prior_montecarlo

June 5, 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
        %matplotlib inline
```

```
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 = 10
```

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)

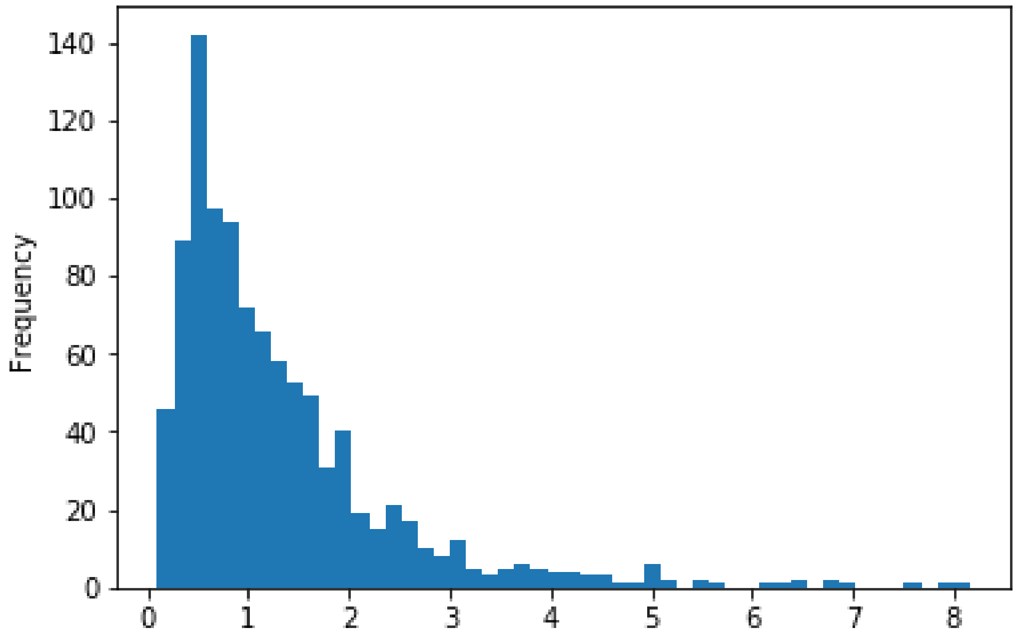
In [6]:
```
pe.loc[:,"hk031"]
```

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]: pe.loc[:,"hk031"].plot.hist(bins=50)
```

```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1818ea1eb8>
```



look! hk is log-normal-ish

```
In [8]: 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[8]:                                        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

name	modelled	residual	weight
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 [9]: m_d = "master_prior_sweep"
        pyemu.os_utils.start_slaves(t_d,"pestpp-swp","freyberg.pst",num_slaves=num_workers,slav
```

1.1.4 Load the output ensemble and plot a few things

```
In [10]: 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
```

1.1.5 drop any failed runs

```
In [11]: 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 [12]: obs_df.iloc[0,:]

Out[12]: 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
obgnme                    0.000000e+00
vol_in-out                0.000000e+00
flx_wells                 0.000000e+00
flx_storage               0.000000e+00
vol_wells                 0.000000e+00
vol_total                 0.000000e+00
flaqx                     0.000000e+00
flx_drains                0.000000e+00
flx_constan               0.000000e+00
vol_stream_               0.000000e+00
hds                       0.000000e+00
flx_total                 0.000000e+00
calflux                   1.887876e+06
vol_recharg               0.000000e+00
flout                     0.000000e+00
vol_storage               0.000000e+00
flx_in-out                0.000000e+00
vol_drains                0.000000e+00
vol_constan               0.000000e+00
vol_percent               0.000000e+00
flx_recharg               0.000000e+00
calhead                   1.875375e+01
flx_stream_               0.000000e+00
flx_percent               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
```

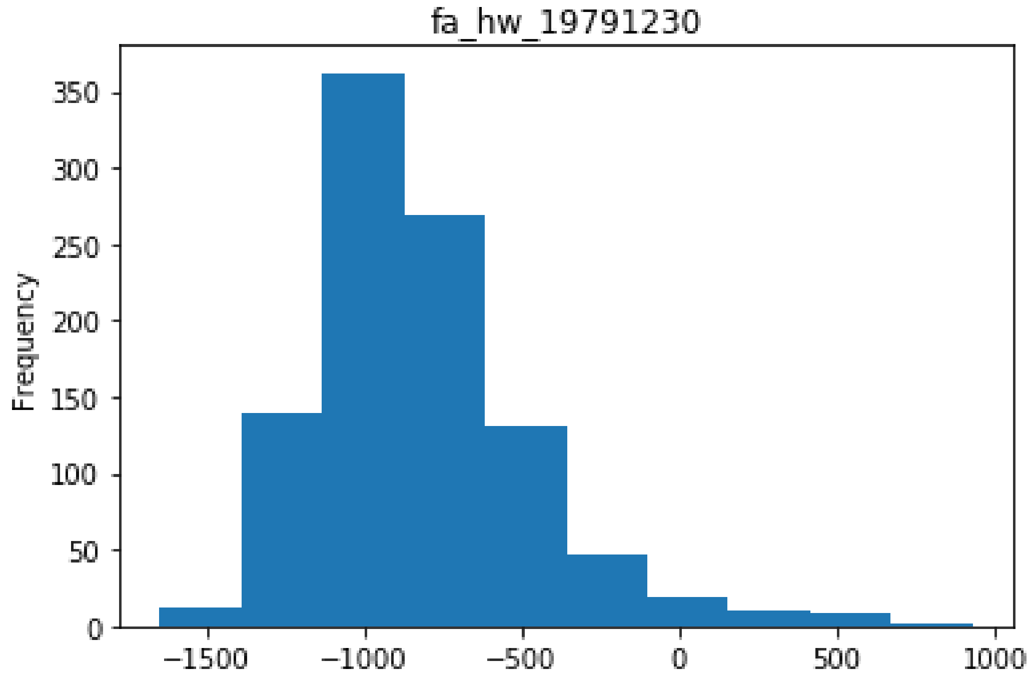
1.1.6 confirm which quantities were identified as forecasts

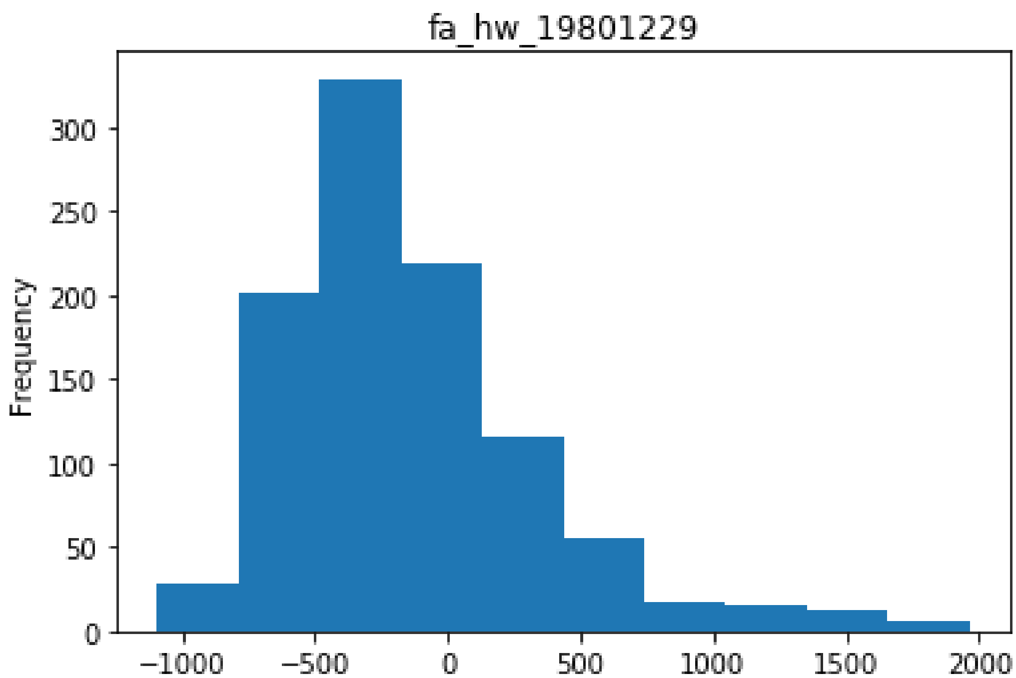
```
In [13]: fnames = pst.pestpp_options["forecasts"].split(',')
         fnames
```

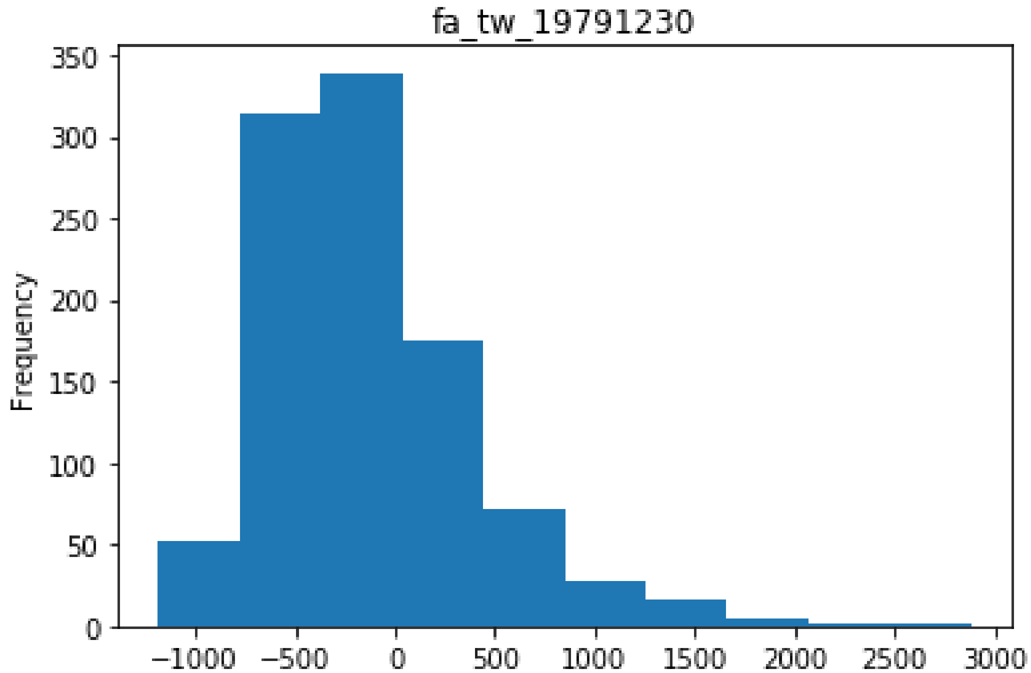
```
Out[13]: ['fa_hw_19791230',
          'fa_hw_19801229',
          'fa_tw_19791230',
          'fa_tw_19801229',
          'hds_00_013_002_000',
          'hds_00_013_002_001',
          'part_time',
          'part_status']
```

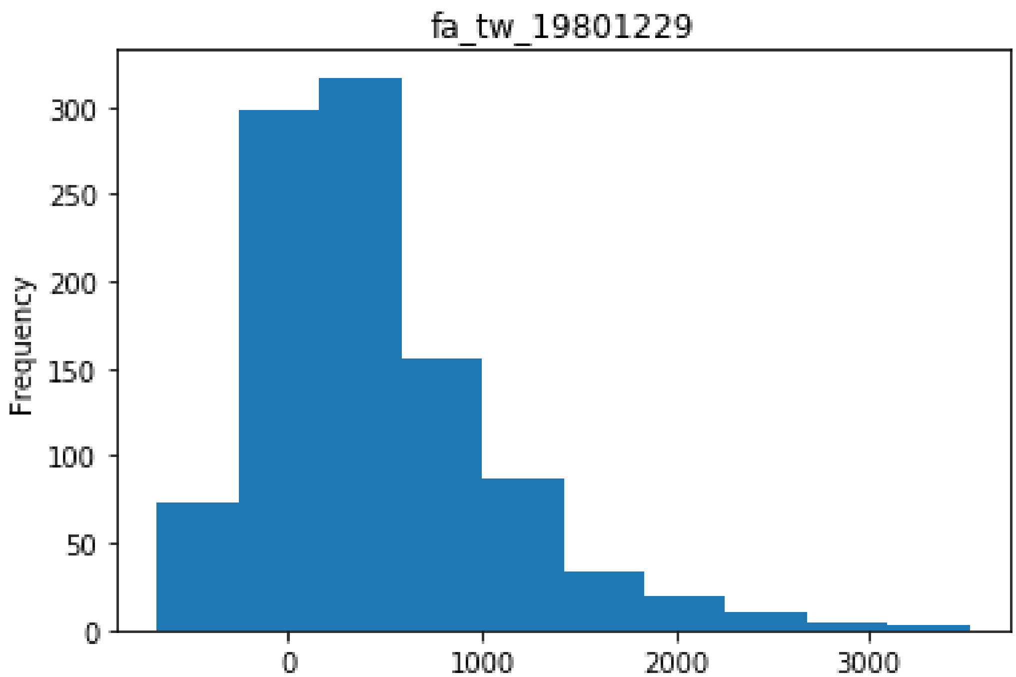
1.1.7 now we can plot the distributions of each forecast

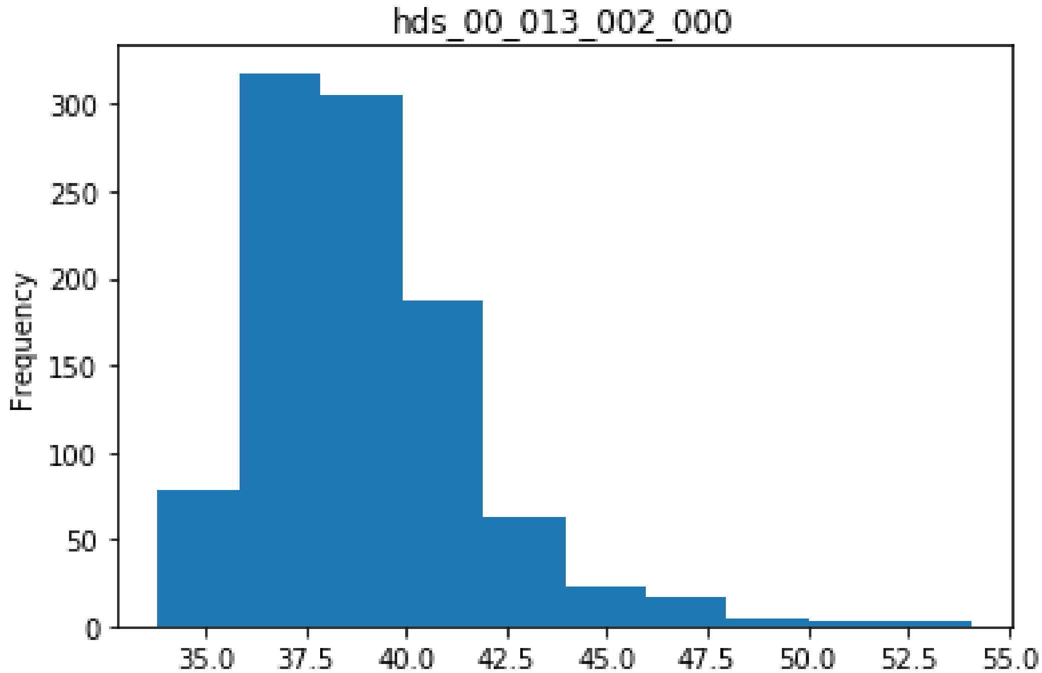
```
In [14]: for forecast in fnames:
             plt.figure()
             ax = obs_df.loc[:,forecast].plot(kind="hist")
             ax.set_title(forecast)
```

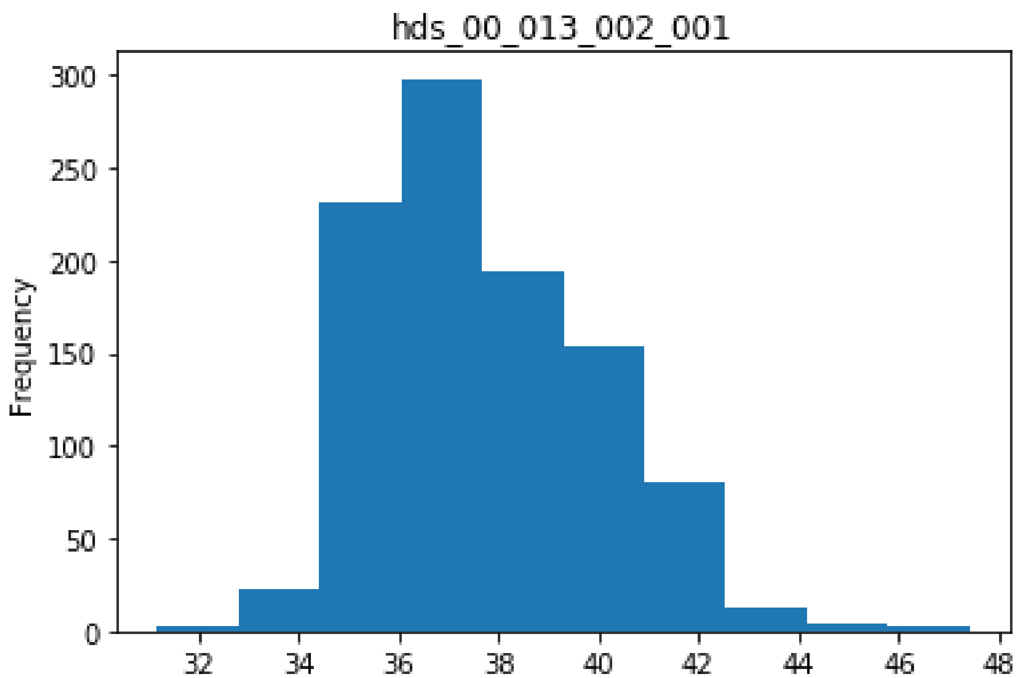

fa_hw_19791230
Frequency
0
50
100
150
200
250
300
350
−1500
−1000
−500
0
500
1000

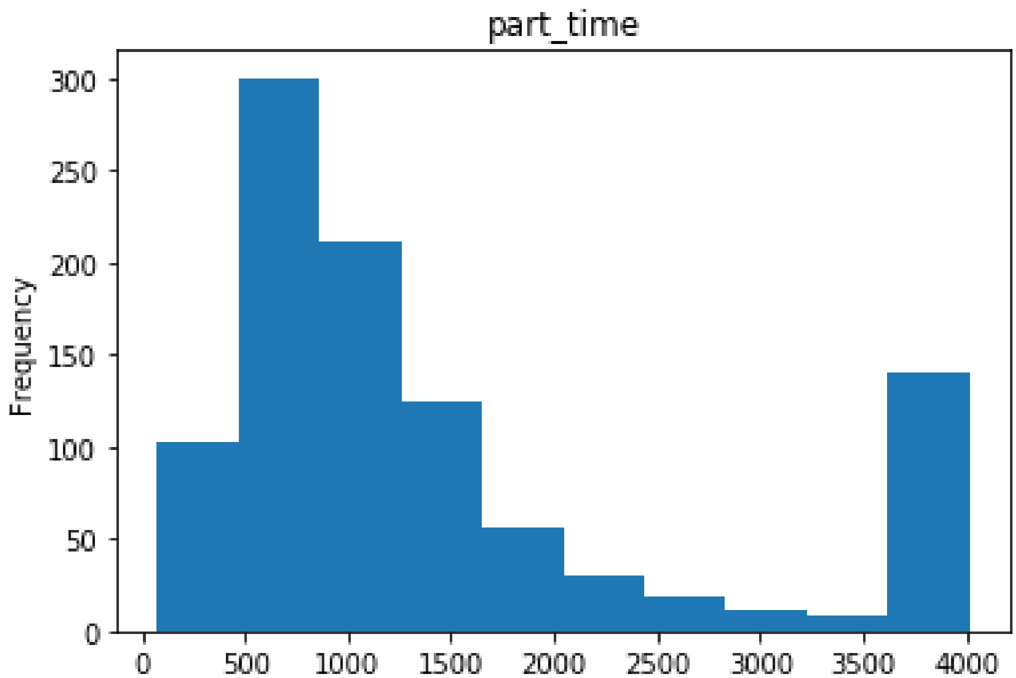

fa_hw_19801229
Frequency
0
50
100
150
200
250
300
−1000
−500
0
500
1000
1500
2000

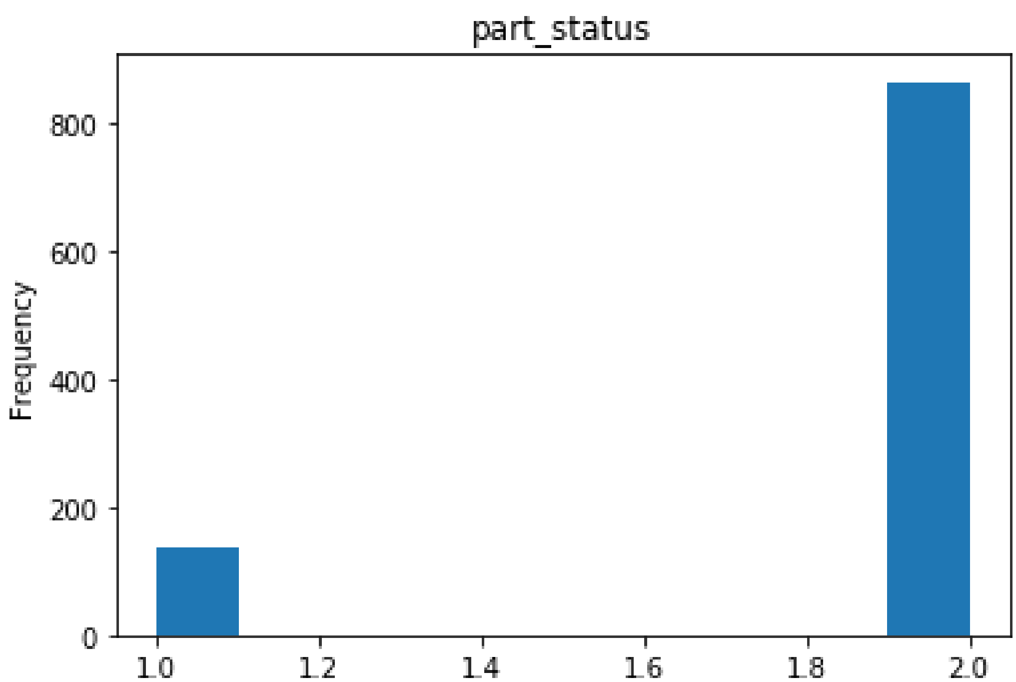

fa_tw_19791230
Frequency
0
50
100
150
200
250
300
350
−1000
−500
0
500
1000
1500
2000
2500
3000


fa_tw_19801229
Frequency
0
50
100
150
200
250
300
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

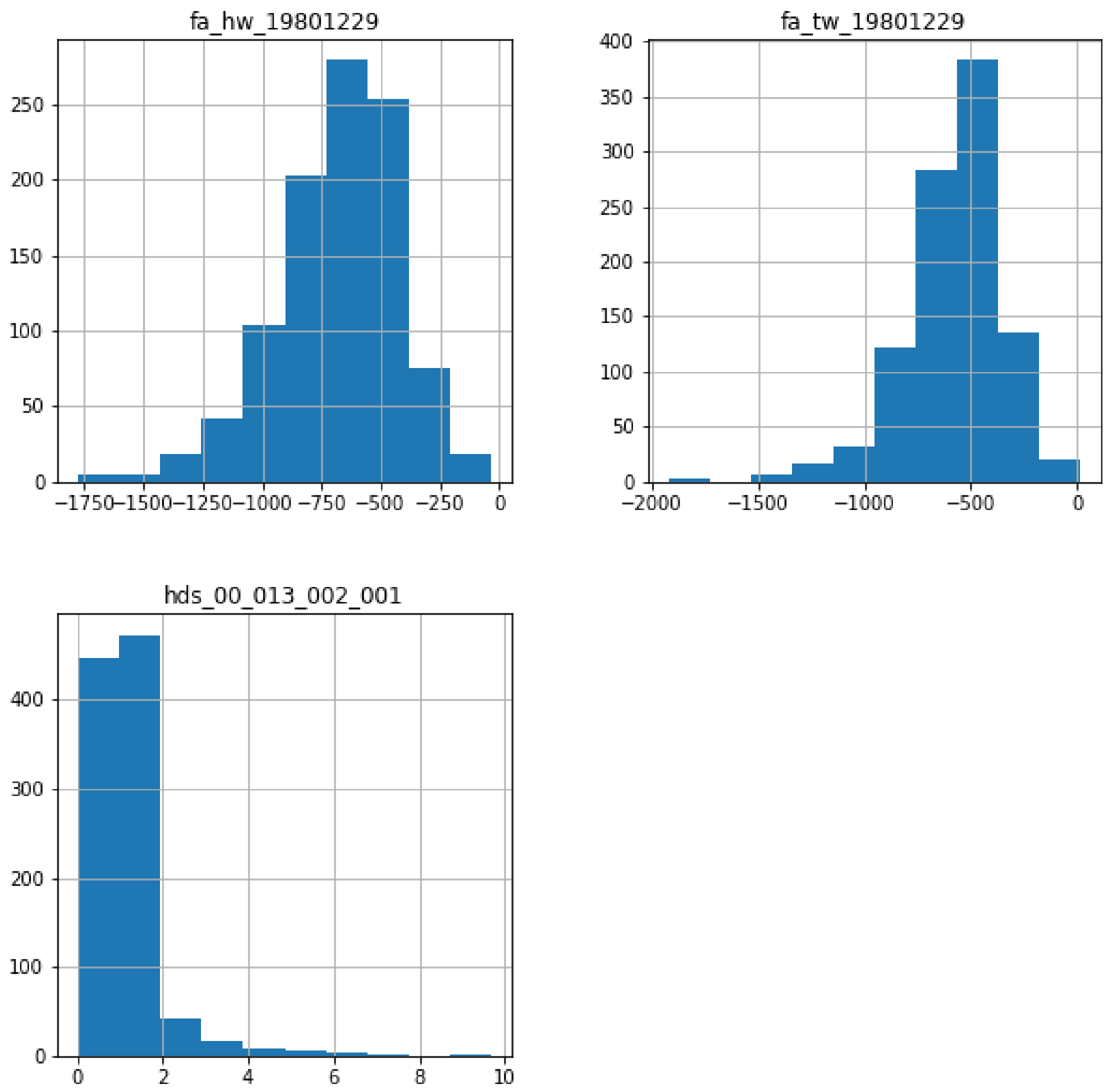




We see that under scenario conditions, many more realizations for the flow to the aquifer in the headwaters are postive (as expected). Lets difference these two:

```
In [15]: 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))
```

```
Out[15]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x18198b9978>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x18190ea588>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x1819102a20>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x1819118f98>]],
               dtype=object)
```



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

1.1.8 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 [16]: sorted_vals = obs_df.loc[:,"part_time"].sort_values()
         idx = sorted_vals.index[100]
         idx
```

```
Out[16]: 495
```

```
In [17]: sorted_vals
```

```
Out[17]: 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 [18]:
```
obs_df.loc[idx,pst.nnz_obs_names]
```

Out[18]:
```
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 [19]: obs_df.loc[idx,fnames]
```

```
Out[19]: 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 [20]: 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 [21]: 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[21]: 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

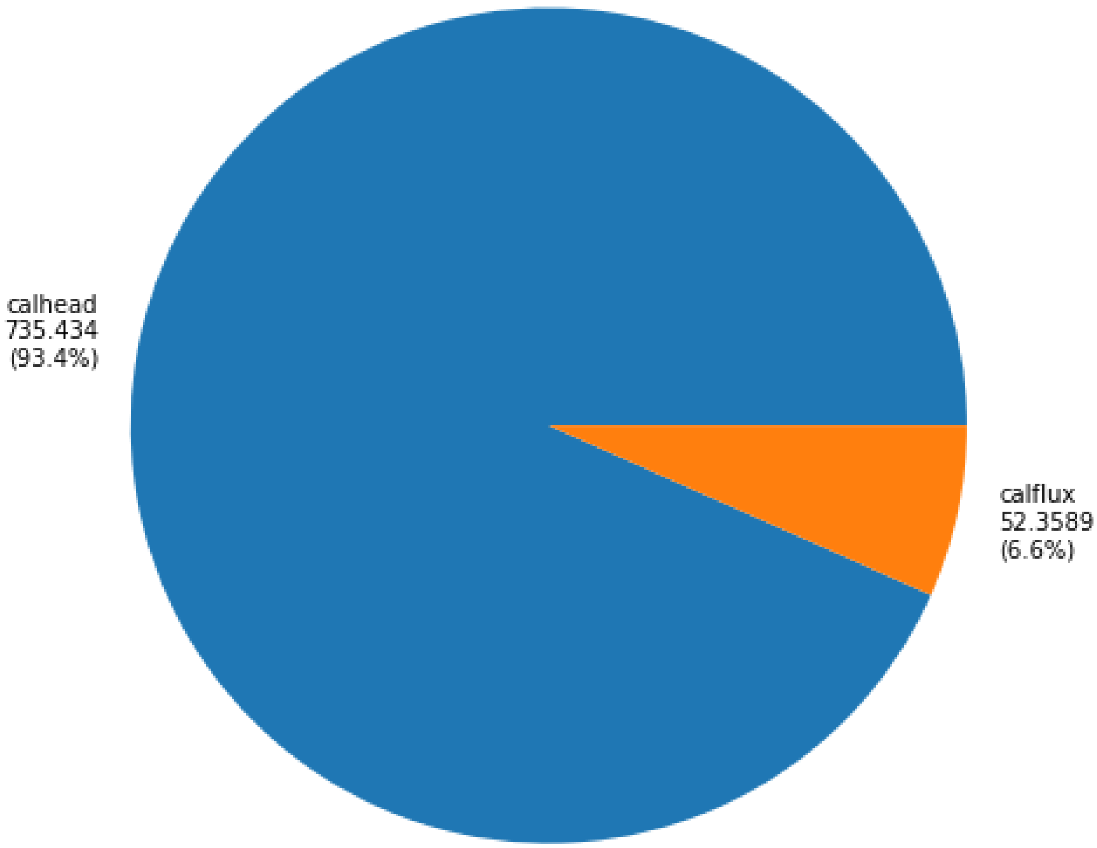
```
In [22]: pst.write(os.path.join(t_d,"freyberg.pst"))
         pyemu.os_utils.run("pestpp-ies freyberg.pst",cwd=t_d)
```

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

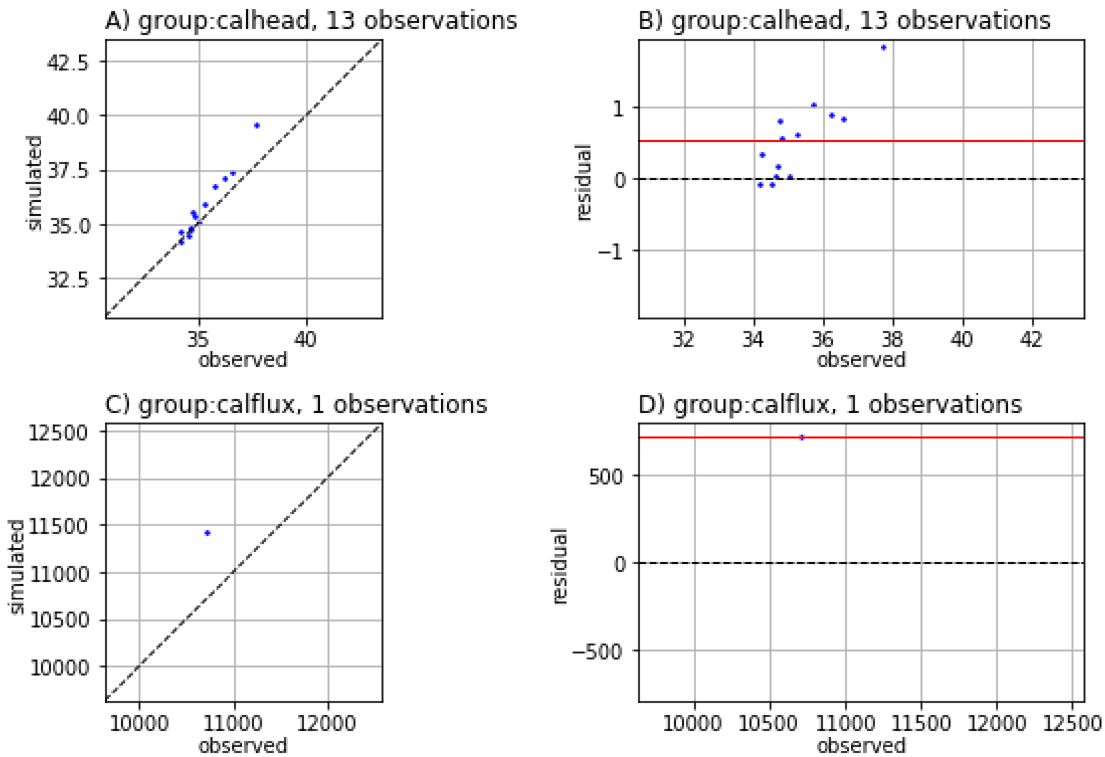
Now we can read in the results and make some figures showing residuals and the balance of the objective function

```
In [23]: 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");
         pst.res.loc[pst.nnz_obs_names,:]
         plt.show()
```

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


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



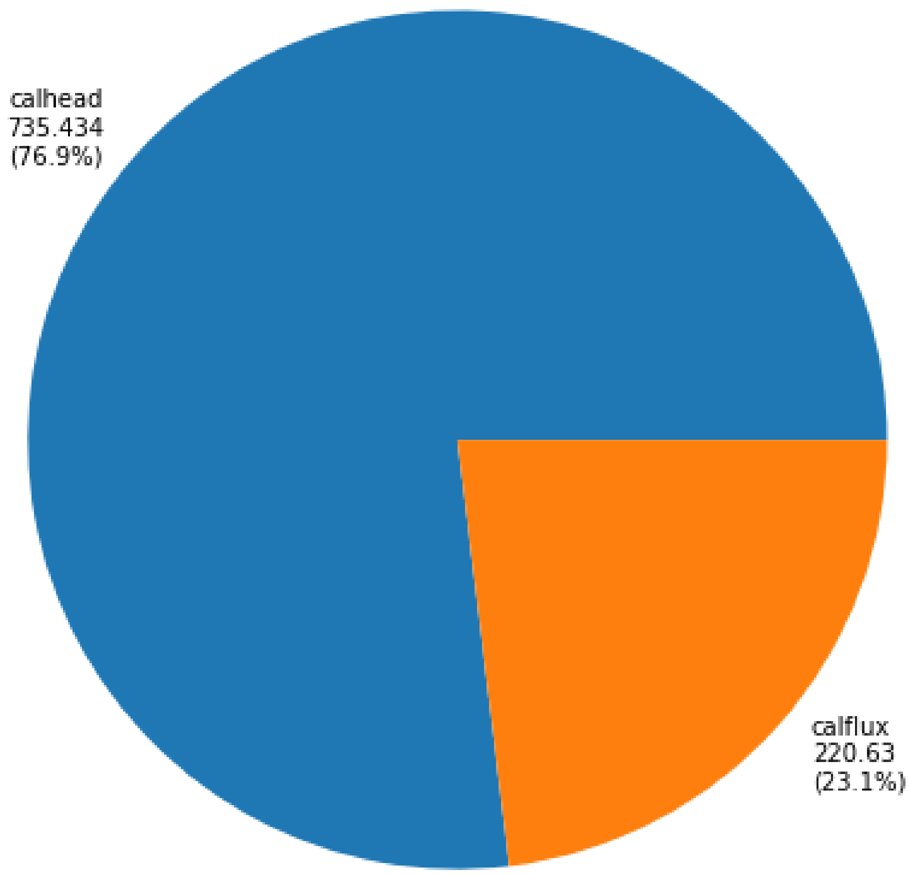
<Figure size 576x756 with 0 Axes>



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 [24]: 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[24]: <matplotlib.axes._subplots.AxesSubplot at 0x1819152710>
```



Lets see what the new flux observation weight is:

```
In [25]: pst.observation_data.loc[pst.nnz_obs_names,"weight"]
```

Out[25]:
```
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 [26]:
```
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
```

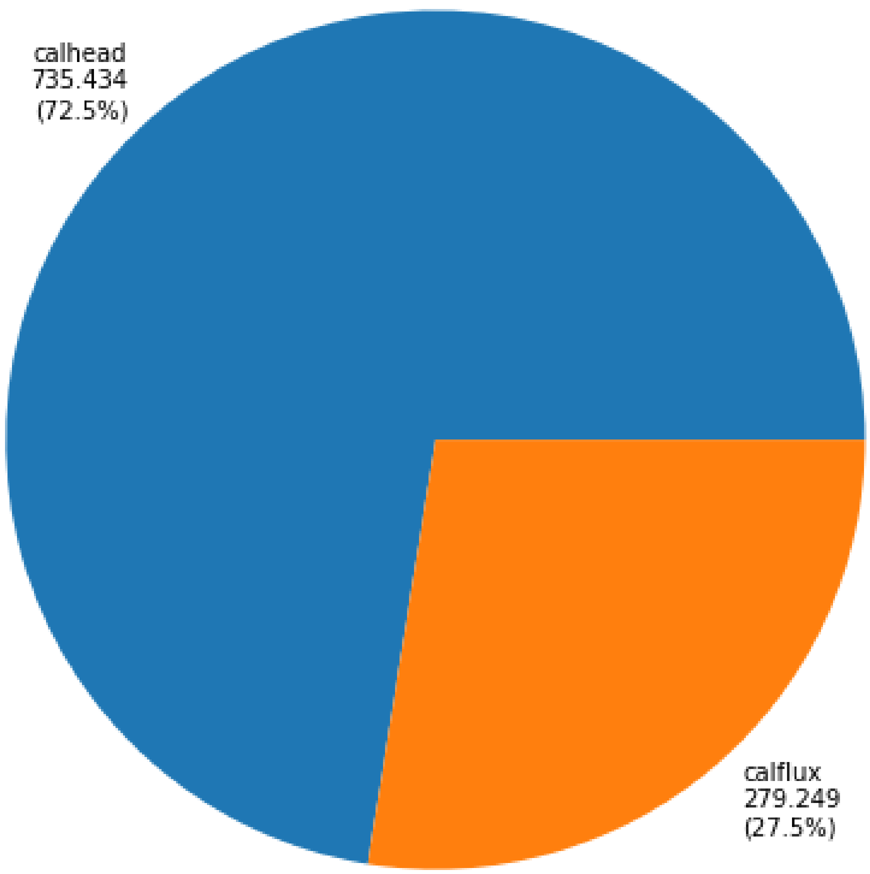
Out[26]:
```
obsnme
fo_39_19791230         85.935831
hds_00_002_009_000      0.040016
hds_00_002_015_000      0.097874
hds_00_003_008_000      0.224089
hds_00_009_001_000      0.186756
hds_00_013_010_000     -0.097728
hds_00_015_016_000      0.095009
hds_00_021_010_000     -0.015136
hds_00_022_015_000     -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 [27]:
```
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')
```

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

```
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x181a30af98>
```



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 [28]: 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.

```
In [29]: 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[29]:                                    name    group      measured      modelled  \
         name
         fo_39_19791230          fo_39_19791230  calflux  10615.935831  10530.000000
         hds_00_002_009_000  hds_00_002_009_000  calhead     36.218498     36.178482
         hds_00_002_015_000  hds_00_002_015_000  calhead     35.025284     34.927410
         hds_00_003_008_000  hds_00_003_008_000  calhead     36.576499     36.352409
         hds_00_009_001_000  hds_00_009_001_000  calhead     37.717926     37.531170
         hds_00_013_010_000  hds_00_013_010_000  calhead     34.763043     34.860771
         hds_00_015_016_000  hds_00_015_016_000  calhead     34.675392     34.580383
         hds_00_021_010_000  hds_00_021_010_000  calhead     34.829576     34.844711
         hds_00_022_015_000  hds_00_022_015_000  calhead     34.239560     34.249882
         hds_00_024_004_000  hds_00_024_004_000  calhead     35.730433     35.689373
         hds_00_026_006_000  hds_00_026_006_000  calhead     35.290600     35.276196
         hds_00_029_015_000  hds_00_029_015_000  calhead     34.538597     34.393169
         hds_00_033_007_000  hds_00_033_007_000  calhead     34.656380     34.580276
         hds_00_034_010_000  hds_00_034_010_000  calhead     34.203959     34.191792

                              residual     weight
         name
         fo_39_19791230      85.935831   0.020528
         hds_00_002_009_000   0.040016  10.000000
         hds_00_002_015_000   0.097874  10.000000
         hds_00_003_008_000   0.224089  10.000000
         hds_00_009_001_000   0.186756  10.000000
         hds_00_013_010_000  -0.097728  10.000000
         hds_00_015_016_000   0.095009  10.000000
         hds_00_021_010_000  -0.015136  10.000000
         hds_00_022_015_000  -0.010322  10.000000
         hds_00_024_004_000   0.041060  10.000000
         hds_00_026_006_000   0.014404  10.000000
         hds_00_029_015_000   0.145427  10.000000
         hds_00_033_007_000   0.076104  10.000000
         hds_00_034_010_000   0.012168  10.000000
```

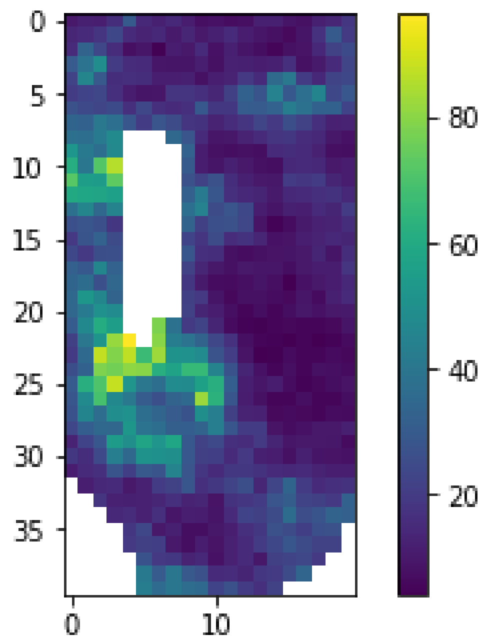
The residual should be exactly the noise values from above. Lets load the model (that was just run using the true pars) and check some things

```
In [30]: m = flopy.modflow.Modflow.load("freyberg.nam",model_ws=m_d)
```

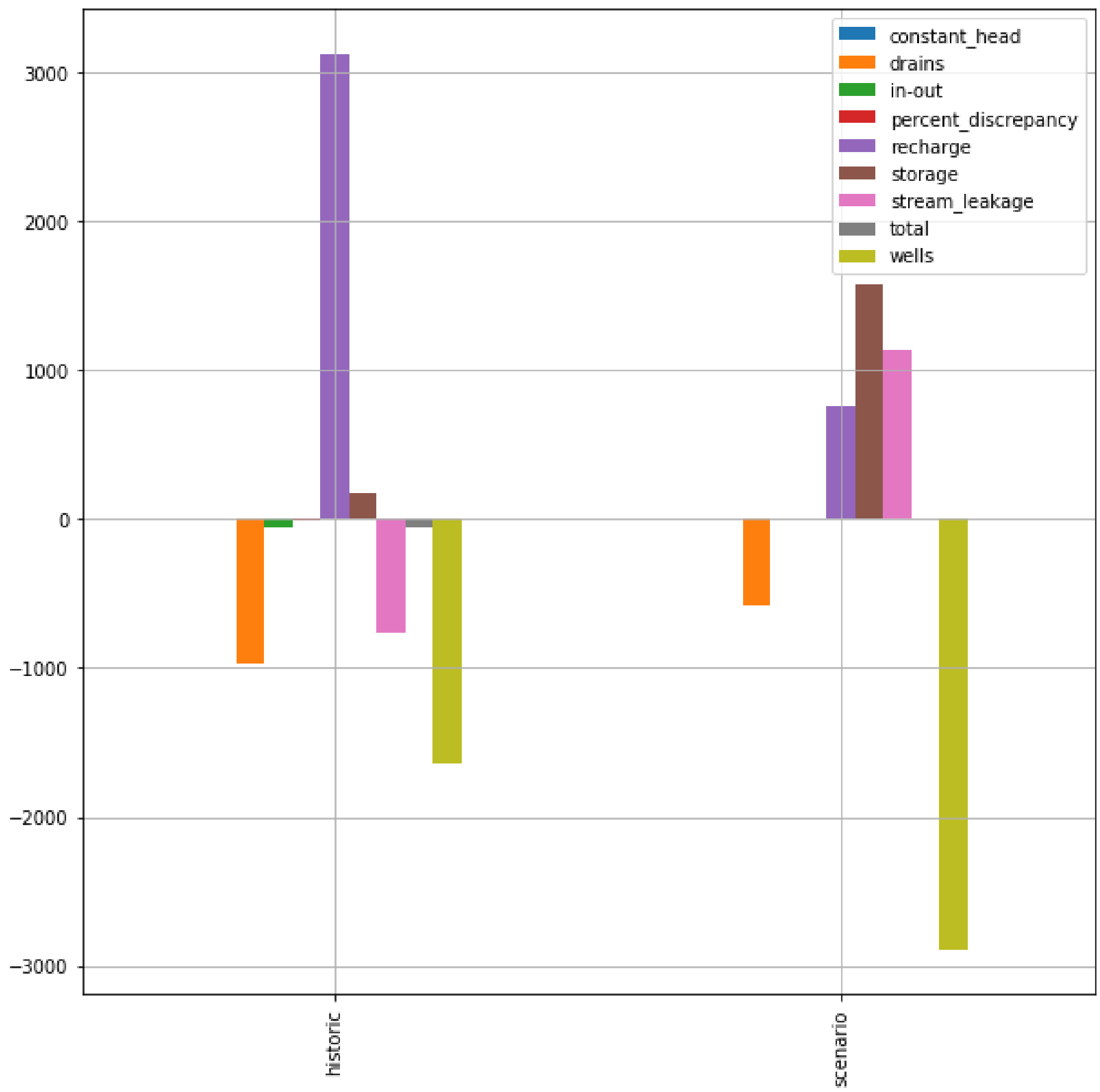
```
In [31]: a = m.upw.hk[0].array
         #a = m.rch.rech[0].array
         a = np.ma.masked_where(m.bas6.ibound[0].array==0,a)
         print(a.min(),a.max())
         c = plt.imshow(a)
         plt.colorbar()
```

```
4.05637 96.48033
```

```
Out[31]: <matplotlib.colorbar.Colorbar at 0x1819cf4358>
```



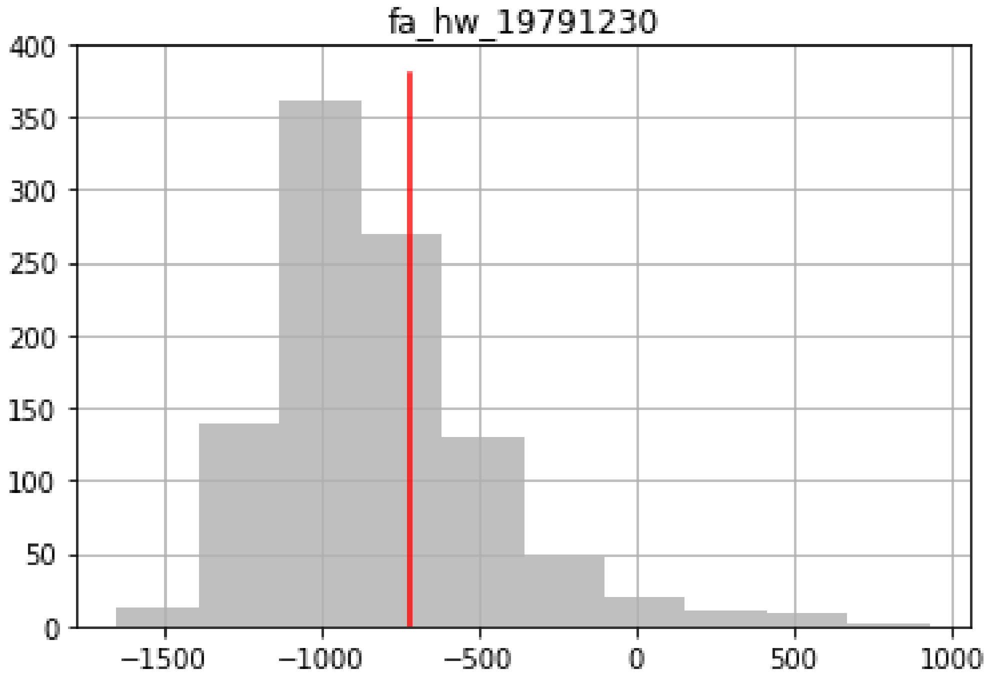

```
In [32]: lst = flopy.utils.MfListBudget(os.path.join(m_d,"freyberg.list"))
         df = lst.get_dataframes(diff=True)[0]
         ax = df.plot(kind="bar",figsize=(10,10), grid=True)
         a = ax.set_xticklabels(["historic","scenario"],rotation=90)
```

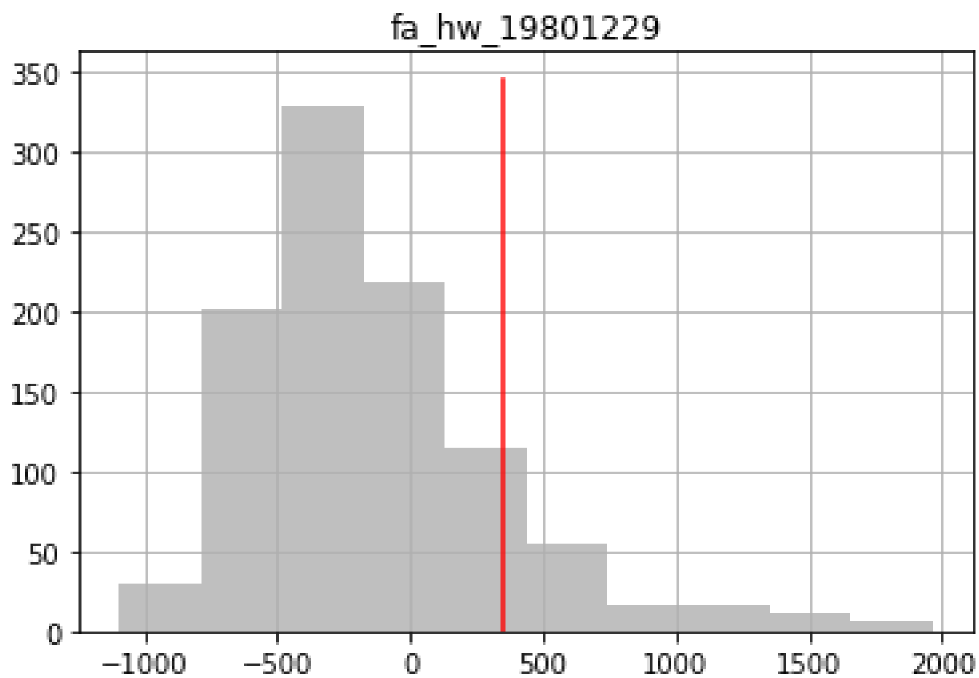


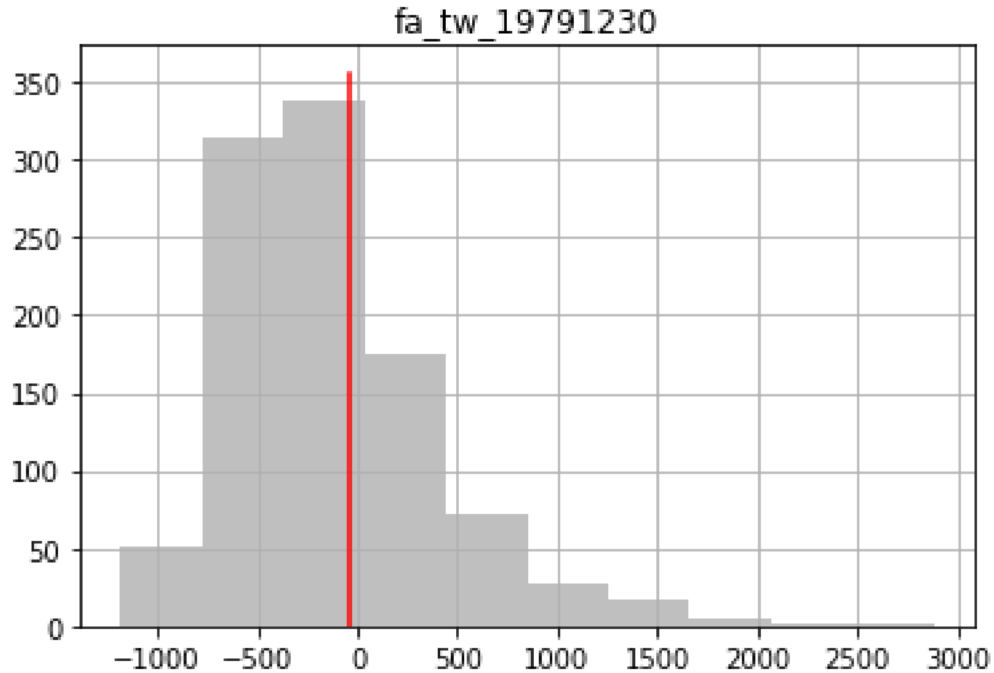
1.1.9 see how our existing observation ensemble compares to the truth

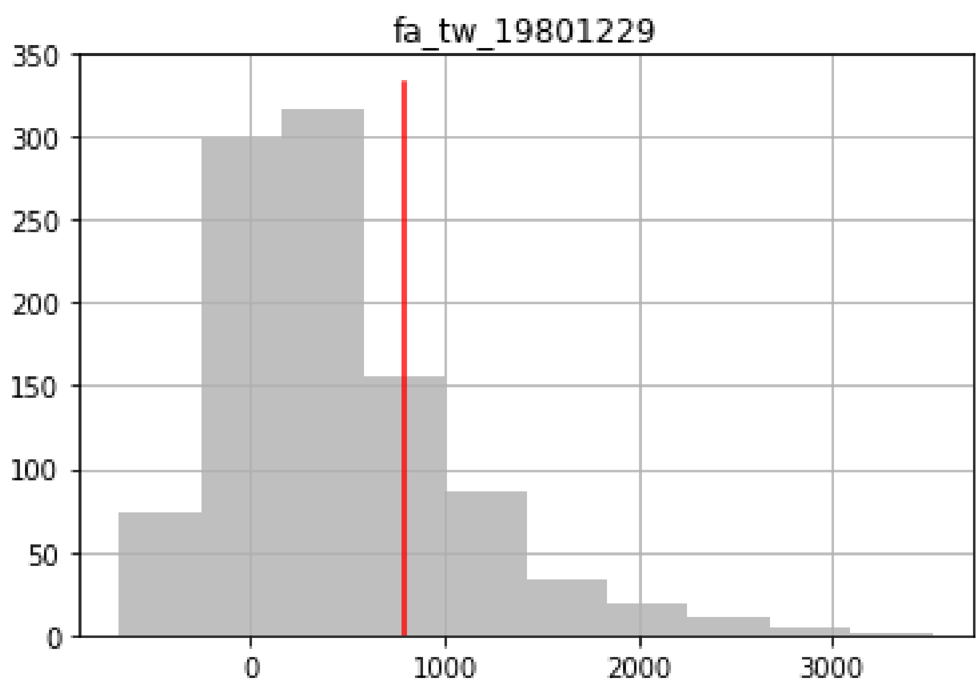
forecasts:

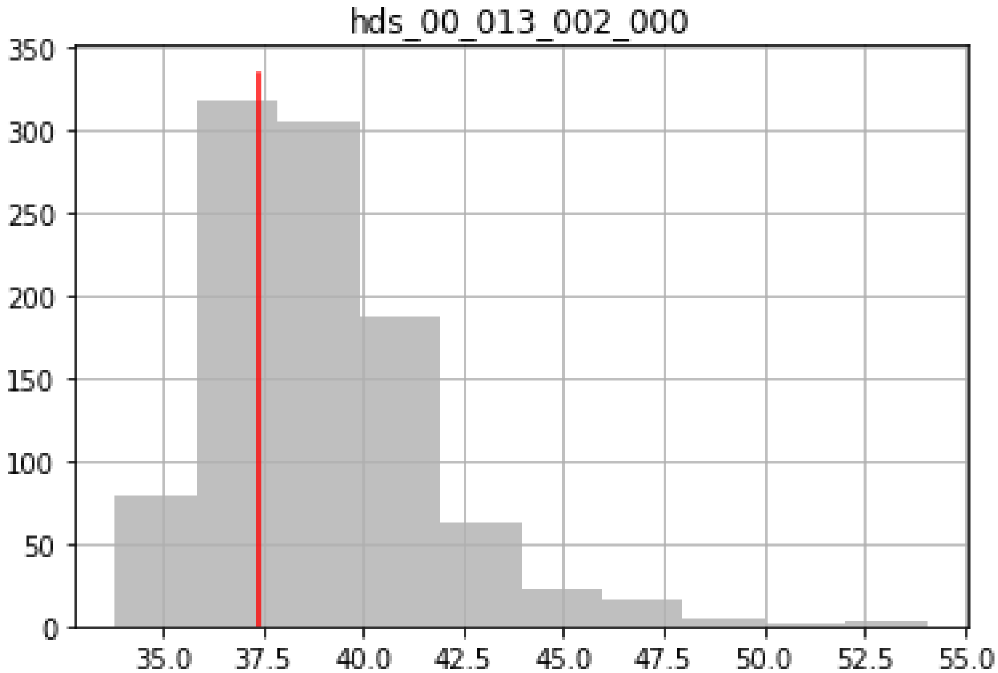
```
In [33]: obs = pst.observation_data
         plt.figure()
         for forecast in fnames:
             ax = plt.subplot(111)
             obs_df.loc[:,forecast].hist(ax=ax,color="0.5",alpha=0.5)
             ax.plot([obs.loc[forecast,"obsval"],obs.loc[forecast,"obsval"]],ax.get_ylim(),"r"
             ax.set_title(forecast)
             plt.show()
```

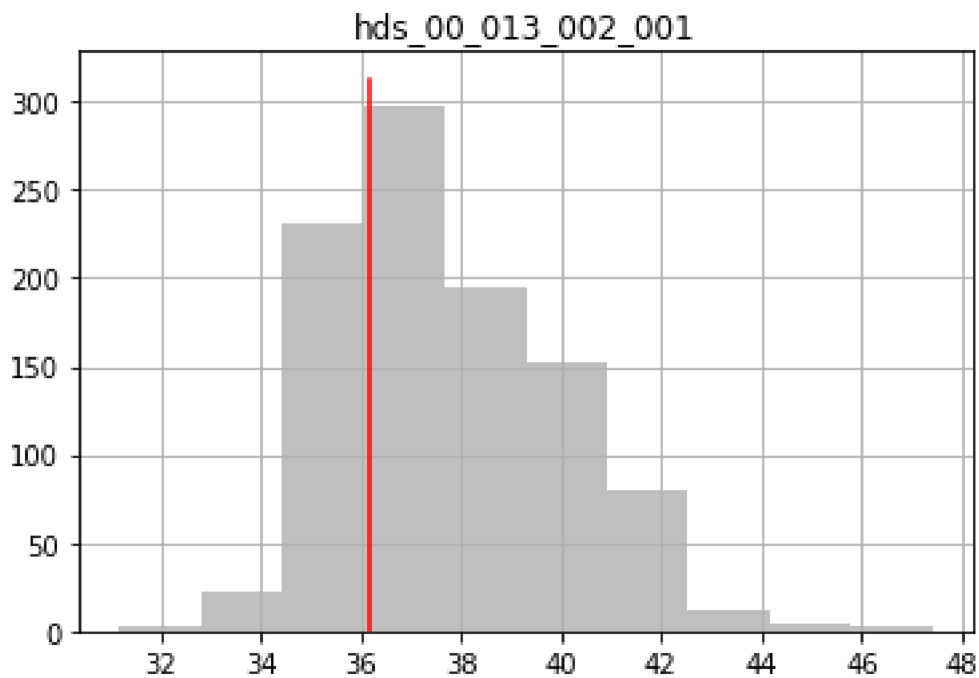

fa_hw_19791230
400
350
300
250
200
150
100
50
0
−1500
−1000
−500
0
500
1000

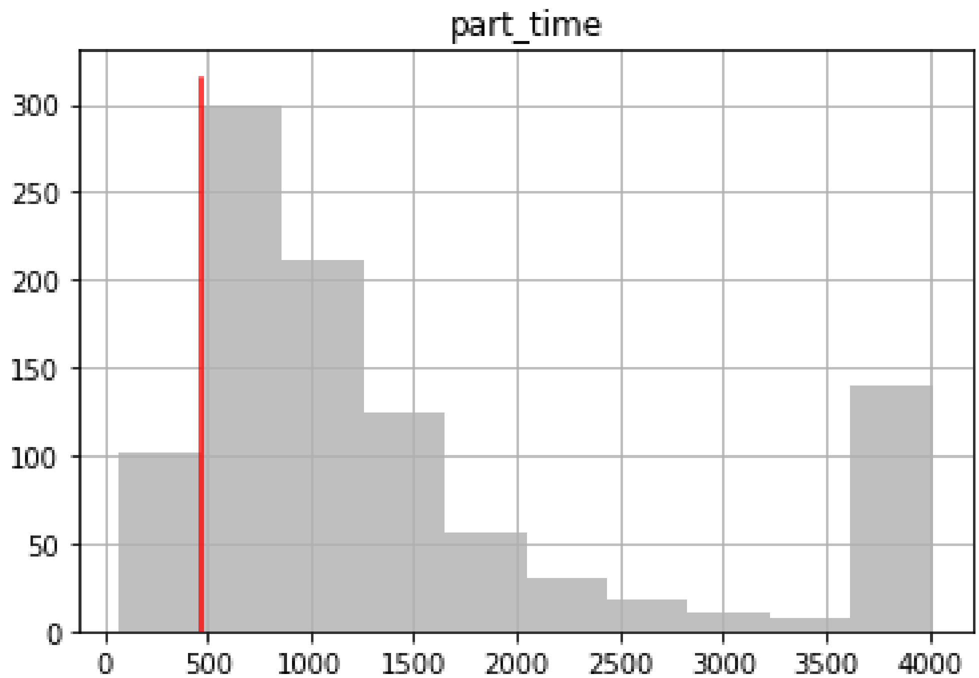

fa_hw_19801229
350
300
250
200
150
100
50
0
−1000
−500
0
500
1000
1500
2000

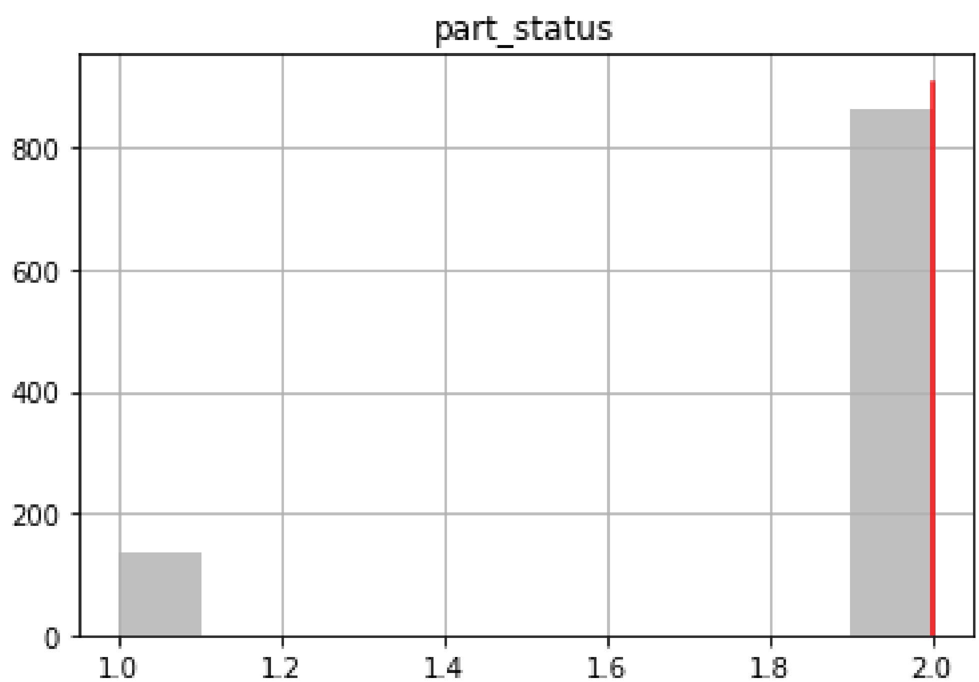

fa_tw_19791230
350
300
250
200
150
100
50
0
−1000
−500
0
500
1000
1500
2000
2500
3000


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


hds_00_013_002_000
350
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

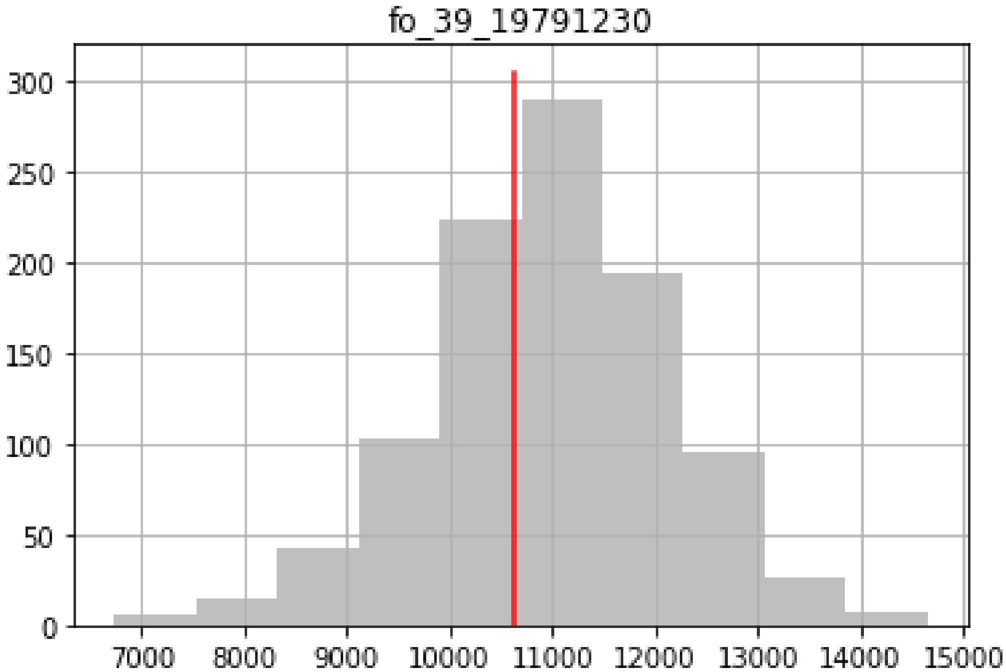

hds_00_013_002_001
300
250
200
150
100
50
0
32
34
36
38
40
42
44
46
48

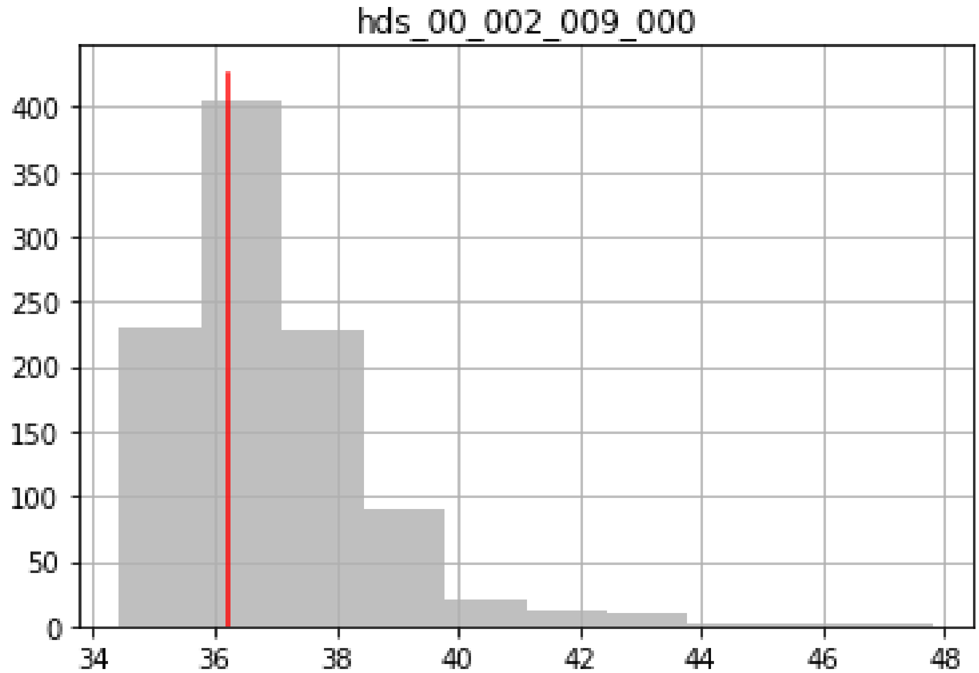


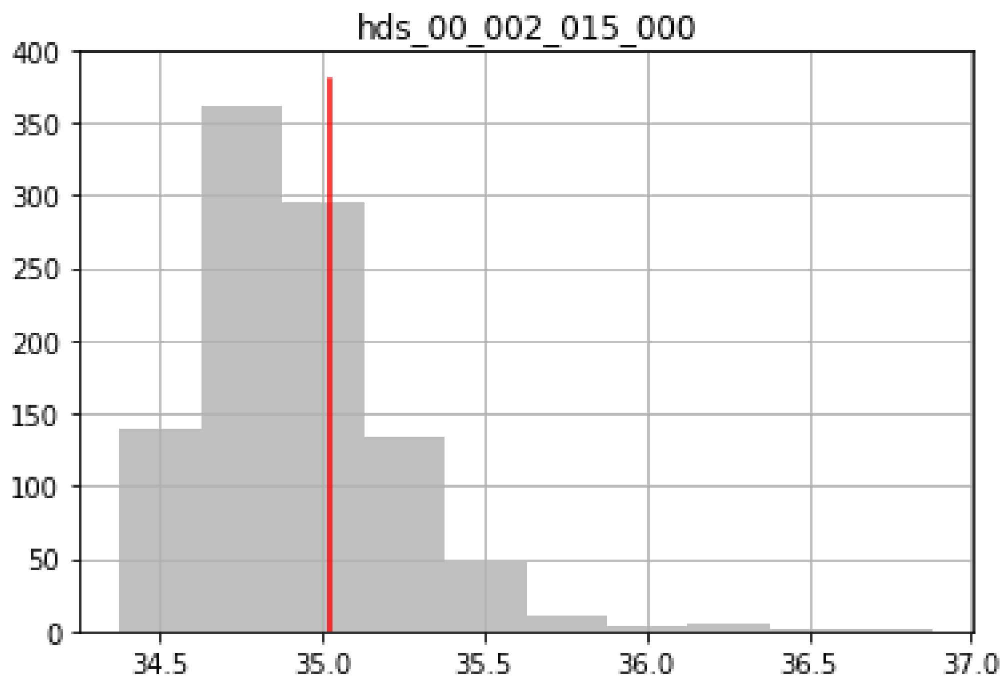


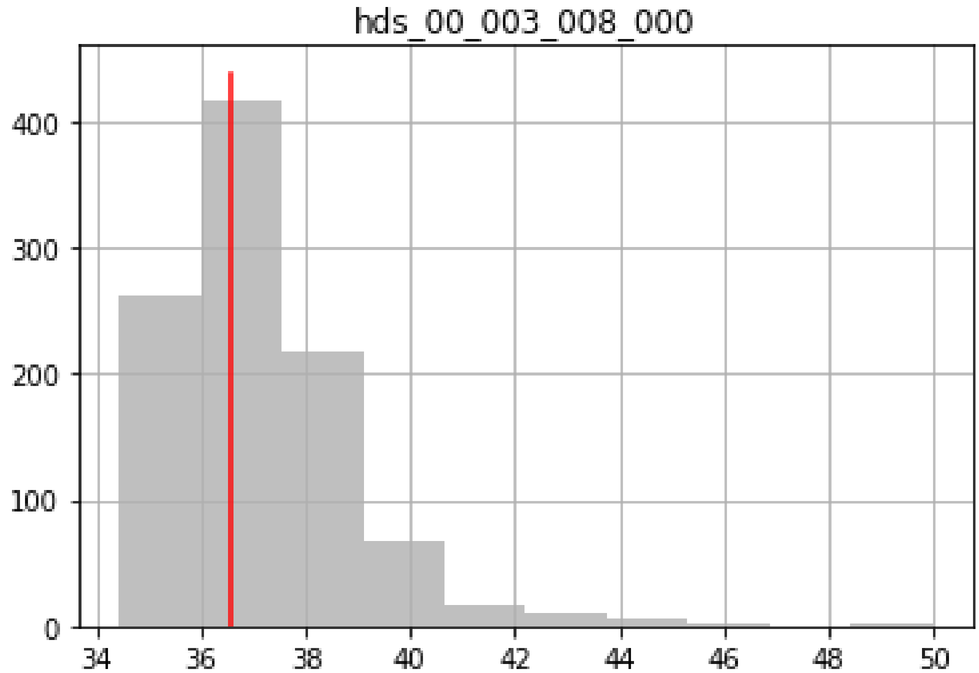
observations:

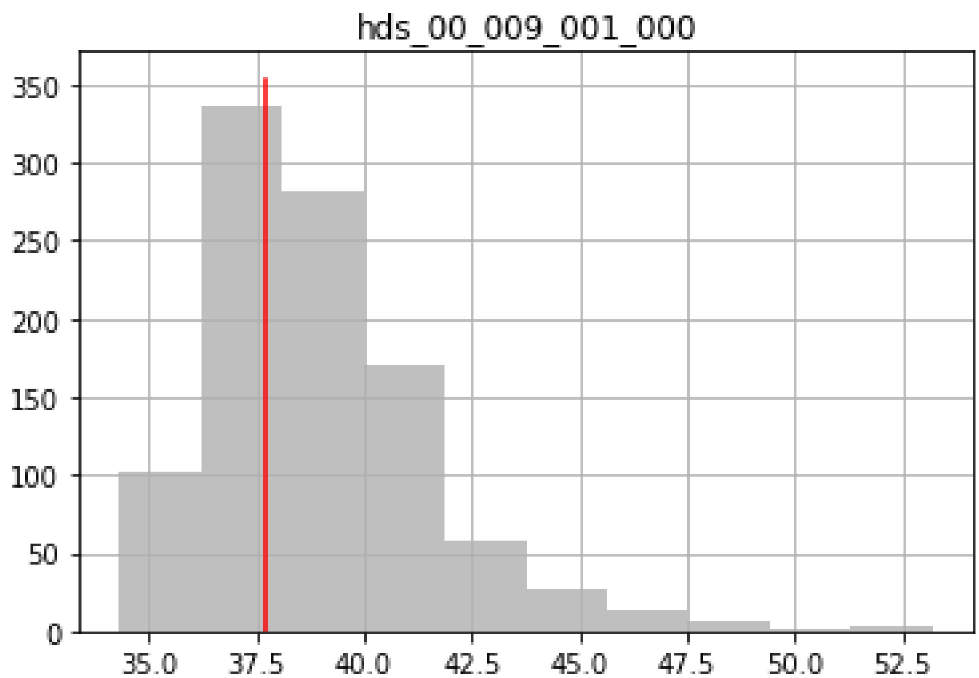
```
In [34]: for oname in pst.nnz_obs_names:
             ax = plt.subplot(111)
             obs_df.loc[:,oname].hist(ax=ax,color="0.5",alpha=0.5)
             ax.plot([obs.loc[oname,"obsval"],obs.loc[oname,"obsval"]],ax.get_ylim(),"r")
             ax.set_title(oname)
             plt.show()
```




hds_00_002_009_000
0
50
100
150
200
250
300
350
400
34
36
38
40
42
44
46
48


hds_00_002_015_000
0
50
100
150
200
250
300
350
400
34.5
35.0
35.5
36.0
36.5
37.0


hds_00_003_008_000
400
300
200
100
0
34
36
38
40
42
44
46
48
50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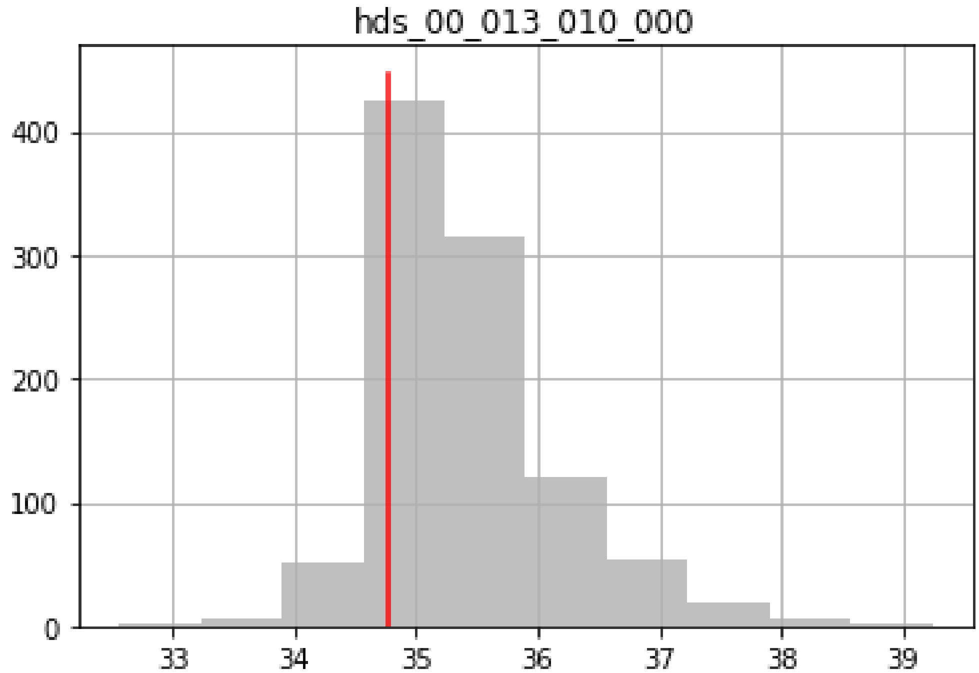
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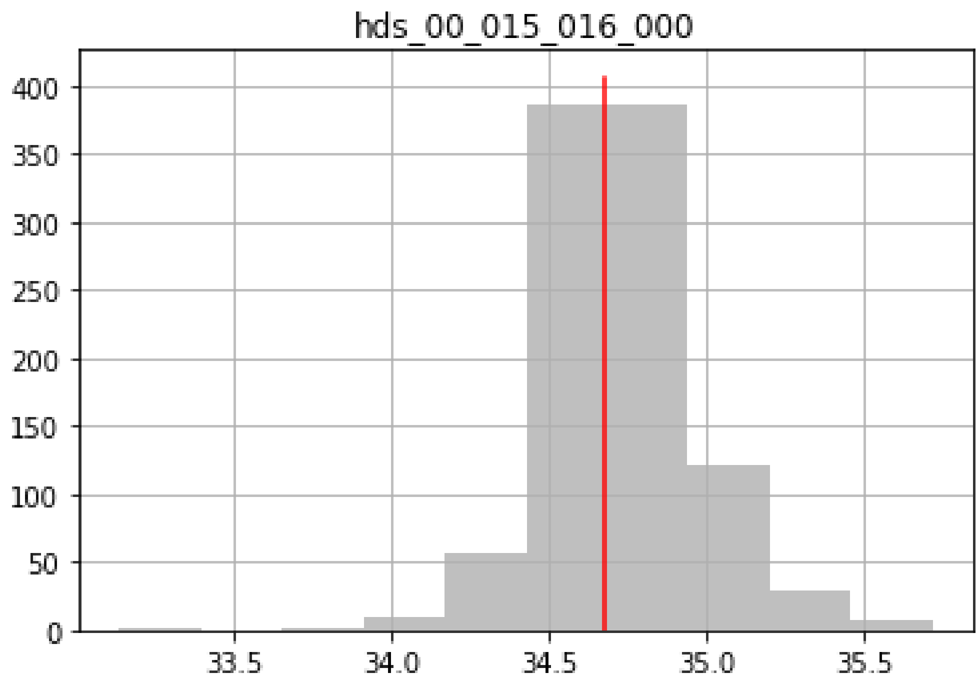
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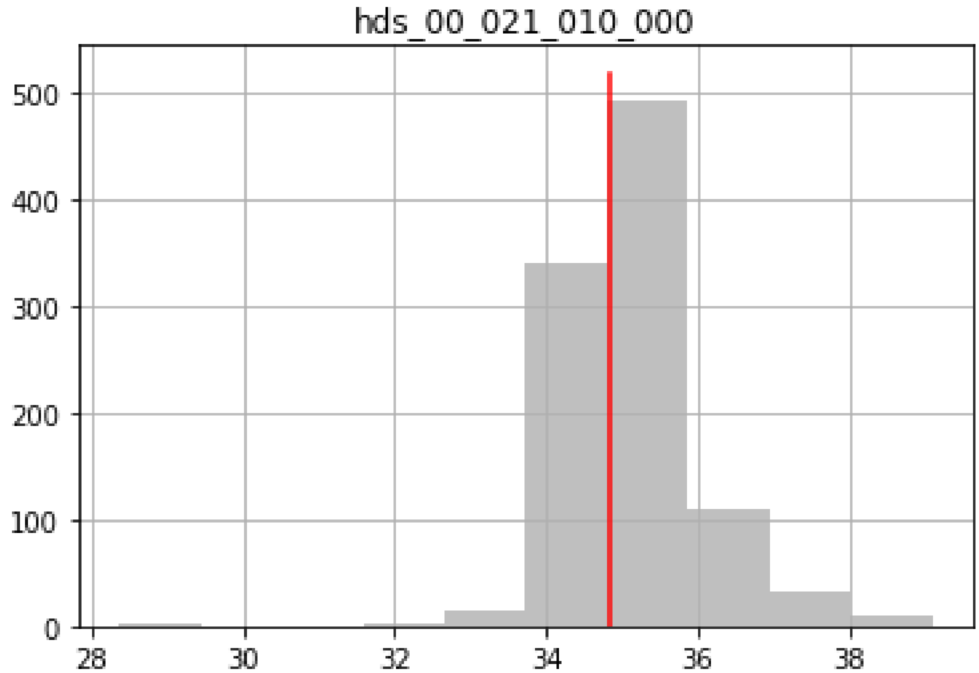
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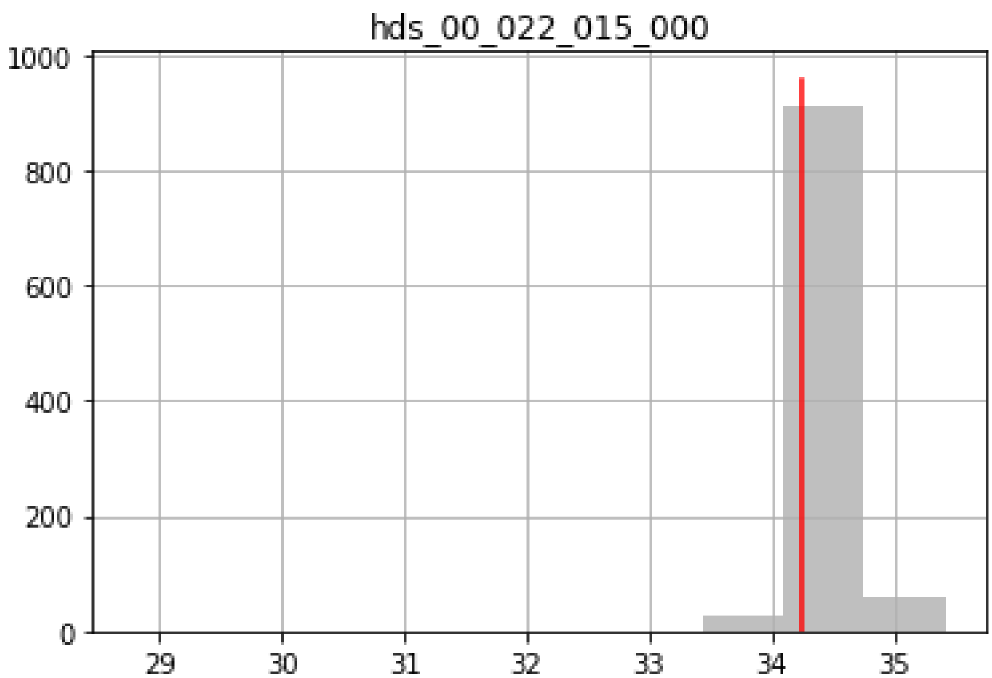
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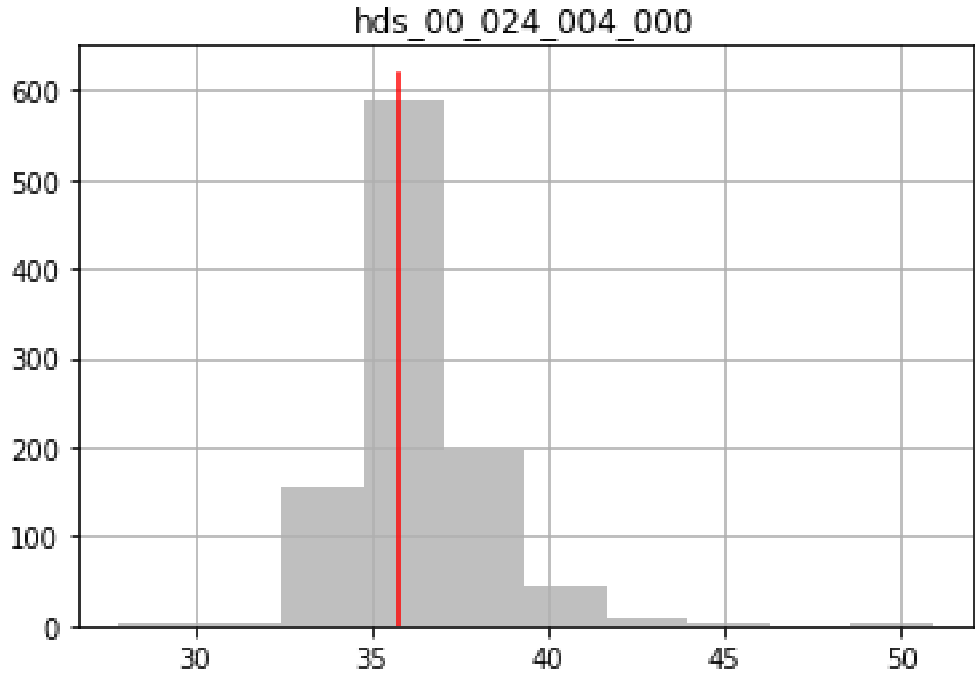
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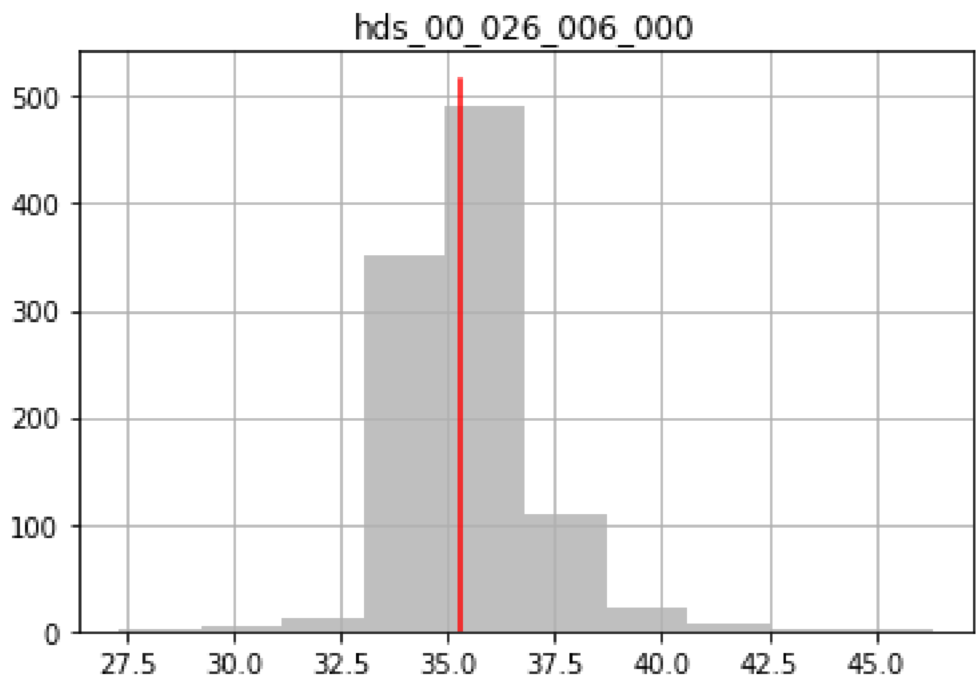
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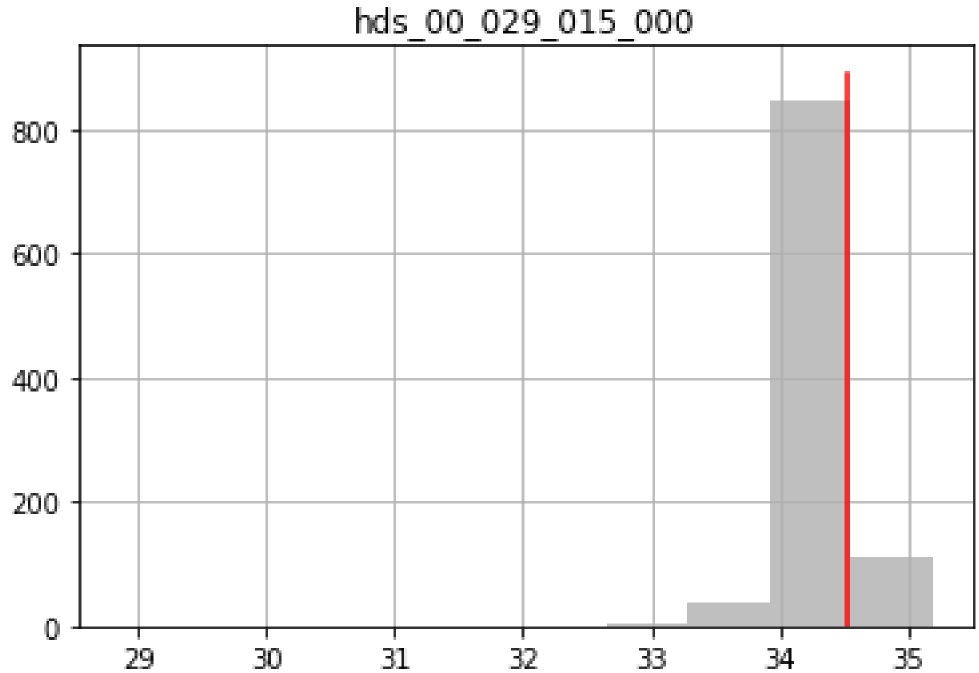
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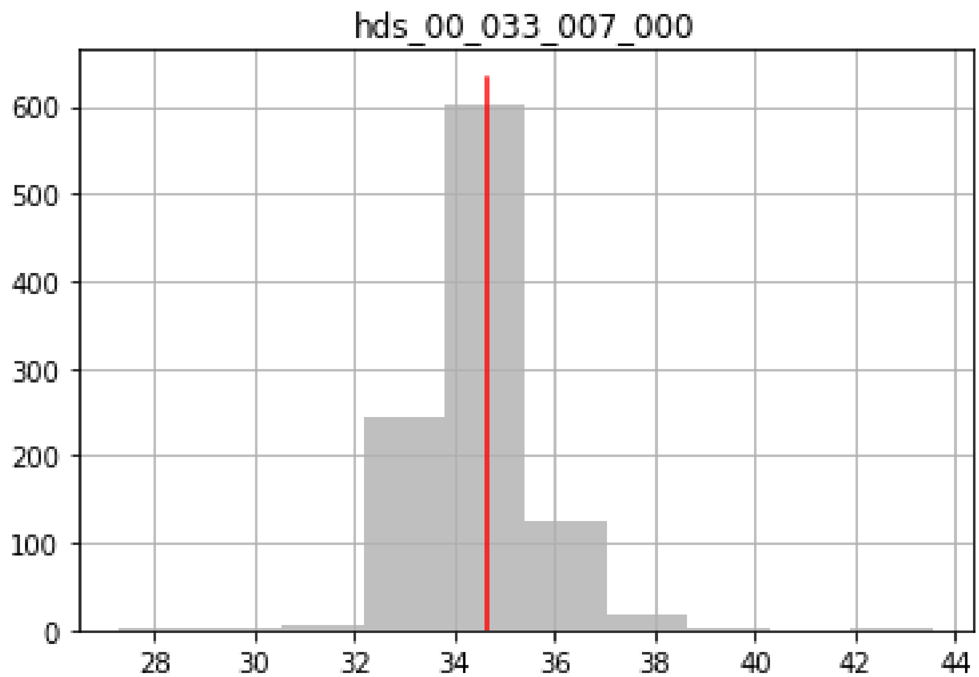
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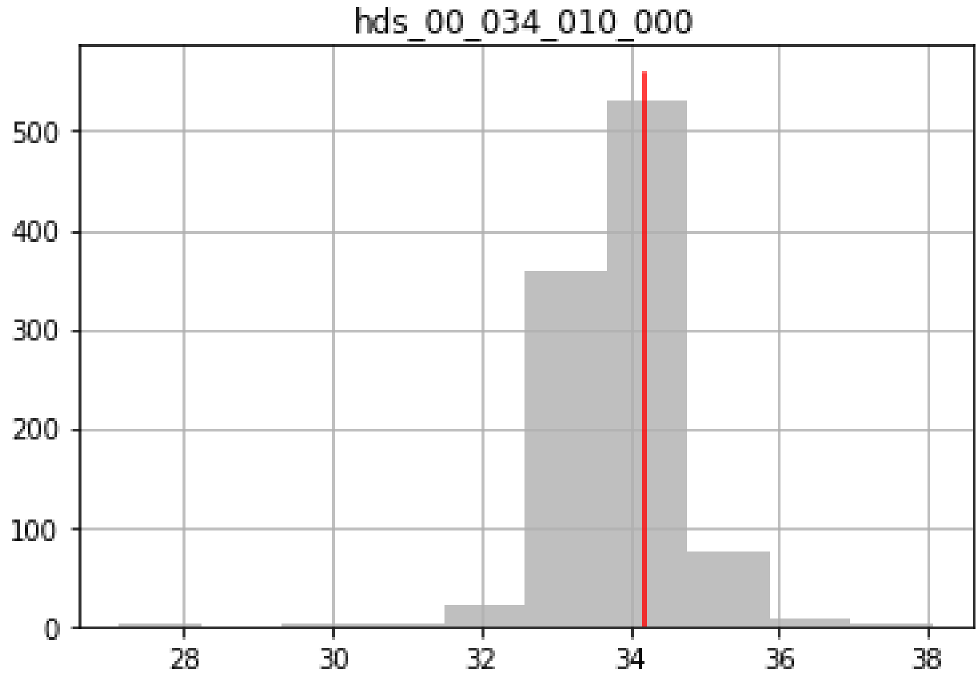
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