prior_montecarlo

May 31, 2019

1 Run and process the prior monte carlo and pick a "truth" realization

A great advantage of exploring a synthetic model is that we can enforce a "truth" and then evaluate how our various attempts to estimate it perform. One way to do this is to run a monte carlo ensemble of multiple parameter realizations and then choose one of them to represent the "truth". That will be accomplished in this notebook.

In [1]:
```
import os
import shutil
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
plt.rcParams['font.size']=12
import flopy
import pyemu
```

```
flopy is installed in /Users/jeremyw/Dev/gw1876/activities_2day_mfm/notebooks/flopy
```

1.1 SUPER IMPORTANT: SET HOW MANY PARALLEL WORKERS TO USE

In [2]:
```
num_workers = 20
```

1.1.1 set the t_d or "template directory" variable to point at the template folder and read in the PEST control file

In [3]:
```
t_d = "template"
pst = pyemu.Pst(os.path.join(t_d,"freyberg.pst"))
```

1.1.2 Decide what pars are uncertain in the truth

We need to decide what our truth looks like - should the pilot points or the grid-scale pars be the source of spatial variability? or both?

In [4]:
```
par = pst.parameter_data
# grid pars
#should_fix = par.loc[par.pargp.apply(lambda x: "gr" in x),"parnme"]
```

```
        # pp pars
        #should_fix = par.loc[par.pargp.apply(lambda x: "pp" in x),"parnme"]
        #pst.npar - should_fix.shape[0]
```

In [5]:
```
pe = pyemu.ParameterEnsemble.from_binary(pst=pst,filename=os.path.join(t_d,"prior.jcb"))
#pe.loc[:,should_fix] = 1.0
pe.to_csv(os.path.join(t_d,"sweep_in.csv"))
pe.shape
```

```
new binary format detected...
```

Out[5]: (1000, 14819)

In [6]:
```
pe.loc[:,"hk031"]
```

Out[6]:
```
0      0.935197
1      2.122076
2      1.657241
3      0.626902
4      0.780509
5      0.500825
6      2.419110
7      0.558504
8      0.257237
9      3.825338
10     1.413887
11     0.991652
12     0.393278
13     1.427654
14     4.727755
15     0.431509
16     1.441612
17     3.049608
18     1.008735
19     0.415130
20     3.075104
21     0.634092
22     0.552351
23     0.720671
24     0.561430
25     1.205299
26     0.333346
27     0.803041
28     2.133155
29     2.505986
         ...
970    0.434642
971    0.526258
```

```
972    1.583272
973    0.277955
974    0.284029
975    0.830765
976    0.872251
977    0.714677
978    1.159863
979    1.512948
980    3.750909
981    0.564394
982    0.779535
983    0.176048
984    0.948359
985    0.807764
986    2.040333
987    0.732289
988    0.372329
989    1.369781
990    0.527716
991    1.513590
992    1.304466
993    0.248067
994    3.707392
995    1.205019
996    0.611359
997    3.635739
998    0.593297
999    1.052875
Name: hk031, Length: 1000, dtype: float64
```

In [7]:
```
pst.parameter_data.loc[pe.columns,"parval1"] = pe.iloc[0,:]
pst.control_data.noptmax = 0
pst.write(os.path.join(t_d,"test.pst"))
pyemu.os_utils.run("pestpp-ies test.pst",cwd=t_d)
res = pyemu.pst_utils.read_resfile(os.path.join(t_d,"test.base.rei"))
res
```

```
noptmax:0, npar_adj:14819, nnz_obs:14
```

Out[7]:

	name	group	measured	\
name				
fa_0_19791230	fa_0_19791230	flaqx	-6.907900e+01	
fa_0_19801229	fa_0_19801229	flaqx	-6.895800e+01	
fa_10_19791230	fa_10_19791230	flaqx	-3.626600e+01	
fa_10_19801229	fa_10_19801229	flaqx	-3.620300e+01	
fa_11_19791230	fa_11_19791230	flaqx	-3.737100e+01	
fa_11_19801229	fa_11_19801229	flaqx	-3.731600e+01	

fa_12_19791230	fa_12_19791230	flaqx	-4.045900e+01
fa_12_19801229	fa_12_19801229	flaqx	-4.041100e+01
fa_13_19791230	fa_13_19791230	flaqx	-4.308200e+01
fa_13_19801229	fa_13_19801229	flaqx	-4.303900e+01
fa_14_19791230	fa_14_19791230	flaqx	-4.471700e+01
fa_14_19801229	fa_14_19801229	flaqx	-4.467800e+01
fa_15_19791230	fa_15_19791230	flaqx	-4.523300e+01
fa_15_19801229	fa_15_19801229	flaqx	-4.519800e+01
fa_16_19791230	fa_16_19791230	flaqx	-4.498900e+01
fa_16_19801229	fa_16_19801229	flaqx	-4.495700e+01
fa_17_19791230	fa_17_19791230	flaqx	-4.367400e+01
fa_17_19801229	fa_17_19801229	flaqx	-4.364200e+01
fa_18_19791230	fa_18_19791230	flaqx	-4.095300e+01
fa_18_19801229	fa_18_19801229	flaqx	-4.092200e+01
fa_19_19791230	fa_19_19791230	flaqx	-3.618200e+01
fa_19_19801229	fa_19_19801229	flaqx	-3.615100e+01
fa_1_19791230	fa_1_19791230	flaqx	-6.944200e+01
fa_1_19801229	fa_1_19801229	flaqx	-6.932200e+01
fa_20_19791230	fa_20_19791230	flaqx	-3.008600e+01
fa_20_19801229	fa_20_19801229	flaqx	-3.005500e+01
fa_21_19791230	fa_21_19791230	flaqx	-3.548400e+01
fa_21_19801229	fa_21_19801229	flaqx	-3.545200e+01
fa_22_19791230	fa_22_19791230	flaqx	-3.935200e+01
fa_22_19801229	fa_22_19801229	flaqx	-3.931800e+01
...	...	...	...
hds_02_039_010_000	hds_02_039_010_000	hds	3.256046e+01
hds_02_039_010_001	hds_02_039_010_001	hds	3.256043e+01
hds_02_039_011_000	hds_02_039_011_000	hds	3.256142e+01
hds_02_039_011_001	hds_02_039_011_001	hds	3.256139e+01
hds_02_039_012_000	hds_02_039_012_000	hds	3.256558e+01
hds_02_039_012_001	hds_02_039_012_001	hds	3.256556e+01
hds_02_039_013_000	hds_02_039_013_000	hds	3.257711e+01
hds_02_039_013_001	hds_02_039_013_001	hds	3.257710e+01
hds_02_039_014_000	hds_02_039_014_000	hds	3.259781e+01
hds_02_039_014_001	hds_02_039_014_001	hds	3.259779e+01
vol_constan_19791230	vol_constan_19791230	vol_constan	0.000000e+00
vol_constan_19801229	vol_constan_19801229	vol_constan	0.000000e+00
vol_drains_19791230	vol_drains_19791230	vol_drains	-2.640137e+06
vol_drains_19801229	vol_drains_19801229	vol_drains	-2.904042e+06
vol_in-out_19791230	vol_in-out_19791230	vol_in-out	4.500000e+01
vol_in-out_19801229	vol_in-out_19801229	vol_in-out	6.300000e+01
vol_percent_19791230	vol_percent_19791230	vol_percent	0.000000e+00
vol_percent_19801229	vol_percent_19801229	vol_percent	0.000000e+00
vol_recharg_19791230	vol_recharg_19791230	vol_recharg	1.111644e+07
vol_recharg_19801229	vol_recharg_19801229	vol_recharg	1.222808e+07
vol_storage_19791230	vol_storage_19791230	vol_storage	2.923828e+04
vol_storage_19801229	vol_storage_19801229	vol_storage	3.134556e+04
vol_stream__19791230	vol_stream__19791230	vol_stream_	-5.220494e+06

```
vol_stream__19801229  vol_stream__19801229  vol_stream_ -5.741824e+06
vol_total_19791230      vol_total_19791230    vol_total  4.500000e+01
vol_total_19801229      vol_total_19801229    vol_total  6.300000e+01
vol_wells_19791230      vol_wells_19791230    vol_wells -3.285000e+06
vol_wells_19801229      vol_wells_19801229    vol_wells -3.613500e+06
part_status                   part_status       obgnme  1.000000e+10
part_time                       part_time       obgnme  1.000000e+10

                          modelled      residual  weight
name
fa_0_19791230        -1.178400e+02  4.876100e+01     0.0
fa_0_19801229        -6.799900e+01 -9.590000e-01     0.0
fa_10_19791230       -4.867000e+01  1.240400e+01     0.0
fa_10_19801229       -5.177400e+00 -3.102560e+01     0.0
fa_11_19791230       -1.340400e+01 -2.396700e+01     0.0
fa_11_19801229       -7.796600e-01 -3.653634e+01     0.0
fa_12_19791230       -3.278900e+01 -7.670000e+00     0.0
fa_12_19801229       -7.499300e-01 -3.966107e+01     0.0
fa_13_19791230       -6.120300e+00 -3.696170e+01     0.0
fa_13_19801229        1.903100e-01 -4.322931e+01     0.0
fa_14_19791230       -8.848300e+01  4.376600e+01     0.0
fa_14_19801229        1.126300e+01 -5.594100e+01     0.0
fa_15_19791230       -4.268900e+00 -4.096410e+01     0.0
fa_15_19801229        1.116600e+00 -4.631460e+01     0.0
fa_16_19791230       -2.666400e+01 -1.832500e+01     0.0
fa_16_19801229        1.543500e+01 -6.039200e+01     0.0
fa_17_19791230       -5.635500e+00 -3.803850e+01     0.0
fa_17_19801229        7.867800e+00 -5.150980e+01     0.0
fa_18_19791230       -5.725000e+00 -3.522800e+01     0.0
fa_18_19801229        2.293400e+01 -6.385600e+01     0.0
fa_19_19791230       -2.970300e-02 -3.615230e+01     0.0
fa_19_19801229        3.335300e+01 -6.950400e+01     0.0
fa_1_19791230        -9.470500e+00 -5.997150e+01     0.0
fa_1_19801229        -5.464700e+00 -6.385730e+01     0.0
fa_20_19791230        2.533400e+01 -5.542000e+01     0.0
fa_20_19801229        1.739600e+02 -2.040150e+02     0.0
fa_21_19791230        3.550900e-01 -3.583909e+01     0.0
fa_21_19801229        2.653500e+00 -3.810550e+01     0.0
fa_22_19791230        1.082900e+01 -5.018100e+01     0.0
fa_22_19801229        8.561700e+01 -1.249350e+02     0.0
...                            ...           ...     ...
hds_02_039_010_000    3.263759e+01 -7.713318e-02     0.0
hds_02_039_010_001    3.260130e+01 -4.086304e-02     0.0
hds_02_039_011_000    3.262994e+01 -6.852341e-02     0.0
hds_02_039_011_001    3.259931e+01 -3.791809e-02     0.0
hds_02_039_012_000    3.267067e+01 -1.050873e-01     0.0
hds_02_039_012_001    3.263583e+01 -7.027054e-02     0.0
hds_02_039_013_000    3.269498e+01 -1.178703e-01     0.0
```

```
hds_02_039_013_001    3.266051e+01 -8.341598e-02     0.0
hds_02_039_014_000    3.274148e+01 -1.436729e-01     0.0
hds_02_039_014_001    3.270523e+01 -1.074409e-01     0.0
vol_constan_19791230  0.000000e+00  0.000000e+00     0.0
vol_constan_19801229  0.000000e+00  0.000000e+00     0.0
vol_drains_19791230  -4.305028e+06  1.664892e+06     0.0
vol_drains_19801229  -4.626494e+06  1.722452e+06     0.0
vol_in-out_19791230  -8.276600e+04  8.281100e+04     0.0
vol_in-out_19801229  -8.255600e+04  8.261900e+04     0.0
vol_percent_19791230 -6.000000e-01  6.000000e-01     0.0
vol_percent_19801229 -5.500000e-01  5.500000e-01     0.0
vol_recharg_19791230  1.171976e+07 -6.033230e+05     0.0
vol_recharg_19801229  1.225148e+07 -2.340100e+04     0.0
vol_storage_19791230  6.845375e+05 -6.552992e+05     0.0
vol_storage_19801229  9.301668e+05 -8.988212e+05     0.0
vol_stream__19791230 -1.352142e+06 -3.868352e+06     0.0
vol_stream__19801229 -1.008945e+06 -4.732879e+06     0.0
vol_total_19791230   -8.276600e+04  8.281100e+04     0.0
vol_total_19801229   -8.255600e+04  8.261900e+04     0.0
vol_wells_19791230   -6.829895e+06  3.544895e+06     0.0
vol_wells_19801229   -7.628768e+06  4.015268e+06     0.0
part_status           2.000000e+00  1.000000e+10     0.0
part_time             6.457774e+02  9.999999e+09     0.0

[4436 rows x 6 columns]
```

1.1.3 run the prior ensemble in parallel locally

This takes advantage of the program `pestpp-swp` which runs a parameter sweep through a set of parameters. By default, `pestpp-swp` reads in the ensemble from a file called `sweep_in.csv` which in this case we made just above.

```
In [8]: m_d = "master_prior_sweep"
        pyemu.os_utils.start_slaves(t_d,"pestpp-swp","freyberg.pst",num_slaves=num_workers,sla
```

1.1.4 Load the output ensemble and plot a few things

```
In [9]: obs_df = pd.read_csv(os.path.join(m_d,"sweep_out.csv"),index_col=0)
        print('number of realization in the ensemble before dropping: ' + str(obs_df.shape[0]))
```

```
number of realization in the ensemble before dropping: 1000
```

drop any failed runs

```
In [10]: obs_df = obs_df.loc[obs_df.failed_flag==0,:]
         print('number of realization in the ensemble **after** dropping: ' + str(obs_df.shape
```

```
number of realization in the ensemble **after** dropping: 1000
```

```
In [11]: obs_df.iloc[0,:]
```

```
Out[11]: input_run_id            0.000000e+00
         failed_flag             0.000000e+00
         phi                     1.887895e+06
         meas_phi                1.887895e+06
         regul_phi               0.000000e+00
         vol_total               0.000000e+00
         flaqx                   0.000000e+00
         vol_constan             0.000000e+00
         vol_storage             0.000000e+00
         flx_drains              0.000000e+00
         flx_stream_             0.000000e+00
         flx_constan             0.000000e+00
         flx_total               0.000000e+00
         calflux                 1.887876e+06
         hds                     0.000000e+00
         flx_percent             0.000000e+00
         vol_wells               0.000000e+00
         flx_storage             0.000000e+00
         flx_wells               0.000000e+00
         flx_in-out              0.000000e+00
         calhead                 1.875375e+01
         flout                   0.000000e+00
         vol_in-out              0.000000e+00
         obgnme                  0.000000e+00
         vol_drains              0.000000e+00
         vol_percent             0.000000e+00
         vol_recharg             0.000000e+00
         vol_stream_             0.000000e+00
         flx_recharg             0.000000e+00
         fa_0_19791230          -1.178400e+02
                                      ...
         hds_02_039_010_000      3.263759e+01
         hds_02_039_010_001      3.260130e+01
         hds_02_039_011_000      3.262994e+01
         hds_02_039_011_001      3.259931e+01
         hds_02_039_012_000      3.267067e+01
         hds_02_039_012_001      3.263583e+01
         hds_02_039_013_000      3.269498e+01
         hds_02_039_013_001      3.266051e+01
         hds_02_039_014_000      3.274148e+01
         hds_02_039_014_001      3.270523e+01
         vol_constan_19791230    0.000000e+00
         vol_constan_19801229    0.000000e+00
         vol_drains_19791230    -4.305028e+06
         vol_drains_19801229    -4.626494e+06
         vol_in-out_19791230    -8.276600e+04
```

```
vol_in-out_19801229    -8.255600e+04
vol_percent_19791230   -6.000000e-01
vol_percent_19801229   -5.500000e-01
vol_recharg_19791230    1.171976e+07
vol_recharg_19801229    1.225148e+07
vol_storage_19791230    6.845375e+05
vol_storage_19801229    9.301668e+05
vol_stream__19791230   -1.352142e+06
vol_stream__19801229   -1.008945e+06
vol_total_19791230     -8.276600e+04
vol_total_19801229     -8.255600e+04
vol_wells_19791230     -6.829895e+06
vol_wells_19801229     -7.628768e+06
part_status             2.000000e+00
part_time               6.457774e+02
Name: 0, Length: 4465, dtype: float64
```

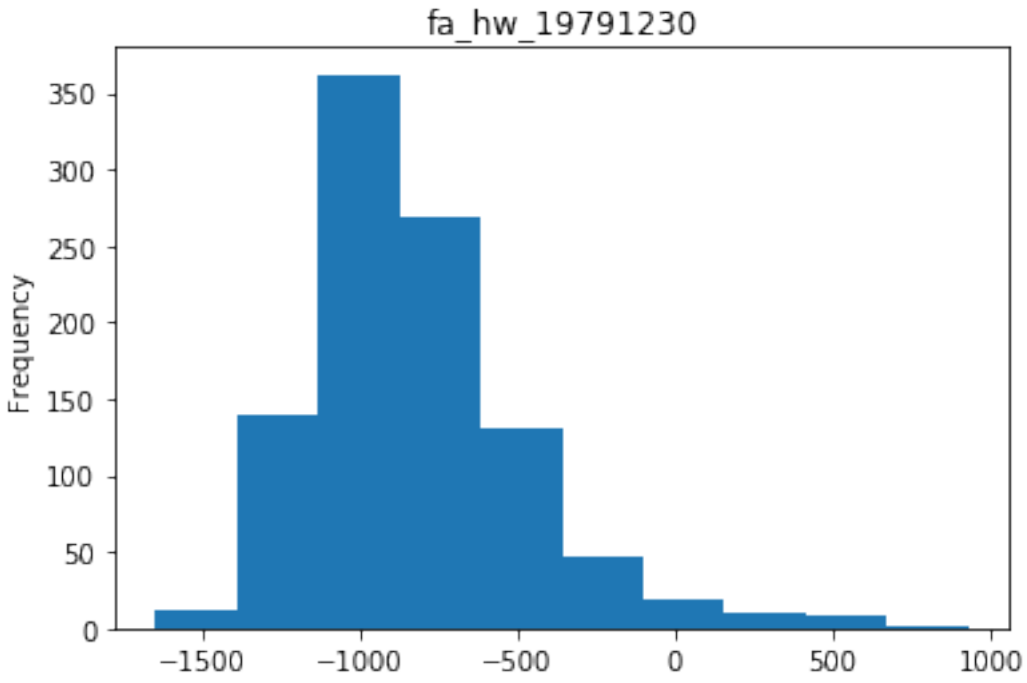
1.1.5 confirm which quantities were identified as forecasts

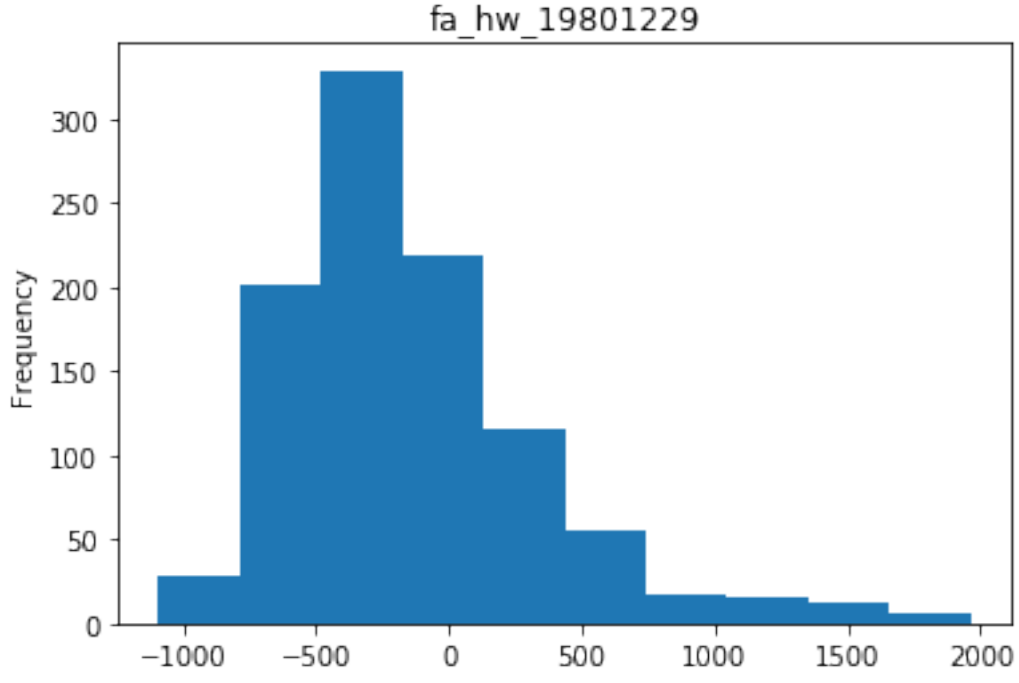
```
In [12]: fnames = pst.pestpp_options["forecasts"].split(',')
         fnames
```

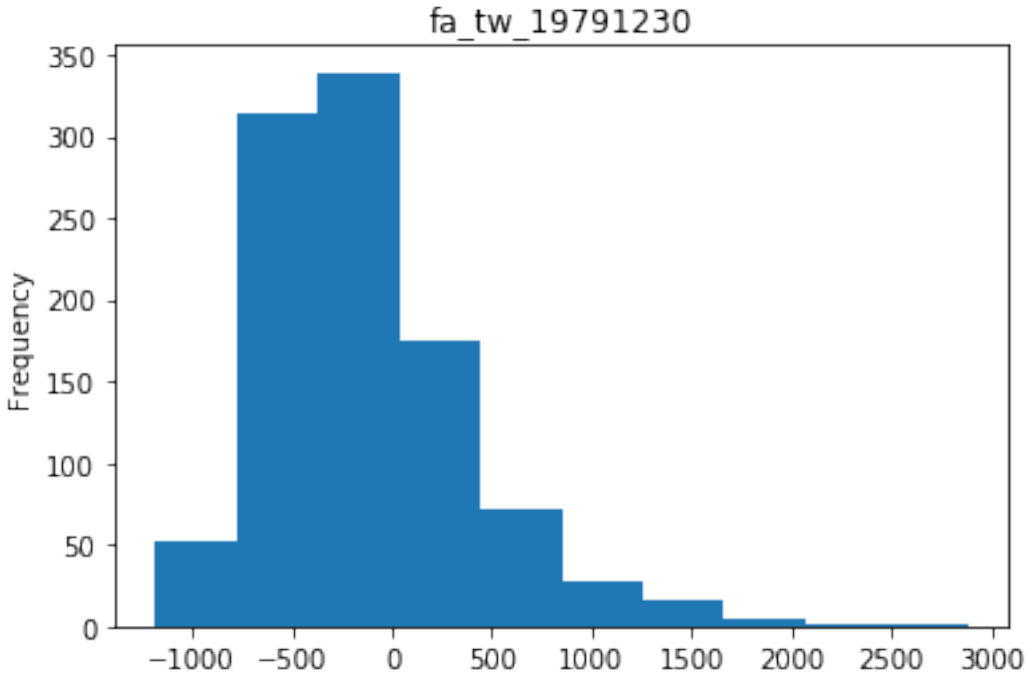
```
Out[12]: ['fa_hw_19791230',
          'fa_hw_19801229',
          'fa_tw_19791230',
          'fa_tw_19801229',
          'hds_00_013_002_000',
          'hds_00_013_002_001',
          'part_time',
          'part_status']
```

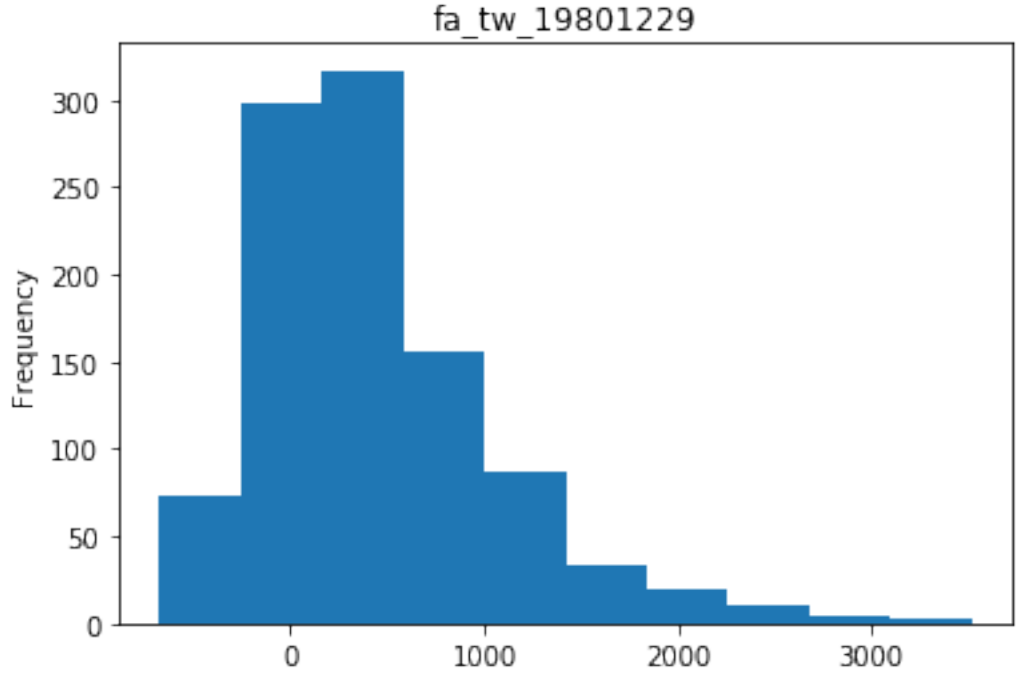
1.1.6 now we can plot the distributions of each forecast

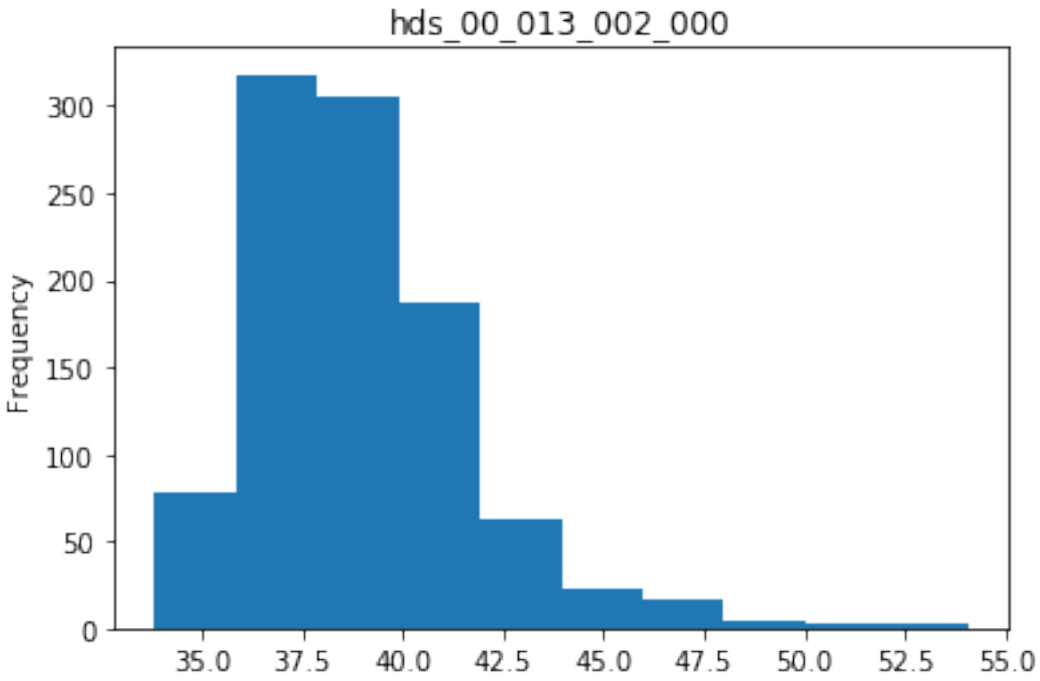
```
In [13]: for forecast in fnames:
             plt.figure()
             ax = obs_df.loc[:,forecast].plot(kind="hist")
             ax.set_title(forecast)
         plt.show()
```

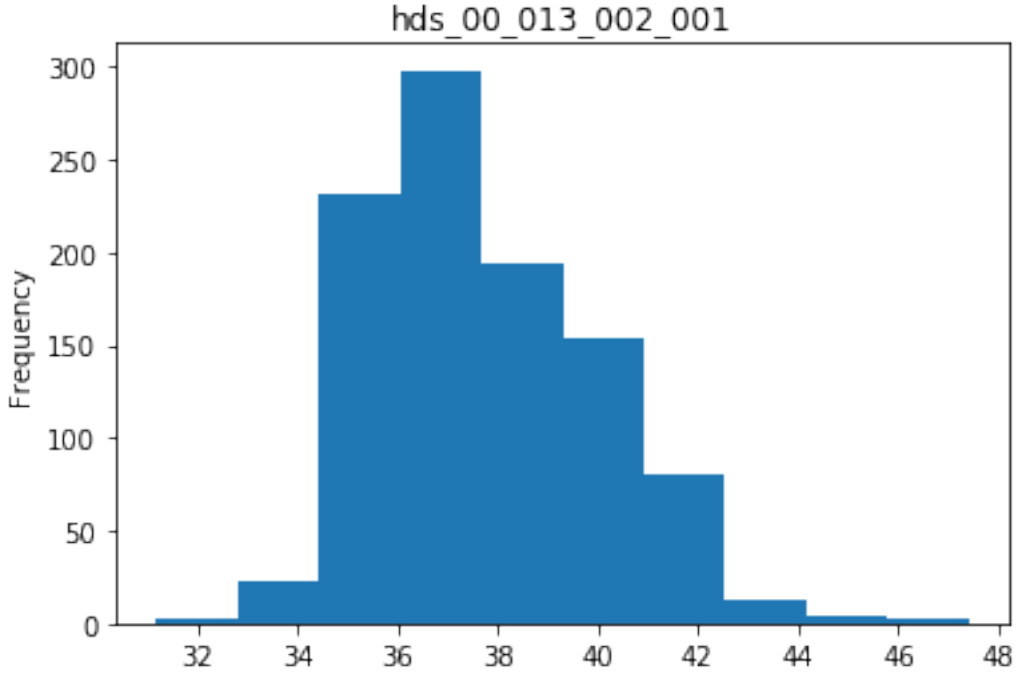

fa_hw_19791230
Frequency
350
300
250
200
150
100
50
0
−1500
−1000
−500
0
500
1000

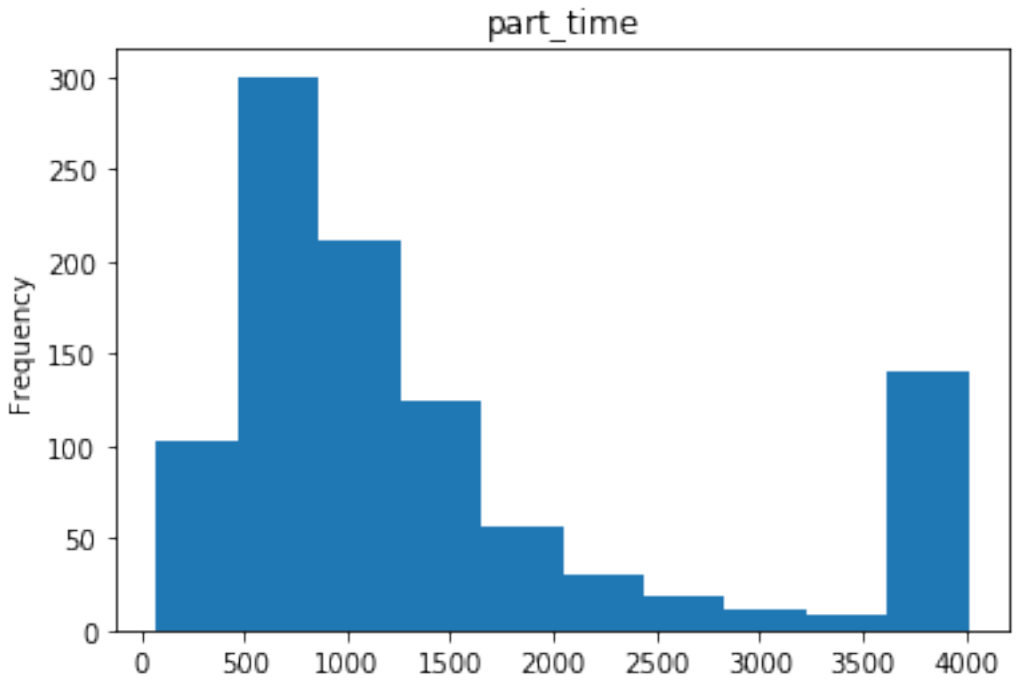

fa_hw_19801229
Frequency
300
250
200
150
100
50
0
−1000
−500
0
500
1000
1500
2000

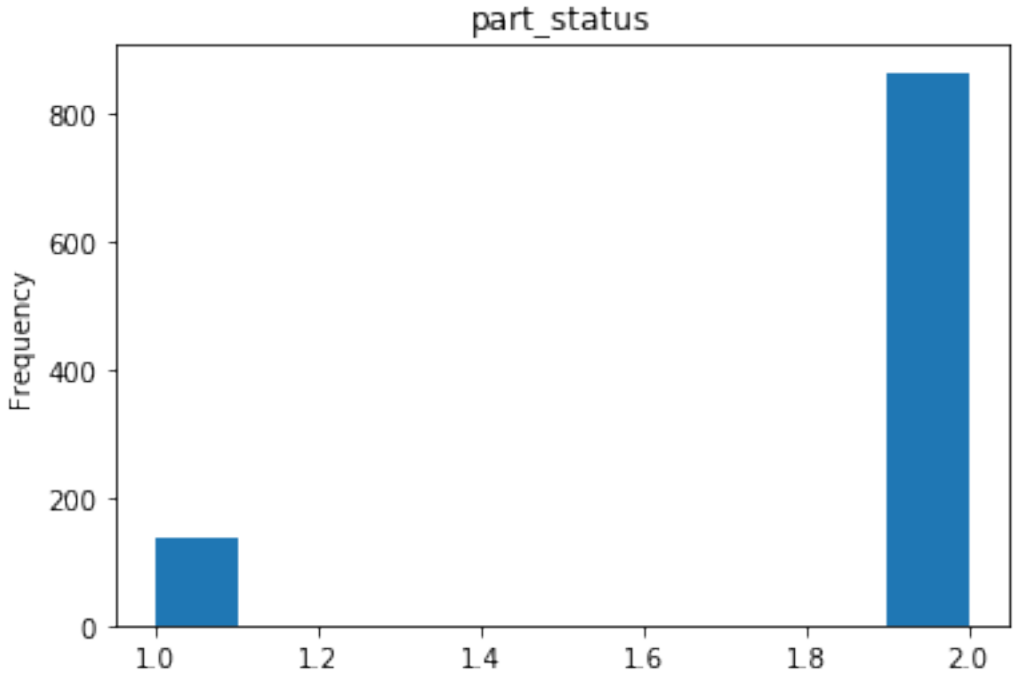

fa_tw_19791230
Frequency
350
300
250
200
150
100
50
0
−1000
−500
0
500
1000
1500
2000
2500
3000


fa_tw_19801229
Frequency
300
250
200
150
100
50
0
0
1000
2000
3000


hds_00_013_002_000
Frequency
300
250
200
150
100
50
0
35.0
37.5
40.0
42.5
45.0
47.5
50.0
52.5
55.0

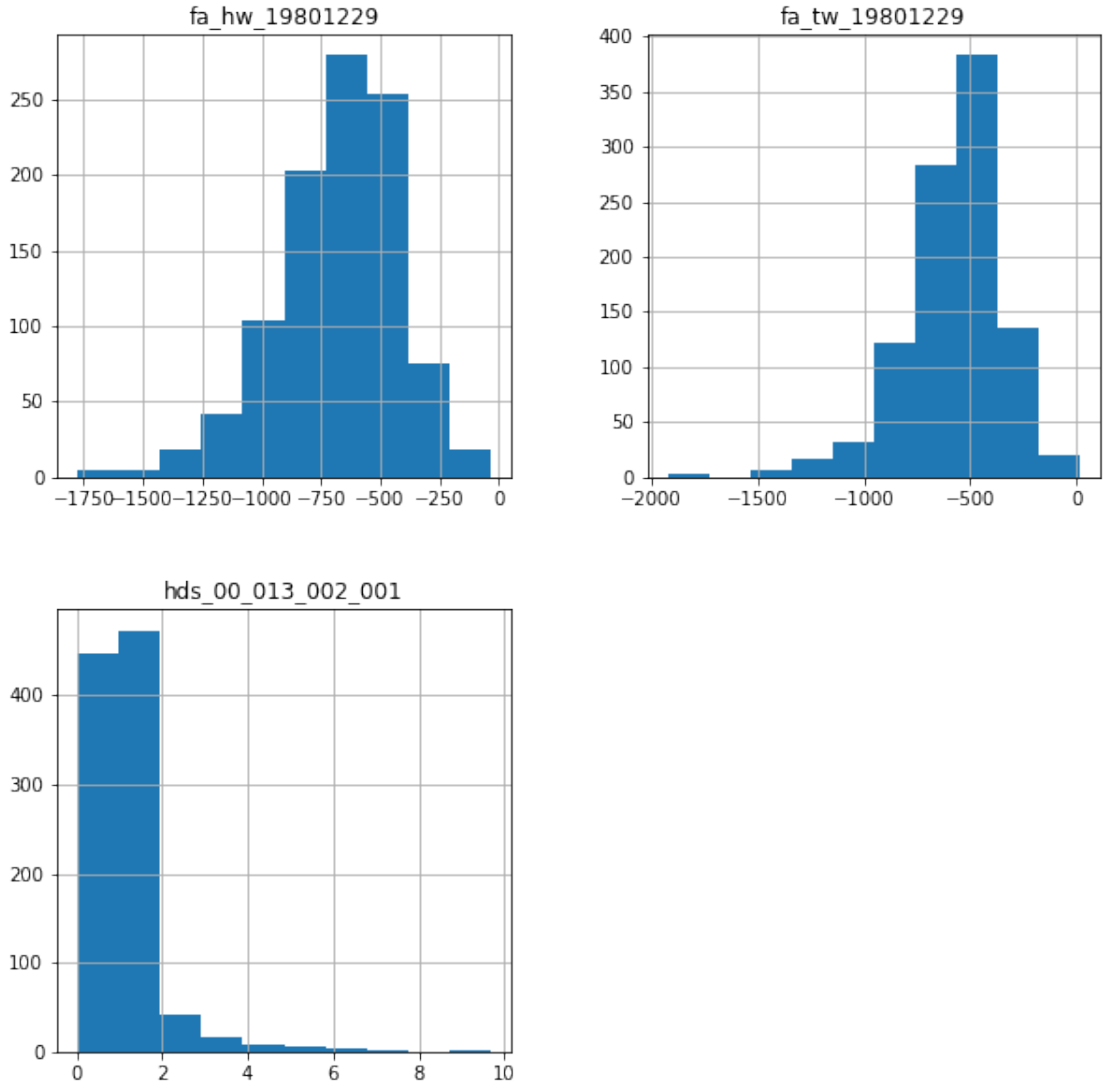

hds_00_013_002_001
Frequency
300
250
200
150
100
50
0
32
34
36
38
40
42
44
46
48





We see that under scenario conditions, many more realizations for the flow to the aquifer in the headwaters are postive (as expected). Lets difference these two:

```
In [14]: sfnames = [f for f in fnames if "1980" in f or "_001" in f]
         hfnames = [f for f in fnames if "1979" in f or "_000" in f]
         diff = obs_df.loc[:,hfnames].values - obs_df.loc[:,sfnames].values
         diff = pd.DataFrame(diff,columns=sfnames)
         diff.hist(figsize=(10,10))
         plt.show()
```



We now see that the most extreme scenario yields a large decrease in flow from the aquifer to the headwaters (the most negative value)

1.1.7 setting the "truth"

We just need to replace the observed values (`obsval`) in the control file with the outputs for one of the realizations on `obs_df`. In this way, we now have the nonzero values for history matching,

but also the `truth` values for comparing how we are doing with other unobserved quantities. I'm going to pick a realization that yields an "average" variability of the observed gw levels:

```
In [15]: sorted_vals = obs_df.loc[:,"part_time"].sort_values()
         idx = sorted_vals.index[100]
         idx
         sorted_vals

Out[15]: run_id
         120      76.4341
         385     159.3529
         100     165.7032
         82      170.2694
         980     207.3890
         71      230.5359
         392     235.9687
         663     240.3898
         217     246.4102
         751     247.6348
         669     251.1703
         596     255.4728
         281     260.8926
         452     267.2885
         632     273.5754
         315     275.9690
         732     277.0921
         954     283.0271
         115     284.2840
         653     293.4041
         457     294.3939
         398     302.9174
         187     303.7302
         723     308.5808
         543     308.8079
         797     310.4536
         43      311.5282
         254     311.6480
         546     311.9860
         761     322.6084
                  ...
         892    4015.0000
         893    4015.0000
         896    4015.0000
         897    4015.0000
         881    4015.0000
         95     4015.0000
         860    4015.0000
         855    4015.0000
```

```
507    4015.0000
819    4015.0000
364    4015.0000
511    4015.0000
655    4015.0000
150    4015.0000
826    4015.0000
361    4015.0000
355    4015.0000
857    4015.0000
353    4015.0000
517    4015.0000
148    4015.0000
648    4015.0000
521    4015.0000
36     4015.0000
35     4015.0000
523    4015.0000
851    4015.0000
337    4015.0000
350    4015.0000
129    4015.0000
Name: part_time, Length: 1000, dtype: float64
```

```
In [16]: obs_df.loc[idx,pst.nnz_obs_names]
```

```
Out[16]: fo_39_19791230        10530.000000
         hds_00_002_009_000       36.178482
         hds_00_002_015_000       34.927410
         hds_00_003_008_000       36.352409
         hds_00_009_001_000       37.531170
         hds_00_013_010_000       34.860771
         hds_00_015_016_000       34.580383
         hds_00_021_010_000       34.844711
         hds_00_022_015_000       34.249882
         hds_00_024_004_000       35.689373
         hds_00_026_006_000       35.276196
         hds_00_029_015_000       34.393169
         hds_00_033_007_000       34.580276
         hds_00_034_010_000       34.191792
         Name: 495, dtype: float64
```

Lets see how our selected truth does with the sw/gw forecasts:

```
In [17]: obs_df.loc[idx,fnames]
```

```
Out[17]: fa_hw_19791230       -718.895900
         fa_hw_19801229        348.943460
         fa_tw_19791230        -38.232140
```

```
fa_tw_19801229        789.050200
hds_00_013_002_000     37.380268
hds_00_013_002_001     36.158752
part_time             466.978300
part_status             2.000000
Name: 495, dtype: float64
```

Assign some initial weights. Now, it is custom to add noise to the observed values…we will use the classic Gaussian noise…zero mean and standard deviation of 1 over the weight

```
In [18]: pst = pyemu.Pst(os.path.join(t_d,"freyberg.pst"))
         obs = pst.observation_data
         obs.loc[:,"obsval"] = obs_df.loc[idx,pst.obs_names]
         obs.loc[obs.obgnme=="calhead","weight"] = 10.0
         obs.loc[obs.obgnme=="calflux","weight"] = 0.01
```

here we just get a sample from a random normal distribution with mean=0 and std=1. The argument indicates how many samples we want - and we choose `pst.nnz_obs` which is the the number of nonzero-weighted observations in the PST file

```
In [19]: np.random.seed(seed=0)
         snd = np.random.randn(pst.nnz_obs)
         noise = snd * 1./obs.loc[pst.nnz_obs_names,"weight"]
         pst.observation_data.loc[noise.index,"obsval"] += noise
         noise
```

```
Out[19]: obsnme
         fo_39_19791230        176.405235
         hds_00_002_009_000      0.040016
         hds_00_002_015_000      0.097874
         hds_00_003_008_000      0.224089
         hds_00_009_001_000      0.186756
         hds_00_013_010_000     -0.097728
         hds_00_015_016_000      0.095009
         hds_00_021_010_000     -0.015136
         hds_00_022_015_000     -0.010322
         hds_00_024_004_000      0.041060
         hds_00_026_006_000      0.014404
         hds_00_029_015_000      0.145427
         hds_00_033_007_000      0.076104
         hds_00_034_010_000      0.012168
         Name: weight, dtype: float64
```

Then we write this out to a new file and run `pestpp-ies` to see how the objective function looks

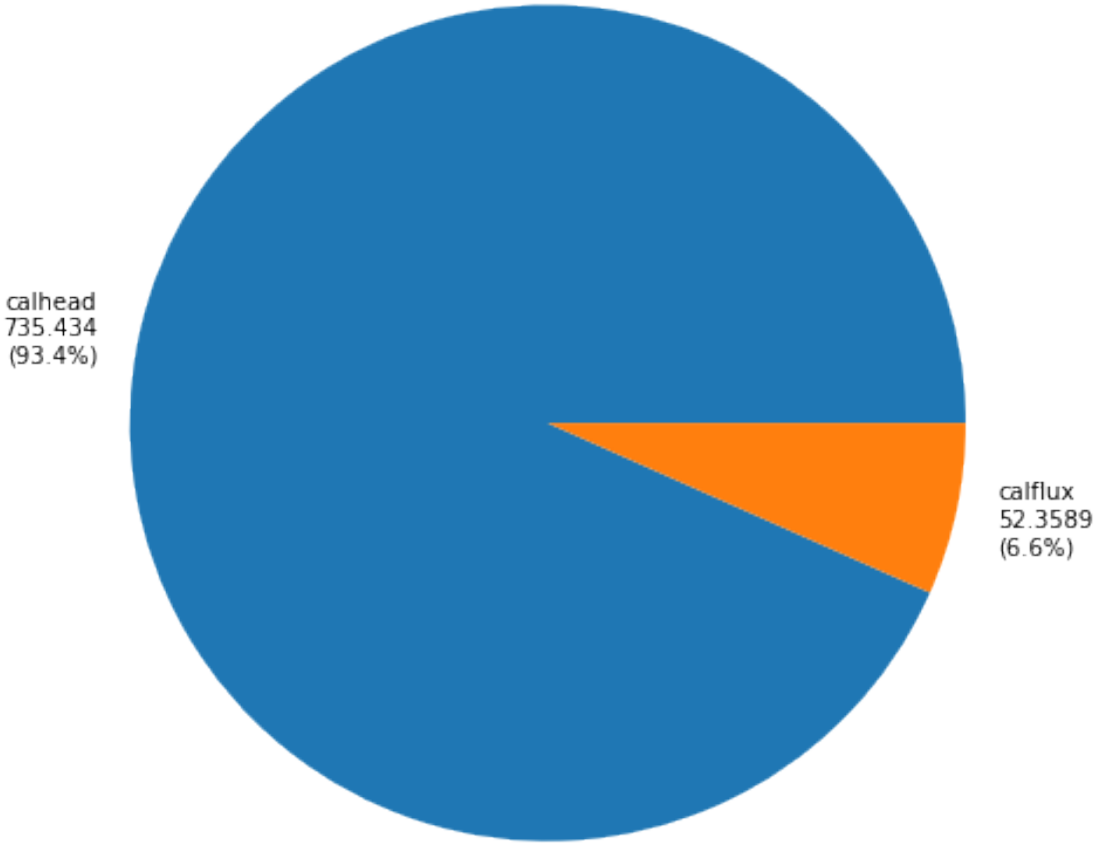
```
In [20]: pst.write(os.path.join(t_d,"freyberg.pst"))
         pyemu.os_utils.run("pestpp-ies freyberg.pst",cwd=t_d)
```

```
noptmax:0, npar_adj:14819, nnz_obs:14
```

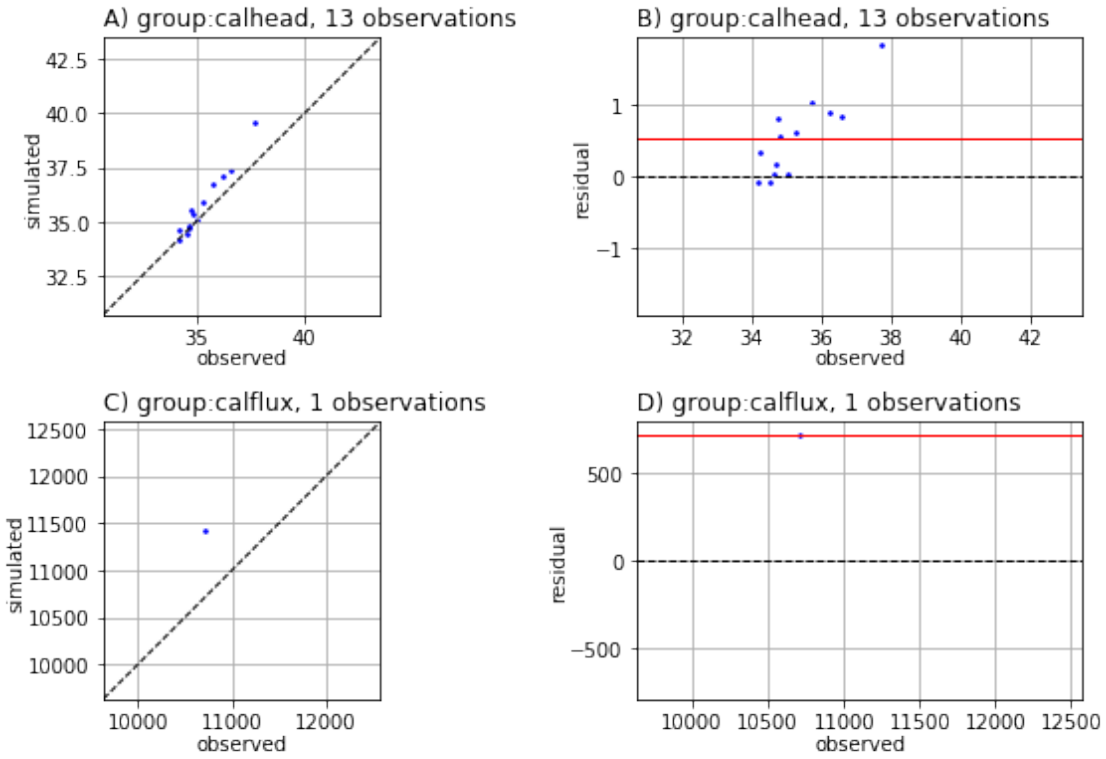
Now we can read in the results and make some figures showing residuals and the balance of the objective function

```
In [21]: pst = pyemu.Pst(os.path.join(t_d,"freyberg.pst"))
         print(pst.phi)
         plt.figure()
         pst.plot(kind='phi_pie')
         print('Here are the non-zero weighted observation names')

         figs = pst.plot(kind="1to1")
         plt.show()
         pst.res.loc[pst.nnz_obs_names,:]
```

```
787.7933620546546
Here are the non-zero weighted observation names


<Figure size 432x288 with 0 Axes>
```




```
<Figure size 576x756 with 0 Axes>
```



Out[21]:

	name	group	measured	modelled	\
name					
fo_39_19791230	fo_39_19791230	calflux	10706.405235	11430.000000	

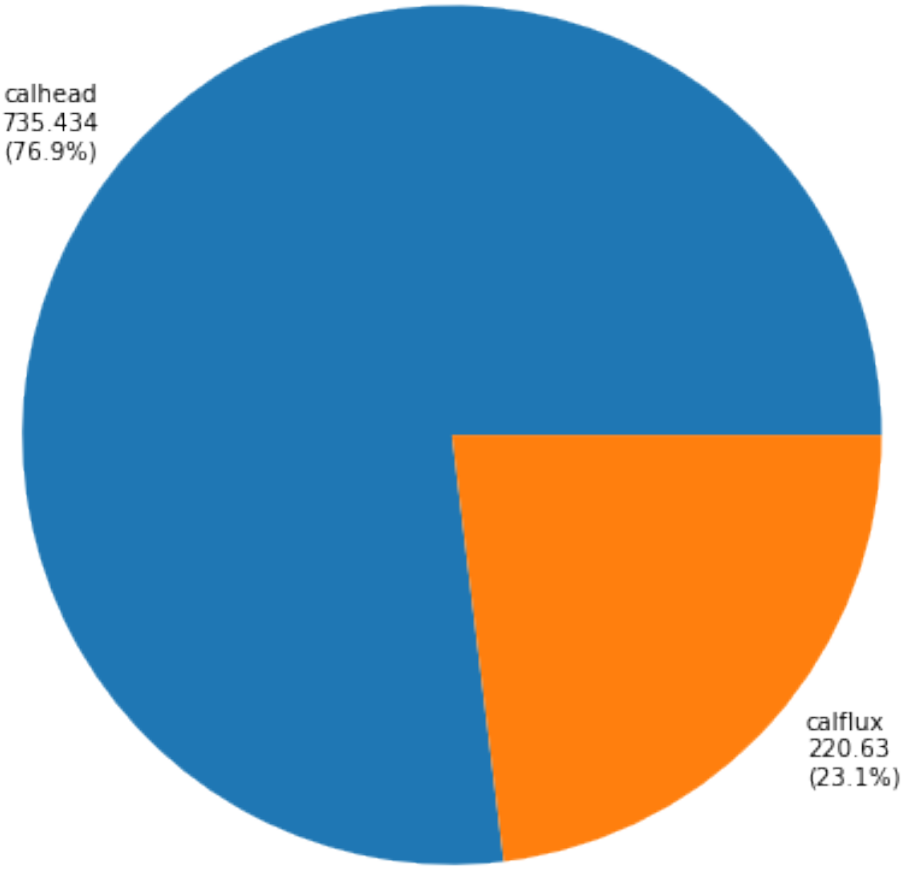
```
hds_00_002_009_000  hds_00_002_009_000  calhead     36.218498     37.107498
hds_00_002_015_000  hds_00_002_015_000  calhead     35.025284     35.045185
hds_00_003_008_000  hds_00_003_008_000  calhead     36.576499     37.397289
hds_00_009_001_000  hds_00_009_001_000  calhead     37.717926     39.546417
hds_00_013_010_000  hds_00_013_010_000  calhead     34.763043     35.571774
hds_00_015_016_000  hds_00_015_016_000  calhead     34.675392     34.835716
hds_00_021_010_000  hds_00_021_010_000  calhead     34.829576     35.386250
hds_00_022_015_000  hds_00_022_015_000  calhead     34.239560     34.577492
hds_00_024_004_000  hds_00_024_004_000  calhead     35.730433     36.760464
hds_00_026_006_000  hds_00_026_006_000  calhead     35.290600     35.896149
hds_00_029_015_000  hds_00_029_015_000  calhead     34.538597     34.453842
hds_00_033_007_000  hds_00_033_007_000  calhead     34.656380     34.678810
hds_00_034_010_000  hds_00_034_010_000  calhead     34.203959     34.118073
```

name	residual	weight
fo_39_19791230	-723.594765	0.01
hds_00_002_009_000	-0.889000	10.00
hds_00_002_015_000	-0.019901	10.00
hds_00_003_008_000	-0.820791	10.00
hds_00_009_001_000	-1.828492	10.00
hds_00_013_010_000	-0.808730	10.00
hds_00_015_016_000	-0.160324	10.00
hds_00_021_010_000	-0.556674	10.00
hds_00_022_015_000	-0.337932	10.00
hds_00_024_004_000	-1.030031	10.00
hds_00_026_006_000	-0.605549	10.00
hds_00_029_015_000	0.084755	10.00
hds_00_033_007_000	-0.022430	10.00
hds_00_034_010_000	0.085887	10.00

Depending on the truth you chose, we may have a problem - we set the weights for both the heads and the flux to reasonable values based on what we expect for measurement noise. But the contributions to total phi might be out of balance - if contribution of the flux measurement to total phi is too low, the history matching excersizes (coming soon!) will focus almost entirely on minimizing head residuals. So we need to balance the objective function. This is a subtle but very important step, especially since some of our forecasts deal with sw-gw exchange

In [22]:
```
pc = pst.phi_components
target = {"calflux":0.3 * pc["calhead"]}
#target = {"calhead":500,"calflux":500}
pst.adjust_weights(obsgrp_dict=target)
pst.plot(kind='phi_pie')
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x10a281dd8>
```



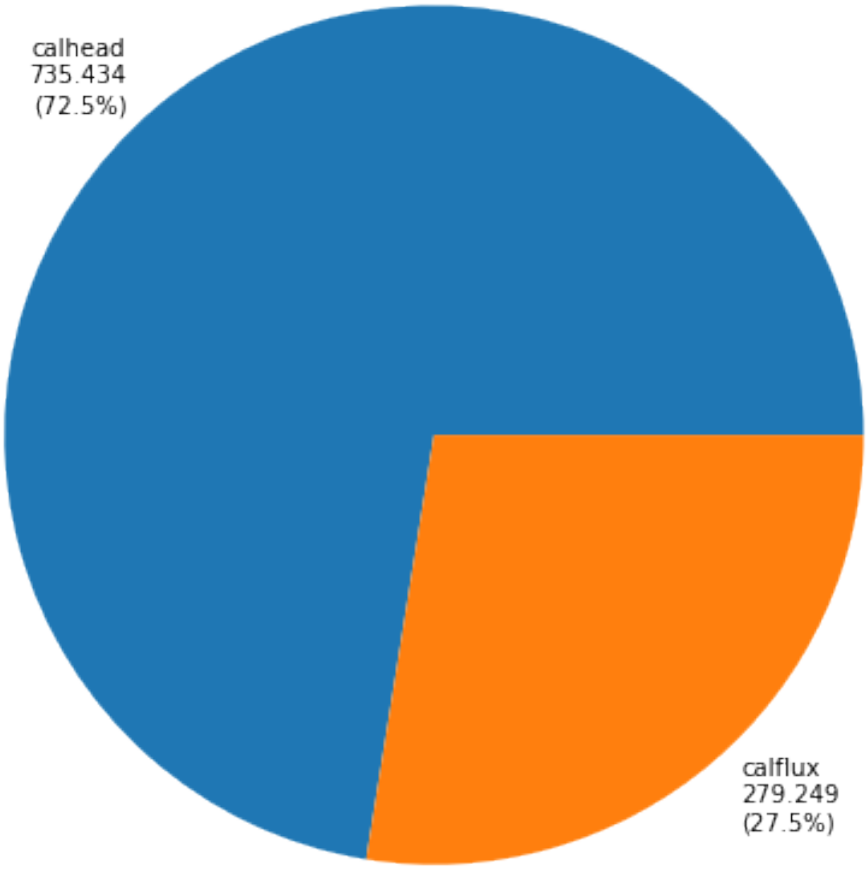
Lets see what the new flux observation weight is:

```
In [23]: pst.observation_data.loc[pst.nnz_obs_names,"weight"]

Out[23]: obsnme
         fo_39_19791230          0.020528
         hds_00_002_009_000     10.000000
         hds_00_002_015_000     10.000000
         hds_00_003_008_000     10.000000
         hds_00_009_001_000     10.000000
         hds_00_013_010_000     10.000000
         hds_00_015_016_000     10.000000
         hds_00_021_010_000     10.000000
         hds_00_022_015_000     10.000000
```

```
hds_00_024_004_000    10.000000
hds_00_026_006_000    10.000000
hds_00_029_015_000    10.000000
hds_00_033_007_000    10.000000
hds_00_034_010_000    10.000000
Name: weight, dtype: float64
```

Now, for some super trickery: since we changed the weight, we need to generate the observation noise using these new weights for the error model (so meta!)

```
In [24]: obs = pst.observation_data
         np.random.seed(seed=0)
         snd = np.random.randn(pst.nnz_obs)
         noise = snd * 1./obs.loc[pst.nnz_obs_names,"weight"]
         obs.loc[:,"obsval"] = obs_df.loc[idx,pst.obs_names]
         pst.observation_data.loc[noise.index,"obsval"] += noise
         noise

Out[24]: obsnme
         fo_39_19791230        85.935831
         hds_00_002_009_000     0.040016
         hds_00_002_015_000     0.097874
         hds_00_003_008_000     0.224089
         hds_00_009_001_000     0.186756
         hds_00_013_010_000    -0.097728
         hds_00_015_016_000     0.095009
         hds_00_021_010_000    -0.015136
         hds_00_022_015_000    -0.010322
         hds_00_024_004_000     0.041060
         hds_00_026_006_000     0.014404
         hds_00_029_015_000     0.145427
         hds_00_033_007_000     0.076104
         hds_00_034_010_000     0.012168
         Name: weight, dtype: float64

In [25]: pst.write(os.path.join(t_d,"freyberg.pst"))
         pyemu.os_utils.run("pestpp-ies freyberg.pst",cwd=t_d)
         pst = pyemu.Pst(os.path.join(t_d,"freyberg.pst"))
         print(pst.phi)
         pst.plot(kind='phi_pie')
         plt.show()

noptmax:0, npar_adj:14819, nnz_obs:14
1014.6834424969986
```



Whew! confused yet? Ok, let's leave all this confusion behind...its mostly academic, just to make sure we are using weights that are in harmony with the noise we added to the truth...Just to make sure we have everything working right, we should be able to load the truth parameters, run the model once and have a `phi` equivalent to the noise vector:

```
In [26]: par_df = pd.read_csv(os.path.join(m_d,"sweep_in.csv"),index_col=0)
         pst.parameter_data.loc[:,"parval1"] = par_df.loc[idx,pst.par_names]
         pst.write(os.path.join(m_d,"test.pst"))

noptmax:0, npar_adj:14819, nnz_obs:14
```

we will run this with `noptmax=0` to preform a single run. Pro-tip: you can use any of the `pestpp-###` binaries/executables to run `noptmax=0`

```
In [27]: pyemu.os_utils.run("pestpp-ies.exe test.pst",cwd=m_d)
         pst = pyemu.Pst(os.path.join(m_d,"test.pst"))
         print(pst.phi)
         pst.res.loc[pst.nnz_obs_names,:]
```

```
17.528847263871818
```

Out[27]:

	name	group	measured	modelled	residual	weight
name						
fo_39_19791230	fo_39_19791230	calflux	10615.935831	10530.000000	85.935831	0.020528
hds_00_002_009_000	hds_00_002_009_000	calhead	36.218498	36.178482	0.040016	10.000000
hds_00_002_015_000	hds_00_002_015_000	calhead	35.025284	34.927410	0.097874	10.000000
hds_00_003_008_000	hds_00_003_008_000	calhead	36.576499	36.352409	0.224089	10.000000
hds_00_009_001_000	hds_00_009_001_000	calhead	37.717926	37.531170	0.186756	10.000000
hds_00_013_010_000	hds_00_013_010_000	calhead	34.763043	34.860771	-0.097728	10.000000
hds_00_015_016_000	hds_00_015_016_000	calhead	34.675392	34.580383	0.095009	10.000000
hds_00_021_010_000	hds_00_021_010_000	calhead	34.829576	34.844711	-0.015136	10.000000
hds_00_022_015_000	hds_00_022_015_000	calhead	34.239560	34.249882	-0.010322	10.000000
hds_00_024_004_000	hds_00_024_004_000	calhead	35.730433	35.689373	0.041060	10.000000
hds_00_026_006_000	hds_00_026_006_000	calhead	35.290600	35.276196	0.014404	10.000000
hds_00_029_015_000	hds_00_029_015_000	calhead	34.538597	34.393169	0.145427	10.000000
hds_00_033_007_000	hds_00_033_007_000	calhead	34.656380	34.580276	0.076104	10.000000
hds_00_034_010_000	hds_00_034_010_000	calhead	34.203959	34.191792	0.012168	10.000000

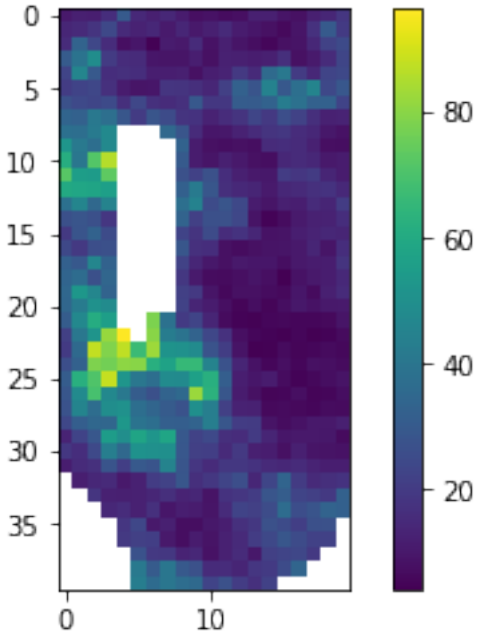
The residual should be exactly the noise values from above. Lets load the model (that was just run using the true pars) and check some things

```
In [28]: m = flopy.modflow.Modflow.load("freyberg.nam",model_ws=m_d)
```

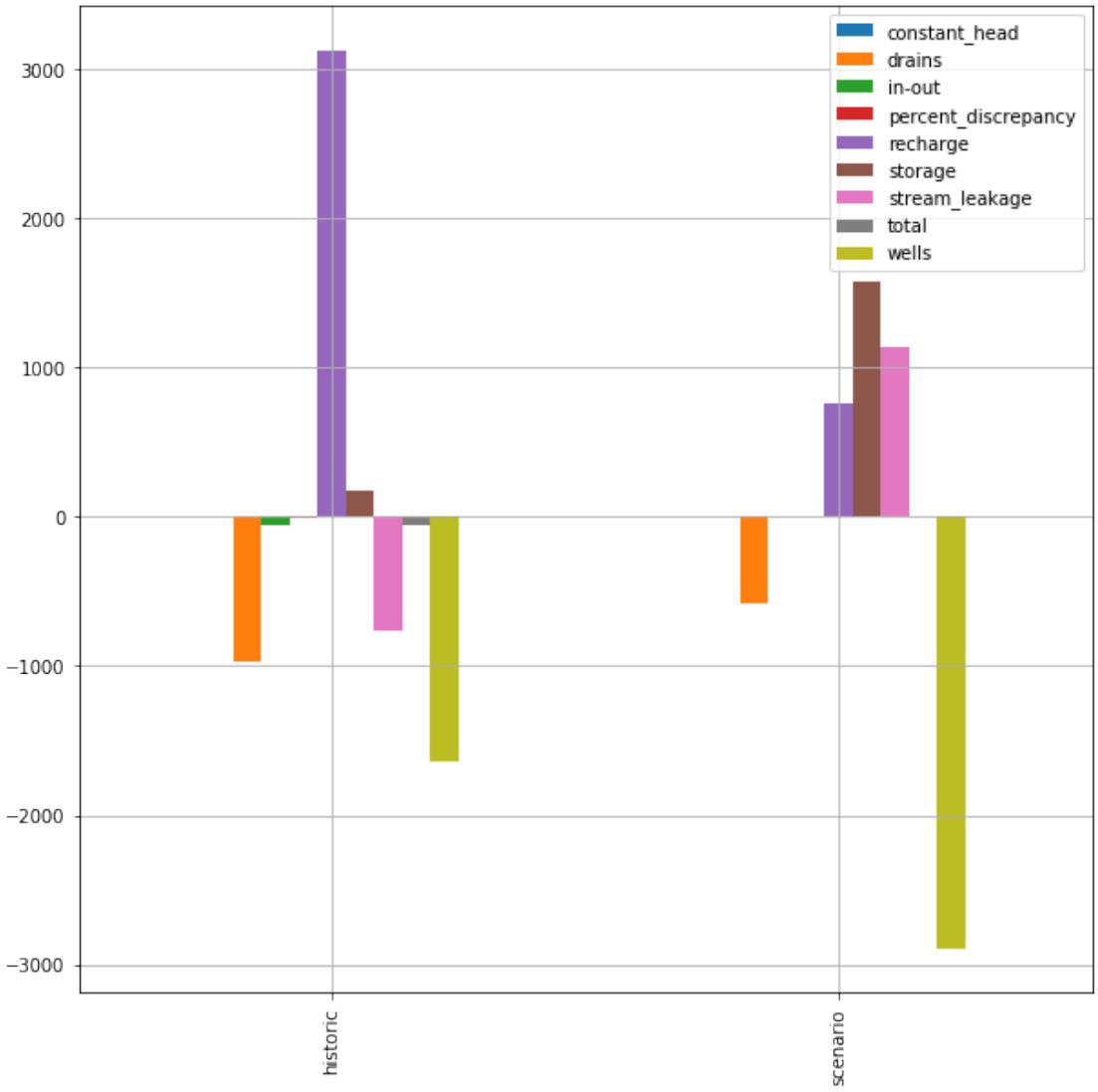
```
In [29]: a = m.upw.hk[0].array
         #a = m.rch.rech[0].array
```

```
        a = np.ma.masked_where(m.bas6.ibound[0].array==0,a)
        print(a.min(),a.max())
        c = plt.imshow(a)
        plt.colorbar()
        plt.show()
```

```
4.05637 96.48033
```



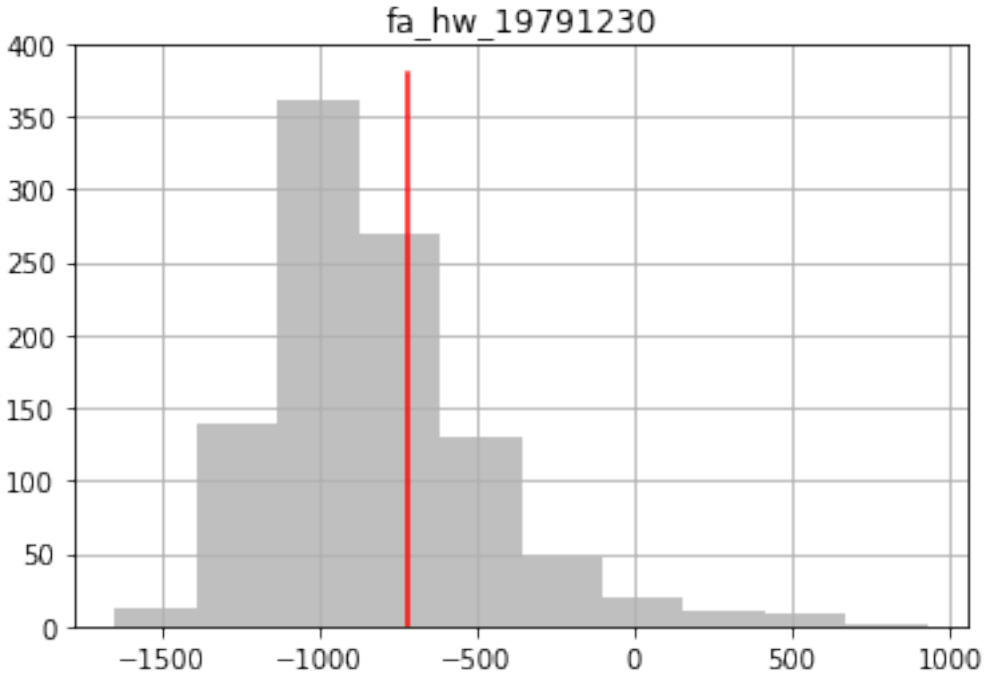

```
In [30]: lst = flopy.utils.MfListBudget(os.path.join(m_d,"freyberg.list"))
         df = lst.get_dataframes(diff=True)[0]
         ax = df.plot(kind="bar",figsize=(10,10), grid=True)
         a = ax.set_xticklabels(["historic","scenario"],rotation=90)
         plt.show(ax)
```

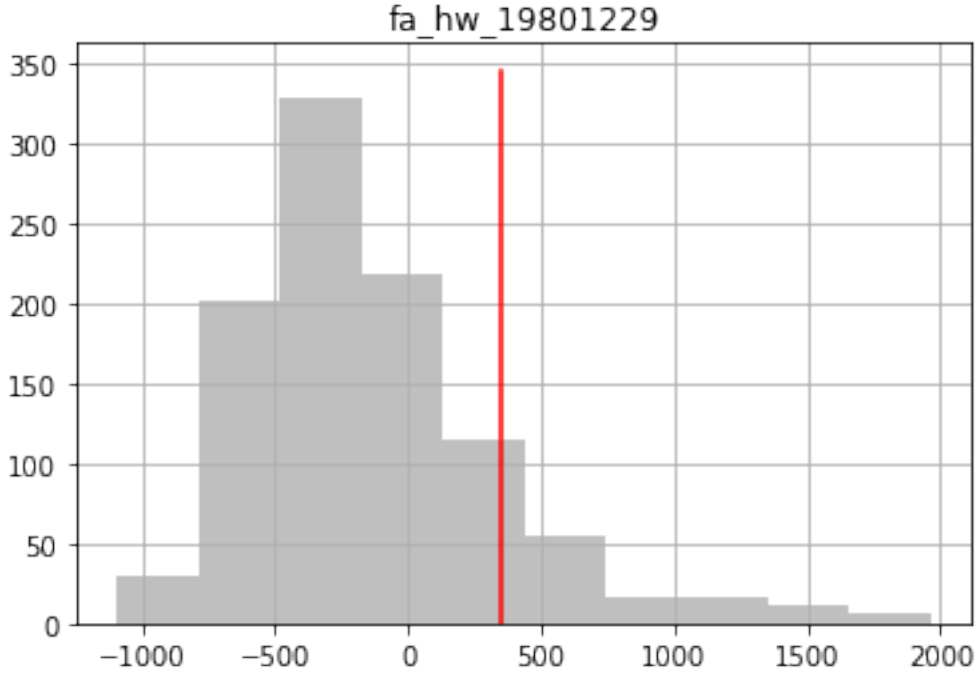


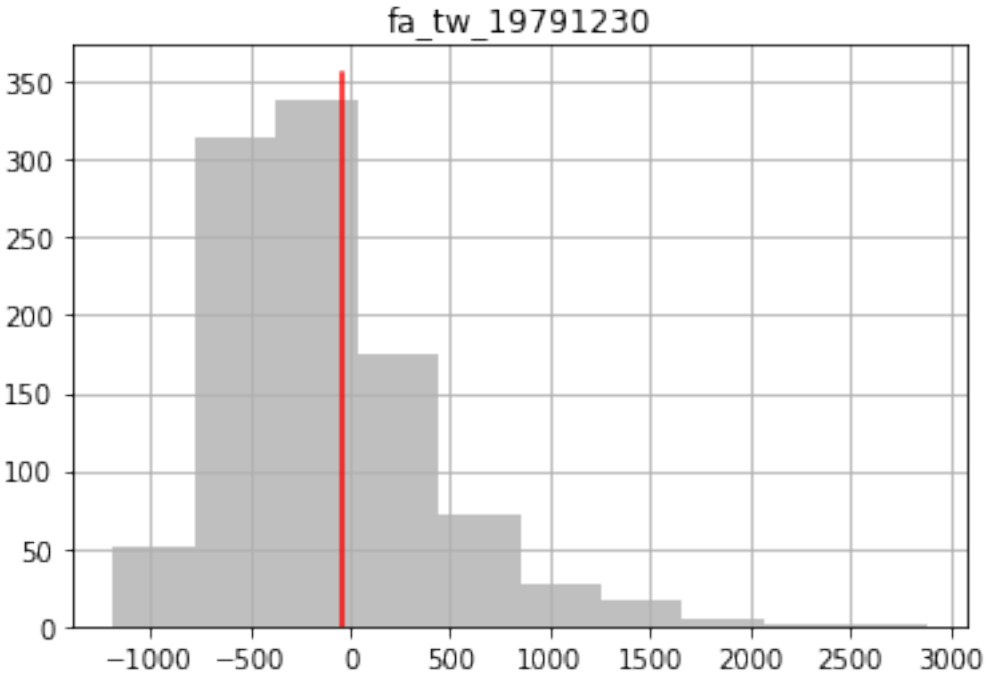
1.1.8 see how our existing observation ensemble compares to the truth

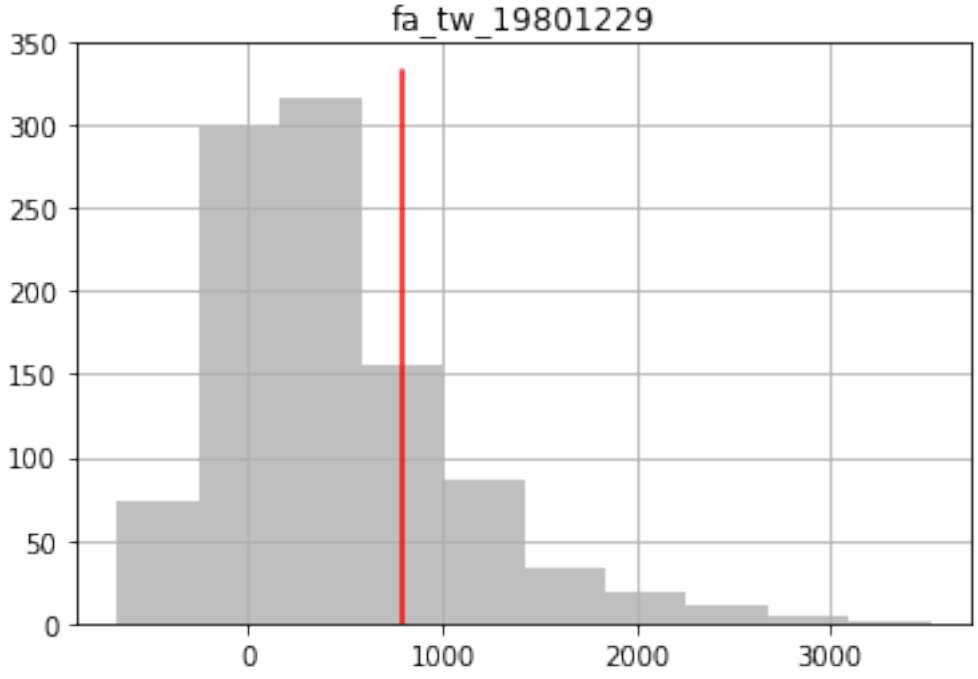
forecasts:

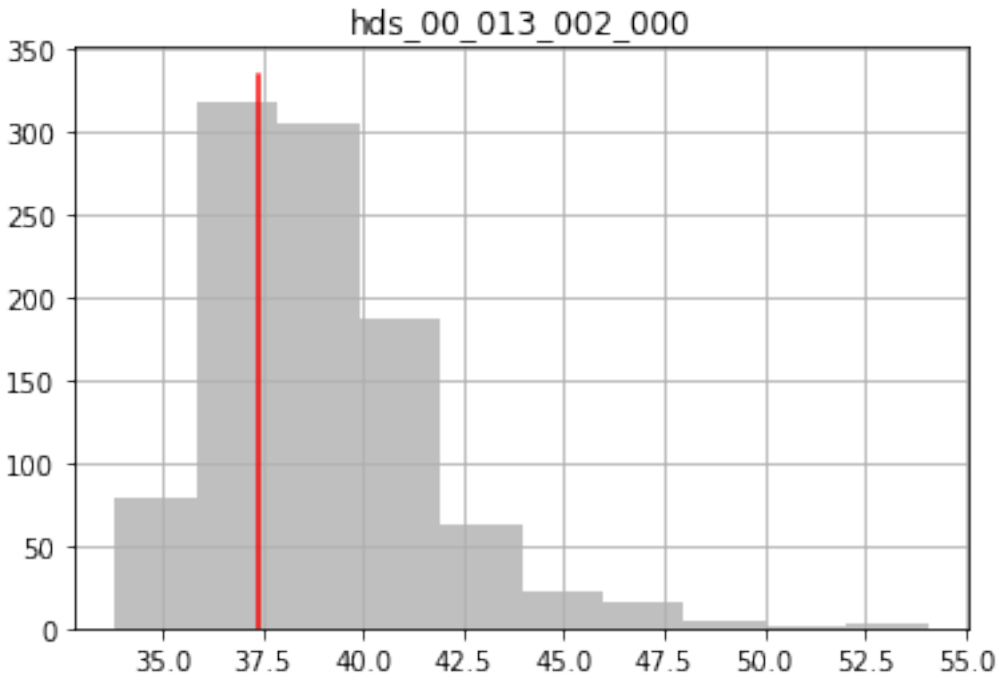
```
In [31]: obs = pst.observation_data
         plt.figure()
         for forecast in fnames:
             ax = plt.subplot(111)
             obs_df.loc[:,forecast].hist(ax=ax,color="0.5",alpha=0.5)
             ax.plot([obs.loc[forecast,"obsval"],obs.loc[forecast,"obsval"]],ax.get_ylim(),"r"
             ax.set_title(forecast)
             plt.show()
```


fa_hw_19791230
400
350
300
250
200
150
100
50
0
−1500
−1000
−500
0
500
1000


fa_hw_19801229
350
300
250
200
150
100
50
0
−1000
−500
0
500
1000
1500
2000


fa_tw_19791230
350
300
250
200
150
100
50
0
−1000
−500
0
500
1000
1500
2000
2500
3000


fa_tw_19801229
350
300
250
200
150
100
50
0
0
1000
2000
3000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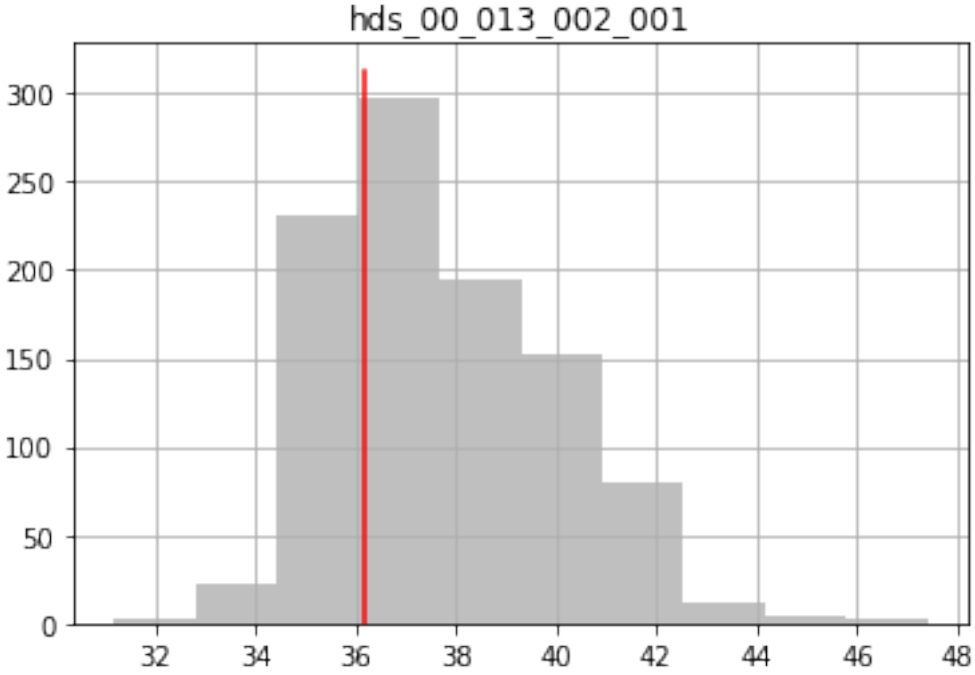
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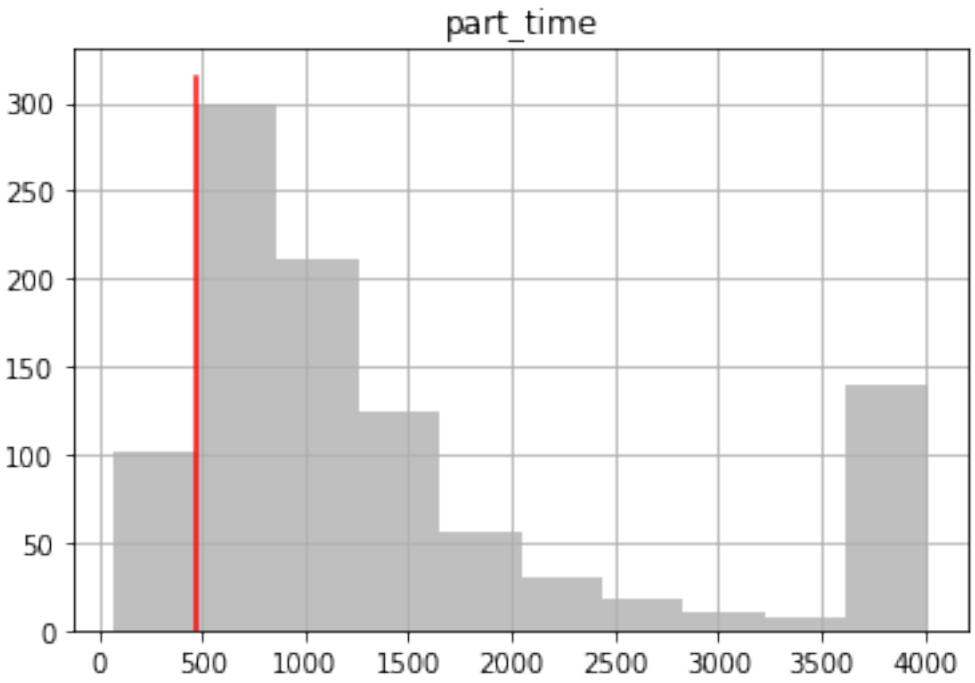
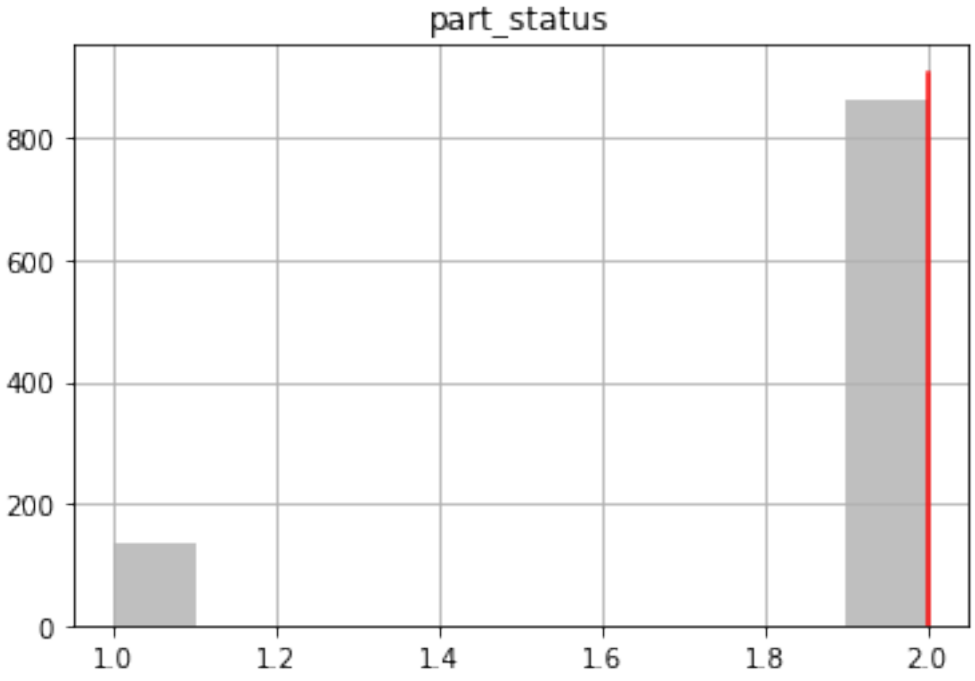
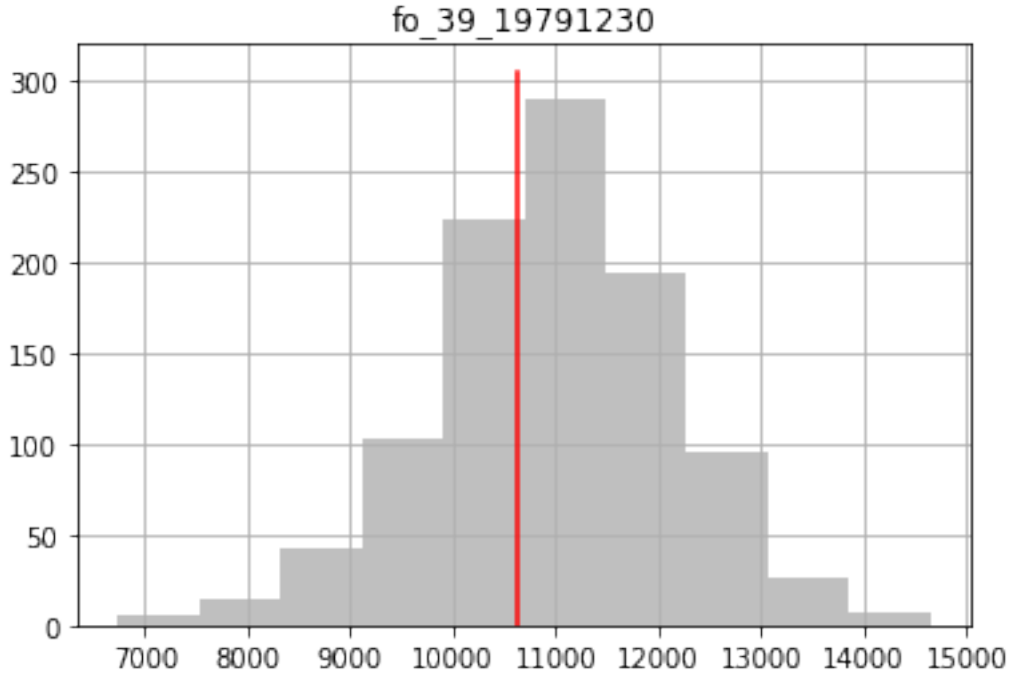
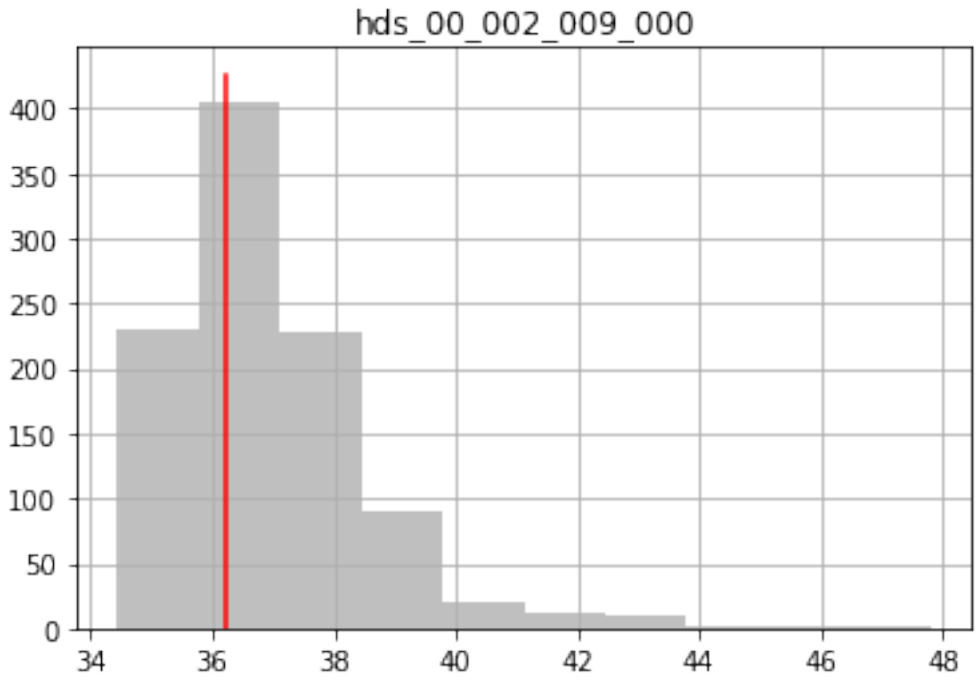




observations:

```
In [32]: for oname in pst.nnz_obs_names:
             ax = plt.subplot(111)
             obs_df.loc[:,oname].hist(ax=ax,color="0.5",alpha=0.5)
             ax.plot([obs.loc[oname,"obsval"],obs.loc[oname,"obsval"]],ax.get_ylim(),"r")
             ax.set_title(oname)
             plt.show()
```

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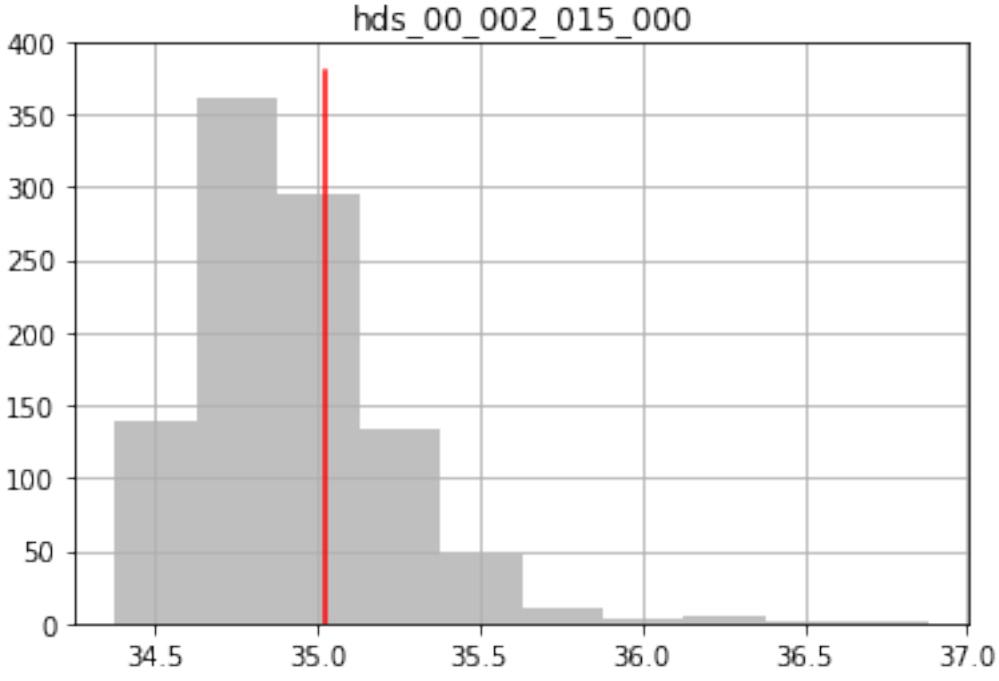
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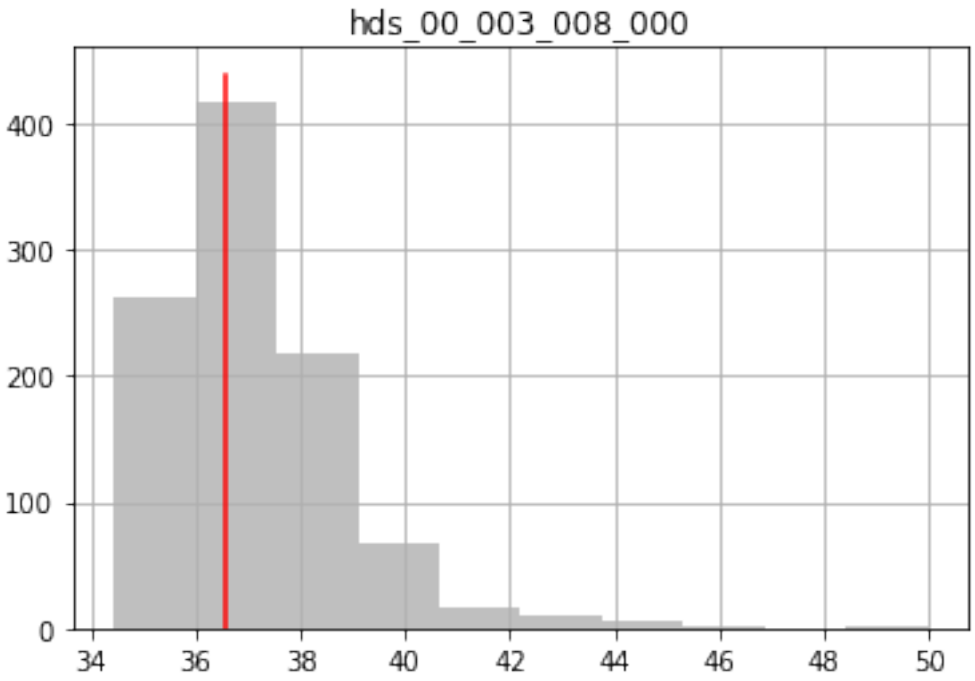
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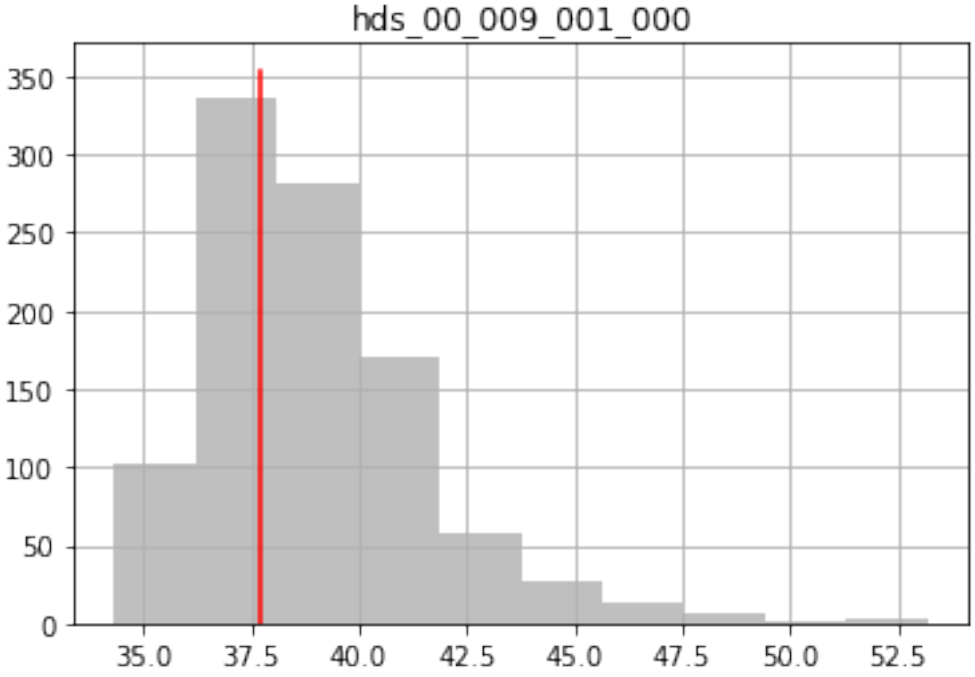
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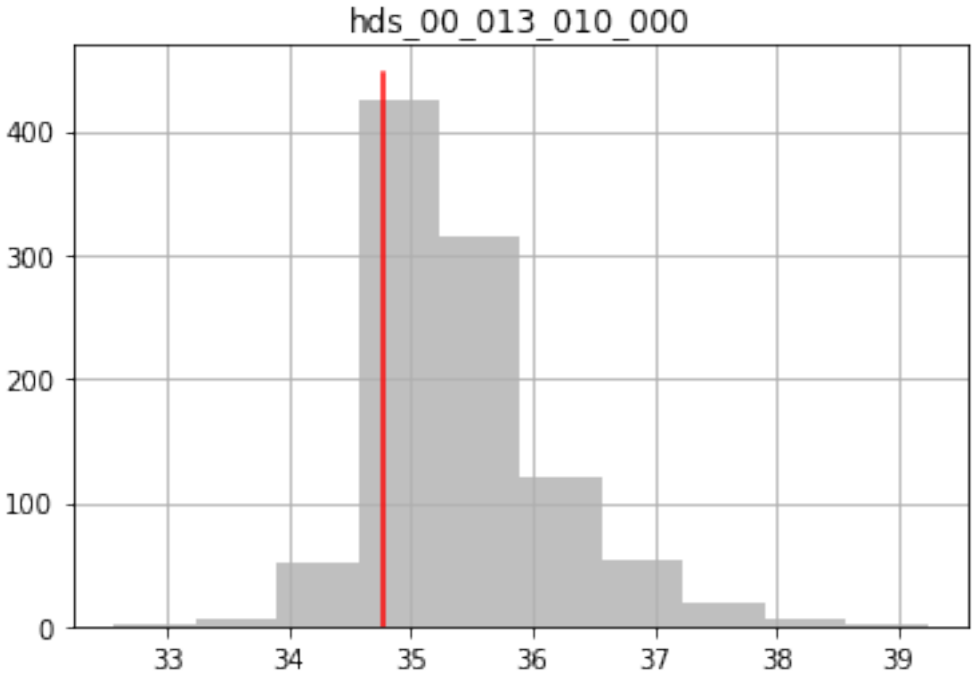
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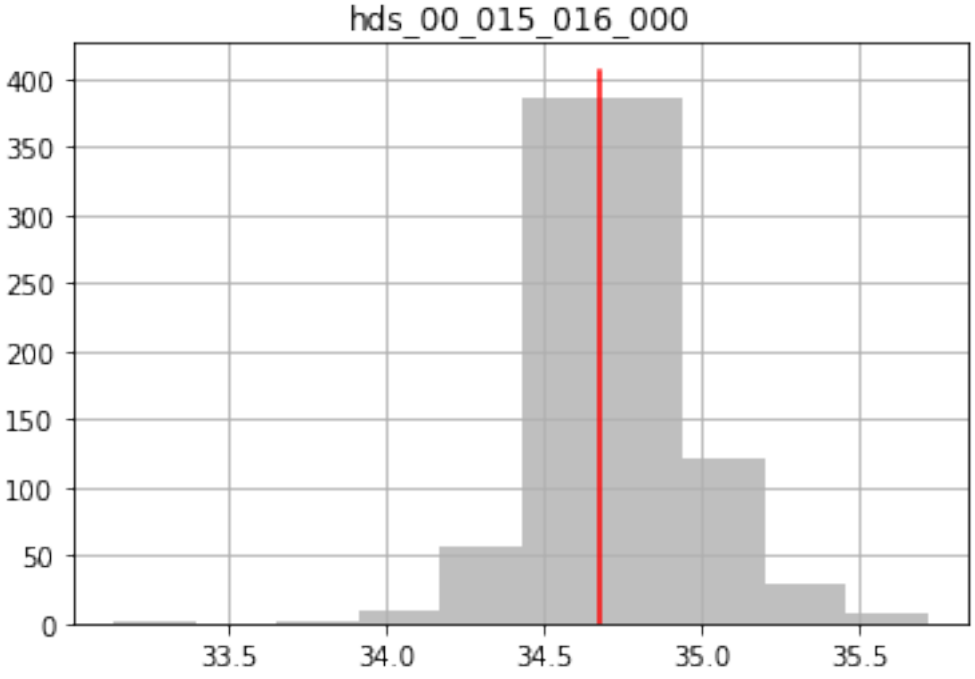
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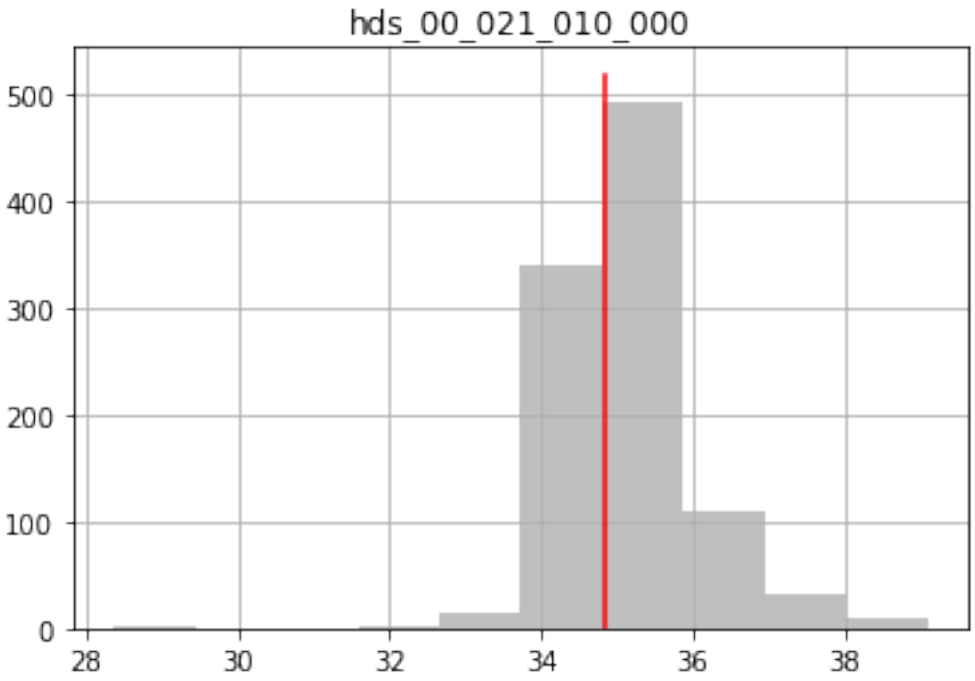
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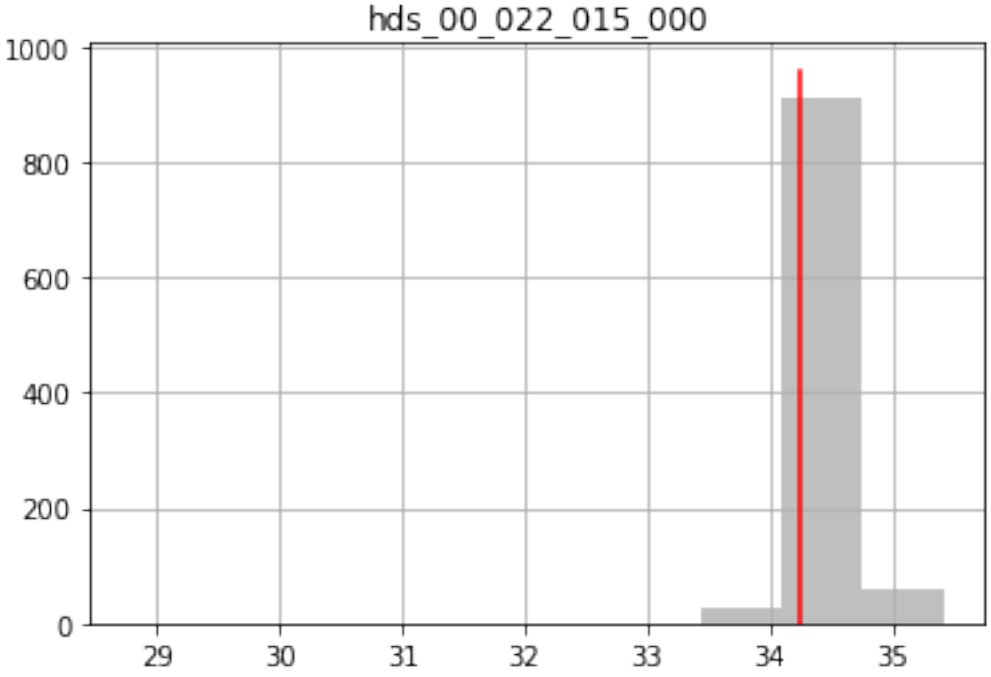
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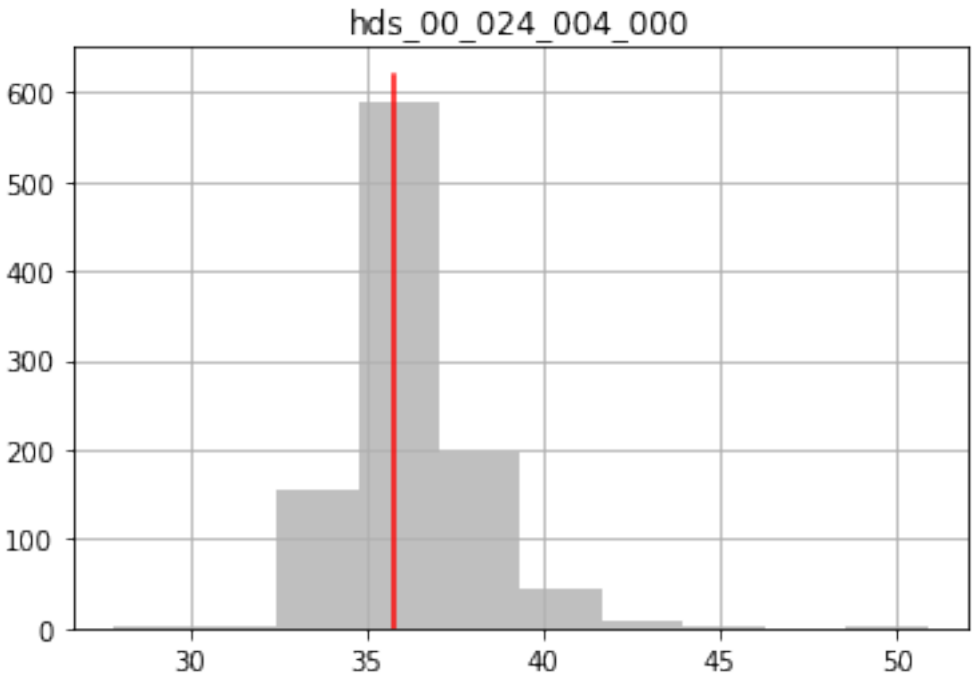
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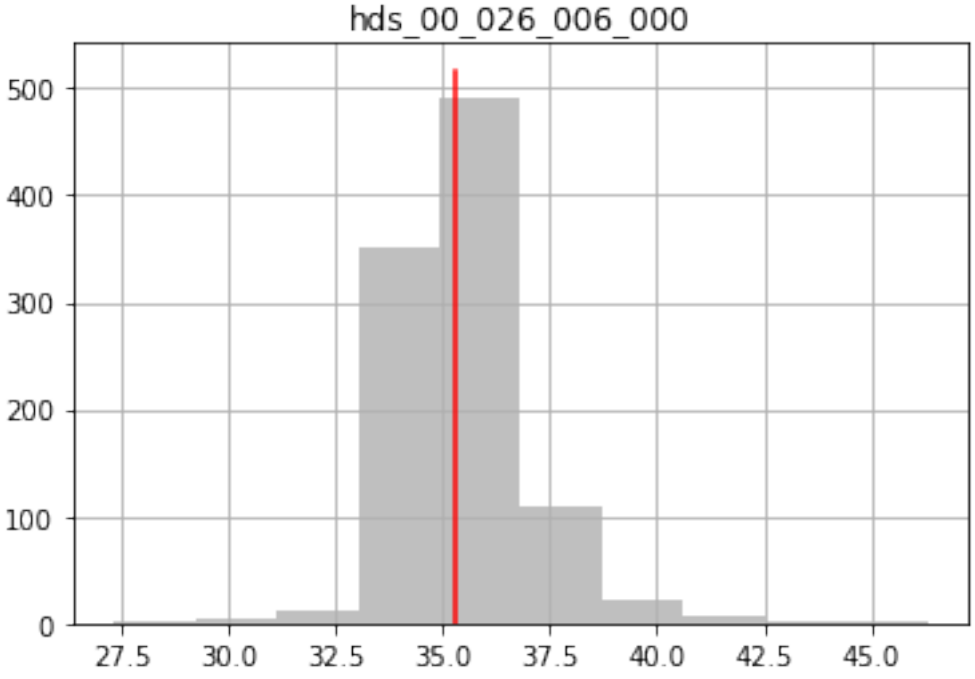
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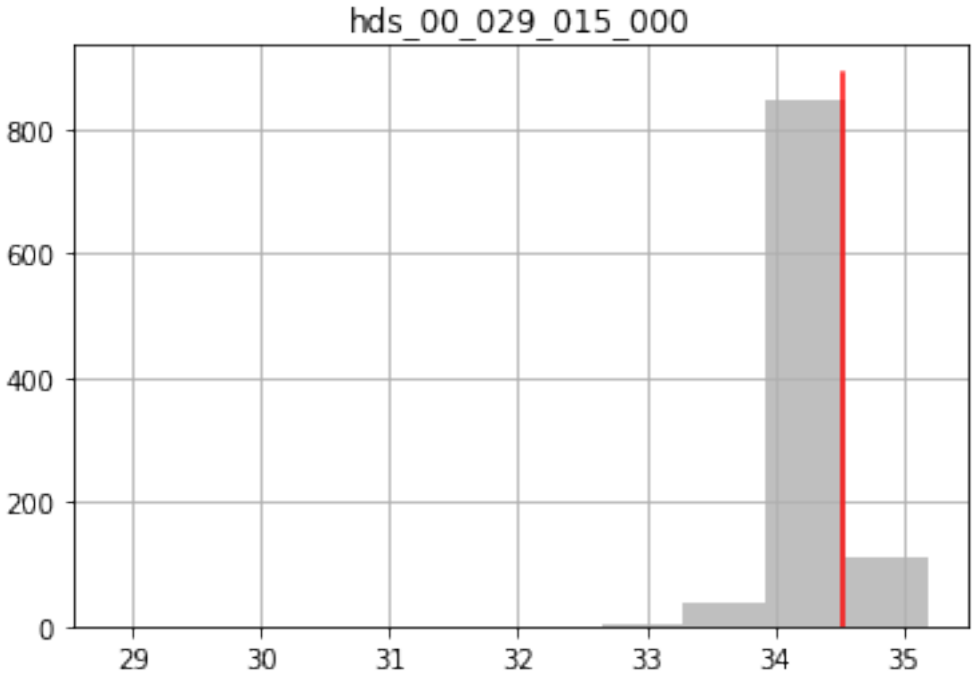
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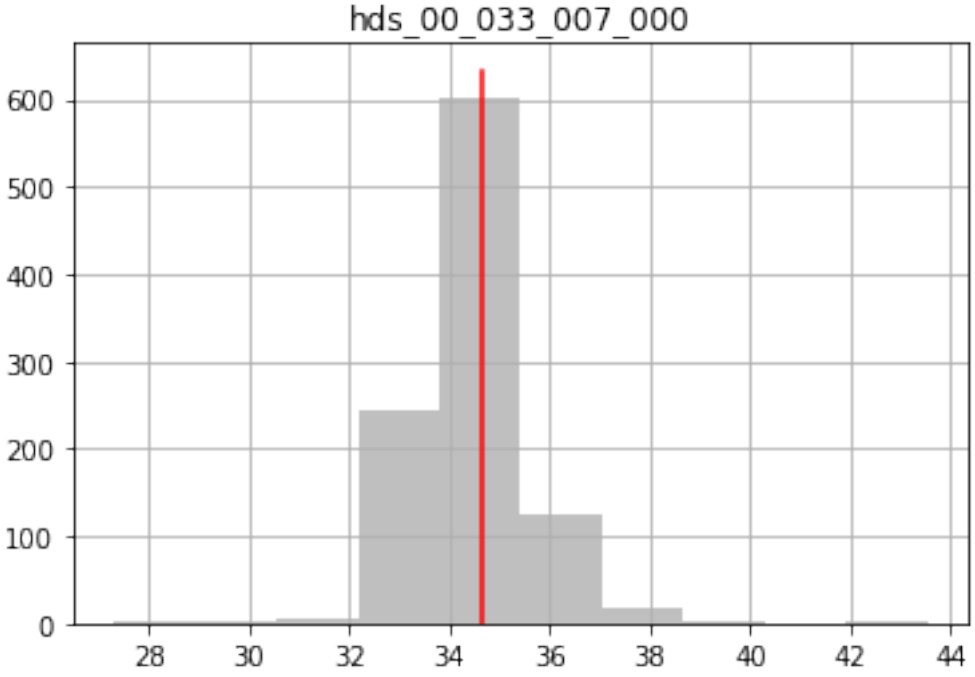
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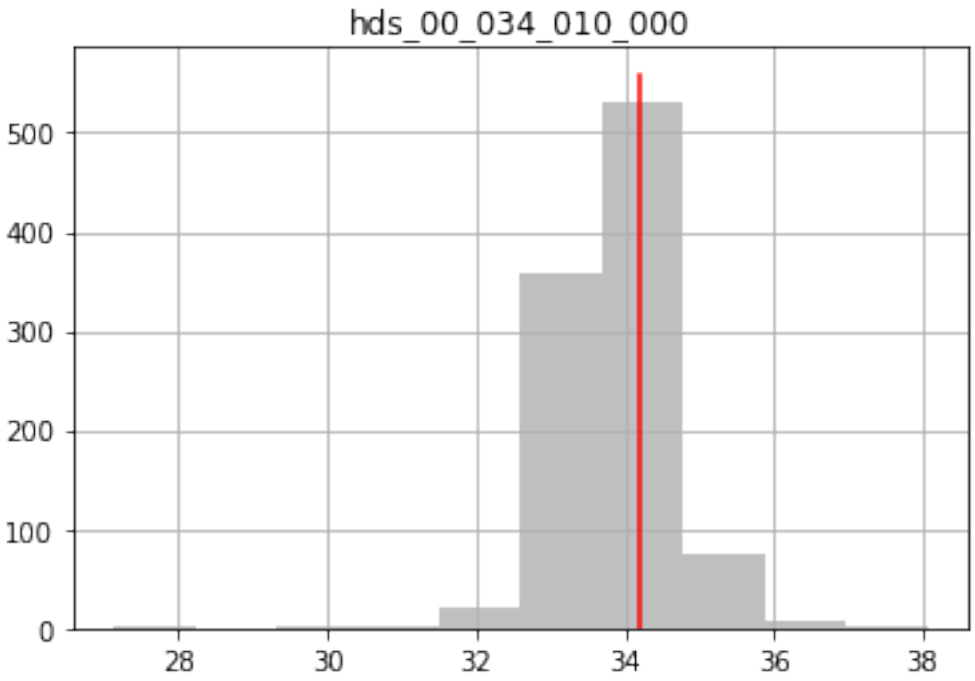
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