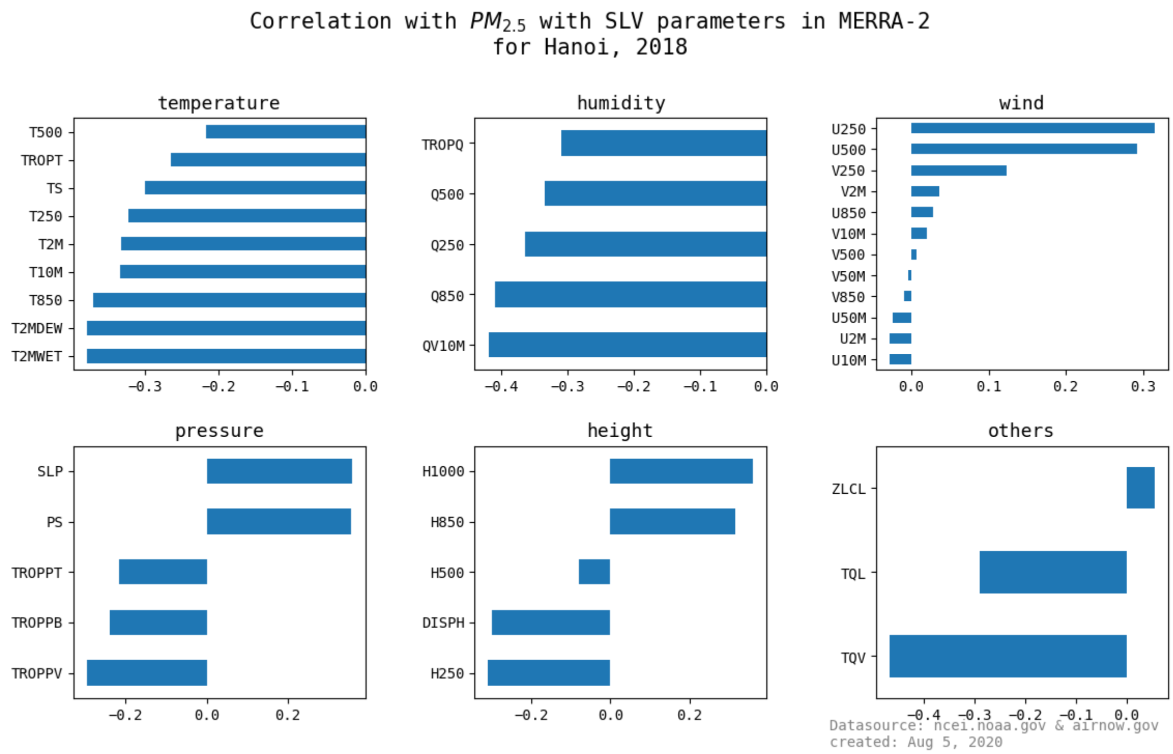
```
['TQL', 'H250', 'Q250', 'Q500', 'DISPH', 'H1000', 'Q850', 'ZLCL', 'TQ
V', 'TROPQ', 'H850', 'H500', 'QV10M']
```

In [28]:

```
# let make a function for it

def plot_topic(axis=None, kw=None, kws=None):
    cols = list()
    if kw == None:
        kw = 'others'
        ignore_cols = dict()
        for word in kws:
            for k, v in name_.items():
                if word in v:
                    ignore_cols[k] = v
        all_cols = name_.keys()
        cols = [col for col in all_cols if col not in ignore_cols.key
s()]
    else:
        for k,v in name_.items():
            if kw in v:
                cols.append(k)
    cols.append('pm25')
    df[cols].corr()['pm25'].sort_values().to_frame().dropna().drop('p
m25').plot.barh(ax=axis)
    axis.get_legend().remove()
    axis.set_title(kw, fontsize=13)
    return axis
```

In [29]:

```
# now, we can split a large selection into each topic
kws = ['temperature', 'humidity', 'wind', 'pressure', 'height']
plt.figure(figsize=(12,8))
plt.subplot(231, fc='gray')
ax1 = plt.subplot(231)
plot_topic(axis=ax1, kw='temperature')

ax2 = plt.subplot(232)
plot_topic(axis=ax2, kw='humidity')

ax3 = plt.subplot(233)
plot_topic(axis=ax3, kw='wind')

ax4 = plt.subplot(234)
plot_topic(axis=ax4, kw='pressure')

ax5 = plt.subplot(235)
plot_topic(axis=ax5, kw='height')

ax6 = plt.subplot(236, )
plot_topic(axis=ax6, kws=kws)
plt.tight_layout(pad=3)
plt.subplots_adjust(top=0.85, bottom=0.15)
plt.suptitle('Correlation with $PM_{2.5}$ with SLV parameters in MERR
A-2\nfor Hanoi, 2018', fontsize=15)
plt.figtext(1,0.1, s='Datasource: ncei.noaa.gov & airnow.gov\ncreate
d: Aug 5, 2020',
            transform=fig.transFigure, ha='left', va='bottom',
           fontsize=10, color='gray')
plt.savefig('img/2020Aug-SLV-subplot.png', dpi=120, optimize=True, ed
gecolor='black')
```



let unpack here

1. increased temperature correlated with decreased $PM_{2.5}$
2. increased specific humidity correlated with decreased $PM_{2.5}$
3. high-altitude (250-500hPa) eastward wind correlated with positively with $PM_{2.5}$
4. a mix correlation of pressure. A higher pressure on the surface correlated with a higher $PM_{2.5}$
5. similar to pressure, increased height (with a band of pressure) correlated with increased $PM_{2.5}$
6. total vapor is one of the largest correlation coefficient with $PM_{2.5}$

FLX

surface turbulent fluxes and related quantities

In [30]:
```
df = pd.read_csv('data/merra2_flx_hanoi_2018.csv')
df.head(3)
```

Out[30]:

	time	FRCAN	CN	BSTAR	QSTAR	PRECANV	ULML	NIRDR	RHOA
0	2018-01-01 00:00:00+07	1.0	0.003122	-0.001672	0.000018	4.568880e-23	0.041627	0.0	1.215108
1	2018-01-01 01:00:00+07	1.0	0.003123	-0.001603	0.000015	9.132591e-23	0.436000	0.0	1.216159
2	2018-01-01 02:00:00+07	1.0	0.003124	-0.001559	0.000013	2.973714e-22	0.551879	0.0	1.217125

3 rows × 47 columns

In [31]:
```
df['time'] = pd.to_datetime(df['time'])
df.set_index('time', inplace=True)
```

In [32]:
```
# the time here has converted to local with timezone, let drop the ti
mezone info
df.index = df.index.tz_localize(None)
df.head()
```

Out[32]:

	FRCAN	CN	BSTAR	QSTAR	PRECANV	ULML	NIRDR	RHOA	TC
time									
2018-01-01 00:00:00	1.000000	0.003122	-0.001672	0.000018	4.568880e-23	0.041627	0.0	1.215108	81.6
2018-01-01 01:00:00	1.000000	0.003123	-0.001603	0.000015	9.132591e-23	0.436000	0.0	1.216159	76.4
2018-01-01 02:00:00	1.000000	0.003124	-0.001559	0.000013	2.973714e-22	0.551879	0.0	1.217125	75.0
2018-01-01 03:00:00	0.993164	0.003125	-0.001562	0.000011	1.638273e-14	0.384402	0.0	1.218085	76.3
2018-01-01 04:00:00	0.927490	0.003125	-0.001616	0.000008	7.294165e-13	0.211296	0.0	1.218972	78.1

5 rows × 46 columns

In [33]:
```
# merge data
df = pd.merge(df, pm25, right_index=True, left_index=True)
df.index.rename('DATE', inplace=True)
df.columns
```

Out[33]:
```
Index(['FRCAN', 'CN', 'BSTAR', 'QSTAR', 'PRECANV', 'ULML', 'NIRDR',
'RHOA',
       'TCZPBL', 'TLML', 'PRECTOT', 'FRCCN', 'USTAR', 'SPEED', 'EVA
P', 'QLML',
       'DISPH', 'TAUX', 'PRECTOTCORR', 'HLML', 'PRECLSC', 'TAUGWX',
'QSH',
       'PGENTOT', 'GHTSKIN', 'PRECSNO', 'TSH', 'FRCLS', 'Z0M', 'Z0H',
'TAUY',
       'TSTAR', 'NIRDF', 'CDM', 'PBLH', 'SPEEDMAX', 'TAUGWY', 'HFLU
X',
       'FRSEAICE', 'PRECCON', 'RISFC', 'EFLUX', 'PREVTOT', 'VLML', 'C
DQ',
       'CDH', 'pm25'],
      dtype='object')
```

In [34]:
```
ds = nc.Dataset('data/nc4/MERRA2_400.tavg1_2d_flx_Nx.20180102.nc4')
```

In [35]:
```python
name_ = dict()
for k in ds.variables.keys():
    name_[k] = f'{ds.variables[k].standard_name}, {ds.variables[k].units}'
name_
```

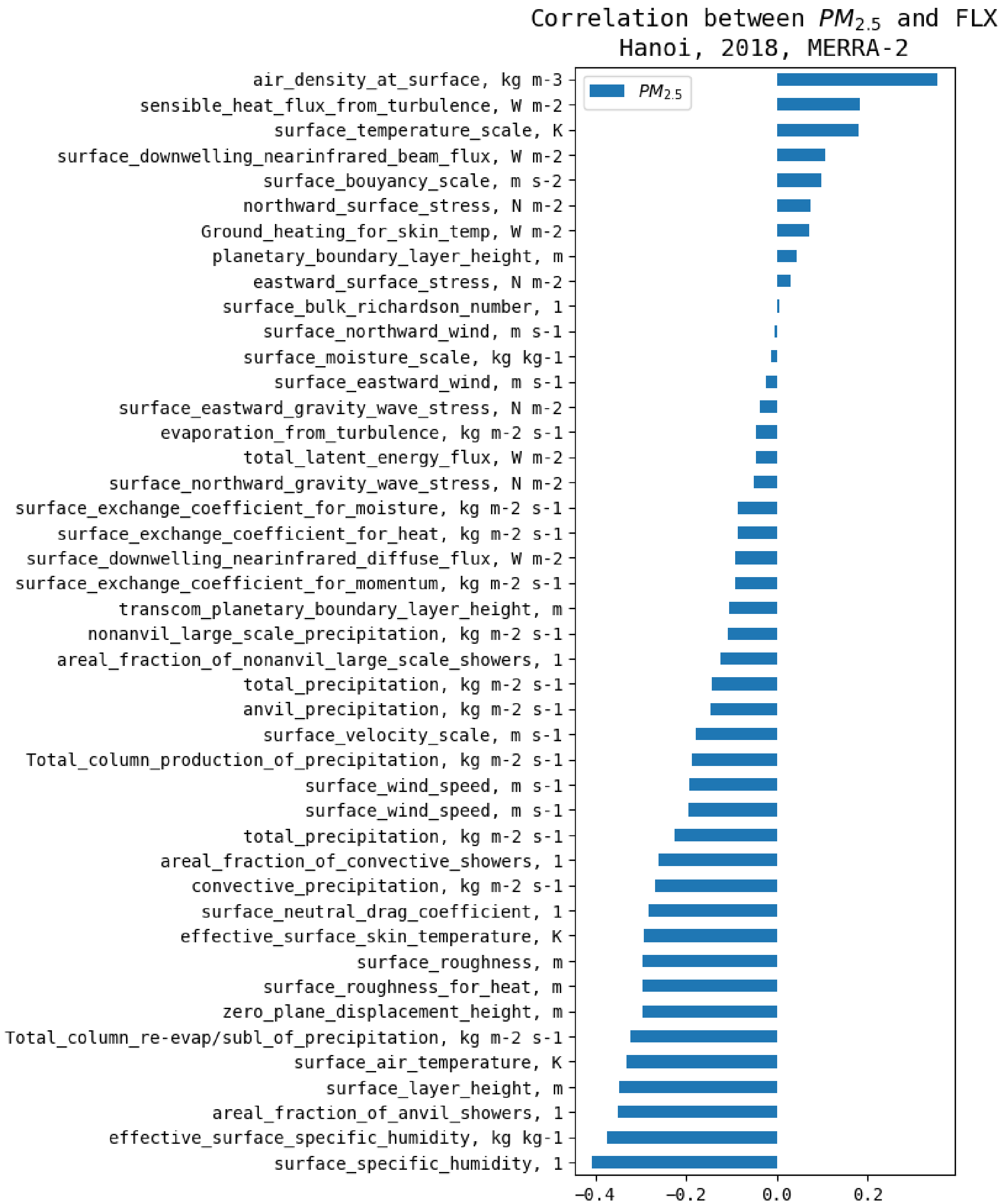
Out[35]:
```
{'FRCAN': 'areal_fraction_of_anvil_showers, 1',
 'CN': 'surface_neutral_drag_coefficient, 1',
 'BSTAR': 'surface_bouyancy_scale, m s-2',
 'QSTAR': 'surface_moisture_scale, kg kg-1',
 'PRECANV': 'anvil_precipitation, kg m-2 s-1',
 'ULML': 'surface_eastward_wind, m s-1',
 'NIRDR': 'surface_downwelling_nearinfrared_beam_flux, W m-2',
 'RHOA': 'air_density_at_surface, kg m-3',
 'TCZPBL': 'transcom_planetary_boundary_layer_height, m',
 'TLML': 'surface_air_temperature, K',
 'PRECTOT': 'total_precipitation, kg m-2 s-1',
 'FRCCN': 'areal_fraction_of_convective_showers, 1',
 'USTAR': 'surface_velocity_scale, m s-1',
 'SPEED': 'surface_wind_speed, m s-1',
 'EVAP': 'evaporation_from_turbulence, kg m-2 s-1',
 'QLML': 'surface_specific_humidity, 1',
 'DISPH': 'zero_plane_displacement_height, m',
 'TAUX': 'eastward_surface_stress, N m-2',
 'PRECTOTCORR': 'total_precipitation, kg m-2 s-1',
 'HLML': 'surface_layer_height, m',
 'PRECLSC': 'nonanvil_large_scale_precipitation, kg m-2 s-1',
 'TAUGWX': 'surface_eastward_gravity_wave_stress, N m-2',
 'QSH': 'effective_surface_specific_humidity, kg kg-1',
 'PGENTOT': 'Total_column_production_of_precipitation, kg m-2 s-1',
 'GHTSKIN': 'Ground_heating_for_skin_temp, W m-2',
 'PRECSNO': 'snowfall, kg m-2 s-1',
 'TSH': 'effective_surface_skin_temperature, K',
 'FRCLS': 'areal_fraction_of_nonanvil_large_scale_showers, 1',
 'Z0M': 'surface_roughness, m',
 'Z0H': 'surface_roughness_for_heat, m',
 'TAUY': 'northward_surface_stress, N m-2',
 'TSTAR': 'surface_temperature_scale, K',
 'NIRDF': 'surface_downwelling_nearinfrared_diffuse_flux, W m-2',
 'CDM': 'surface_exchange_coefficient_for_momentum, kg m-2 s-1',
 'PBLH': 'planetary_boundary_layer_height, m',
 'SPEEDMAX': 'surface_wind_speed, m s-1',
 'TAUGWY': 'surface_northward_gravity_wave_stress, N m-2',
 'HFLUX': 'sensible_heat_flux_from_turbulence, W m-2',
 'FRSEAICE': 'ice_covered_fraction_of_tile, 1',
 'PRECCON': 'convective_precipitation, kg m-2 s-1',
 'RISFC': 'surface_bulk_richardson_number, 1',
 'EFLUX': 'total_latent_energy_flux, W m-2',
 'PREVTOT': 'Total_column_re-evap/subl_of_precipitation, kg m-2 s-1',
 'VLML': 'surface_northward_wind, m s-1',
 'CDQ': 'surface_exchange_coefficient_for_moisture, kg m-2 s-1',
 'CDH': 'surface_exchange_coefficient_for_heat, kg m-2 s-1'}
```

In [36]:
```
new_label = dict()
labels = list(df.columns)
for label in labels:
#     print(label)
    if label in list(name_.keys()):
        new_label[label] = name_[label]
#         print(label)
    else:
#         print('.')
        new_label[label] = label
new_label
```

Out[36]:

```
{'FRCAN': 'areal_fraction_of_anvil_showers, 1',
 'CN': 'surface_neutral_drag_coefficient, 1',
 'BSTAR': 'surface_bouyancy_scale, m s-2',
 'QSTAR': 'surface_moisture_scale, kg kg-1',
 'PRECANV': 'anvil_precipitation, kg m-2 s-1',
 'ULML': 'surface_eastward_wind, m s-1',
 'NIRDR': 'surface_downwelling_nearinfrared_beam_flux, W m-2',
 'RHOA': 'air_density_at_surface, kg m-3',
 'TCZPBL': 'transcom_planetary_boundary_layer_height, m',
 'TLML': 'surface_air_temperature, K',
 'PRECTOT': 'total_precipitation, kg m-2 s-1',
 'FRCCN': 'areal_fraction_of_convective_showers, 1',
 'USTAR': 'surface_velocity_scale, m s-1',
 'SPEED': 'surface_wind_speed, m s-1',
 'EVAP': 'evaporation_from_turbulence, kg m-2 s-1',
 'QLML': 'surface_specific_humidity, 1',
 'DISPH': 'zero_plane_displacement_height, m',
 'TAUX': 'eastward_surface_stress, N m-2',
 'PRECTOTCORR': 'total_precipitation, kg m-2 s-1',
 'HLML': 'surface_layer_height, m',
 'PRECLSC': 'nonanvil_large_scale_precipitation, kg m-2 s-1',
 'TAUGWX': 'surface_eastward_gravity_wave_stress, N m-2',
 'QSH': 'effective_surface_specific_humidity, kg kg-1',
 'PGENTOT': 'Total_column_production_of_precipitation, kg m-2 s-1',
 'GHTSKIN': 'Ground_heating_for_skin_temp, W m-2',
 'PRECSNO': 'snowfall, kg m-2 s-1',
 'TSH': 'effective_surface_skin_temperature, K',
 'FRCLS': 'areal_fraction_of_nonanvil_large_scale_showers, 1',
 'Z0M': 'surface_roughness, m',
 'Z0H': 'surface_roughness_for_heat, m',
 'TAUY': 'northward_surface_stress, N m-2',
 'TSTAR': 'surface_temperature_scale, K',
 'NIRDF': 'surface_downwelling_nearinfrared_diffuse_flux, W m-2',
 'CDM': 'surface_exchange_coefficient_for_momentum, kg m-2 s-1',
 'PBLH': 'planetary_boundary_layer_height, m',
 'SPEEDMAX': 'surface_wind_speed, m s-1',
 'TAUGWY': 'surface_northward_gravity_wave_stress, N m-2',
 'HFLUX': 'sensible_heat_flux_from_turbulence, W m-2',
 'FRSEAICE': 'ice_covered_fraction_of_tile, 1',
 'PRECCON': 'convective_precipitation, kg m-2 s-1',
 'RISFC': 'surface_bulk_richardson_number, 1',
 'EFLUX': 'total_latent_energy_flux, W m-2',
 'PREVTOT': 'Total_column_re-evap/subl_of_precipitation, kg m-2 s-1',
 'VLML': 'surface_northward_wind, m s-1',
 'CDQ': 'surface_exchange_coefficient_for_moisture, kg m-2 s-1',
 'CDH': 'surface_exchange_coefficient_for_heat, kg m-2 s-1',
 'pm25': 'pm25'}
```

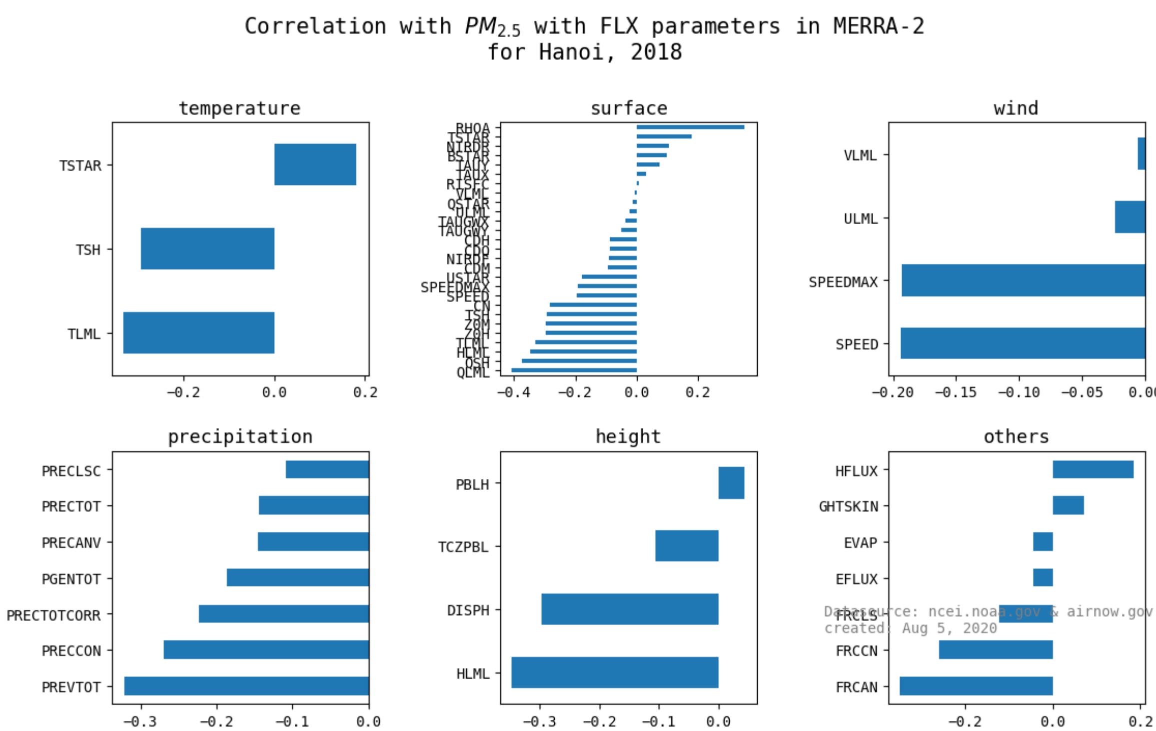
In [37]:
```
# let make one graph for whole group
fig, ax = plt.subplots(figsize=(8,10))
df.corr()['pm25'].sort_values().to_frame().dropna().drop('pm25').plot
.barh(ax=ax)
ax.legend(['$PM_{2.5}$'], frameon=True)
ax.set_title('Correlation between $PM_{2.5}$ and FLX\nHanoi, 2018, ME
RRA-2', fontsize=14)

labels = [item.get_text() for item in ax.get_yticklabels()]

# looking for a standard name for each abbreviation
new_label = dict()
for label in labels:
    if label in list(name_.keys()):
        new_label[label] = name_[label]
    else:
        new_label[label] = label

ax.set_yticklabels(new_label.values())
fig.tight_layout()
fig.savefig('img/2020Aug-FLX.png', dpi=120, optimize=True)
```



Correlation between $PM_{2.5}$ and FLX
Hanoi, 2018, MERRA-2
$PM_{2.5}$
air_density_at_surface, kg m-3
sensible_heat_flux_from_turbulence, W m-2
surface_temperature_scale, K
surface_downwelling_nearinfrared_beam_flux, W m-2
surface_bouyancy_scale, m s-2
northward_surface_stress, N m-2
Ground_heating_for_skin_temp, W m-2
planetary_boundary_layer_height, m
eastward_surface_stress, N m-2
surface_bulk_richardson_number, 1
surface_northward_wind, m s-1
surface_moisture_scale, kg kg-1
surface_eastward_wind, m s-1
surface_eastward_gravity_wave_stress, N m-2
evaporation_from_turbulence, kg m-2 s-1
total_latent_energy_flux, W m-2
surface_northward_gravity_wave_stress, N m-2
surface_exchange_coefficient_for_moisture, kg m-2 s-1
surface_exchange_coefficient_for_heat, kg m-2 s-1
surface_downwelling_nearinfrared_diffuse_flux, W m-2
surface_exchange_coefficient_for_momentum, kg m-2 s-1
transcom_planetary_boundary_layer_height, m
nonanvil_large_scale_precipitation, kg m-2 s-1
areal_fraction_of_nonanvil_large_scale_showers, 1
total_precipitation, kg m-2 s-1
anvil_precipitation, kg m-2 s-1
surface_velocity_scale, m s-1
Total_column_production_of_precipitation, kg m-2 s-1
surface_wind_speed, m s-1
surface_wind_speed, m s-1
total_precipitation, kg m-2 s-1
areal_fraction_of_convective_showers, 1
convective_precipitation, kg m-2 s-1
surface_neutral_drag_coefficient, 1
effective_surface_skin_temperature, K
surface_roughness, m
surface_roughness_for_heat, m
zero_plane_displacement_height, m
Total_column_re-evap/subl_of_precipitation, kg m-2 s-1
surface_air_temperature, K
surface_layer_height, m
areal_fraction_of_anvil_showers, 1
effective_surface_specific_humidity, kg kg-1
surface_specific_humidity, 1
−0.4
−0.2
0.0
0.2

In [38]:

```python
# now, we can split a large selection into each topic
kws = ['temperature', 'surface', 'wind', 'precipitation', 'height']
plt.figure(figsize=(12,8))
plt.subplot(231, fc='gray')
ax1 = plt.subplot(231)
plot_topic(axis=ax1, kw='temperature')

ax2 = plt.subplot(232)
plot_topic(axis=ax2, kw='surface')

ax3 = plt.subplot(233)
plot_topic(axis=ax3, kw='wind')

ax4 = plt.subplot(234)
plot_topic(axis=ax4, kw='precipitation')

ax5 = plt.subplot(235)
plot_topic(axis=ax5, kw='height')

ax6 = plt.subplot(236, )
plot_topic(axis=ax6, kws=kws)
plt.tight_layout(pad=3)
plt.subplots_adjust(top=0.85, bottom=0.15)
plt.suptitle('Correlation with $PM_{2.5}$ with FLX parameters in MERRA-2\nfor Hanoi, 2018', fontsize=15)
plt.figtext(1,0.1, s='Datasource: ncei.noaa.gov & airnow.gov\ncreated: Aug 5, 2020',
            transform=fig.transFigure, ha='left', va='bottom',
           fontsize=10, color='gray')
plt.savefig('img/2020Aug-FLX-subplot.png', dpi=120, optimize=True, edgecolor='black')
```



summary

- not easy to filter the flux group into several topic like with single level
- denser air is positively correlated with $PM_{2.5}$ (similar to pressure does)
- high humidity or shower is correlated inversely with $PM_{2.5}$
- height for roughness, surface layer or zero-plane-displacement is correlated inversely with $PM_{2.5}$

AER

aerosol mixing ratio

In [39]:
```
df = pd.read_csv('data/merra2_aer_hanoi_2018.csv',
                 parse_dates=['date_utc'],
                 index_col=['date_utc'])
df.head(3)
```

Out[39]:

	SSSMASS25	DUSCATAU	BCSCATAU	DUEXTTAU	BCFLUXU	OCFLUXV	BCANGSTR
date_utc							
2018-01-01 00:00:00	7.230483e-10	0.034630	0.011679	0.036952	8.302304e-07	0.000025	1.456636
2018-01-01 01:00:00	7.119070e-10	0.034171	0.011854	0.036463	1.970886e-06	0.000025	1.457095
2018-01-01 02:00:00	6.959923e-10	0.033618	0.011953	0.035879	2.143218e-06	0.000025	1.456786

3 rows × 50 columns

In [40]:
```
# merge data
df = pd.merge(df, pm25, right_index=True, left_index=True)
df.index.rename('DATE', inplace=True)
df.head(3)
```

Out[40]:

	SSSMASS25	DUSCATAU	BCSCATAU	DUEXTTAU	BCFLUXU	OCFLUXV	BCANGSTR
DATE							
2018-01-01 01:00:00	7.119070e-10	0.034171	0.011854	0.036463	0.000002	0.000025	1.457095
2018-01-01 02:00:00	6.959923e-10	0.033618	0.011953	0.035879	0.000002	0.000025	1.456786
2018-01-01 03:00:00	6.832592e-10	0.032991	0.012047	0.035206	0.000001	0.000026	1.456983

3 rows × 51 columns

In [41]:
```
ds = nc.Dataset('data/nc4/MERRA2_400.tavg1_2d_aer_Nx.20180101.nc4')
```

In [42]:

```
name_ = dict()
for k in ds.variables.keys():
#     print(k)
#     name_[k] = 'None'
    name_[k] = f'{ds.variables[k].standard_name}, {ds.variables[k].units}'.lower()
name_
```

Out[42]:

```
{'SSSMASS25': 'sea salt surface mass concentration - pm 2.5, kg m-3',
 'DUSCATAU': 'dust scattering aot [550 nm], 1',
 'BCSCATAU': 'black carbon scattering aot [550 nm], 1',
 'DUEXTTAU': 'dust extinction aot [550 nm], 1',
 'BCFLUXU': 'black carbon column u-wind mass flux, kg m-1 s-1',
 'OCFLUXV': 'organic carbon column v-wind mass flux __ensemble__, kg
m-1 s-1',
 'BCANGSTR': 'black carbon angstrom parameter [470-870 nm], 1',
 'SUFLUXV': 'so4 column v-wind mass flux __ensemble__, kg m-1 s-1',
 'SSSMASS': 'sea salt surface mass concentration, kg m-3',
 'OCSMASS': 'organic carbon surface mass concentration __ensemble__,
kg m-3',
 'BCCMASS': 'black carbon column mass density, kg m-2',
 'BCSMASS': 'black carbon surface mass concentration, kg m-3',
 'SO4CMASS': 'so4 column mass density __ensemble__, kg m-2',
 'SSFLUXU': 'sea salt column u-wind mass flux, kg m-1 s-1',
 'DUCMASS': 'dust column mass density, kg m-2',
 'SSEXTTAU': 'sea salt extinction aot [550 nm], 1',
 'SO2CMASS': 'so2 column mass density __ensemble__, kg m-2',
 'OCANGSTR': 'organic carbon angstrom parameter [470-870 nm] __ensemb
le__, 1',
 'OCCMASS': 'organic carbon column mass density __ensemble__, kg m-
2',
 'TOTEXTTAU': 'total aerosol extinction aot [550 nm], 1',
 'DUSCAT25': 'dust scattering aot [550 nm] - pm 2.5, 1',
 'TOTANGSTR': 'total aerosol angstrom parameter [470-870 nm], 1',
 'DMSCMASS': 'dms column mass density __ensemble__, kg m-2',
 'SSEXTT25': 'sea salt extinction aot [550 nm] - pm 2.5, 1',
 'DUANGSTR': 'dust angstrom parameter [470-870 nm], 1',
 'DMSSMASS': 'dms surface mass concentration __ensemble__, kg m-3',
 'BCEXTTAU': 'black carbon extinction aot [550 nm], 1',
 'SSSCATAU': 'sea salt scattering aot [550 nm], 1',
 'DUFLUXV': 'dust column v-wind mass flux, kg m-1 s-1',
 'DUFLUXU': 'dust column u-wind mass flux, kg m-1 s-1',
 'SUEXTTAU': 'so4 extinction aot [550 nm] __ensemble__, 1',
 'SSFLUXV': 'sea salt column v-wind mass flux, kg m-1 s-1',
 'DUCMASS25': 'dust column mass density - pm 2.5, kg m-2',
 'OCEXTTAU': 'organic carbon extinction aot [550 nm] __ensemble__,
1',
 'SUANGSTR': 'so4 angstrom parameter [470-870 nm] __ensemble__, 1',
 'SSSCAT25': 'sea salt scattering aot [550 nm] - pm 2.5, 1',
 'SSCMASS25': 'sea salt column mass density - pm 2.5, kg m-2',
 'SO4SMASS': 'so4 surface mass concentration __ensemble__, kg m-3',
 'DUSMASS': 'dust surface mass concentration, kg m-3',
 'SUFLUXU': 'so4 column u-wind mass flux __ensemble__, kg m-1 s-1',
 'BCFLUXV': 'black carbon column v-wind mass flux, kg m-1 s-1',
 'DUSMASS25': 'dust surface mass concentration - pm 2.5, kg m-3',
 'SSCMASS': 'sea salt column mass density, kg m-2',
 'SUSCATAU': 'so4 scattering aot [550 nm] __ensemble__, 1',
 'SO2SMASS': 'so2 surface mass concentration __ensemble__, kg m-3',
 'SSANGSTR': 'sea salt angstrom parameter [470-870 nm], 1',
 'DUEXTT25': 'dust extinction aot [550 nm] - pm 2.5, 1',
 'OCFLUXU': 'organic carbon column u-wind mass flux __ensemble__, kg
m-1 s-1',
 'OCSCATAU': 'organic carbon scattering aot [550 nm] __ensemble__,
1',
 'TOTSCATAU': 'total aerosol scattering aot [550 nm], 1'}
```

In [43]:
```
df.corr()['pm25'].sort_values().to_frame().dropna().drop('pm25')
```

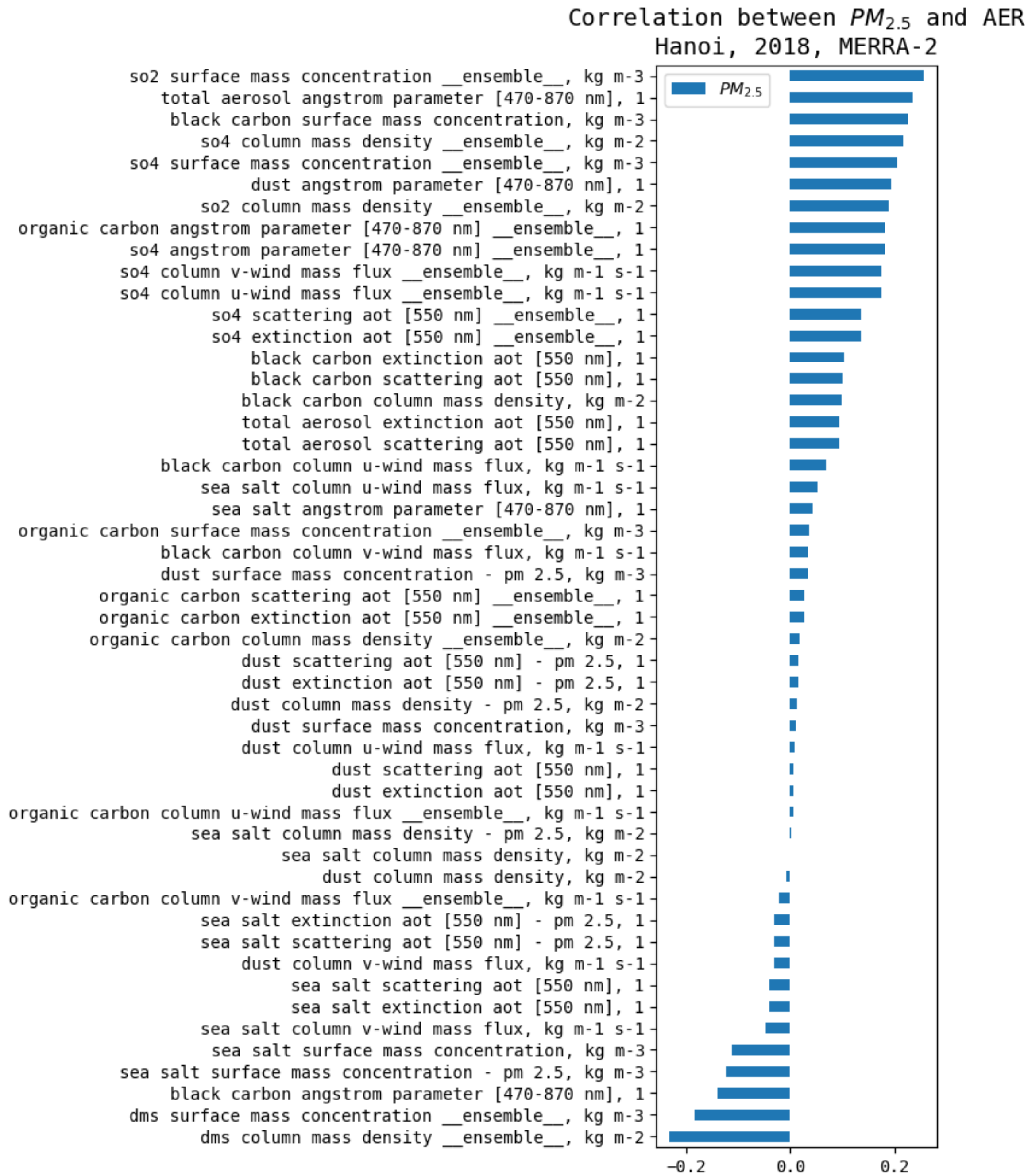
Out[43]:

	pm25
DMSCMASS	-0.232325
DMSSMASS	-0.182772
BCANGSTR	-0.139689
SSSMASS25	-0.122650
SSSMASS	-0.112831
SSFLUXV	-0.047410
SSEXTTAU	-0.039720
SSSCATAU	-0.039720
DUFLUXV	-0.030967
SSSCAT25	-0.030423
SSEXTT25	-0.030423
OCFLUXV	-0.021505
DUCMASS	-0.007796
SSCMASS	-0.002014
SSCMASS25	0.001905
OCFLUXU	0.005658
DUEXTTAU	0.005894
DUSCATAU	0.006446
DUFLUXU	0.007068
DUSMASS	0.011084
DUCMASS25	0.012861
DUEXTT25	0.015269
DUSCAT25	0.015350
OCCMASS	0.016910
OCEXTTAU	0.027543
OCSCATAU	0.027741
DUSMASS25	0.033828
BCFLUXV	0.034157
OCSMASS	0.034721
SSANGSTR	0.042832
SSFLUXU	0.051709
BCFLUXU	0.067402
TOTSCATAU	0.093900
TOTEXTTAU	0.094060
BCCMASS	0.098560

	pm25
BCSCATAU	0.101324
BCEXTTAU	0.102098
SUEXTTAU	0.134530
SUSCATAU	0.134530
SUFLUXU	0.174666
SUFLUXV	0.174772
SUANGSTR	0.180727
OCANGSTR	0.180835
SO2CMASS	0.187421
DUANGSTR	0.192490
SO4SMASS	0.205338
SO4CMASS	0.215542
BCSMASS	0.226259
TOTANGSTR	0.235356
SO2SMASS	0.256301

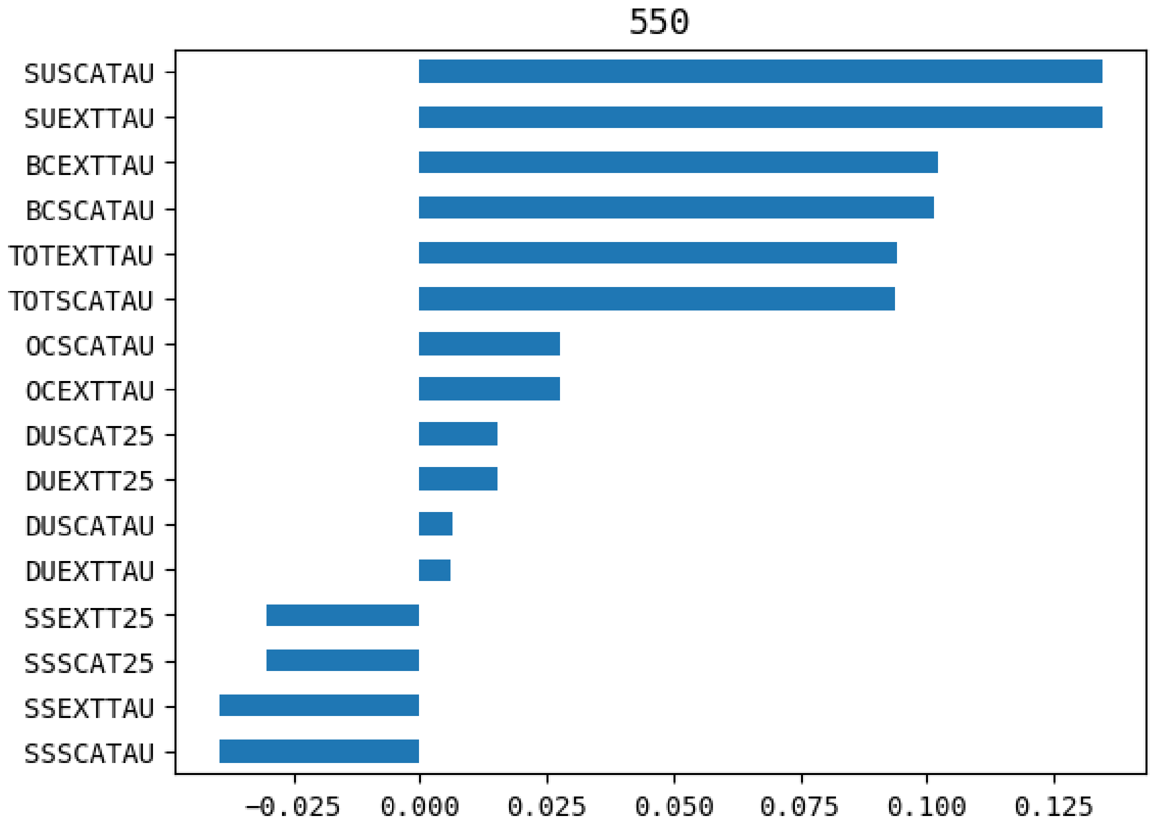
In [44]:

```
# let make one graph for whole group
fig, ax = plt.subplots(figsize=(8,10))
df.corr()['pm25'].sort_values().to_frame().dropna().drop('pm25').plot
.barh(ax=ax)
ax.legend(['$PM_{2.5}$'], frameon=True)
ax.set_title('Correlation between $PM_{2.5}$ and AER\nHanoi, 2018, ME
RRA-2', fontsize=14)

labels = [item.get_text() for item in ax.get_yticklabels()]

new_label = dict()
for label in labels:
    if label in list(name_.keys()):
        new_label[label] = name_[label]
    else:
        new_label[label] = label

ax.set_yticklabels(new_label.values())
fig.tight_layout()
fig.savefig('img/2020Aug-AER.png', dpi=120, optimize=True)
```


Correlation between $PM_{2.5}$ and AER
Hanoi, 2018, MERRA-2
$PM_{2.5}$
so2 surface mass concentration __ensemble__, kg m-3
total aerosol angstrom parameter [470-870 nm], 1
black carbon surface mass concentration, kg m-3
so4 column mass density __ensemble__, kg m-2
so4 surface mass concentration __ensemble__, kg m-3
dust angstrom parameter [470-870 nm], 1
so2 column mass density __ensemble__, kg m-2
organic carbon angstrom parameter [470-870 nm] __ensemble__, 1
so4 angstrom parameter [470-870 nm] __ensemble__, 1
so4 column v-wind mass flux __ensemble__, kg m-1 s-1
so4 column u-wind mass flux __ensemble__, kg m-1 s-1
so4 scattering aot [550 nm] __ensemble__, 1
so4 extinction aot [550 nm] __ensemble__, 1
black carbon extinction aot [550 nm], 1
black carbon scattering aot [550 nm], 1
black carbon column mass density, kg m-2
total aerosol extinction aot [550 nm], 1
total aerosol scattering aot [550 nm], 1
black carbon column u-wind mass flux, kg m-1 s-1
sea salt column u-wind mass flux, kg m-1 s-1
sea salt angstrom parameter [470-870 nm], 1
organic carbon surface mass concentration __ensemble__, kg m-3
black carbon column v-wind mass flux, kg m-1 s-1
dust surface mass concentration - pm 2.5, kg m-3
organic carbon scattering aot [550 nm] __ensemble__, 1
organic carbon extinction aot [550 nm] __ensemble__, 1
organic carbon column mass density __ensemble__, kg m-2
dust scattering aot [550 nm] - pm 2.5, 1
dust extinction aot [550 nm] - pm 2.5, 1
dust column mass density - pm 2.5, kg m-2
dust surface mass concentration, kg m-3
dust column u-wind mass flux, kg m-1 s-1
dust scattering aot [550 nm], 1
dust extinction aot [550 nm], 1
organic carbon column u-wind mass flux __ensemble__, kg m-1 s-1
sea salt column mass density - pm 2.5, kg m-2
sea salt column mass density, kg m-2
dust column mass density, kg m-2
organic carbon column v-wind mass flux __ensemble__, kg m-1 s-1
sea salt extinction aot [550 nm] - pm 2.5, 1
sea salt scattering aot [550 nm] - pm 2.5, 1
dust column v-wind mass flux, kg m-1 s-1
sea salt scattering aot [550 nm], 1
sea salt extinction aot [550 nm], 1
sea salt column v-wind mass flux, kg m-1 s-1
sea salt surface mass concentration, kg m-3
sea salt surface mass concentration - pm 2.5, kg m-3
black carbon angstrom parameter [470-870 nm], 1
dms surface mass concentration __ensemble__, kg m-3
dms column mass density __ensemble__, kg m-2
−0.2
0.0
0.2

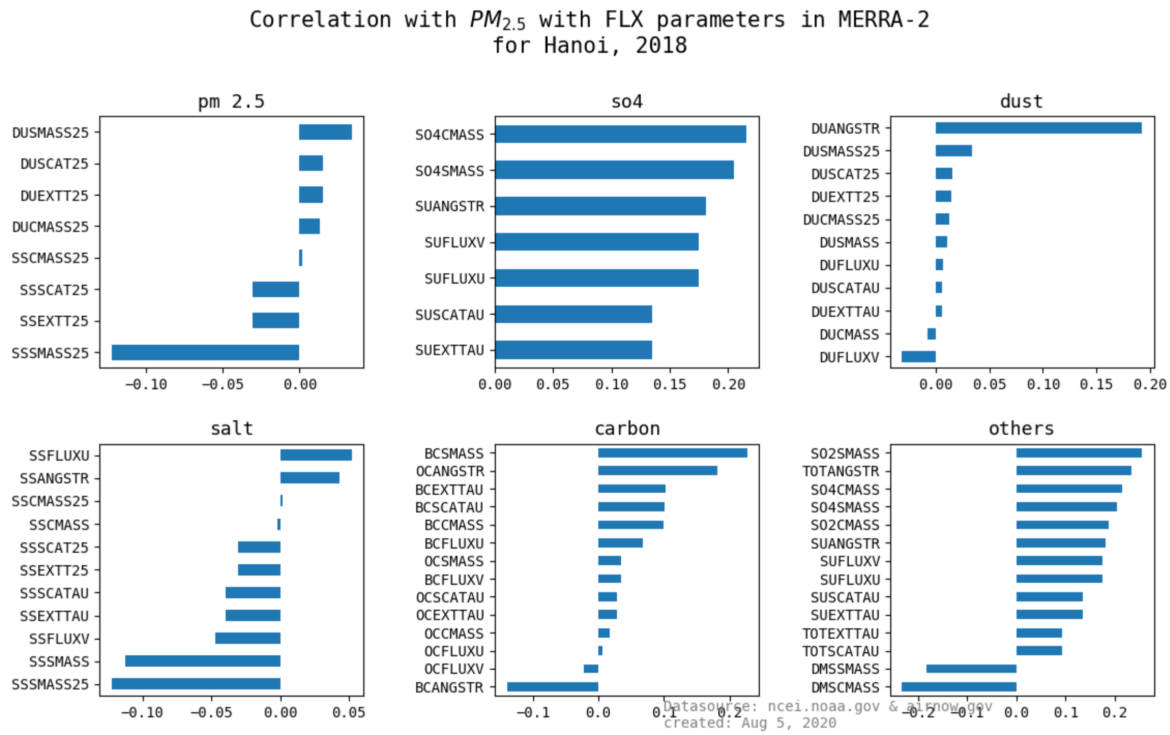
In [45]:
```
fig, ax = plt.subplots()
plot_topic(axis=ax, kw='550')
```

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7fec29bdf198>



In [46]:

```
# now, we can split a large selection into each topic
kws = ['pm 2.5' 'so4', 'dust', 'salt', 'carbon']
plt.figure(figsize=(12,8))
plt.subplot(231, fc='gray')

ax1 = plt.subplot(231)
plot_topic(axis=ax1, kw='pm 2.5')

ax2 = plt.subplot(232)
plot_topic(axis=ax2, kw='so4')

ax3 = plt.subplot(233)
plot_topic(axis=ax3, kw='dust')

ax4 = plt.subplot(234)
plot_topic(axis=ax4, kw='salt')

ax5 = plt.subplot(235)
plot_topic(axis=ax5, kw='carbon')

ax6 = plt.subplot(236, )
plot_topic(axis=ax6, kws=kws)
plt.tight_layout(pad=3)
plt.subplots_adjust(top=0.85, bottom=0.15)
plt.suptitle('Correlation with $PM_{2.5}$ with FLX parameters in MERR
A-2\nfor Hanoi, 2018', fontsize=15)
plt.figtext(1,0.1, s='Datasource: ncei.noaa.gov & airnow.gov\ncreate
d: Aug 5, 2020',
            transform=fig.transFigure, ha='left', va='bottom',
           fontsize=10, color='gray')
plt.savefig('img/2020Aug-AER-subplot.png', dpi=120, optimize=True, ed
gecolor='black')
```



summary

- no strong correlation with aerosol parameters to $PM_{2.5}$
- sulfate and black carbon are possitively correlated with $PM_{2.5}$

Concluding notes

- MERRA-2 is an extensive collection of data of Earth atmosphere. It provides global data on the ground and in upper air
- no strong to moderate correlation of atmospheric paramter to $PM_{2.5}$. The highest coeeficient is -0.4, and a few other in a range of 0.3-0.4
- increment of temperature and humidity is inversely correlated with $PM_{2.5}$
- high surface pressure or high sulfate is positively correlated with $PM_{2.5}$
- current format of wind data (eastward and northward) is not sufficient to correlate with $PM_{2.5}$ concentration