

prova

February 9, 2023

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mplt
import seaborn as sns
import arviz as az
import datetime

[2]: import fit_arima

[3]: import open_data
df = open_data.open()

[4]: ritorno = fit_arima.compute(2, 1, catene=4, samples_per_chain=2500, burnin=1000)
```

```
20:24:12 - cmdstanpy - INFO - CmdStan start processing
chain 1 |      00:00 Status
chain 2 |      00:00 Status
chain 3 |      00:00 Status
chain 4 |      00:00 Status
```

```
20:49:49 - cmdstanpy - INFO - CmdStan done processing.
20:49:49 - cmdstanpy - WARNING - Non-fatal error during sampling:
Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in '/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 157, column 4 to column 34)
    Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in '/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 157, column 4 to column 34)
        Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in '/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 157, column 4 to column 34)
            Exception: code_model_namespace::log_prob: phi[1][1] is -nan, but must be greater than or equal to -1.000000 (in '/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column
```

47)

```
    Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in
'./home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code
.stan', line 157, column 4 to column 34)
Exception: normal_lpdf: Scale parameter is -1.77241, but must be positive! (in '
./home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.
stan', line 143, column 4 to column 61)
    Exception: normal_lpdf: Scale parameter is -1.33685, but must be
positive! (in './home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoC
ovariates/code.stan', line 143, column 4 to column 61)
    Exception: normal_lpdf: Scale parameter is -1.88462, but must be
positive! (in './home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoC
ovariates/code.stan', line 143, column 4 to column 61)
    Exception: code_model_namespace::log_prob: phi[2][49] is 1, but must be
less than or equal to 1.000000 (in './home/br1/PythonProjects/PythonStats/git_bay
esian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column 47)
    Exception: code_model_namespace::log_prob: phi[1][17] is 1, but must be
less than or equal to 1.000000 (in './home/br1/PythonProjects/PythonStats/git_bay
esian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column 47)
    Exception: normal_lpdf: Scale parameter is -1.63119, but must be
positive! (in './home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoC
ovariates/code.stan', line 143, column 4 to column 61)
    Exception: code_model_namespace::log_prob: phi[1][1] is -nan, but must
be greater than or equal to -1.000000 (in './home/br1/PythonProjects/PythonStats/
git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column
47)
    Exception: code_model_namespace::log_prob: phi[2][24] is -nan, but must
be greater than or equal to -1.000000 (in './home/br1/PythonProjects/PythonStats/
git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column
47)
    Exception: normal_lpdf: Scale parameter is -0.00166804, but must be
positive! (in './home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoC
ovariates/code.stan', line 143, column 4 to column 61)
    Exception: normal_lpdf: Scale parameter is -0.014183, but must be
positive! (in './home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoC
ovariates/code.stan', line 143, column 4 to column 61)
Exception: normal_lpdf: Scale parameter is -1.93972, but must be positive! (in '
./home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.
stan', line 143, column 4 to column 61)
    Exception: normal_lpdf: Scale parameter is -0.38646, but must be
positive! (in './home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoC
ovariates/code.stan', line 143, column 4 to column 61)
    Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in
'./home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code
.stan', line 157, column 4 to column 34)
    Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in
'./home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code
.stan', line 157, column 4 to column 34)
```

```

Exception: normal_lpdf: Scale parameter is 0, but must be positive! (in
'/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code
.stan', line 157, column 4 to column 34)
Exception: code_model_namespace::log_prob: phi[1][1] is -nan, but must
be greater than or equal to -1.000000 (in '/home/br1/PythonProjects/PythonStats/
git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column
47)
Exception: code_model_namespace::log_prob: phi[1][5] is 1, but must be
less than or equal to 1.000000 (in '/home/br1/PythonProjects/PythonStats/git_bay
esian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column 47)
Exception: code_model_namespace::log_prob: phi[2][37] is 1, but must be less
than or equal to 1.000000 (in '/home/br1/PythonProjects/PythonStats/git_bayesian
_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column 47)
Exception: code_model_namespace::log_prob: phi[2][11] is 1, but must be
less than or equal to 1.000000 (in '/home/br1/PythonProjects/PythonStats/git_bay
esian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column 47)
Exception: code_model_namespace::log_prob: phi[1][8] is -nan, but must
be greater than or equal to -1.000000 (in '/home/br1/PythonProjects/PythonStats/
git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column
47)
Exception: code_model_namespace::log_prob: phi[1][8] is 1, but must be
less than or equal to 1.000000 (in '/home/br1/PythonProjects/PythonStats/git_bay
esian_copie/ARIMA/NoCovariates/code.stan', line 83, column 2 to column 47)
Consider re-running with show_console=True if the above output is unclear!

```

```

/home/br1/PythonProjects/PythonStats/ARIMA_last_computation/NoCovariates/fit_ari
ma.py:37: FutureWarning: Indexing with a float is deprecated, and will raise an
IndexError in pandas 2.0. You can manually convert to an integer key instead.
y_missing_list.append({'Stazione':df.columns[v[i]],'Data':df.index[u[i]],'Samp
les':inference_data.posterior.w.values[:, :, i].reshape(catene*samples_per_chain)})

```

Tempo di computazione: 25:37

```
[5]: res = az.loo(ritorno['inference_data'], var_name="log_li
k", pointwise=True)
res
```

```

/home/br1/PythonProjects/PythonStats/.venv/lib/python3.10/site-
packages/arviz/stats/stats.py:803: UserWarning: Estimated shape parameter of
Pareto distribution is greater than 0.7 for one or more samples. You should
consider using a more robust model, this is because importance sampling is less
likely to work well if the marginal posterior and LOO posterior are very
different. This is more likely to happen with a non-robust model and highly
influential observations.
warnings.warn(

```

[5]: Computed from 10000 posterior samples and 17191 observations log-likelihood matrix.

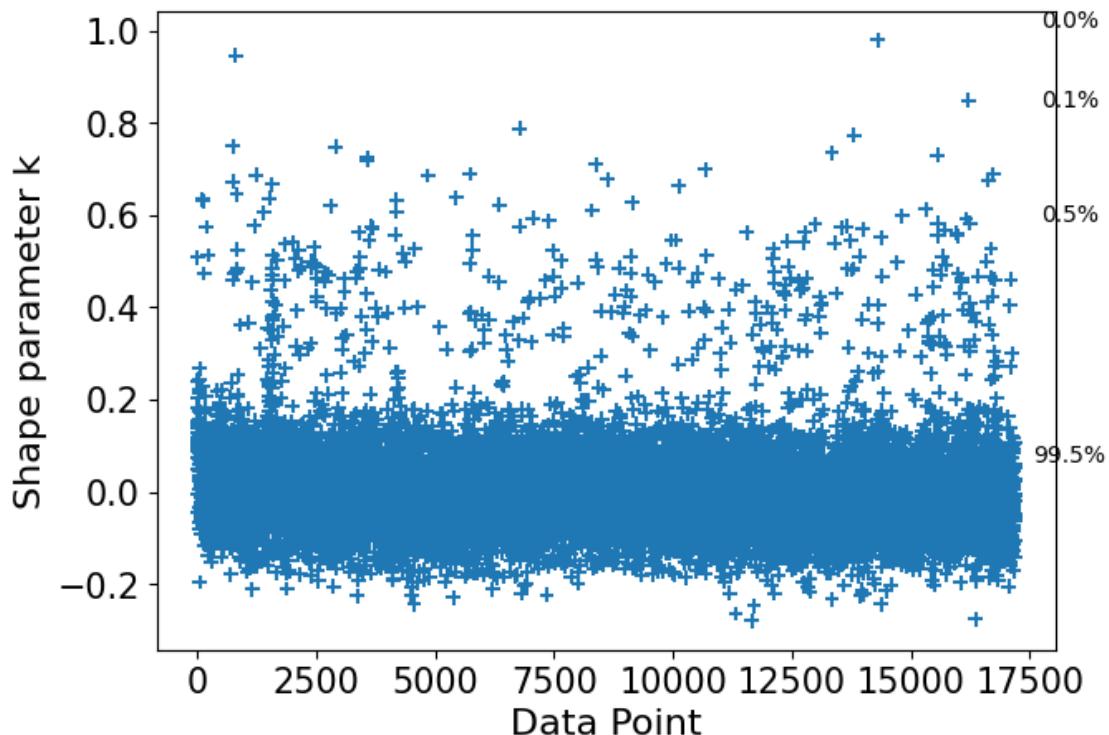
	Estimate	SE
elpd_loo	7252.62	154.96
p_loo	296.80	-

There has been a warning during the calculation. Please check the results.

Pareto k diagnostic values:

	Count	Pct.
(-Inf, 0.5] (good)	17099	99.5%
(0.5, 0.7] (ok)	80	0.5%
(0.7, 1] (bad)	12	0.1%
(1, Inf) (very bad)	0	0.0%

[6]: aux_plt = az.plot_khat(res, show_bins=True, figsize=(7,5))



[7]: res = az.waic(ritorno['inference_data'], var_name="log_lik")
res

/home/br1/PythonProjects/PythonStats/.venv/lib/python3.10/site-

```
packages/arviz/stats/stats.py:1645: UserWarning: For one or more samples the posterior variance of the log predictive densities exceeds 0.4. This could be indication of WAIC starting to fail.
```

```
See http://arxiv.org/abs/1507.04544 for details
```

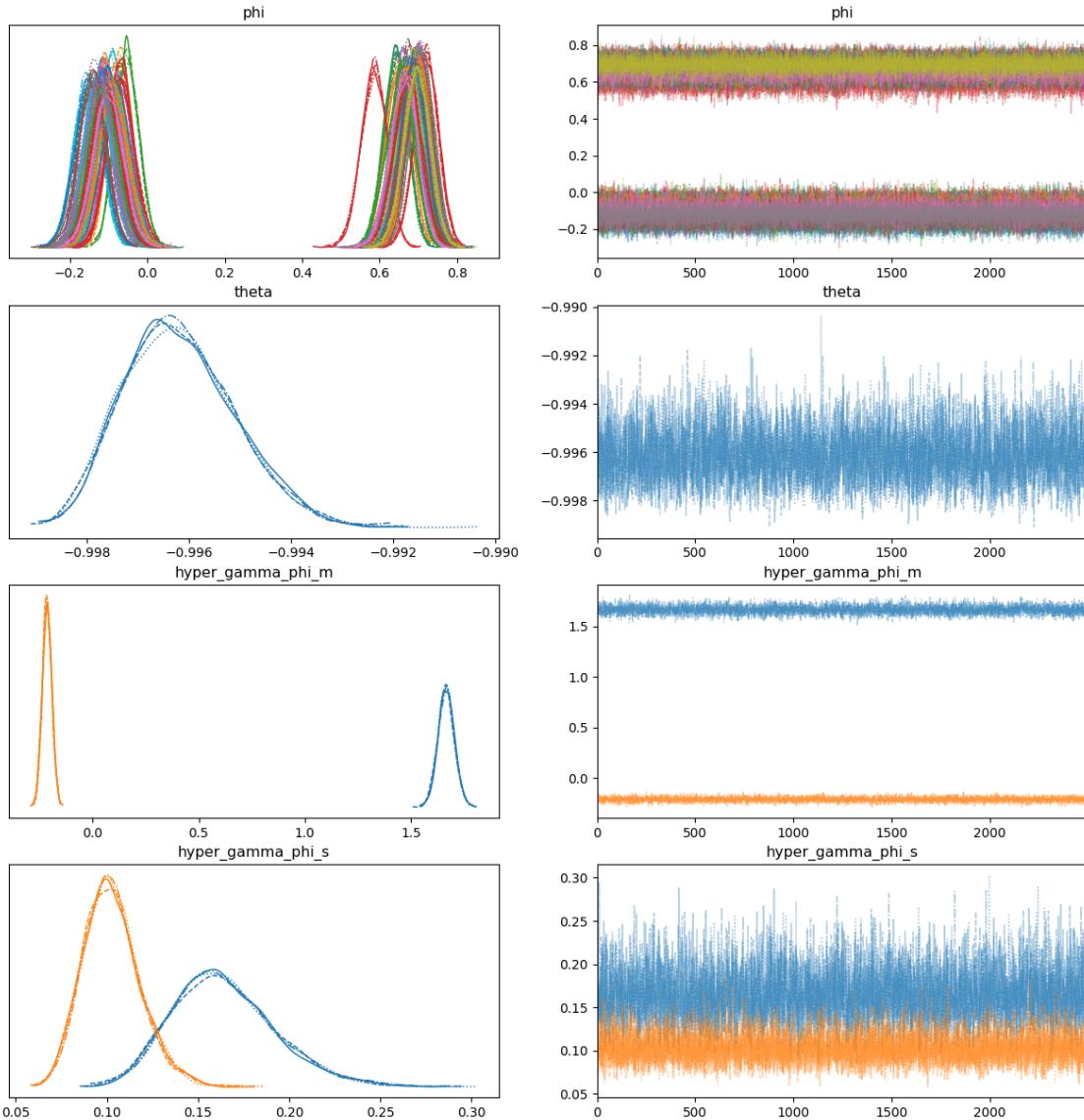
```
warnings.warn(
```

```
[7]: Computed from 10000 posterior samples and 17191 observations log-likelihood matrix.
```

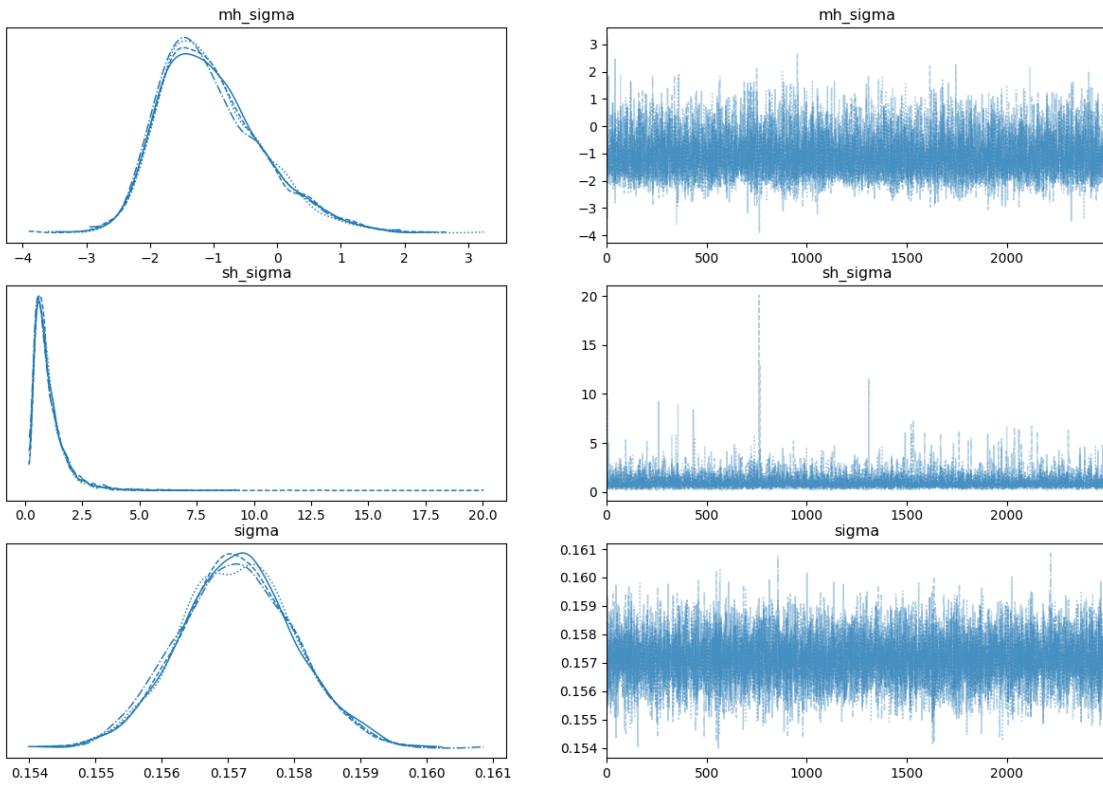
	Estimate	SE
elpd_waic	7264.00	154.85
p_waic	285.43	-

There has been a warning during the calculation. Please check the results.

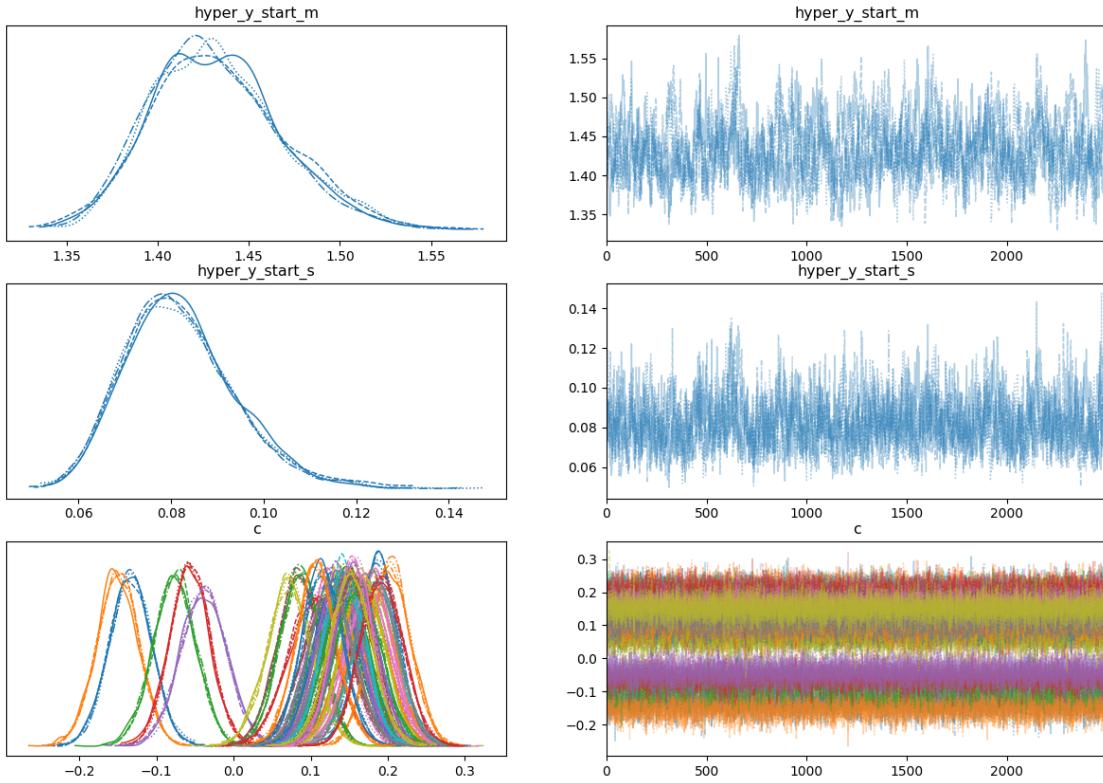
```
[8]: plt_aux = az.plot_trace(ritorno['inference_data'],  
    ↪var_names=['phi','theta','hyper_gamma_phi_m','hyper_gamma_phi_s'],  
    ↪divergences=True, figsize=(15,15))
```



```
[9]: plt_aux = az.plot_trace(ritorno['inference_data'],  
                           var_names=['mh_sigma', 'sh_sigma', 'sigma'], divergences=True, figsize=(15,10))
```



```
[10]: plt_aux = az.plot_trace(ritorno['inference_data'],
    var_names=['hyper_y_start_m', 'hyper_y_start_s', 'c'], divergences=True,
    figsize=(15,10))
```



```
[11]: az.summary(ritorno['inference_data'], var_names=['y_start'])
```

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	\
y_start[0, 0]	1.421	0.089	1.254	1.588	0.002	0.001	2237.0	
y_start[0, 1]	1.420	0.089	1.247	1.586	0.002	0.001	2358.0	
y_start[0, 2]	1.424	0.093	1.249	1.597	0.002	0.001	2835.0	
y_start[0, 3]	1.424	0.090	1.248	1.588	0.002	0.001	3154.0	
y_start[0, 4]	1.427	0.091	1.259	1.600	0.002	0.001	2664.0	
...	
y_start[2, 44]	1.445	0.054	1.346	1.549	0.001	0.001	1481.0	
y_start[2, 45]	1.442	0.055	1.338	1.545	0.001	0.001	1620.0	
y_start[2, 46]	1.438	0.054	1.338	1.538	0.001	0.001	1732.0	
y_start[2, 47]	1.452	0.055	1.347	1.552	0.001	0.001	1487.0	
y_start[2, 48]	1.459	0.056	1.355	1.562	0.001	0.001	1563.0	
	ess_tail	r_hat						
y_start[0, 0]	3725.0	1.0						
y_start[0, 1]	3599.0	1.0						
y_start[0, 2]	4100.0	1.0						
y_start[0, 3]	4000.0	1.0						
y_start[0, 4]	3541.0	1.0						
...						

```

y_start[2, 44]    2555.0    1.0
y_start[2, 45]    2722.0    1.0
y_start[2, 46]    2540.0    1.0
y_start[2, 47]    2769.0    1.0
y_start[2, 48]    2712.0    1.0

```

[147 rows x 9 columns]

```
[12]: az.summary(ritorno['inference_data'], var_names=['hyper_y_start_m', ↴'hyper_y_start_s'])
```

```

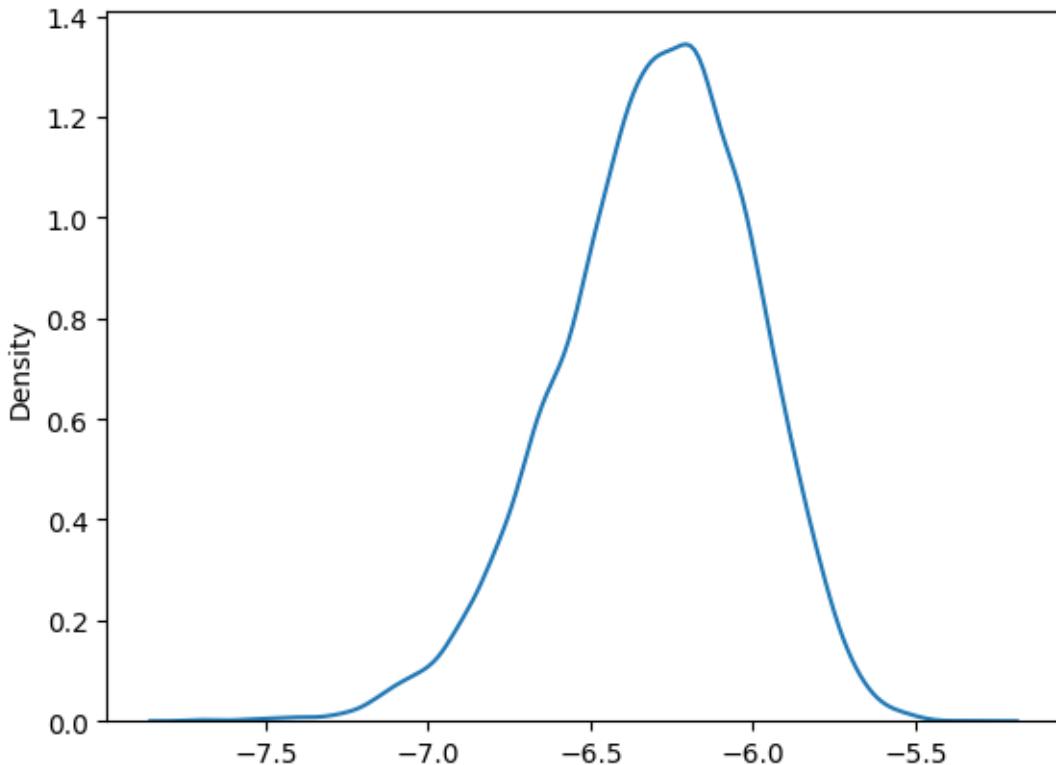
[12]:          mean      sd  hdi_3%  hdi_97%  mcse_mean  mcse_sd  ess_bulk \
hyper_y_start_m  1.432  0.037   1.367   1.504     0.002     0.001    431.0
hyper_y_start_s  0.082  0.012   0.061   0.105     0.001     0.000    580.0

                  ess_tail  r_hat
hyper_y_start_m    772.0   1.0
hyper_y_start_s   1215.0   1.0

```

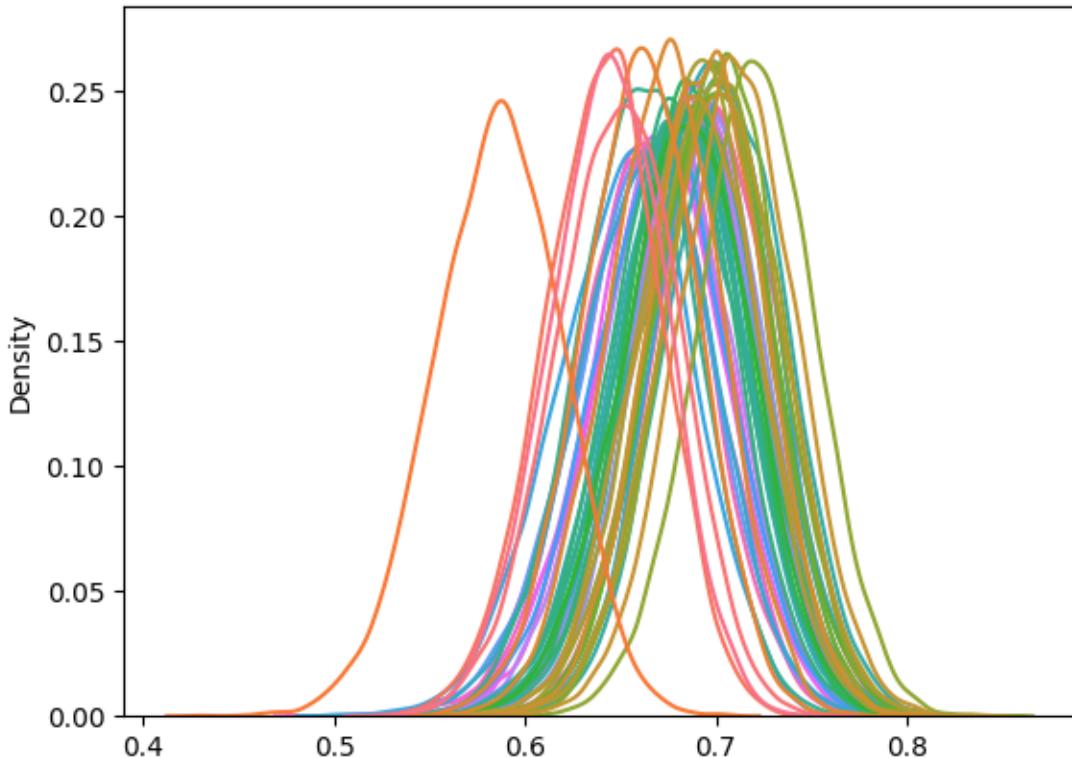
```
[13]: aux_shape = ritorno['inference_data'].posterior.gamma_th.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.gamma_th.values.
             ↴reshape((aux_shape[0]*aux_shape[1])), legend=False)
```

```
[13]: <AxesSubplot: ylabel='Density'>
```



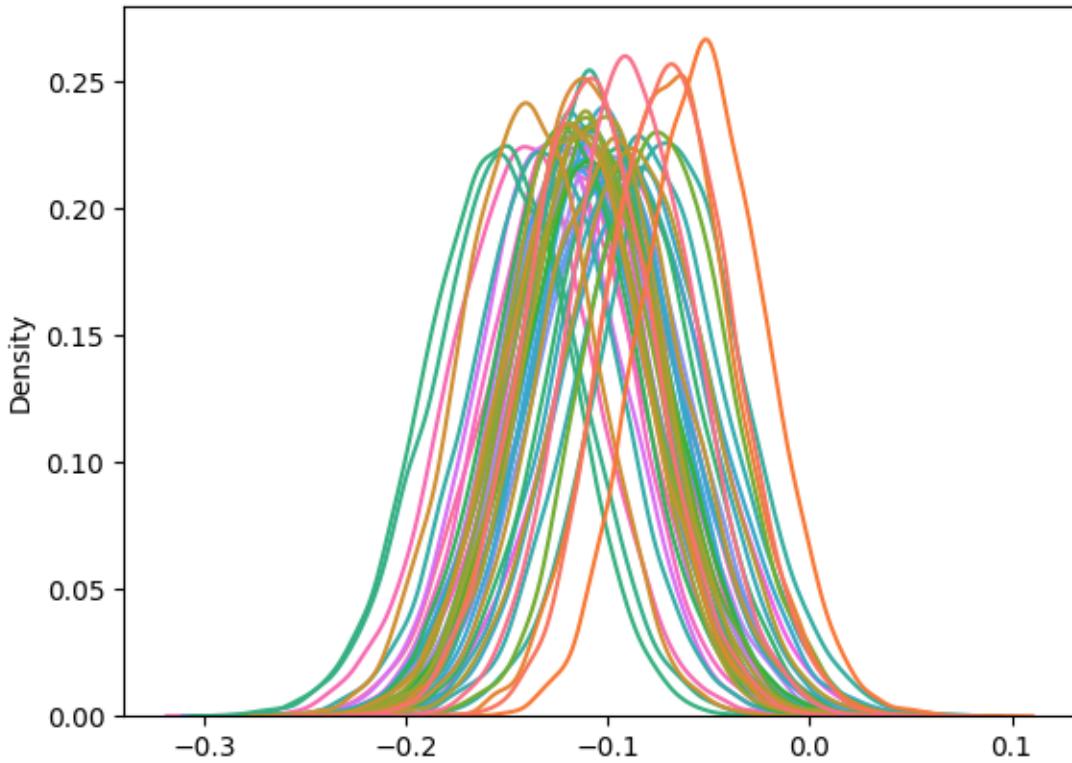
```
[14]: aux_shape = ritorno['inference_data'].posterior.phi.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.phi.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2],aux_shape[3]))[:,0,:,:],  
            legend=False)
```

```
[14]: <AxesSubplot: ylabel='Density'>
```



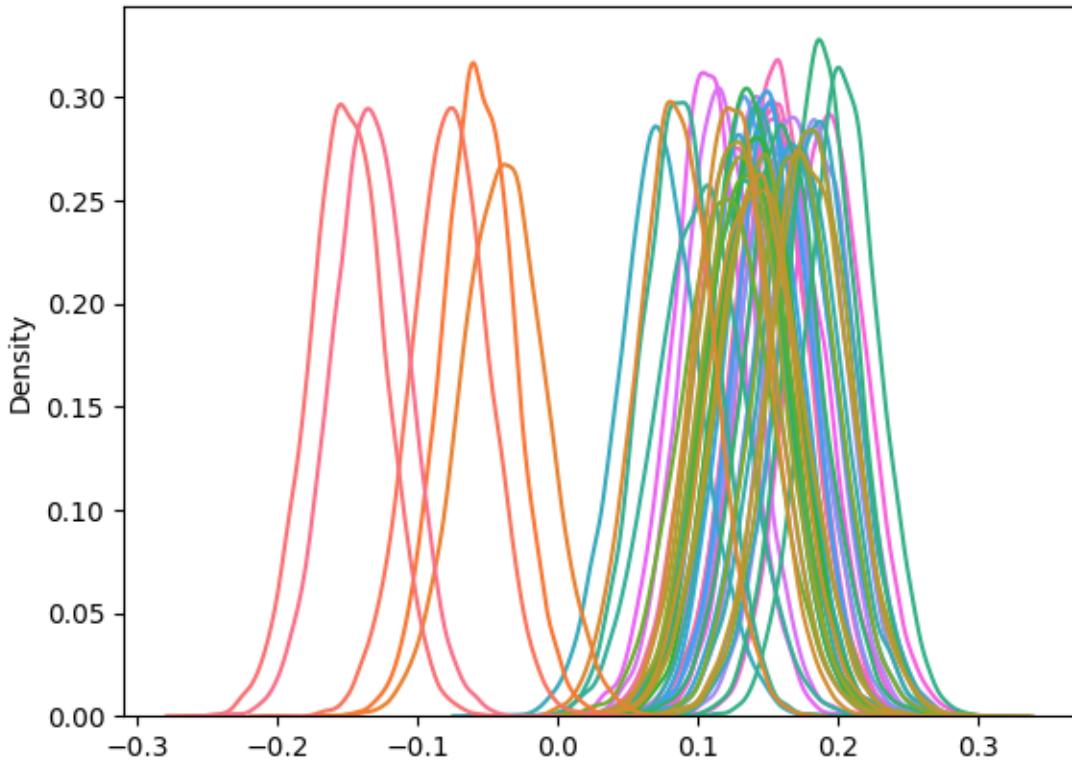
```
[15]: aux_shape = ritorno['inference_data'].posterior.phi.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.phi.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2],aux_shape[3]))[:,1,:,:],  
            legend=False)
```

```
[15]: <AxesSubplot: ylabel='Density'>
```



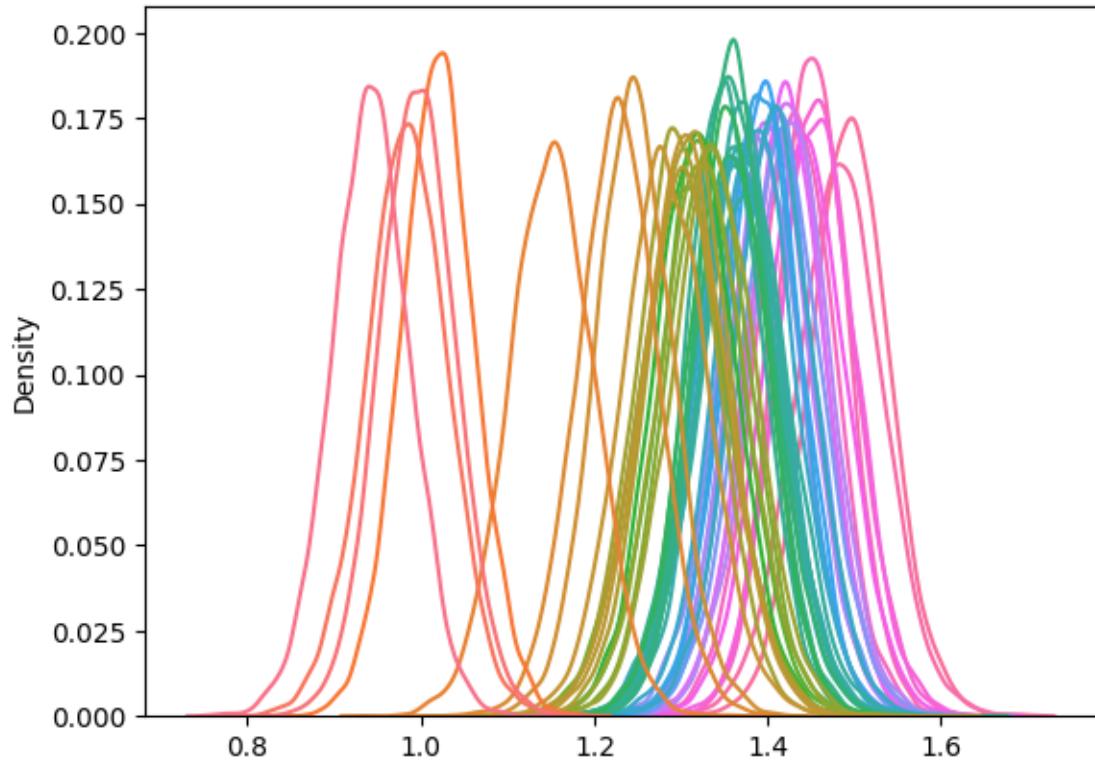
```
[16]: aux_shape = ritorno['inference_data'].posterior.c.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.c.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

```
[16]: <AxesSubplot: ylabel='Density'>
```



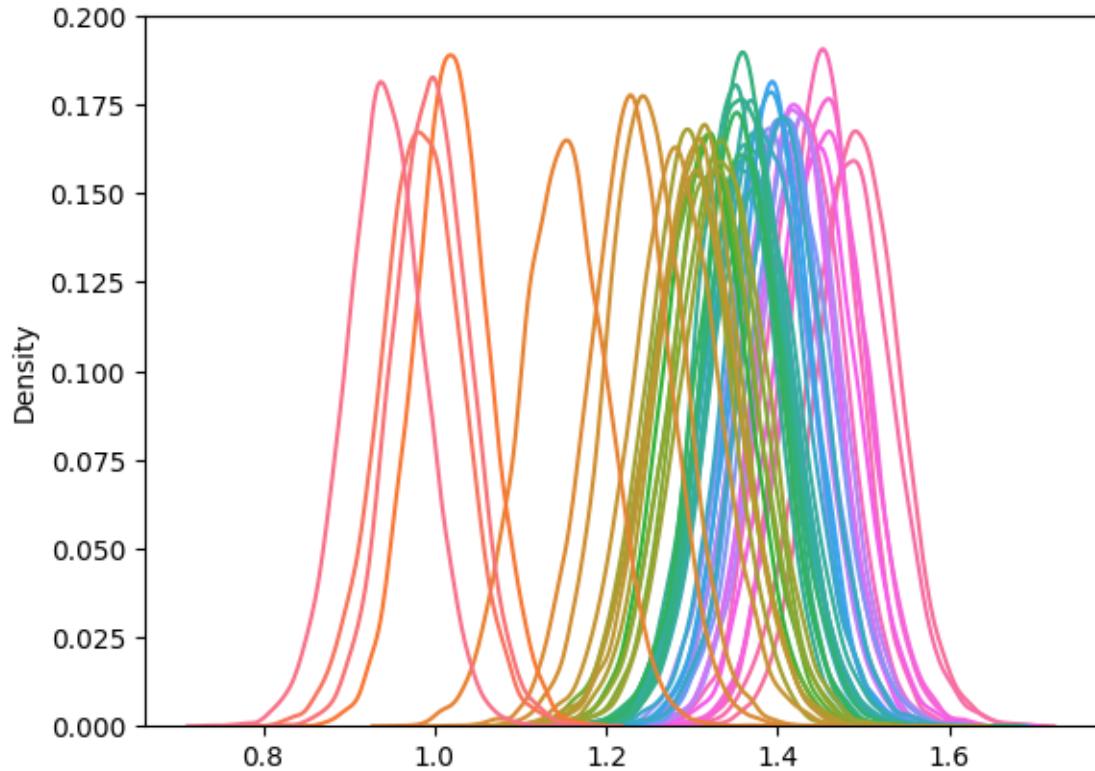
```
[17]: aux_shape = ritorno['inference_data'].posterior.annual_mean.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.annual_mean.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

```
[17]: <AxesSubplot: ylabel='Density'>
```



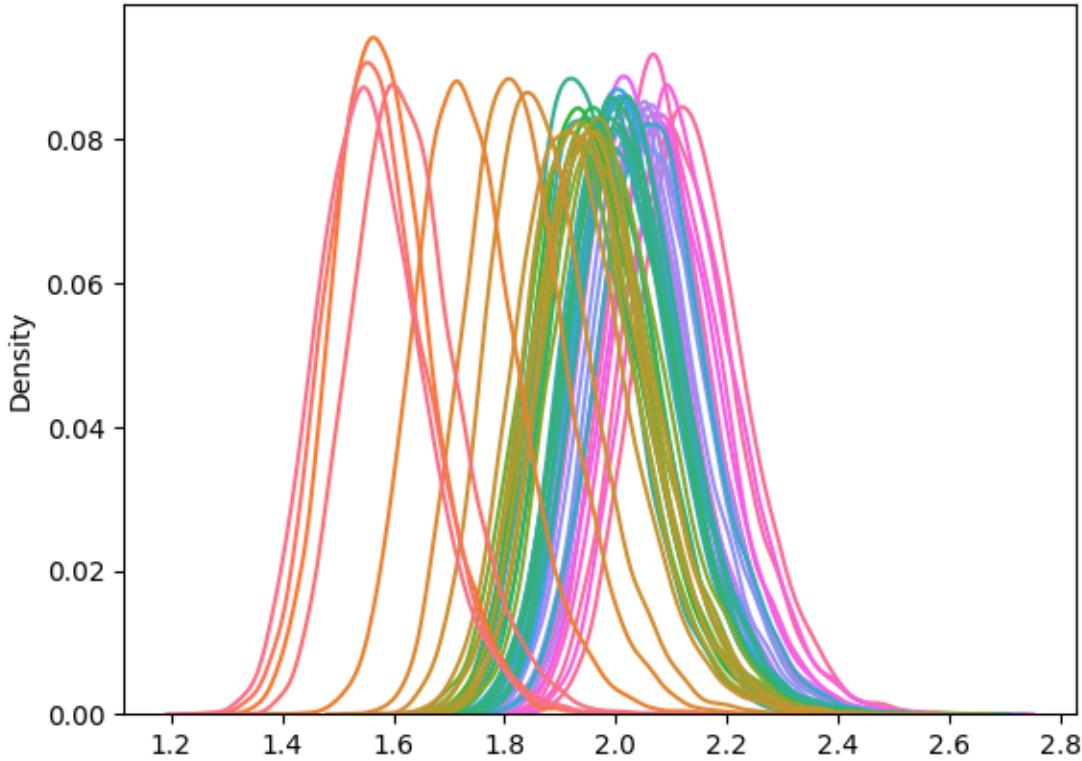
```
[18]: aux_shape = ritorno['inference_data'].posterior.annual_median.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.annual_median.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

```
[18]: <AxesSubplot: ylabel='Density'>
```



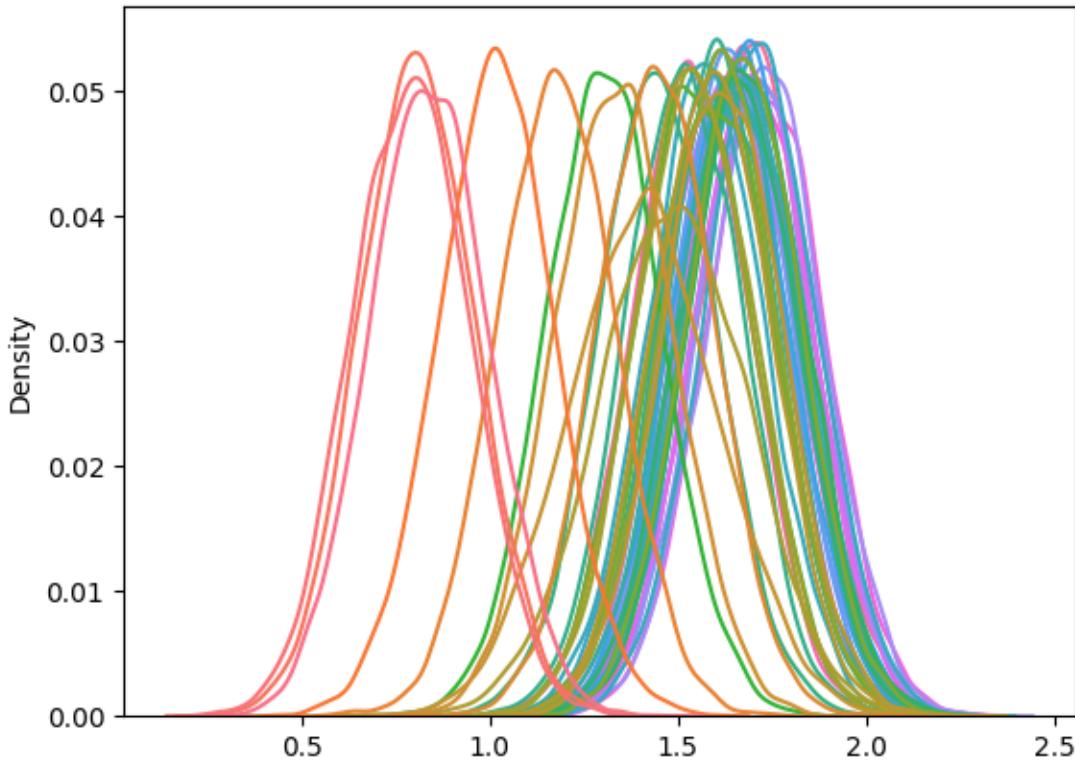
```
[19]: aux_shape = ritorno['inference_data'].posterior.annual_max.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.annual_max.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

```
[19]: <AxesSubplot: ylabel='Density'>
```



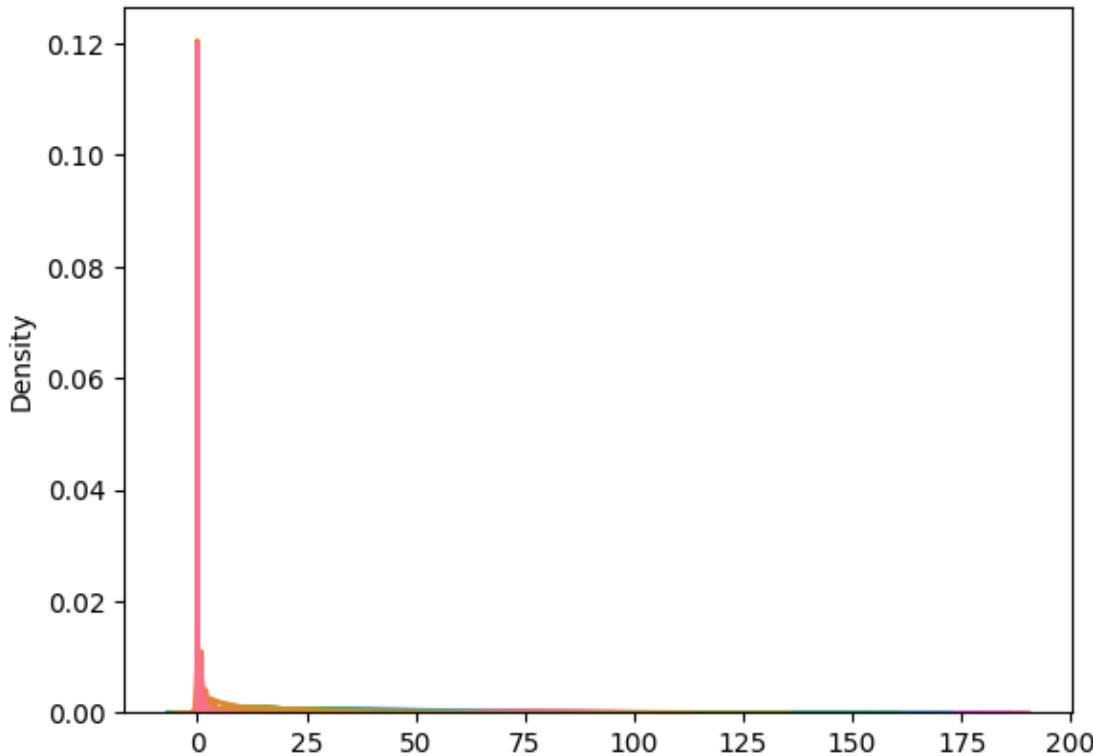
```
[20]: valori_31_dic = []
for dizionario in ritorno['missing']:
    if dizionario['Data'] == '2018-12-31':
        valori_31_dic.append(dizionario['Samples'])

res_plot = sns.kdeplot(valori_31_dic, legend=False)
```



```
[21]: aux_shape = ritorno['inference_data'].posterior.annual_days_over_threshold.  
       .values.shape  
sns.kdeplot(ritorno['inference_data'].posterior.annual_days_over_threshold.  
       .values.reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

```
[21]: <AxesSubplot: ylabel='Density'>
```



```
[22]: pd.set_option('display.max_columns', 500)
aux_results = pd.DataFrame(ritorno['inference_data'].posterior.
    ↪annual_days_over_threshold.values.
    ↪reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), columns=df.columns).
    ↪describe()
aux_results.sort_values('mean', axis=1, ascending=True)
```

	CASTELLUCCHIO	SAVIGNANO DI RIGO	CORTE BRUGNATELLA	FEBBIO \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.106700	0.116400	0.119700	0.289000
std	0.391574	0.382185	0.408642	0.673739
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	5.000000	4.000000	7.000000	7.000000
	SAN LEO	VERUCCHIO	BADIA	GIARDINI MARGHERITA \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	1.559900	4.887700	7.687600	13.404600
std	1.934473	4.081612	5.397863	8.422006
min	0.000000	0.000000	0.000000	0.000000

25%	0.000000	2.000000	4.000000	7.000000
50%	1.000000	4.000000	7.000000	12.000000
75%	2.000000	7.000000	10.000000	18.000000
max	21.000000	46.000000	46.000000	71.000000

	MARECCHIA	SAN PIETRO	CAPOFIUME	PARCO BERTOZZI	LUGAGNANO	\
count	10000.000000		10000.000000	10000.000000	10000.000000	
mean	15.672500		15.793200	17.390400	17.684900	
std	8.934071		9.851515	10.357901	9.836335	
min	0.000000		0.000000	0.000000	0.000000	
25%	9.000000		9.000000	10.000000	11.000000	
50%	14.000000		14.000000	16.000000	16.000000	
75%	20.000000		21.000000	23.000000	23.000000	
max	82.000000		104.000000	131.000000	93.000000	

	DE AMICIS	DELTA CERVIA	SAN LAZZARO	PARCO RESISTENZA	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	17.879000	17.911000	18.899100	19.614500	
std	9.548742	9.619789	10.460395	10.308885	
min	0.000000	0.000000	0.000000	0.000000	
25%	11.000000	11.000000	11.000000	12.000000	
50%	16.000000	16.000000	17.000000	18.000000	
75%	23.000000	23.000000	24.000000	25.000000	
max	86.000000	84.000000	92.000000	108.000000	

	FRANCHINI-ANGELONI	GHERARDI	VIA CHIARINI	GAVELLO	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	20.996000	21.328200	21.453700	23.363100	
std	11.223385	11.700238	11.404677	11.355472	
min	0.000000	0.000000	0.000000	0.000000	
25%	13.000000	13.000000	13.000000	15.000000	
50%	19.000000	19.000000	19.000000	22.000000	
75%	27.000000	28.000000	27.000000	30.000000	
max	105.000000	104.000000	104.000000	99.000000	

	SAVIGNANO	BESENZONE	VILLA FULVIA	ROMA	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	23.59780	24.217700	28.324600	28.342200	
std	11.55254	12.700694	13.488366	13.409634	
min	0.00000	0.000000	0.000000	0.000000	
25%	15.00000	15.000000	19.000000	19.000000	
50%	22.00000	22.000000	26.000000	26.000000	
75%	30.00000	31.000000	36.000000	36.000000	
max	103.00000	108.000000	112.000000	154.000000	

	PORTA SAN FELICE	CASTELLARANO	CAORLE	PARCO MONTECUCCO	\
count	10000.000000	10000.000000	10000.000000	10000.000000	

mean	28.789300	29.24280	29.529800	30.391600
std	13.087469	11.81637	14.628524	13.945031
min	0.000000	2.000000	0.000000	0.000000
25%	19.000000	21.00000	19.000000	20.000000
50%	27.000000	28.00000	27.000000	28.000000
75%	36.000000	36.00000	38.000000	38.000000
max	110.000000	113.00000	146.000000	122.000000

	ZALAMELLA	CENTO	PARCO EDILCARANI	BOGOLESE	\
count	10000.000000	10000.00000	10000.000000	10000.000000	
mean	30.775400	31.16390	31.796000	32.263300	
std	14.034288	14.23678	12.686799	13.744761	
min	0.000000	2.000000	3.000000	2.000000	
25%	21.000000	21.00000	23.000000	22.000000	
50%	29.000000	29.00000	30.000000	30.000000	
75%	39.000000	39.00000	39.000000	40.000000	
max	135.000000	127.00000	98.000000	142.000000	

	SARAGAT	PARADIGNA	S. LAZZARO	MALCANTONE	REMESINA	\
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	
mean	34.652500	35.675200	36.286400	36.308700	37.110300	
std	14.303105	14.884061	15.056349	15.017036	14.948314	
min	3.000000	3.000000	3.000000	3.000000	2.000000	
25%	24.000000	25.000000	26.000000	26.000000	26.000000	
50%	33.000000	34.000000	34.000000	34.000000	35.000000	
75%	43.000000	44.000000	45.000000	45.000000	46.000000	
max	106.000000	136.000000	127.000000	114.000000	129.000000	

	S. ROCCO	ISONZO	CENO	PARCO FERRARI	CITTADELLA	\
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	
mean	38.380500	42.287200	42.403800	42.96810	46.064900	
std	15.692971	16.041161	17.171483	16.33913	16.927479	
min	2.000000	2.000000	4.000000	5.00000	6.000000	
25%	27.000000	31.000000	30.000000	31.00000	34.000000	
50%	36.000000	41.000000	40.000000	41.00000	44.000000	
75%	48.000000	52.000000	52.000000	52.00000	56.000000	
max	127.000000	144.000000	160.000000	165.00000	132.000000	

	GIORDANI-FARNESE	SAN FRANCESCO	FLAMINIA	MONTEBELLO	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	46.171700	50.864500	51.161100	54.630100	
std	17.198482	17.002725	18.762461	18.677081	
min	3.000000	6.000000	5.000000	8.000000	
25%	34.000000	39.000000	38.000000	41.000000	
50%	44.000000	49.000000	49.000000	53.000000	
75%	57.000000	61.000000	62.000000	66.000000	
max	146.000000	136.000000	177.000000	145.000000	

	GIARDINI	GERBIDO	TIMAVO
count	10000.000000	10000.000000	10000.000000
mean	60.347000	63.473900	70.158600
std	19.584973	22.603575	21.960589
min	5.000000	5.000000	8.000000
25%	46.000000	48.000000	55.000000
50%	59.000000	61.000000	68.000000
75%	72.000000	77.000000	84.000000
max	169.000000	179.000000	180.000000

```
[23]: pd.set_option('display.max_columns', 500)
aux_results = pd.DataFrame(ritorno['inference_data'].posterior.
    ↪is_over_daily_limit.values.
    ↪reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), columns=df.columns).
    ↪describe()
aux_results.sort_values('mean', axis=1, ascending=True)
```

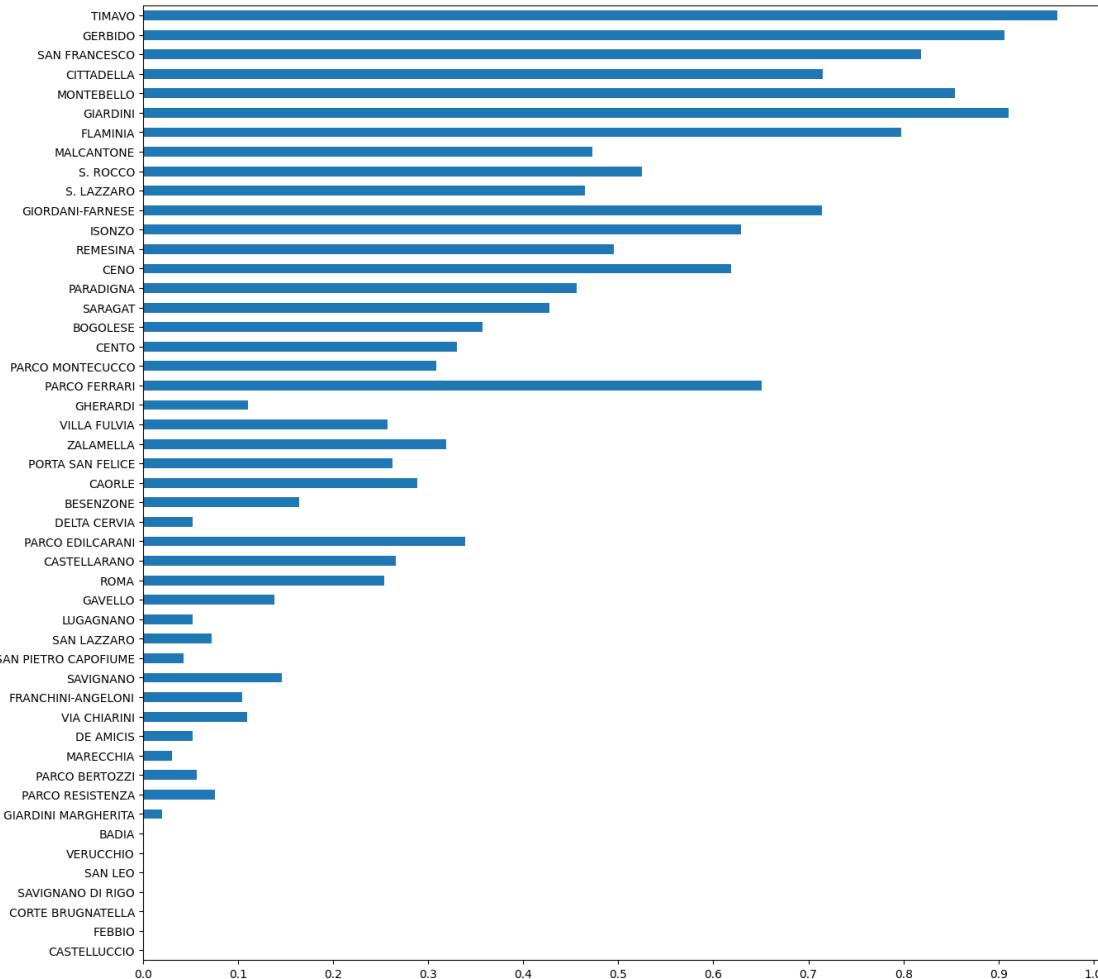
	CASTELLUCCIO	FEBBIO	CORTE BRUGNATELLA	SAVIGNANO DI RIGO	SAN LEO	\
count	10000.0	10000.0	10000.0	10000.0	10000.0	
mean	0.0	0.0	0.0	0.0	0.0	
std	0.0	0.0	0.0	0.0	0.0	
min	0.0	0.0	0.0	0.0	0.0	
25%	0.0	0.0	0.0	0.0	0.0	
50%	0.0	0.0	0.0	0.0	0.0	
75%	0.0	0.0	0.0	0.0	0.0	
max	0.0	0.0	0.0	0.0	0.0	
	VERUCCHIO	BADIA	GIARDINI MARGHERITA	MARECCHIA	\	
count	10000.000000	10000.000000	10000.000000	10000.000000		
mean	0.000400	0.001300	0.019800	0.030800		
std	0.019997	0.036034	0.139319	0.172784		
min	0.000000	0.000000	0.000000	0.000000		
25%	0.000000	0.000000	0.000000	0.000000		
50%	0.000000	0.000000	0.000000	0.000000		
75%	0.000000	0.000000	0.000000	0.000000		
max	1.000000	1.000000	1.000000	1.000000		
	SAN PIETRO CAPOFIUME	DE AMICIS	DELTA CERVIA	LUGAGNANO	\	
count	10000.000000	10000.000000	10000.000000	10000.000000		
mean	0.042900	0.051900	0.051900	0.052600		
std	0.202642	0.221836	0.221836	0.223245		
min	0.000000	0.000000	0.000000	0.000000		
25%	0.000000	0.000000	0.000000	0.000000		
50%	0.000000	0.000000	0.000000	0.000000		
75%	0.000000	0.000000	0.000000	0.000000		
max	1.000000	1.000000	1.000000	1.000000		

	PARCO BERTOZZI	SAN LAZZARO	PARCO RESISTENZA	FRANCHINI-ANGELONI	\
count	10000.00000	10000.000000	10000.000000	10000.000000	
mean	0.05670	0.072300	0.075800	0.104700	
std	0.23128	0.258997	0.264691	0.306182	
min	0.00000	0.000000	0.000000	0.000000	
25%	0.00000	0.000000	0.000000	0.000000	
50%	0.00000	0.000000	0.000000	0.000000	
75%	0.00000	0.000000	0.000000	0.000000	
max	1.00000	1.000000	1.000000	1.000000	
	VIA CHIARINI	GHERARDI	GAVELLO	SAVIGNANO	BESENZONE \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.110000	0.110300	0.138200	0.146200	0.164400
std	0.312905	0.313279	0.345127	0.353324	0.370657
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000
	ROMA	VILLA FULVIA	PORTA SAN FELICE	CASTELLARANO	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	0.253800	0.257000	0.262300	0.265700	
std	0.435206	0.437001	0.439907	0.441727	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	
	CAORLE	PARCO MONTECUCCO	ZALAMELLA	CENTO	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	0.289000	0.308800	0.318600	0.330200	
std	0.453321	0.462022	0.465957	0.470308	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	
	PARCO EDILCARANI	BOGOLESE	SARAGAT	PARADIGNA	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	0.339400	0.357600	0.428000	0.456100	
std	0.473529	0.479317	0.494814	0.498094	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	

50%	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	
	S. LAZZARO	MALCANTONE	REMESINA	S. ROCCO	CENO \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.464900	0.472600	0.495100	0.525300	0.618500
std	0.498791	0.499274	0.500001	0.499384	0.485779
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	1.000000	1.000000
75%	1.000000	1.000000	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000
	ISONZO	PARCO FERRARI	GIORDANI-FARNESE	CITTADELLA \	
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	0.629300	0.651200	0.714200	0.715000	
std	0.483016	0.476614	0.451817	0.451437	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	1.000000	1.000000	1.000000	1.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	
	FLAMINIA	SAN FRANCESCO	MONTEBELLO	GERBIDO	GIARDINI \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.797300	0.81890	0.854000	0.906000	0.911000
std	0.402031	0.38512	0.353124	0.291843	0.284758
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	1.000000	1.000000	1.000000	1.000000
50%	1.000000	1.000000	1.000000	1.000000	1.000000
75%	1.000000	1.000000	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000
	TIMAVO				
count	10000.000000				
mean	0.961900				
std	0.191447				
min	0.000000				
25%	1.000000				
50%	1.000000				
75%	1.000000				
max	1.000000				

```
[24]: aux_results.loc['mean',:].plot(kind='barh', figsize=(15,15), xticks=np.linspace(0,1,11))
#res = plt.xticks(rotation = 30)
```

[24]: <AxesSubplot: >



```
[25]: pd.set_option('display.max_columns', 500)
aux_results = pd.DataFrame(ritorno['inference_data'].posterior.
    ↪is_over_annual_limit.values.
    ↪reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), columns=df.columns).
    ↪describe()
aux_results.sort_values('mean', axis=1, ascending=True)
```

```
[25]:      CASTELLUCIO  SARAGAT  CENTO  PARCO MONTECUCCO  S. ROCCO  GHERARDI \
count    10000.0    10000.0   10000.0     10000.0    10000.0   10000.0
mean      0.0       0.0       0.0        0.0       0.0       0.0
std       0.0       0.0       0.0        0.0       0.0       0.0
min       0.0       0.0       0.0        0.0       0.0       0.0
25%       0.0       0.0       0.0        0.0       0.0       0.0
50%       0.0       0.0       0.0        0.0       0.0       0.0
75%       0.0       0.0       0.0        0.0       0.0       0.0
```

max	0.0	0.0	0.0		0.0	0.0	0.0	\
VILLA	FULVIA	PORTA	SAN FELICE	MALCANTONE	BESENZONE	DELTA	CERVIA	\
count	10000.0		10000.0	10000.0	10000.0		10000.0	
mean	0.0		0.0	0.0	0.0		0.0	
std	0.0		0.0	0.0	0.0		0.0	
min	0.0		0.0	0.0	0.0		0.0	
25%	0.0		0.0	0.0	0.0		0.0	
50%	0.0		0.0	0.0	0.0		0.0	
75%	0.0		0.0	0.0	0.0		0.0	
max	0.0		0.0	0.0	0.0		0.0	
PARCO	EDILCARANI	CASTELLARANO	S. LAZZARO	LUGAGNANO	SAN LAZZARO		\	
count	10000.0		10000.0	10000.0	10000.0		10000.0	
mean	0.0		0.0	0.0	0.0		0.0	
std	0.0		0.0	0.0	0.0		0.0	
min	0.0		0.0	0.0	0.0		0.0	
25%	0.0		0.0	0.0	0.0		0.0	
50%	0.0		0.0	0.0	0.0		0.0	
75%	0.0		0.0	0.0	0.0		0.0	
max	0.0		0.0	0.0	0.0		0.0	
GAVELLO	SAVIGNANO	FEBBIO	CORTE BRUGNATELLA	SAVIGNANO DI RIGO		\		
count	10000.0	10000.0	10000.0		10000.0		10000.0	
mean	0.0	0.0	0.0		0.0		0.0	
std	0.0	0.0	0.0		0.0		0.0	
min	0.0	0.0	0.0		0.0		0.0	
25%	0.0	0.0	0.0		0.0		0.0	
50%	0.0	0.0	0.0		0.0		0.0	
75%	0.0	0.0	0.0		0.0		0.0	
max	0.0	0.0	0.0		0.0		0.0	
SAN LEO	VERUCCHIO	BADIA	SAN PIETRO	CAPOFIUME	REMESINA		\	
count	10000.0	10000.0	10000.0		10000.0		10000.0	
mean	0.0	0.0	0.0		0.0		0.0	
std	0.0	0.0	0.0		0.0		0.0	
min	0.0	0.0	0.0		0.0		0.0	
25%	0.0	0.0	0.0		0.0		0.0	
50%	0.0	0.0	0.0		0.0		0.0	
75%	0.0	0.0	0.0		0.0		0.0	
max	0.0	0.0	0.0		0.0		0.0	
PARCO	RESISTENZA	MARECCHIA	DE AMICIS	VIA CHIARINI		\		
count	10000.0	10000.0	10000.0		10000.0			
mean	0.0	0.0	0.0		0.0			
std	0.0	0.0	0.0		0.0			
min	0.0	0.0	0.0		0.0			

25%	0.0	0.0	0.0	0.0
50%	0.0	0.0	0.0	0.0
75%	0.0	0.0	0.0	0.0
max	0.0	0.0	0.0	0.0

	FRANCHINI-ANGELONI	GIARDINI MARGHERITA	PARCO BERTOZZI	ROMA \
count	10000.0	10000.0	10000.0000	10000.0000
mean	0.0	0.0	0.0001	0.0001
std	0.0	0.0	0.0100	0.0100
min	0.0	0.0	0.0000	0.0000
25%	0.0	0.0	0.0000	0.0000
50%	0.0	0.0	0.0000	0.0000
75%	0.0	0.0	0.0000	0.0000
max	0.0	0.0	1.0000	1.0000

	BOGOLESE	PARADIGNA	ZALAMELLA	CAORLE	ISONZO \
count	10000.0000	10000.0000	10000.0000	10000.000000	10000.000000
mean	0.0001	0.0001	0.0001	0.000200	0.000200
std	0.0100	0.0100	0.0100	0.014141	0.014141
min	0.0000	0.0000	0.0000	0.000000	0.000000
25%	0.0000	0.0000	0.0000	0.000000	0.000000
50%	0.0000	0.0000	0.0000	0.000000	0.000000
75%	0.0000	0.0000	0.0000	0.000000	0.000000
max	1.0000	1.0000	1.0000	1.000000	1.000000

	PARCO FERRARI	CITTADELLA	GIORDANI-FARNESE	SAN FRANCESCO \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.000300	0.000300	0.000400	0.000400
std	0.017319	0.017319	0.019997	0.019997
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

	CENO	FLAMINIA	GIARDINI	MONTEBELLO	GERBIDO \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.000500	0.001200	0.001400	0.00180	0.012300
std	0.022356	0.034622	0.037392	0.04239	0.110227
min	0.000000	0.000000	0.000000	0.00000	0.000000
25%	0.000000	0.000000	0.000000	0.00000	0.000000
50%	0.000000	0.000000	0.000000	0.00000	0.000000
75%	0.000000	0.000000	0.000000	0.00000	0.000000
max	1.000000	1.000000	1.000000	1.00000	1.000000

	TIMAVO
count	10000.000000

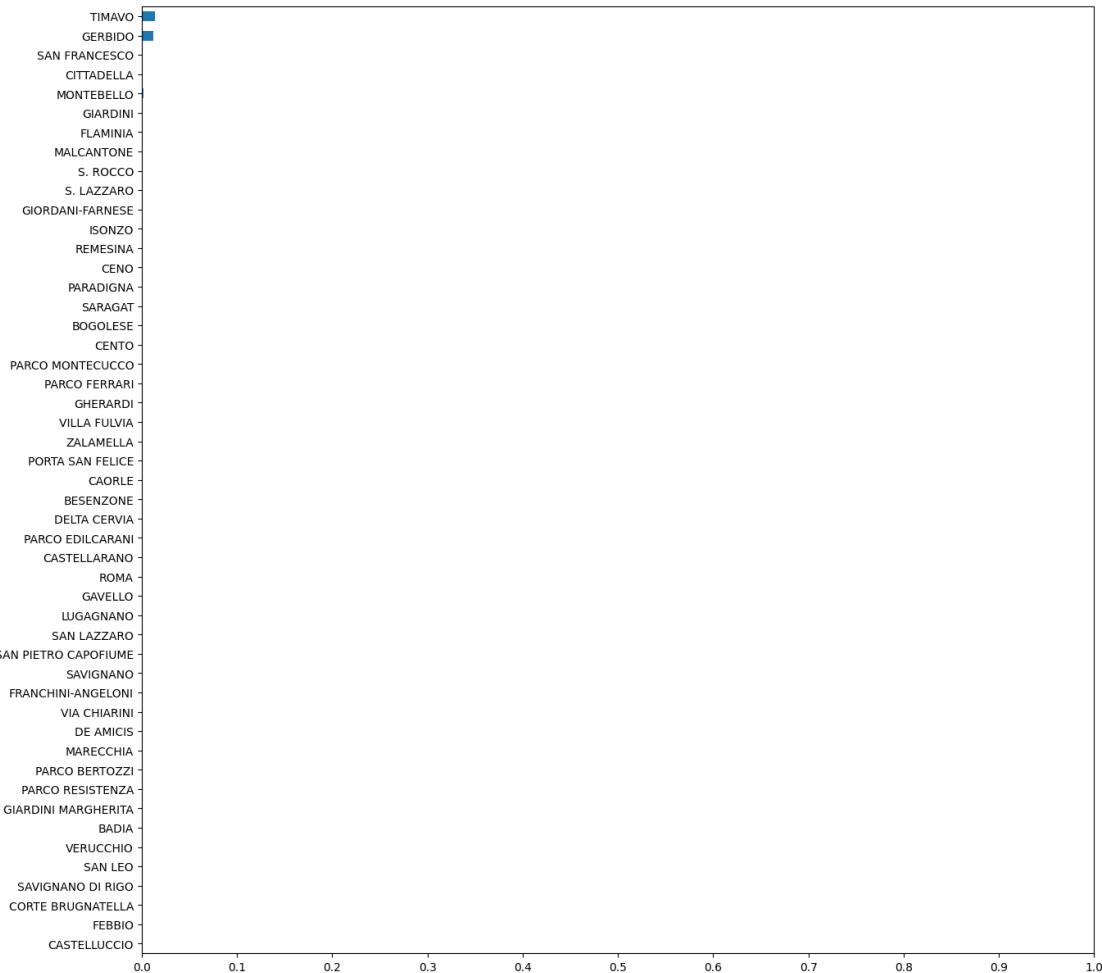
```

mean      0.013500
std       0.115408
min       0.000000
25%      0.000000
50%      0.000000
75%      0.000000
max       1.000000

```

```
[26]: aux_results.loc['mean', :].plot(kind='barh', figsize=(15,15), xticks=np.linspace(0,1,11))
#res = plt.xticks(rotation = 30)
```

[26]: <AxesSubplot: >



```
[27]: y_post_pred = ritorno['inference_data'].posterior.y_post_pred.to_numpy()
y_post_pred = y_post_pred.reshape(y_post_pred.shape[0]*y_post_pred.shape[1], y_post_pred.shape[2], y_post_pred.shape[3])
```

```
y_post_pred.shape
```

```
[27]: (10000, 365, 49)
```

```
[28]: import ipywidgets as widgets
from ipywidgets import HBox, VBox
from IPython.display import display
```

```
[29]: @widgets.interact(stazione = df.columns)
def f(stazione):
    col_map = sns.light_palette((20, 75, 70), input='husl', as_cmap=True)

    plt.figure(figsize=(14,8))
    ax = plt.subplot(1,1,1)

    idx_stazione = df.columns.to_list().index(stazione)

    """
    sns.lineplot(np.transpose(y_post_pred[0:50,:,:idx_stazione]))
    """

    lower_lim = np.zeros(len(df.index))
    upper_lim = np.zeros(len(df.index))
    for i in range(len(df.index)):
        lower_lim[i] = np.percentile(y_post_pred[:,i,idx_stazione],2.5)
        upper_lim[i] = np.percentile(y_post_pred[:,i,idx_stazione],97.5)

    # sns.lineplot(lower_lim)
    # sns.lineplot(upper_lim)

    for i in range(len(df.index)):
        ax.add_patch(mppt.patches.Rectangle((i,lower_lim[i]),1,upper_lim[i]-lower_lim[i], fill=True,color=col_map(180)))

    sns.lineplot(df[stazione])
    sns.lineplot(np.mean(y_post_pred[:, :, idx_stazione], axis=0))

    index = 0
    for line in ax.get_lines():
        if index == 0:
            col_map = sns.dark_palette((230,90,65), input='husl', as_cmap=True)
            line.set_c(col_map(155))
        else:
            col_map = sns.dark_palette((10,90,65), input='husl', as_cmap=True)
```

```

        line.set_c(col_map(175))
        index += 1

    plt.ylim(bottom=0,top=2.5)

    primo_giorno = datetime.date(2018,1,1)
    date_da_segnare = []
    date_da_segnare_posizioni = []

    for i in range(12):
        date_da_segnare.append(datetime.date(2018,i+1,1))
        date_da_segnare_posizioni.append((date_da_segnare[2*i] - primo_giorno).
        ↪days)
        date_da_segnare.append(datetime.date(2018,i+1,15))
        date_da_segnare_posizioni.append((date_da_segnare[2*i+1] -
        ↪primo_giorno).days)
        date_da_segnare[2*i] = date_da_segnare[2*i].isoformat()
        date_da_segnare[2*i+1] = date_da_segnare[2*i+1].isoformat()

    plt.xticks(date_da_segnare_posizioni,date_da_segnare,rotation=65)
    plt.tick_params(
        axis='x',          # changes apply to the x-axis
        which='both',      # both major and minor ticks are affected
        bottom=True,       # ticks along the bottom edge are off
        top=False,         # ticks along the top edge are off
        labelbottom=True)
    plt.grid()

    """
    ax.get_legend().remove()
    col_vals = np.linspace(1,255,num=len(df.columns))
    index = 0
    for line in ax.get_lines():
        if(index == len(ax.get_lines()) - 1):
            col_map = sns.dark_palette((230,90,65), input='husl', as_cmap=True)
            line.set_c(col_map(175))
            continue
        if(index == len(ax.get_lines()) - 2):
            col_map = sns.dark_palette((120,90,65), input='husl', as_cmap=True)
            line.set_c(col_map(175))
            index += 1
            continue

        #line.set_c(col_map(int(np.round(col_vals[index]))))
        line.set_c(col_map(220))
        line.set_alpha(0.3)
        index += 1
    """

```

```

    """
plt.show()

interactive(children=(Dropdown(description='stazione', options=('CASTELLUCCIO', 'FEBBIO', 'CORTE BRUGNATELLA',...,
[30]: def f(stazione):
    col_map = sns.light_palette((20, 75, 70), input='husl', as_cmap=True)

    plt.figure(figsize=(14,8))
    ax = plt.subplot(1,1,1)

    idx_stazione = df.columns.to_list().index(stazione)

    """
    sns.lineplot(np.transpose(y_post_pred[0:50,:,:idx_stazione]))
    """

    lower_lim = np.zeros(len(df.index))
    upper_lim = np.zeros(len(df.index))
    for i in range(len(df.index)):
        lower_lim[i] = np.percentile(y_post_pred[:,i,idx_stazione],2.5)
        upper_lim[i] = np.percentile(y_post_pred[:,i,idx_stazione],97.5)

    # sns.lineplot(lower_lim)
    # sns.lineplot(upper_lim)

    for i in range(len(df.index)):
        ax.add_patch(mpct.patches.Rectangle((i,lower_lim[i]),1,upper_lim[i]-lower_lim[i], fill=True,color=col_map(180)))

    sns.lineplot(df[stazione])
    sns.lineplot(np.mean(y_post_pred[:,:,:idx_stazione], axis=0))

    index = 0
    for line in ax.get_lines():
        if index == 0:
            col_map = sns.dark_palette((230,90,65), input='husl', as_cmap=True)
            line.set_c(col_map(155))
        else:
            col_map = sns.dark_palette((10,90,65), input='husl', as_cmap=True)

```

```

        line.set_c(col_map(175))
        index += 1

plt.ylim(bottom=0,top=2.5)

primo_giorno = datetime.date(2018,1,1)
date_da_segnare = []
date_da_segnare_posizioni = []

for i in range(12):
    date_da_segnare.append(datetime.date(2018,i+1,1))
    date_da_segnare_posizioni.append((date_da_segnare[2*i] - primo_giorno).
days)
    date_da_segnare.append(datetime.date(2018,i+1,15))
    date_da_segnare_posizioni.append((date_da_segnare[2*i+1] - primo_giorno).days)
    date_da_segnare[2*i] = date_da_segnare[2*i].isoformat()
    date_da_segnare[2*i+1] = date_da_segnare[2*i+1].isoformat()

plt.xticks(date_da_segnare_posizioni,date_da_segnare,rotation=65)
plt.tick_params(
    axis='x',          # changes apply to the x-axis
    which='both',      # both major and minor ticks are affected
    bottom=True,       # ticks along the bottom edge are off
    top=False,         # ticks along the top edge are off
    labelbottom=True)
plt.grid()

"""

ax.get_legend().remove()
col_vals = np.linspace(1,255,num=len(df.columns))
index = 0
for line in ax.get_lines():
    if(index == len(ax.get_lines()) - 1):
        col_map = sns.dark_palette((230,90,65), input='husl', as_cmap=True)
        line.set_c(col_map(175))
        continue
    if(index == len(ax.get_lines()) - 2):
        col_map = sns.dark_palette((120,90,65), input='husl', as_cmap=True)
        line.set_c(col_map(175))
        index += 1
        continue

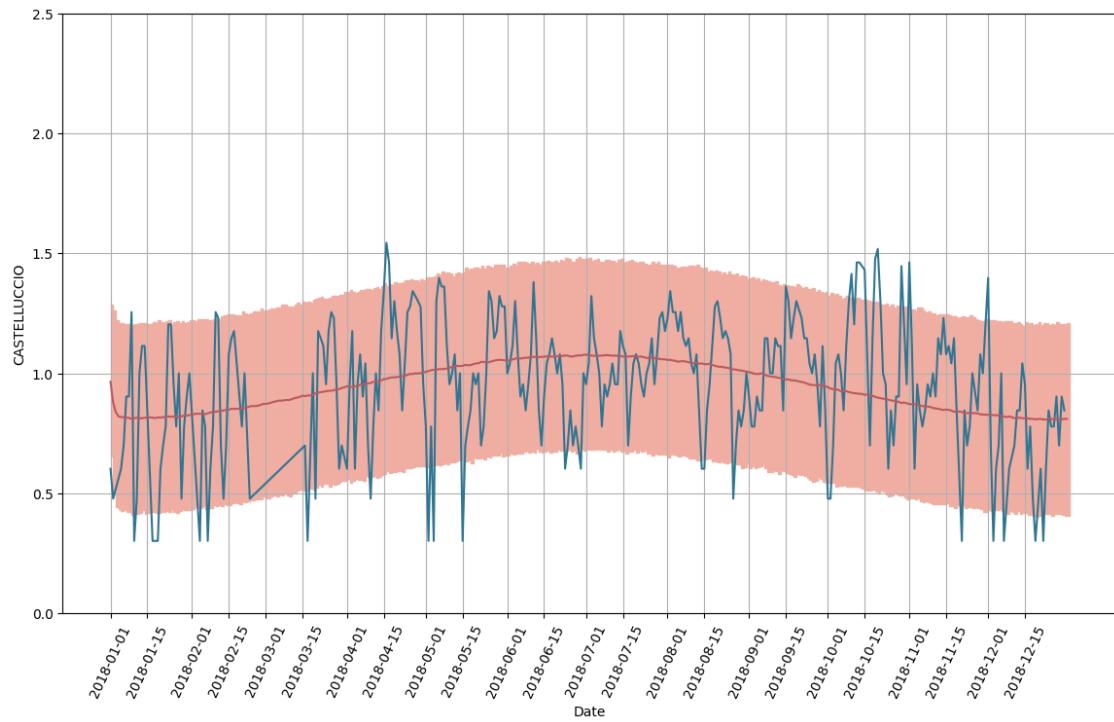
#line.set_c(col_map(int(np.round(col_vals[index]))))
line.set_c(col_map(220))
line.set_alpha(0.3)
index += 1

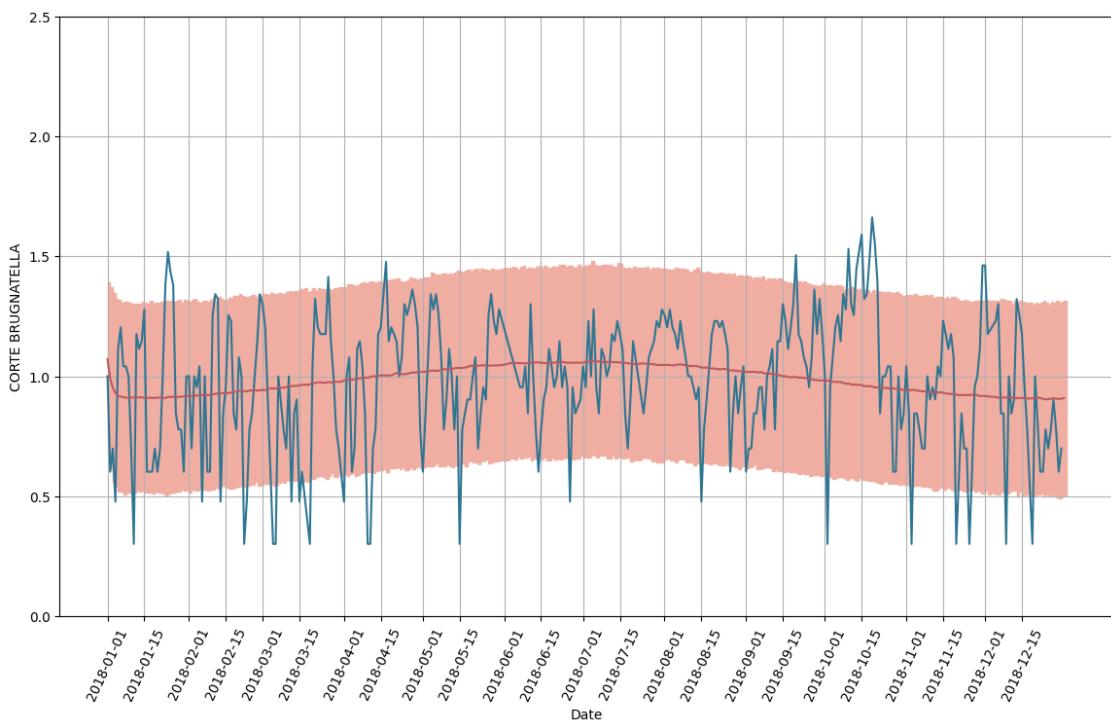
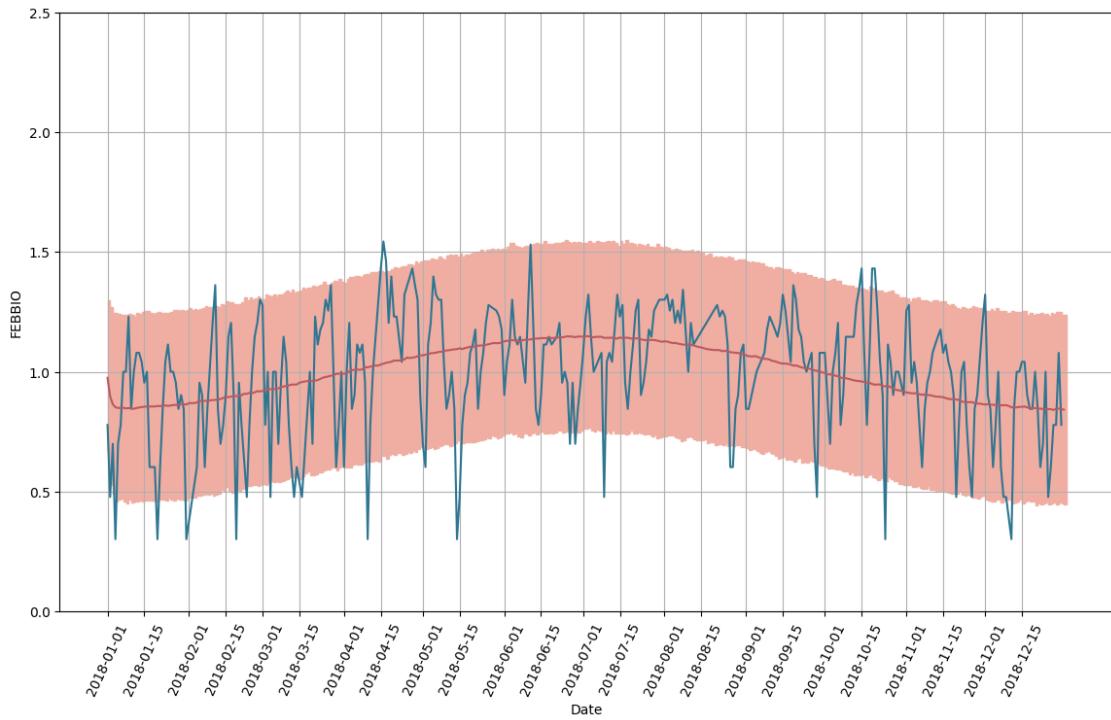
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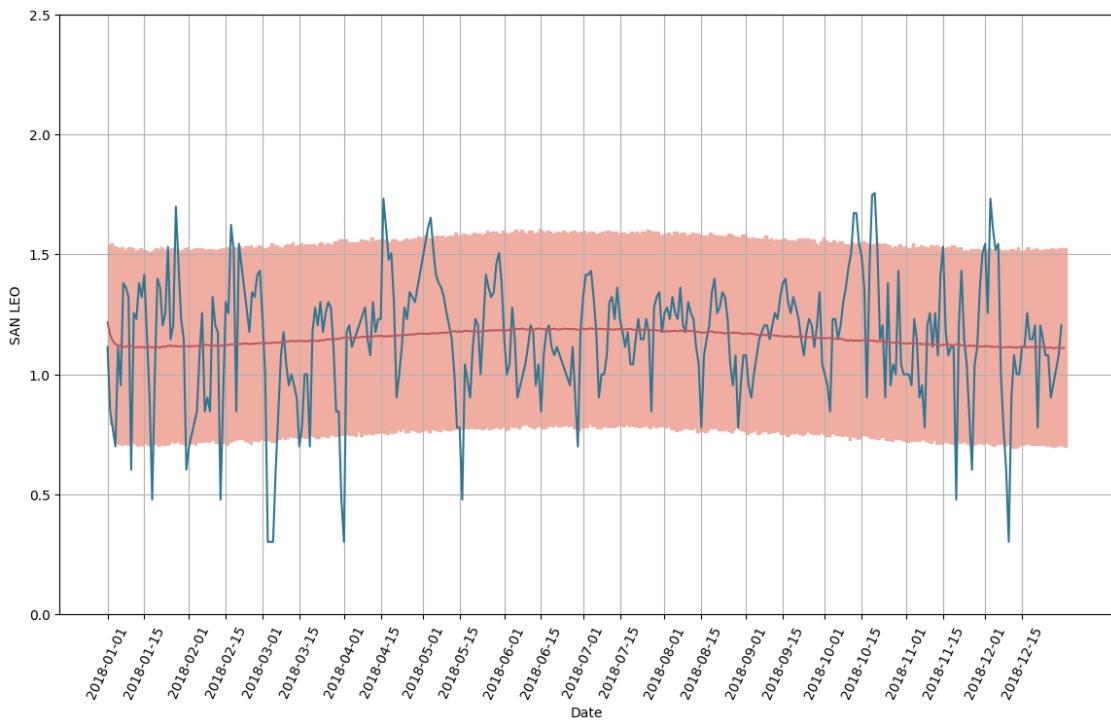
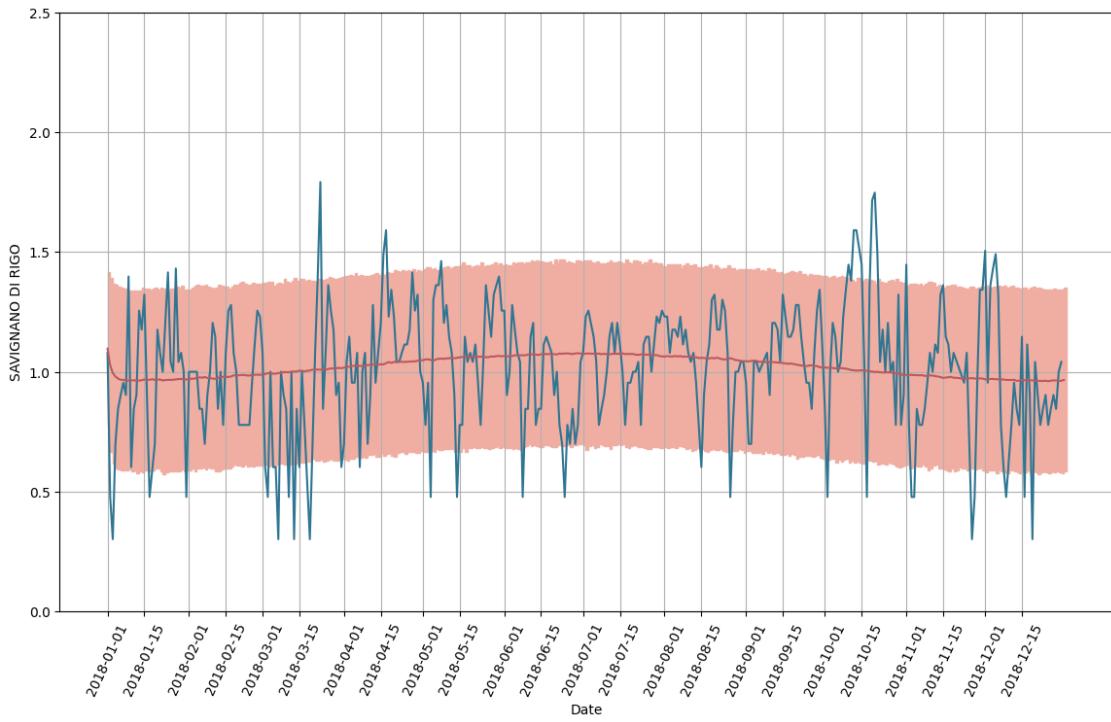
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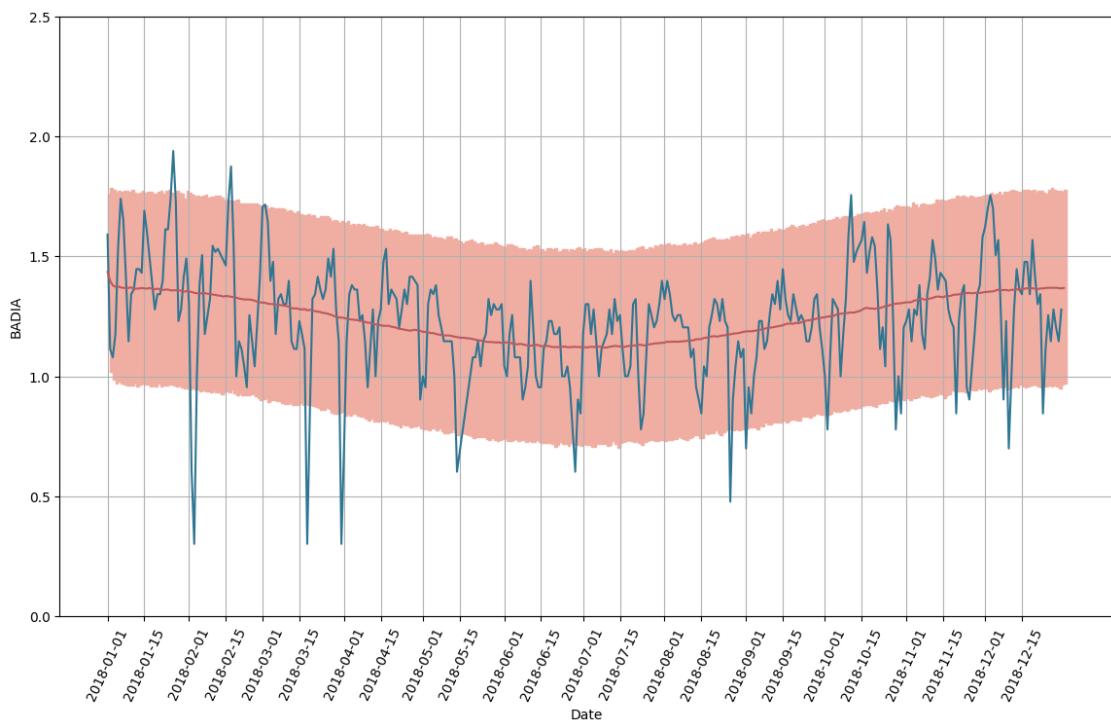
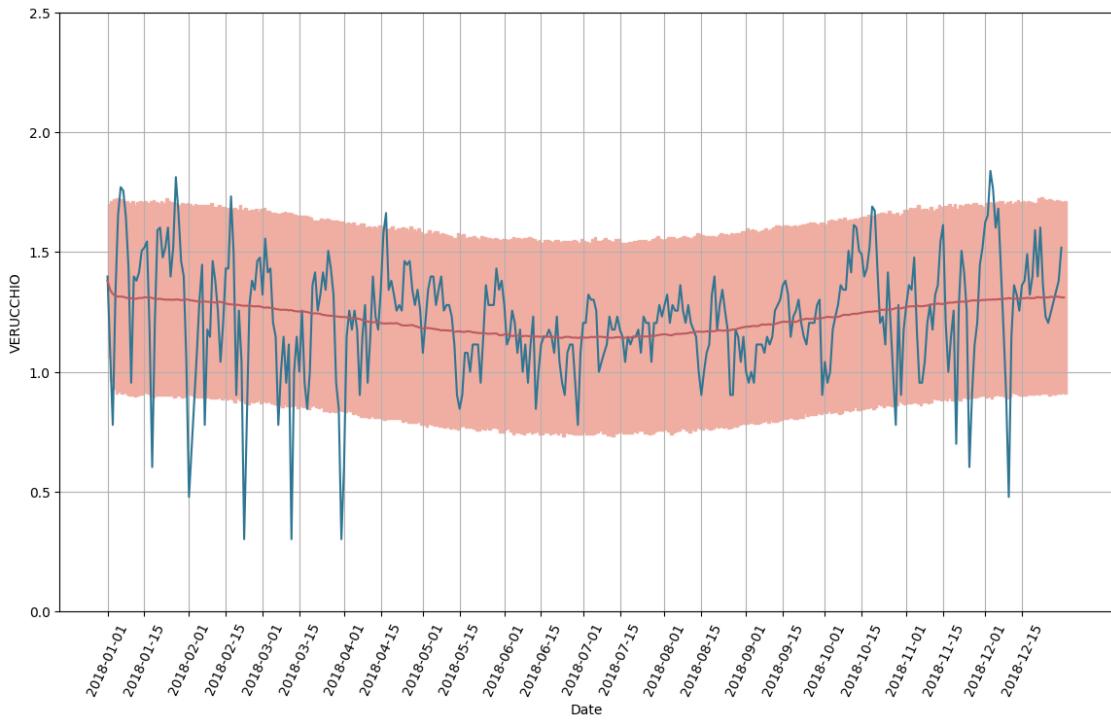
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plt.show()
```

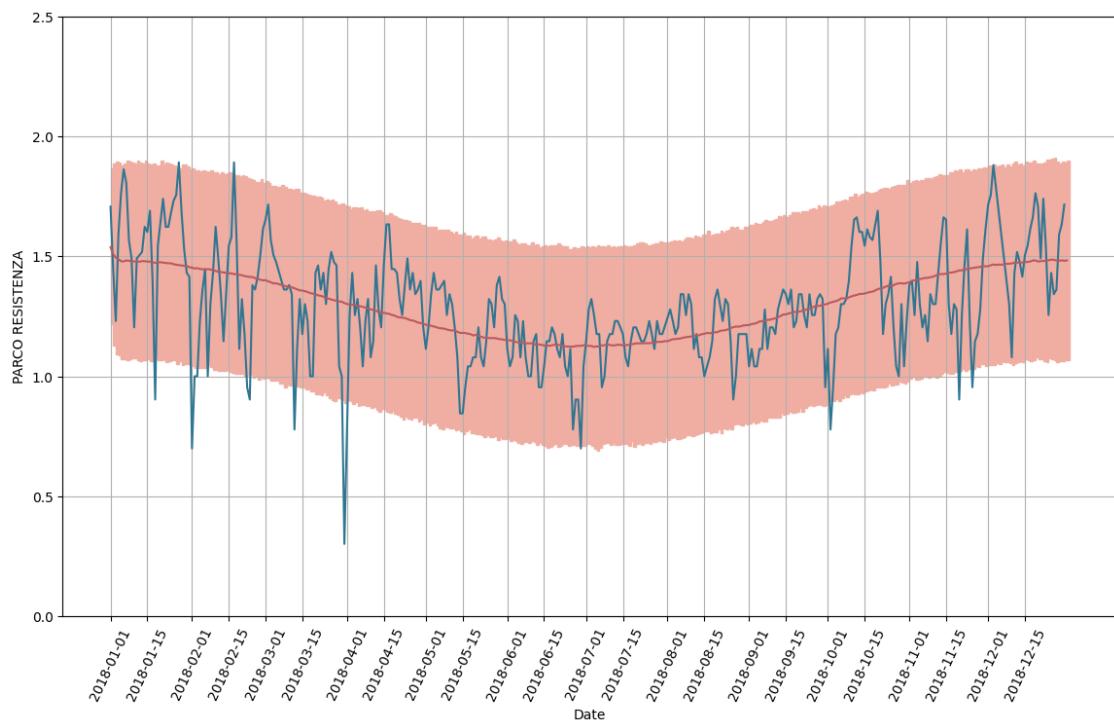
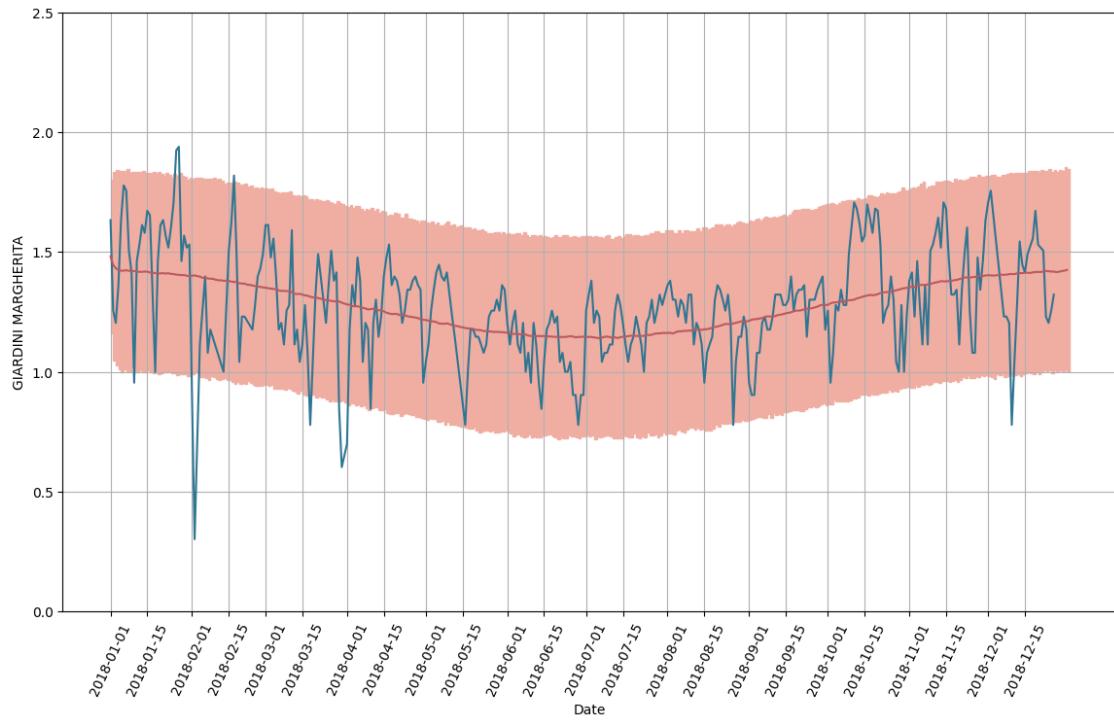
```
[31]: for stazione in df.columns:  
    f(stazione)
```

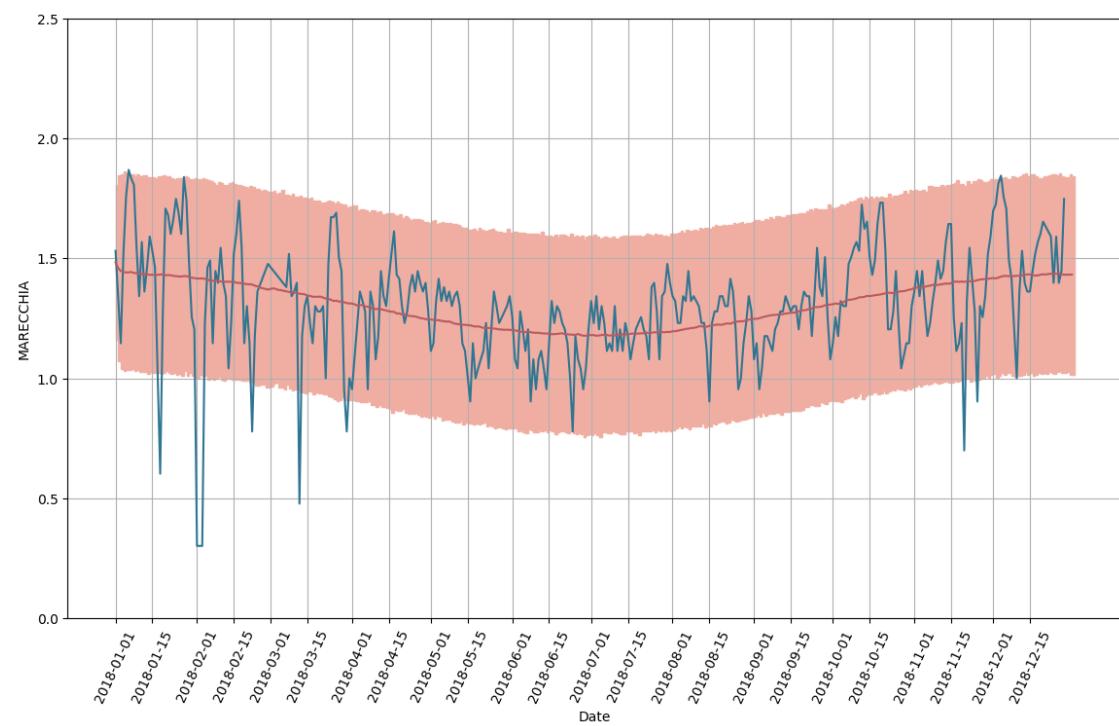
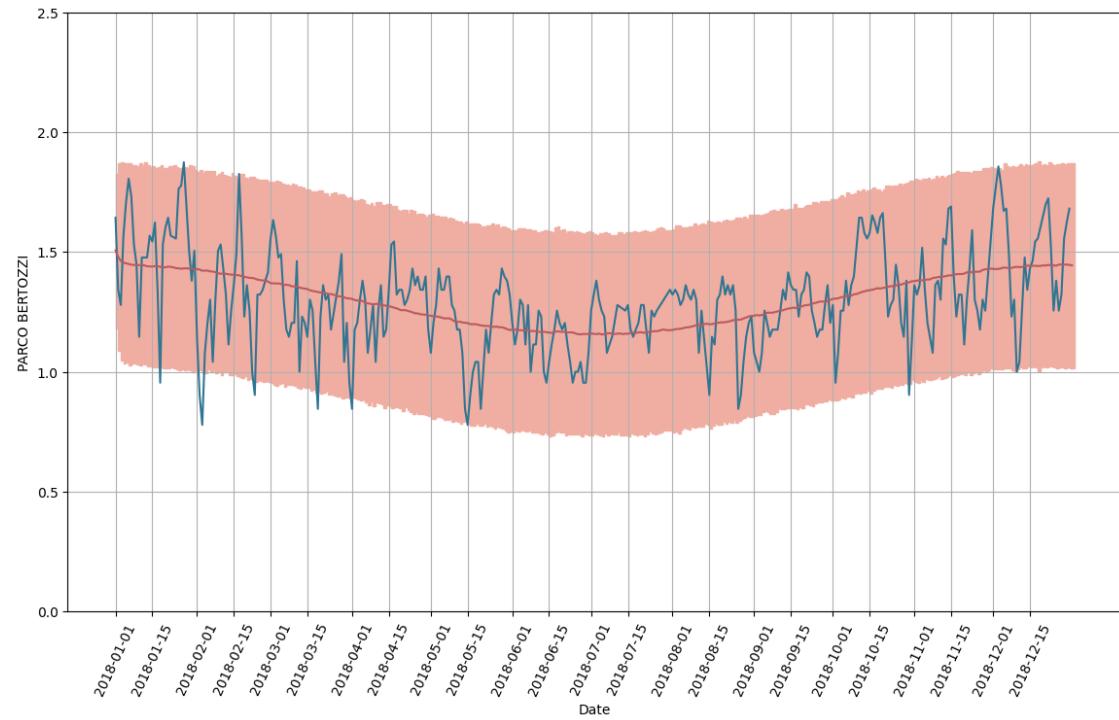


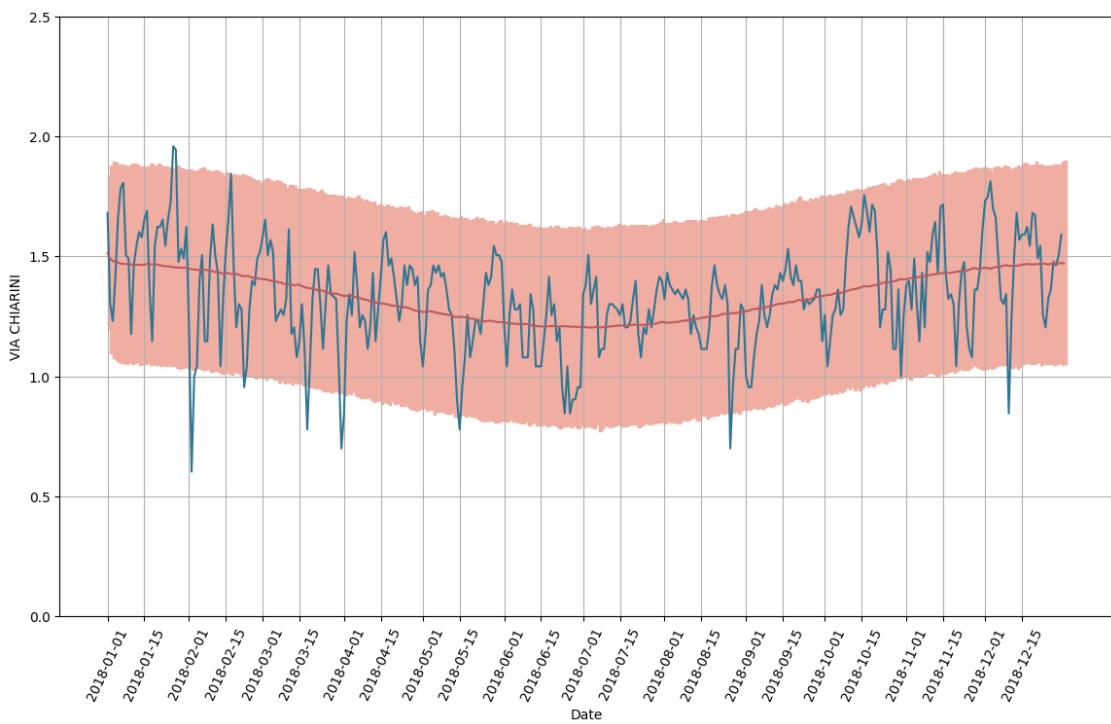
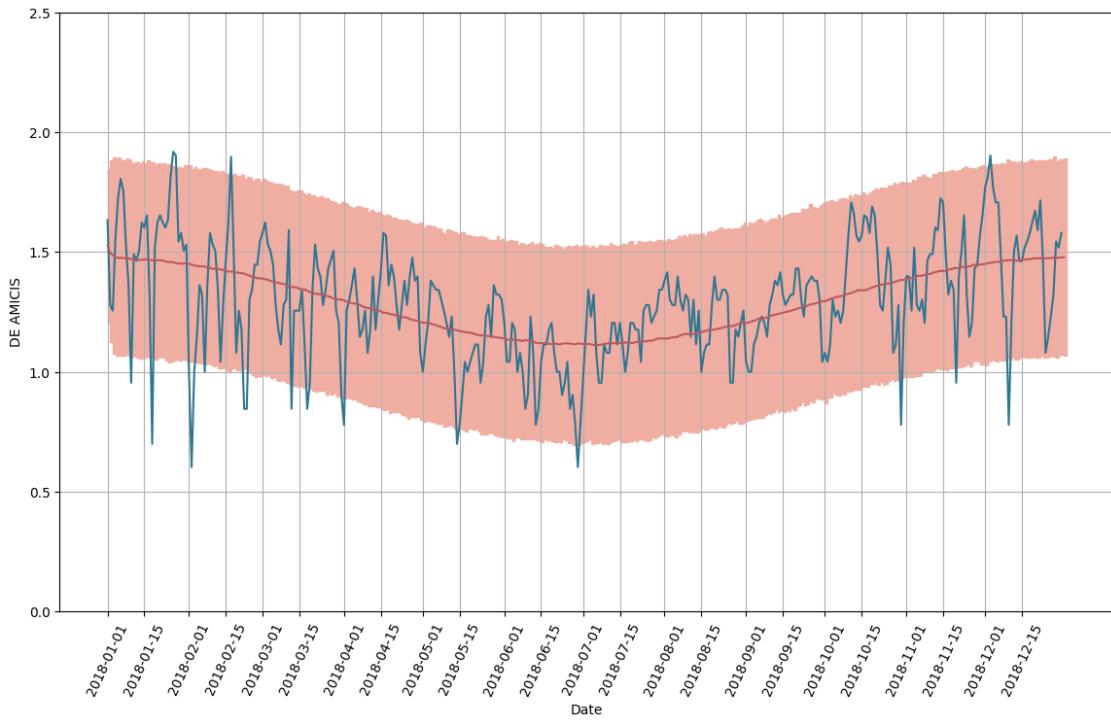


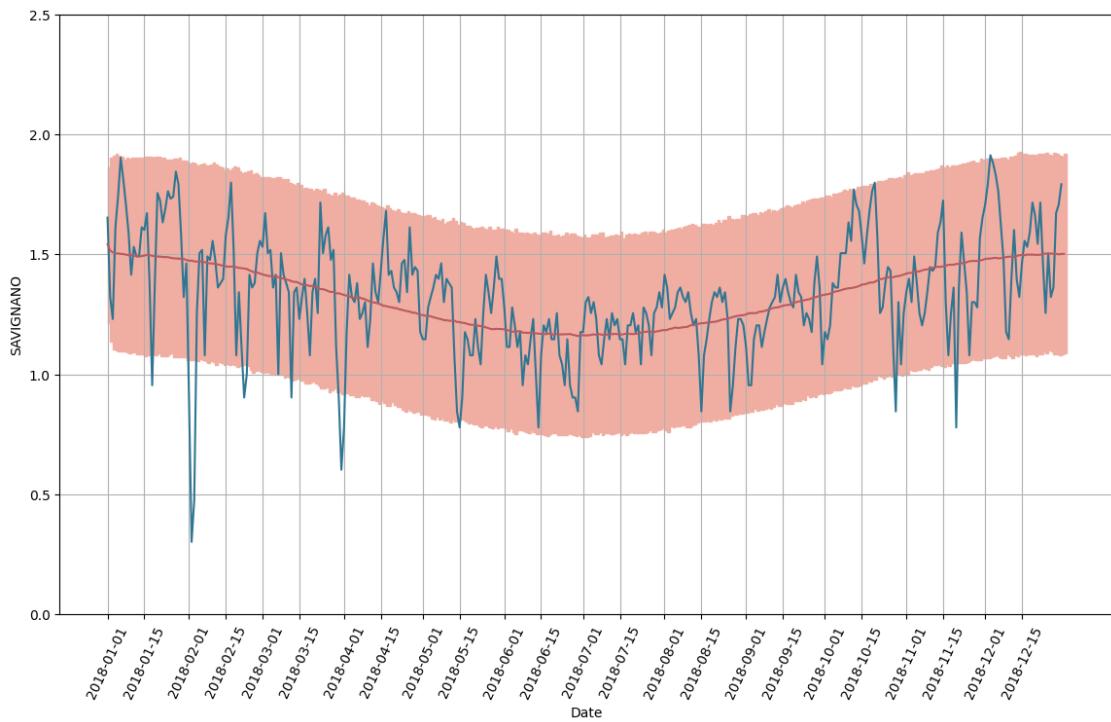
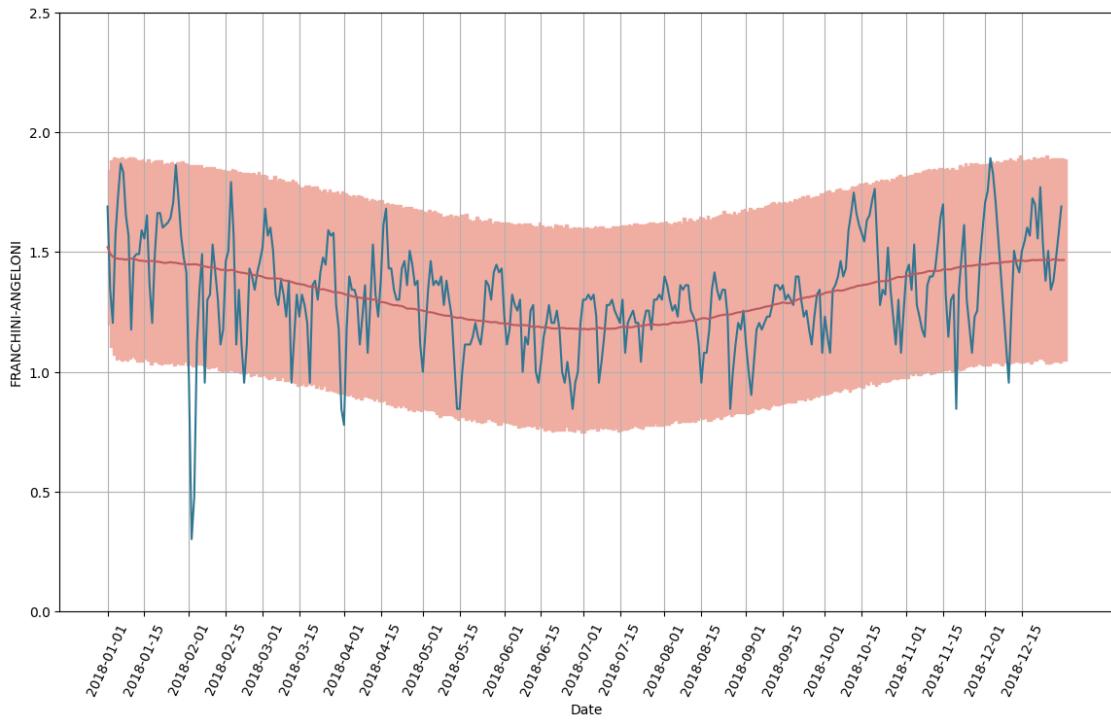


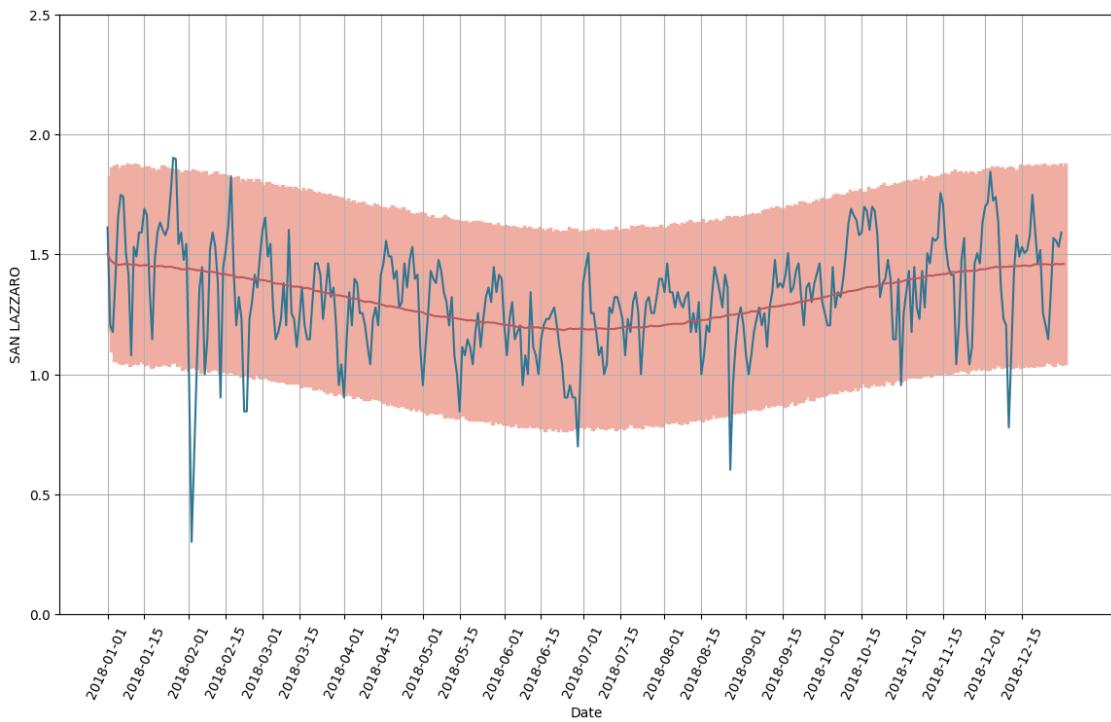
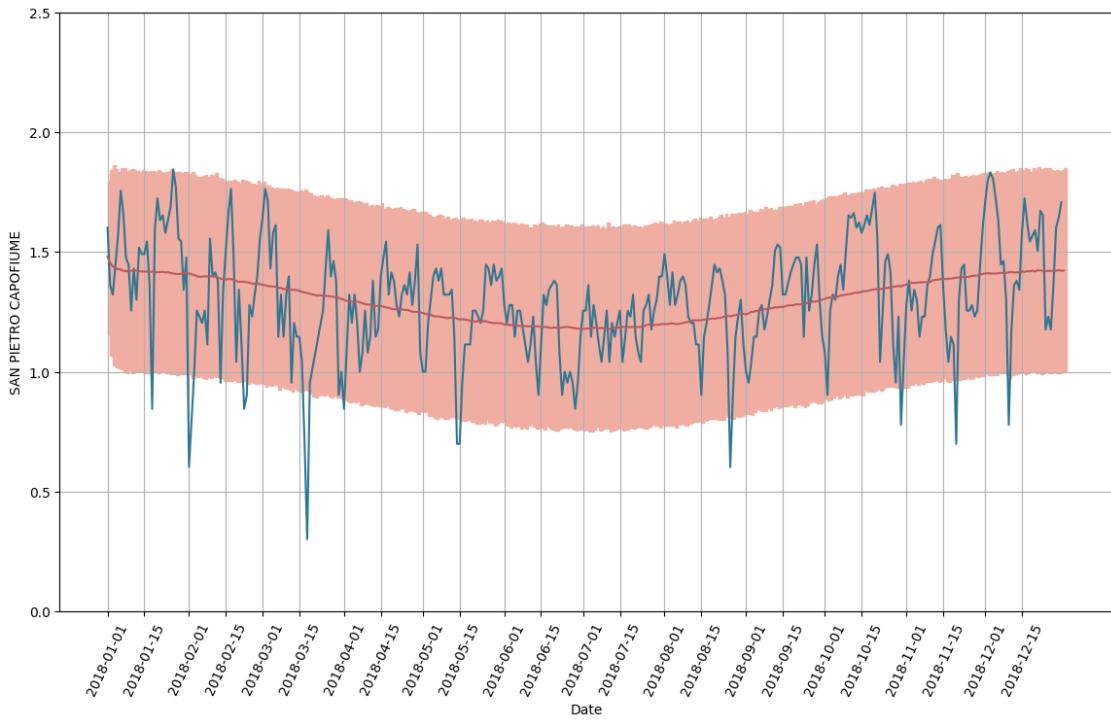


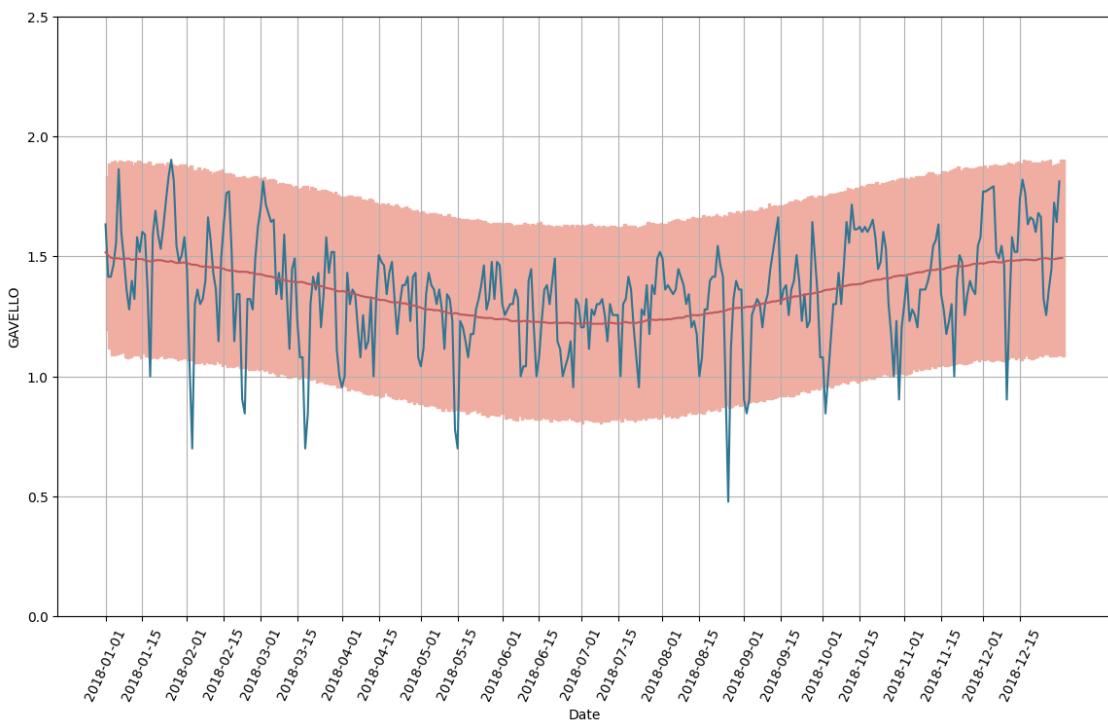
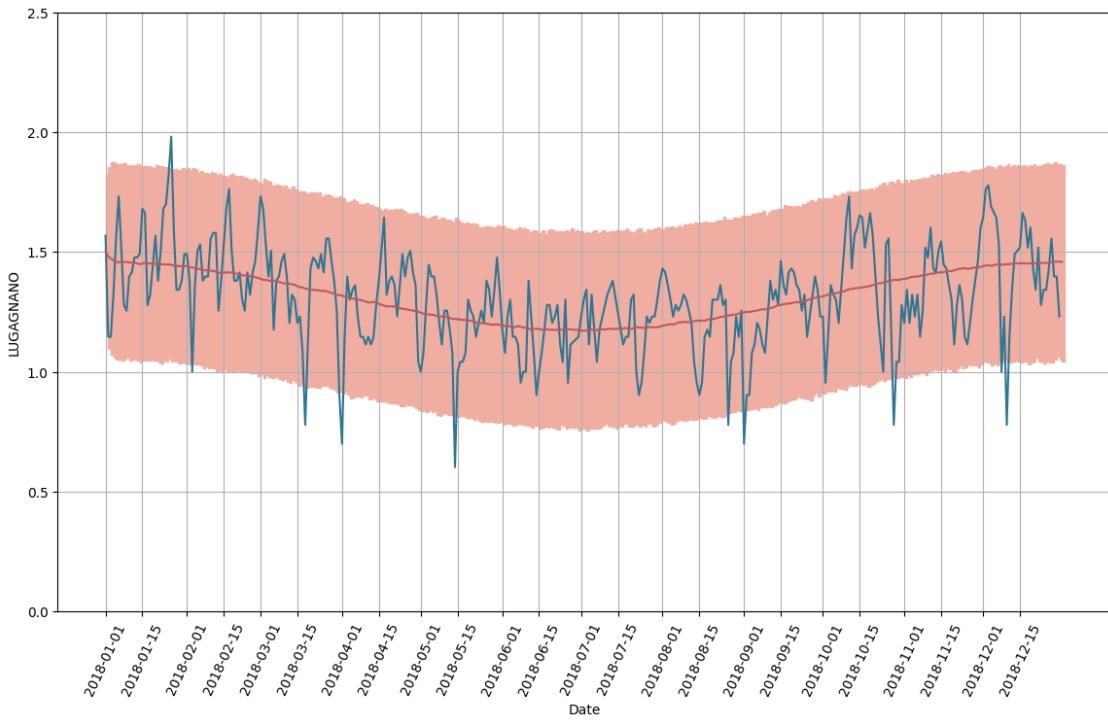


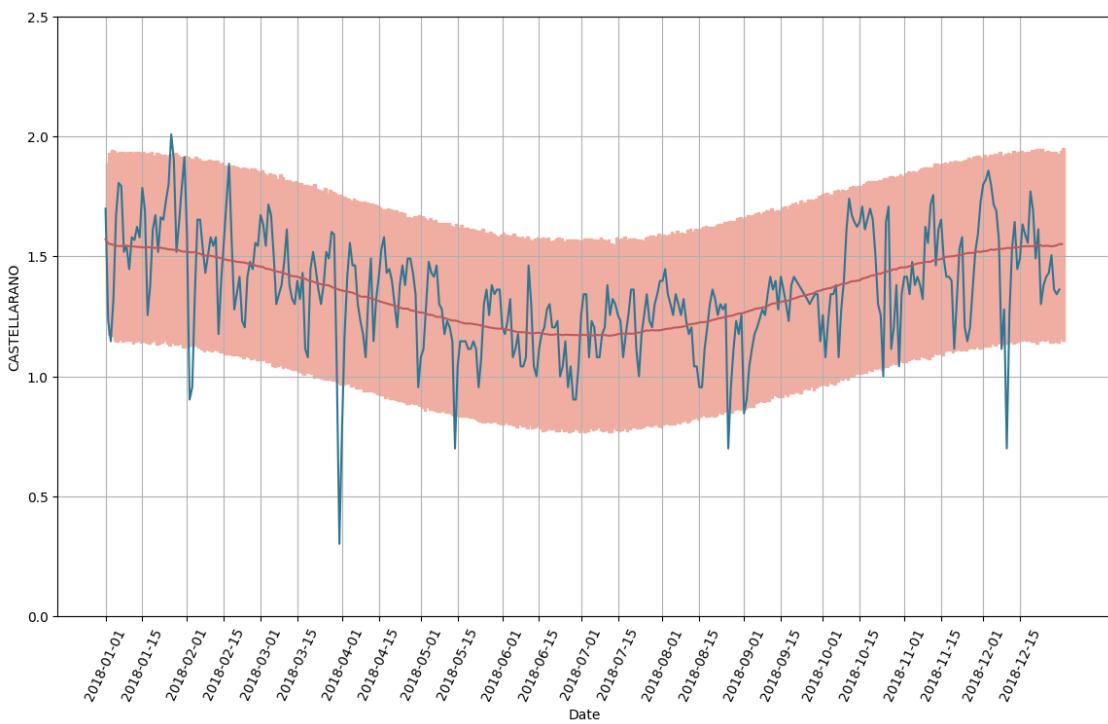
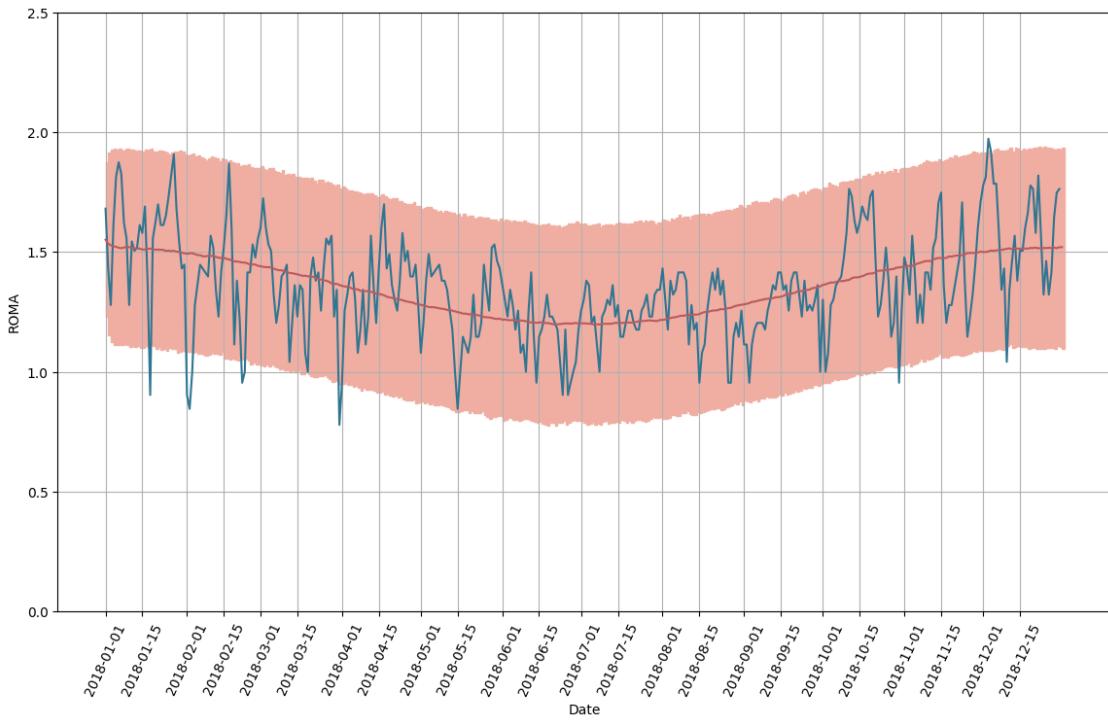


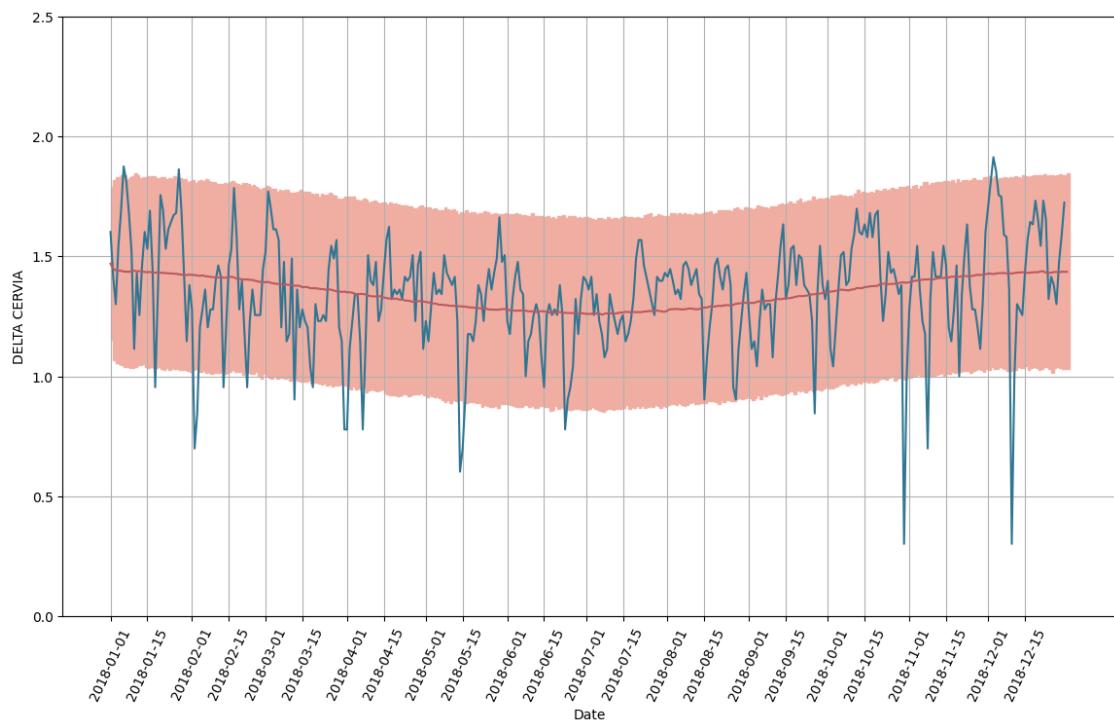
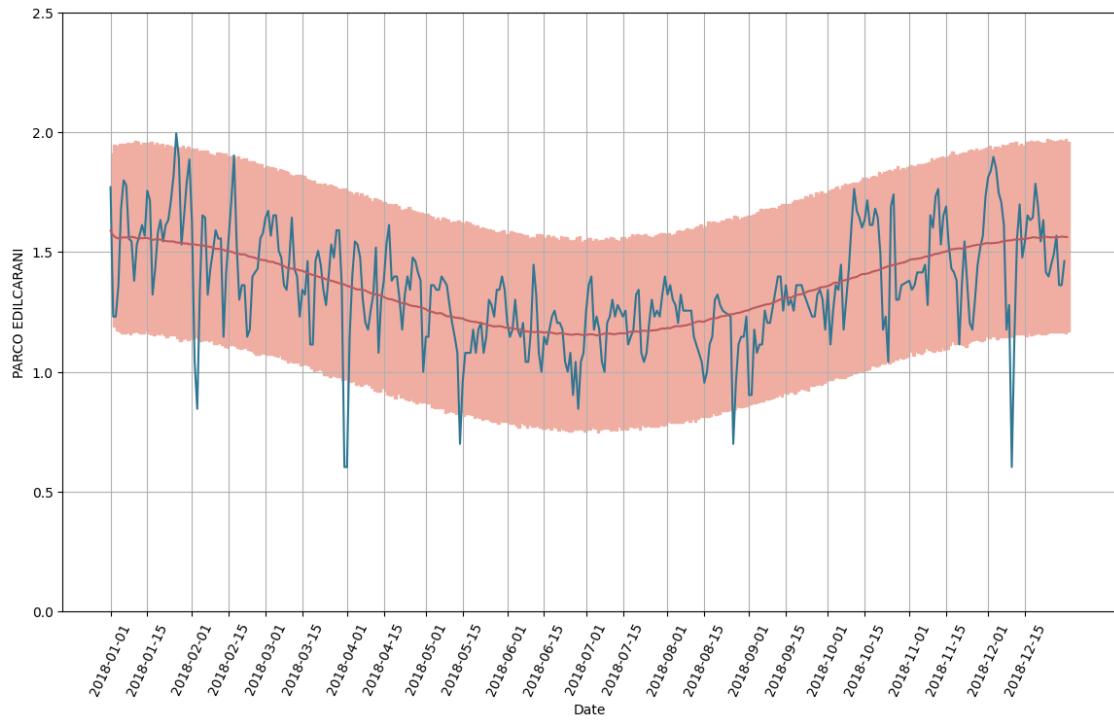


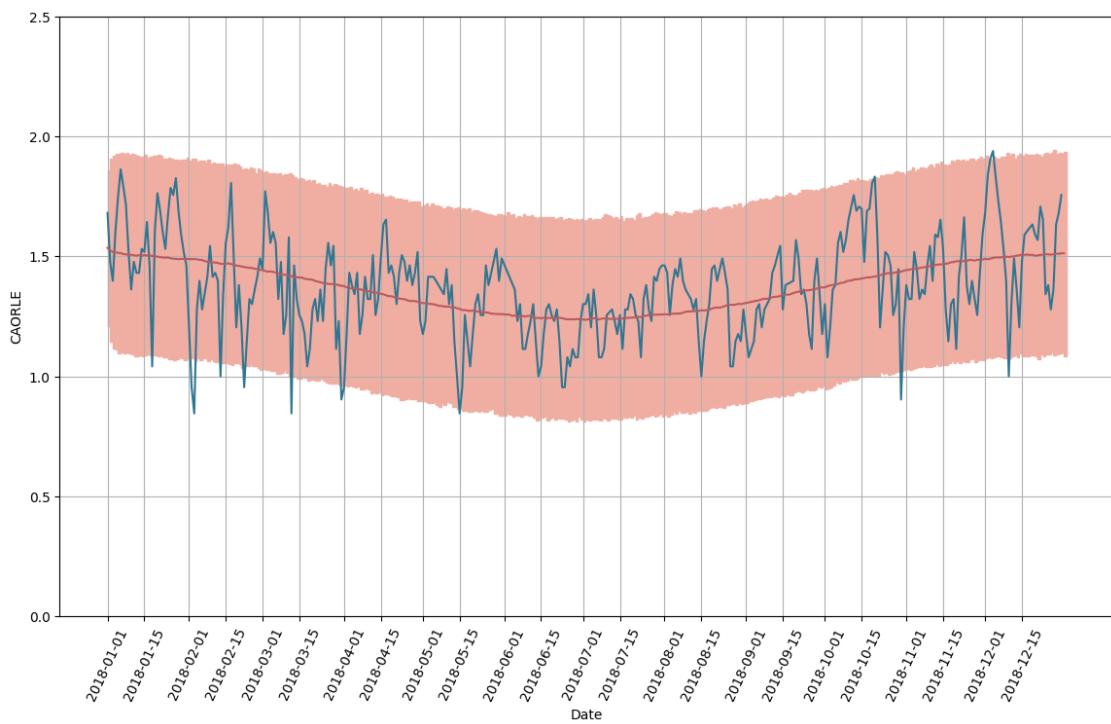
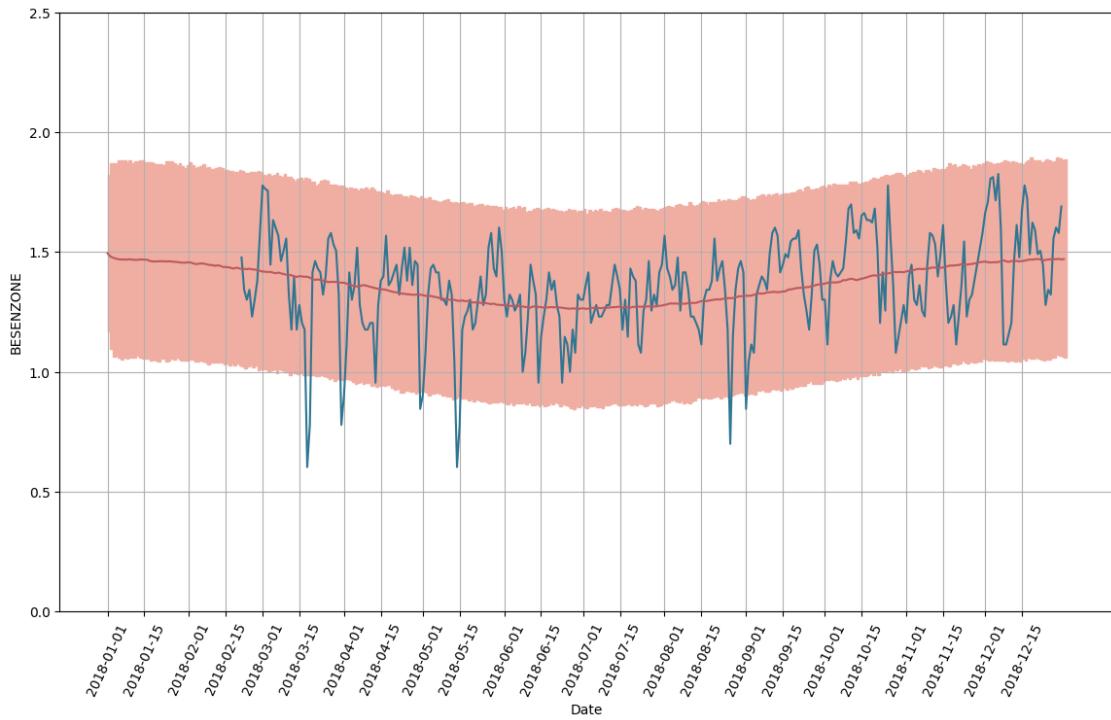


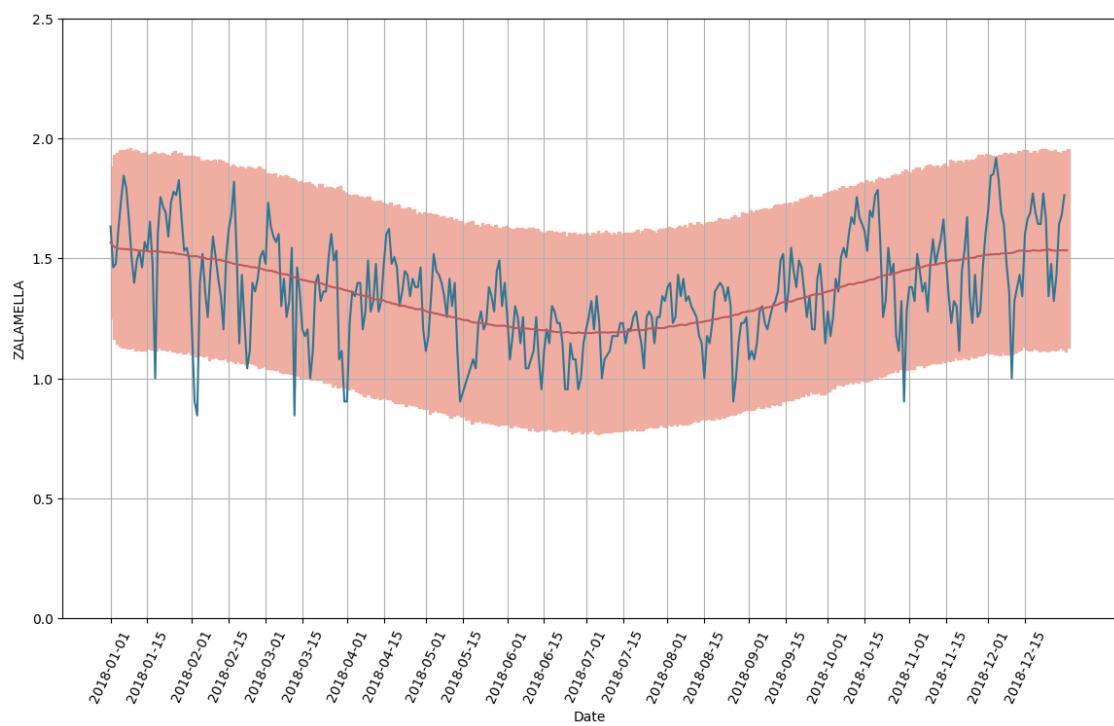
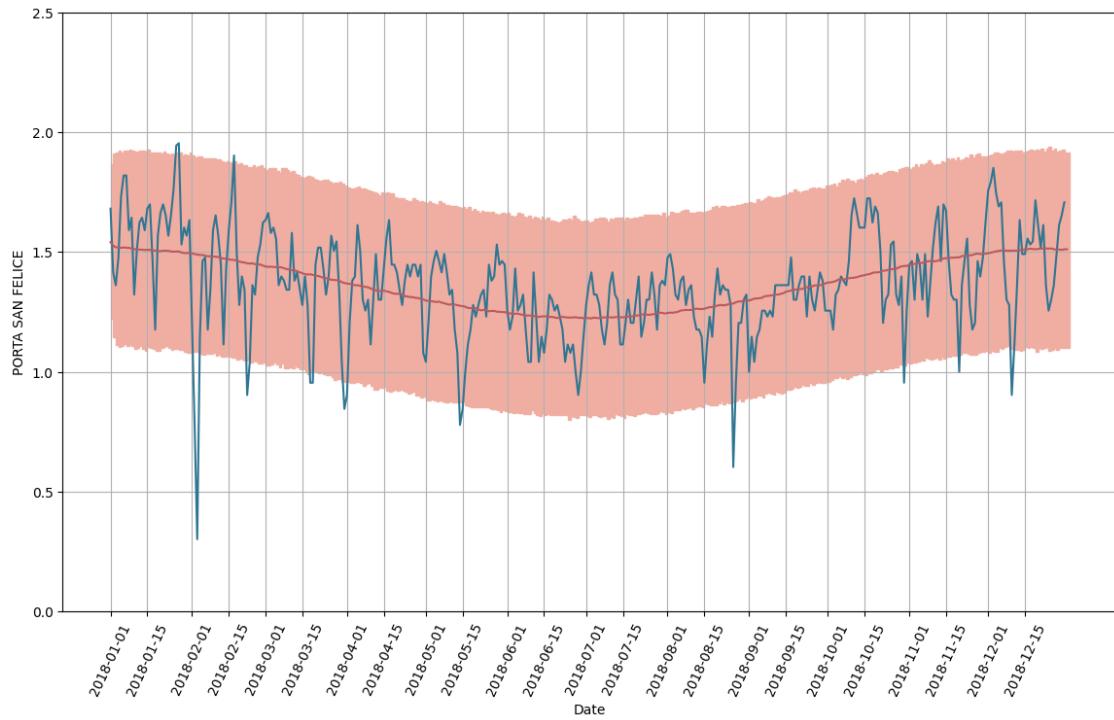


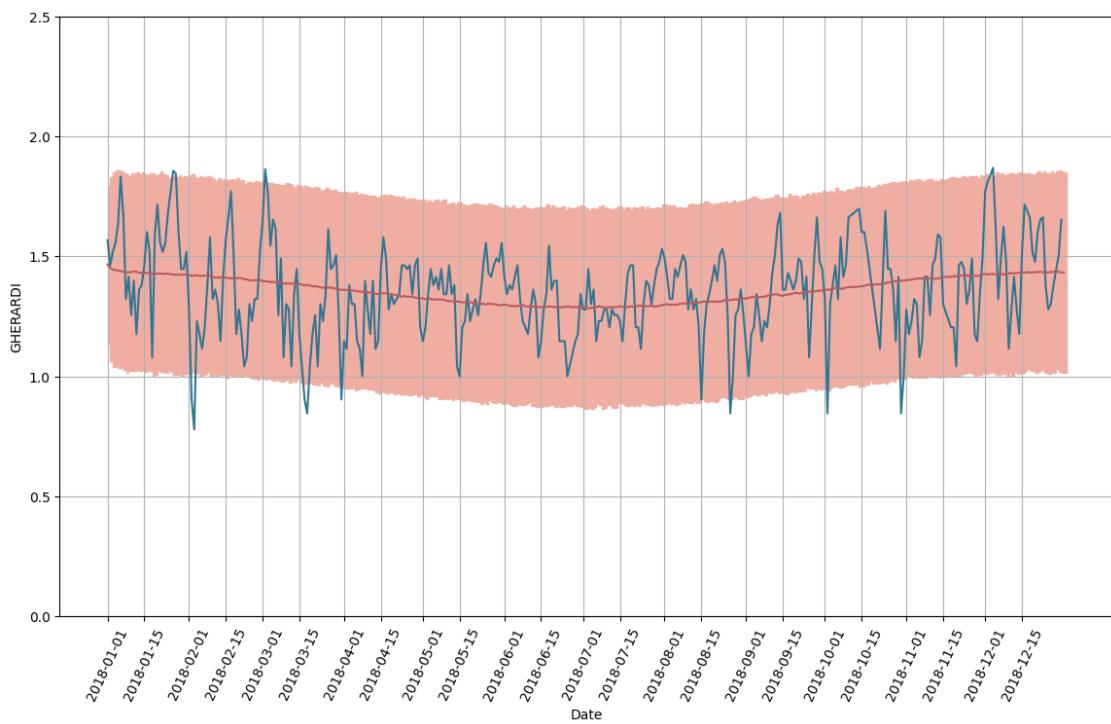
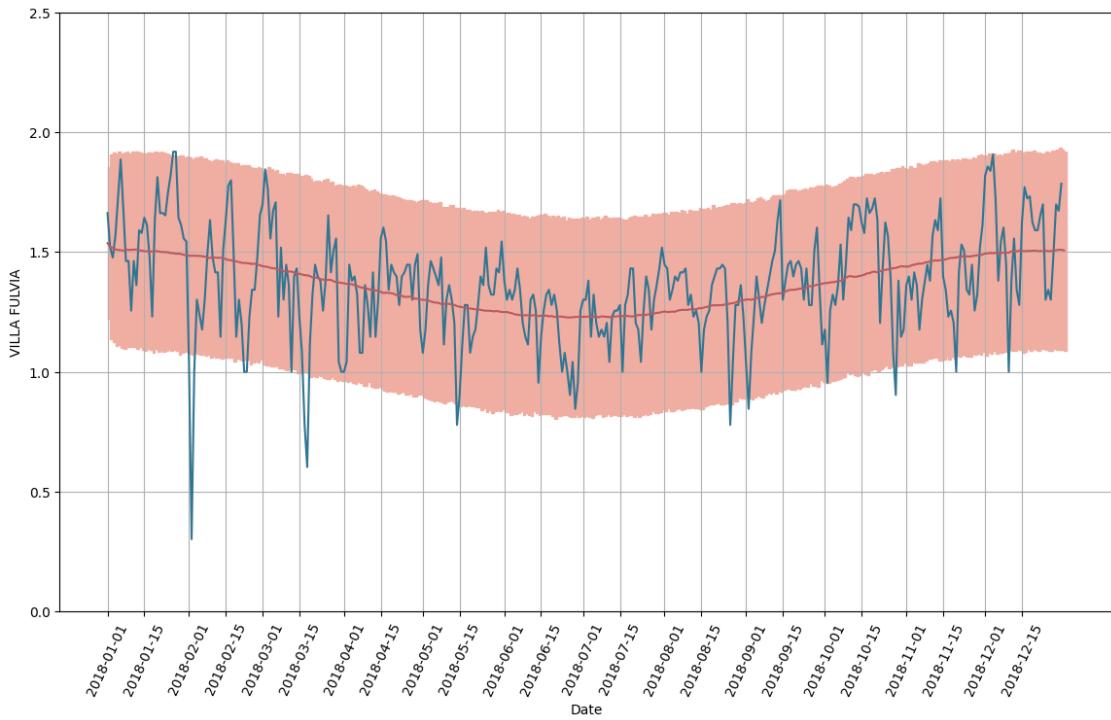


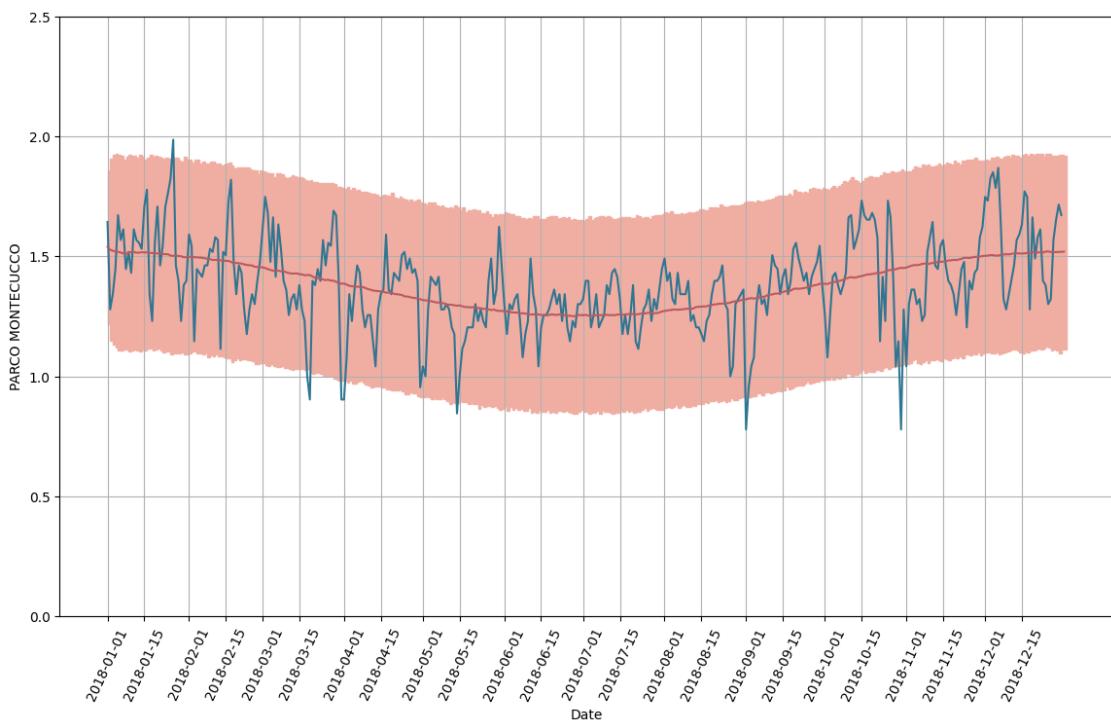
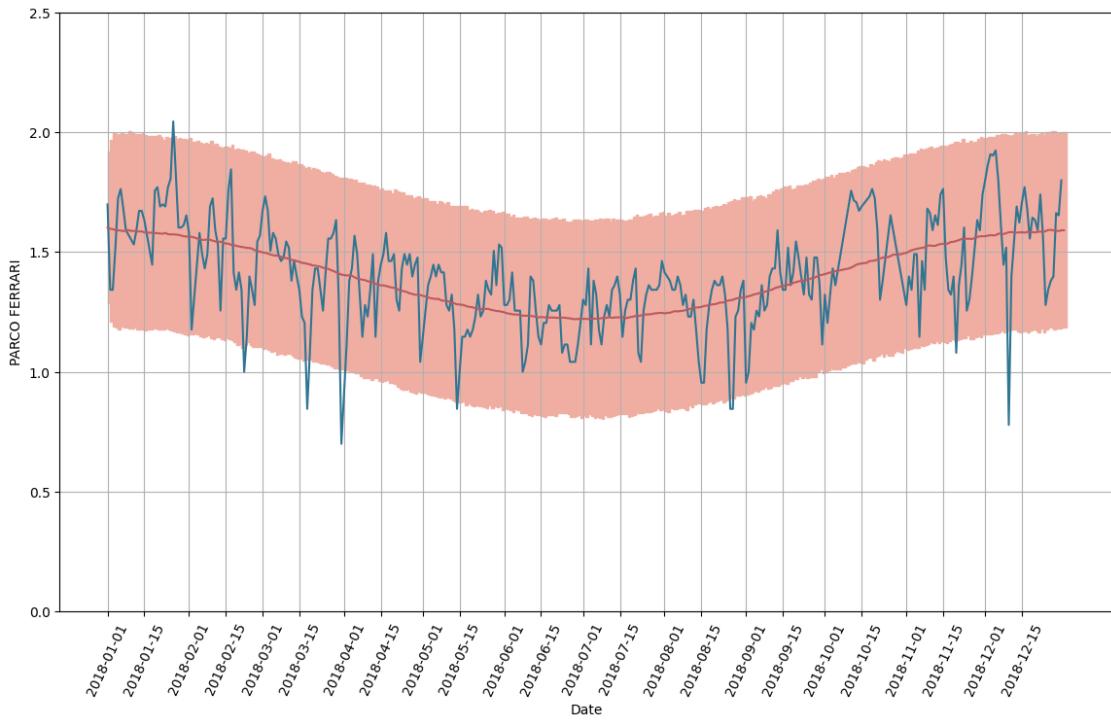


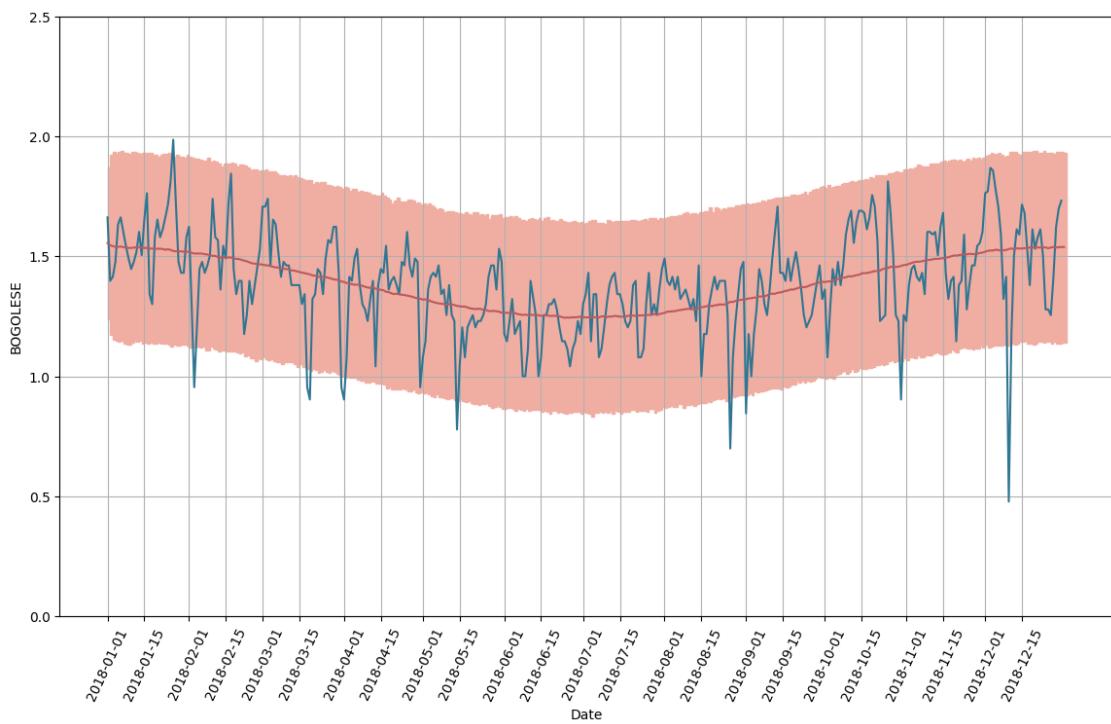
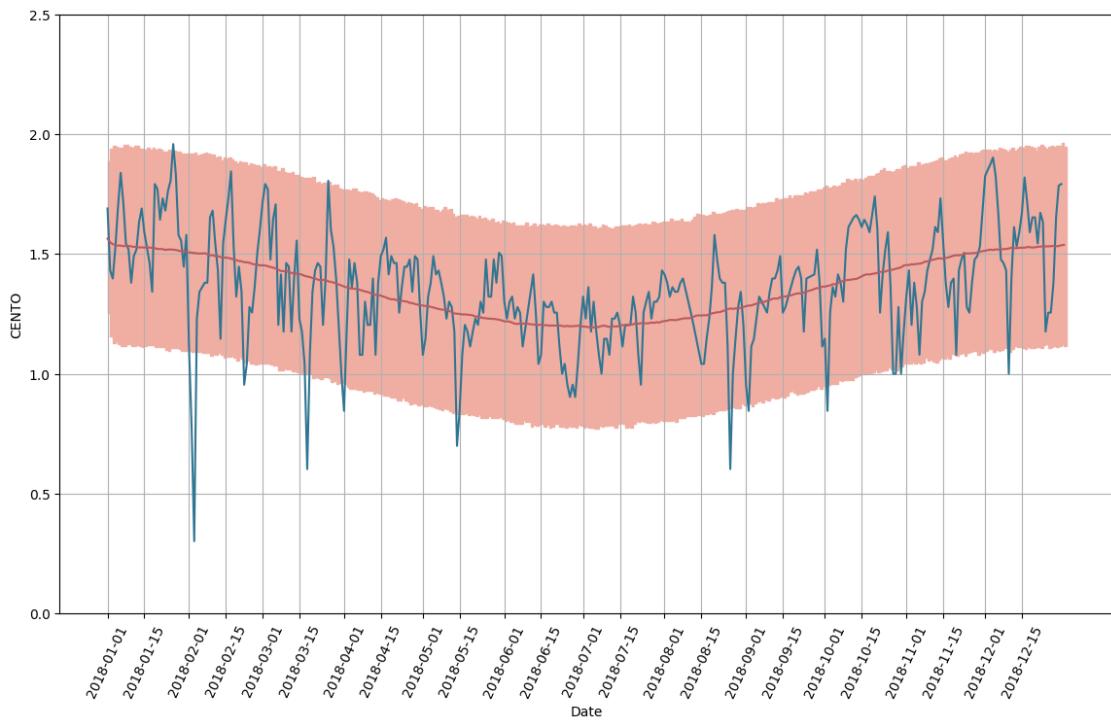


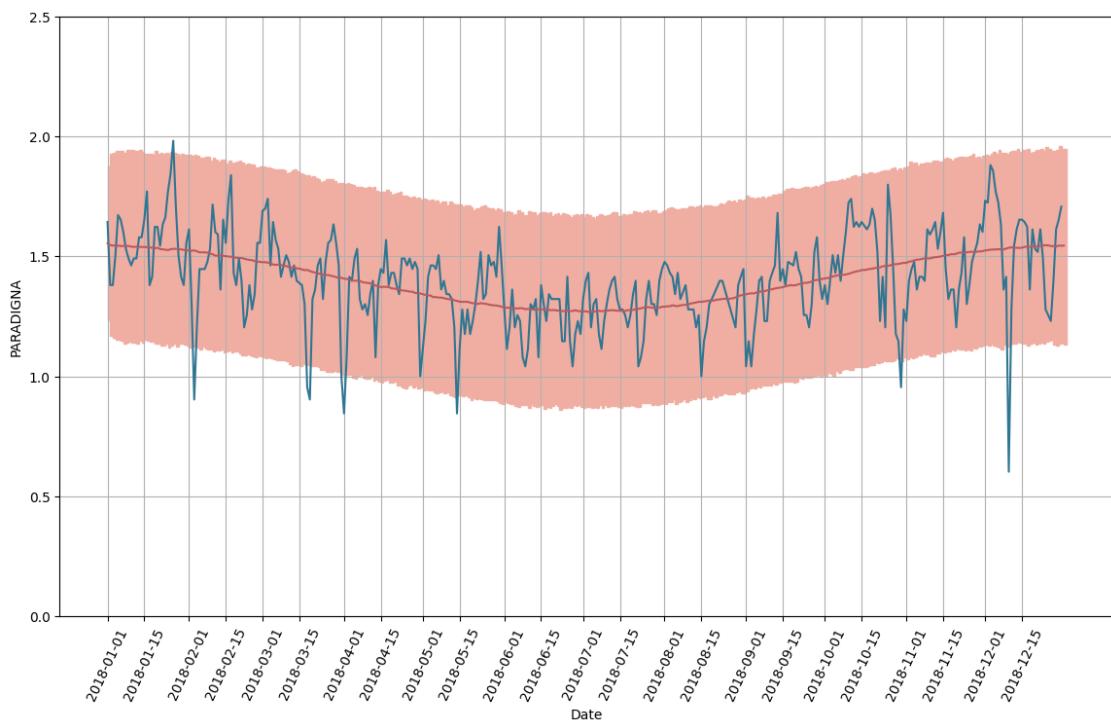
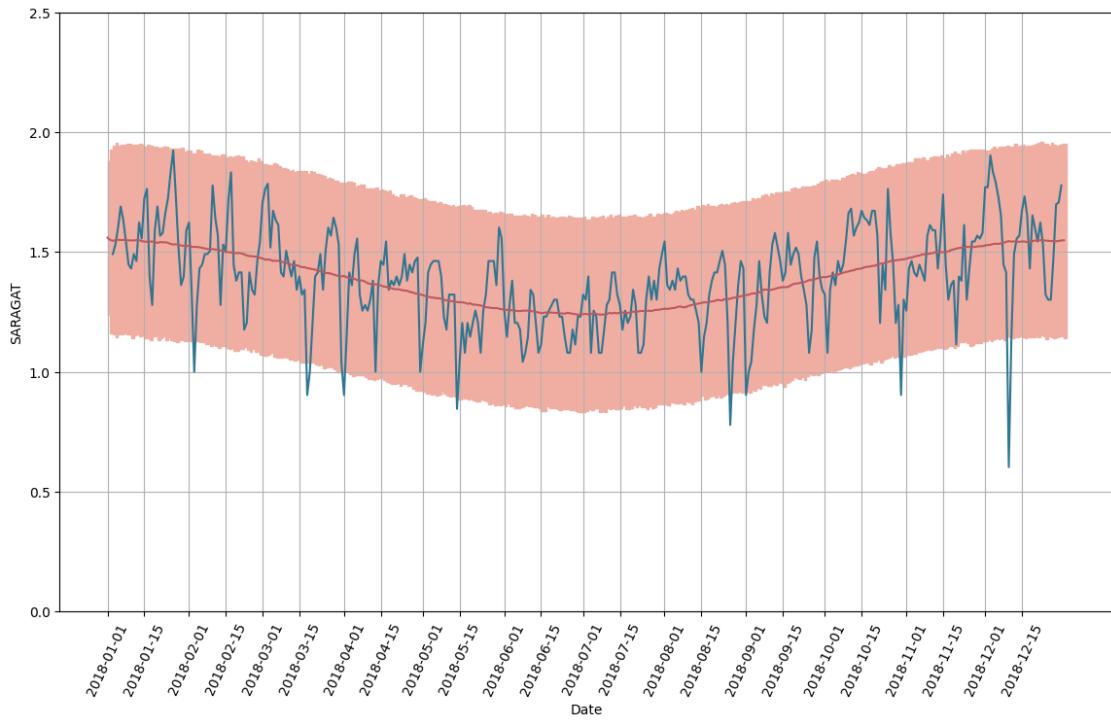


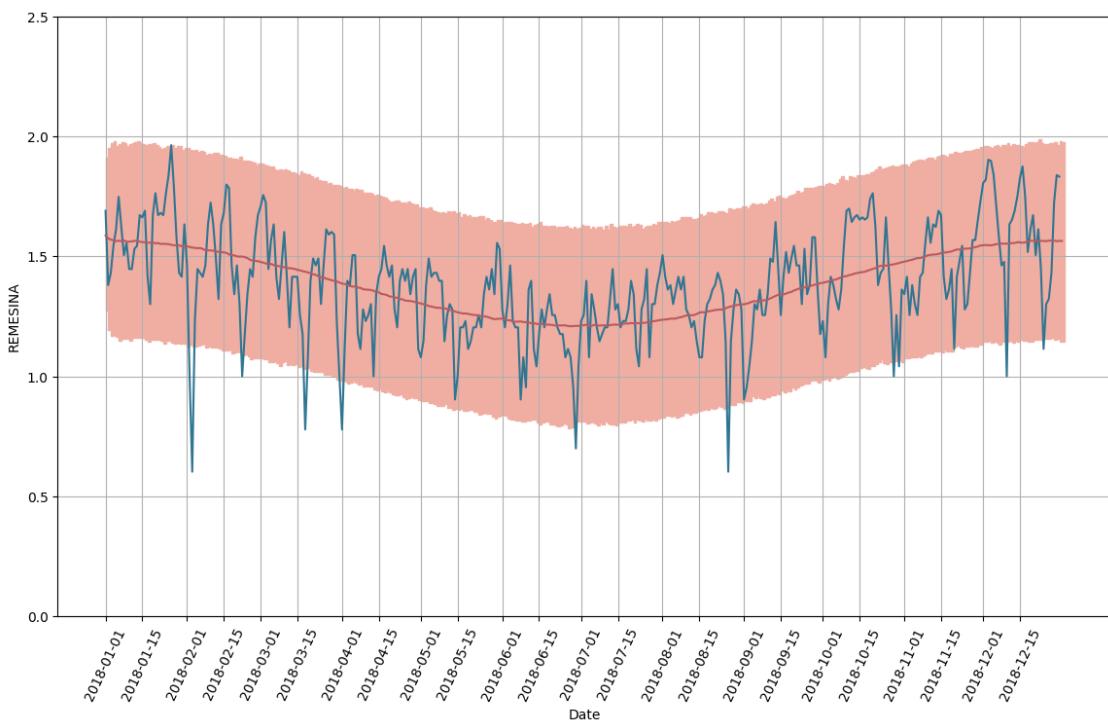
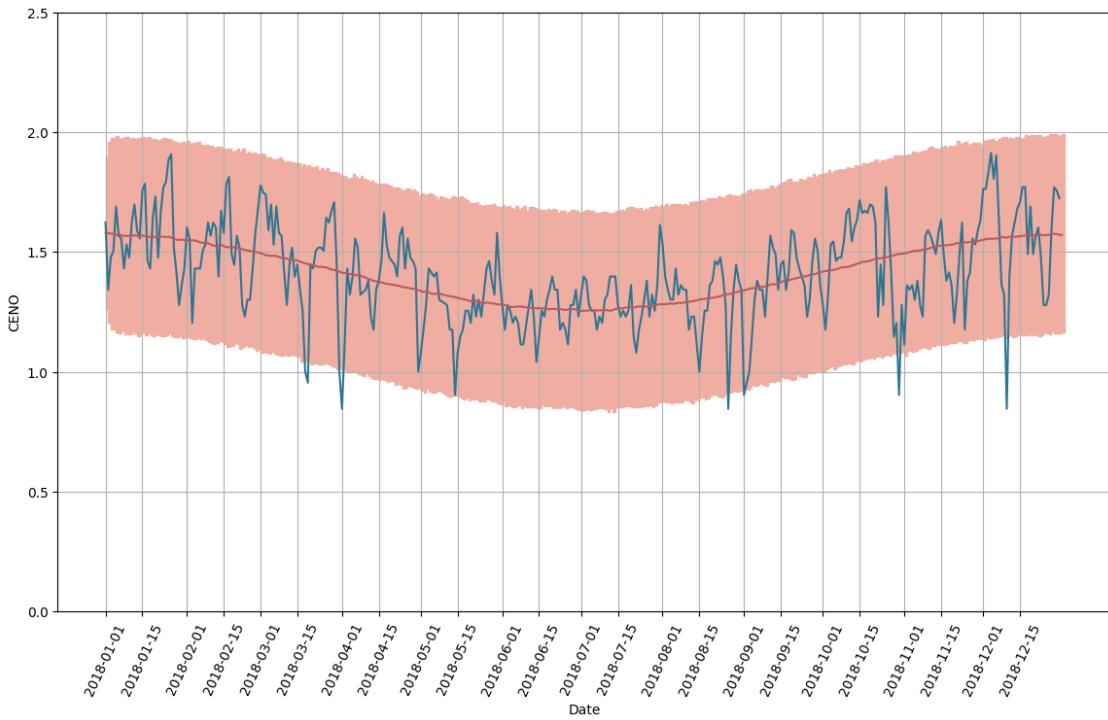


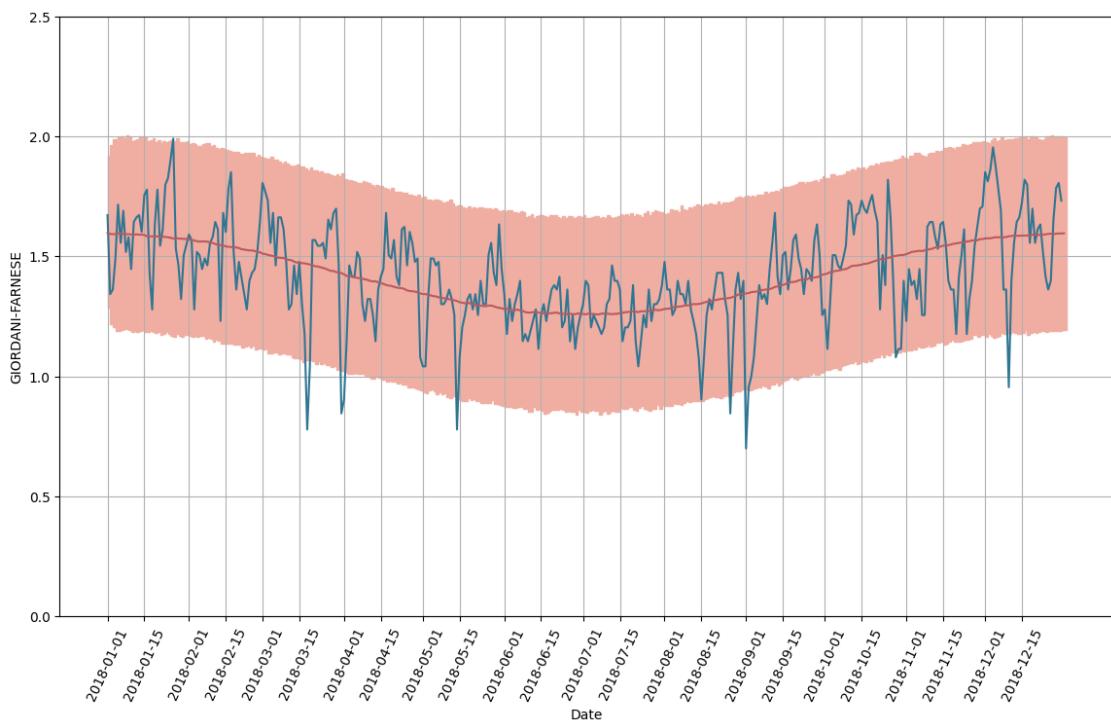
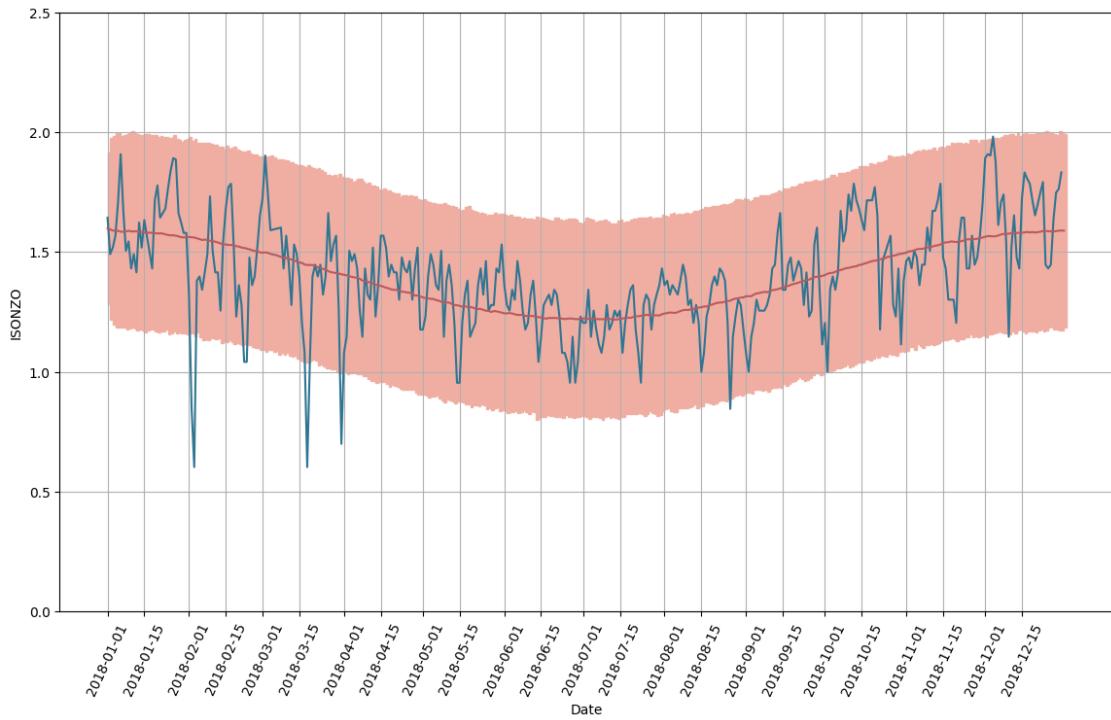


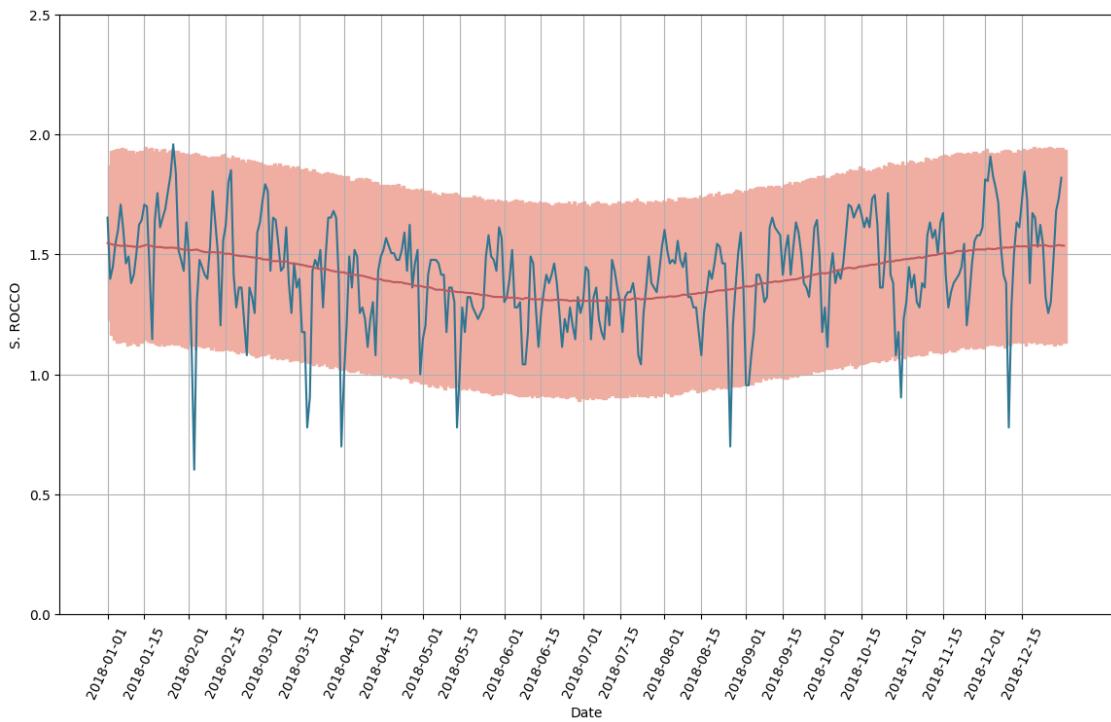
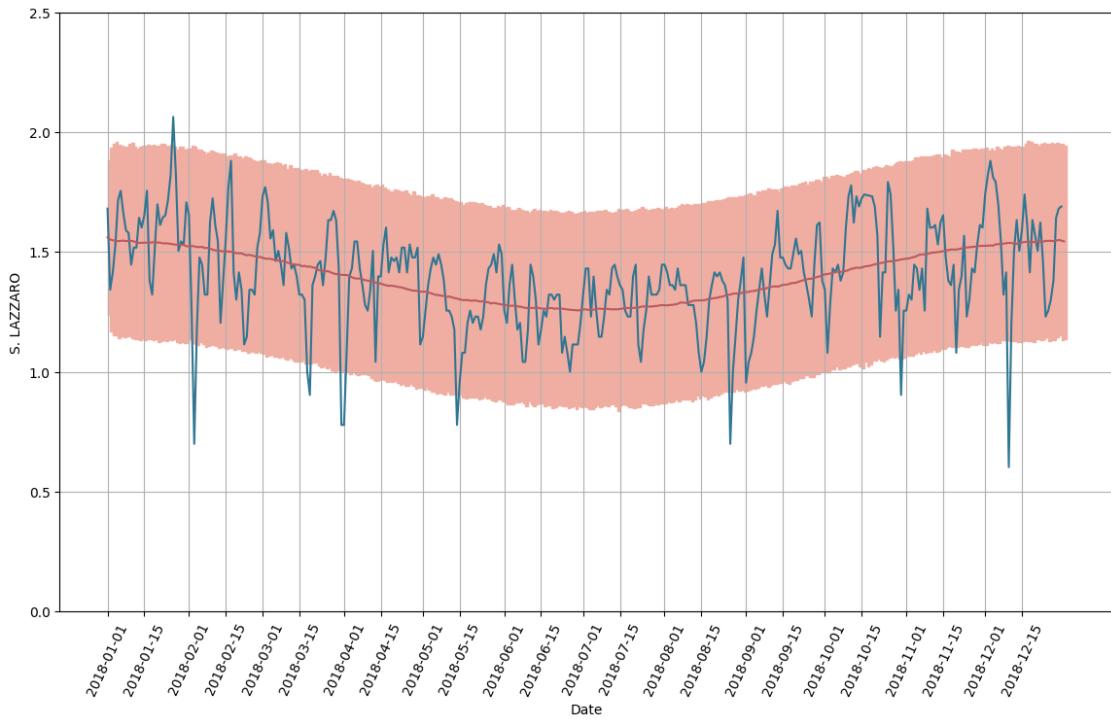


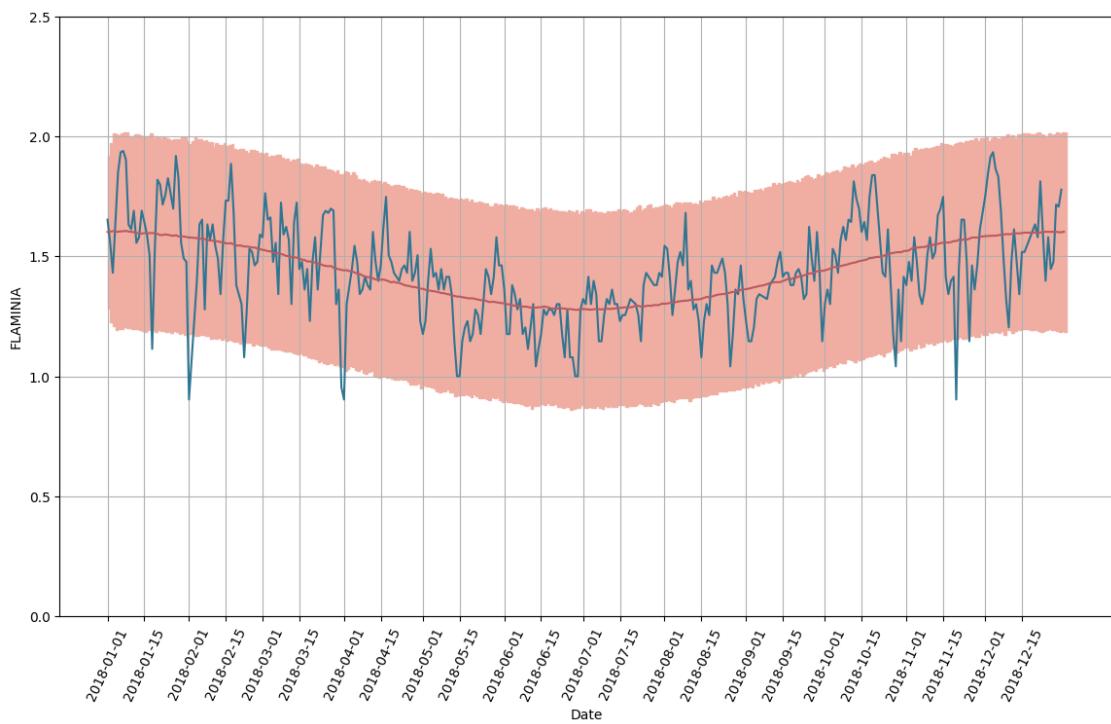
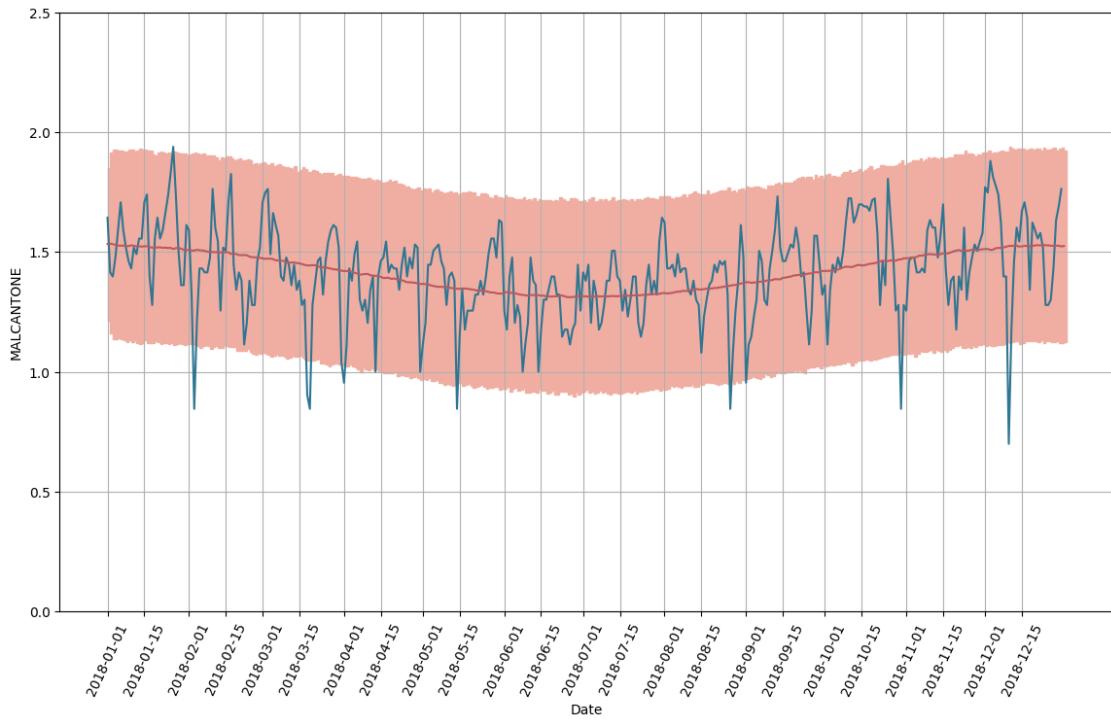


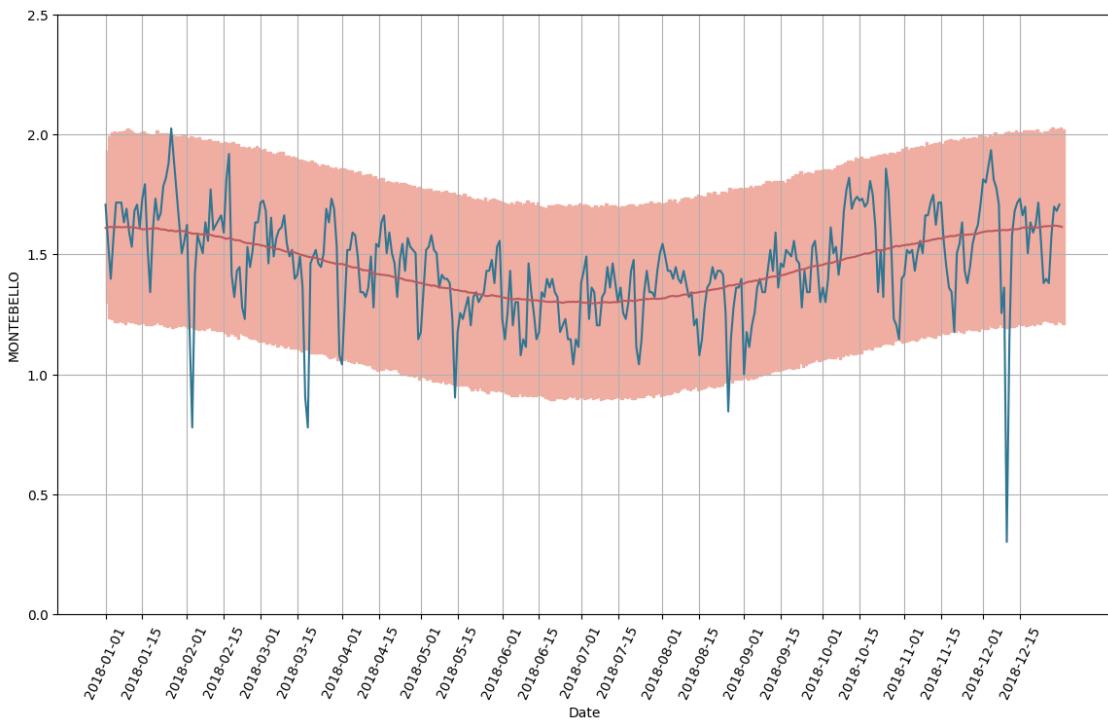
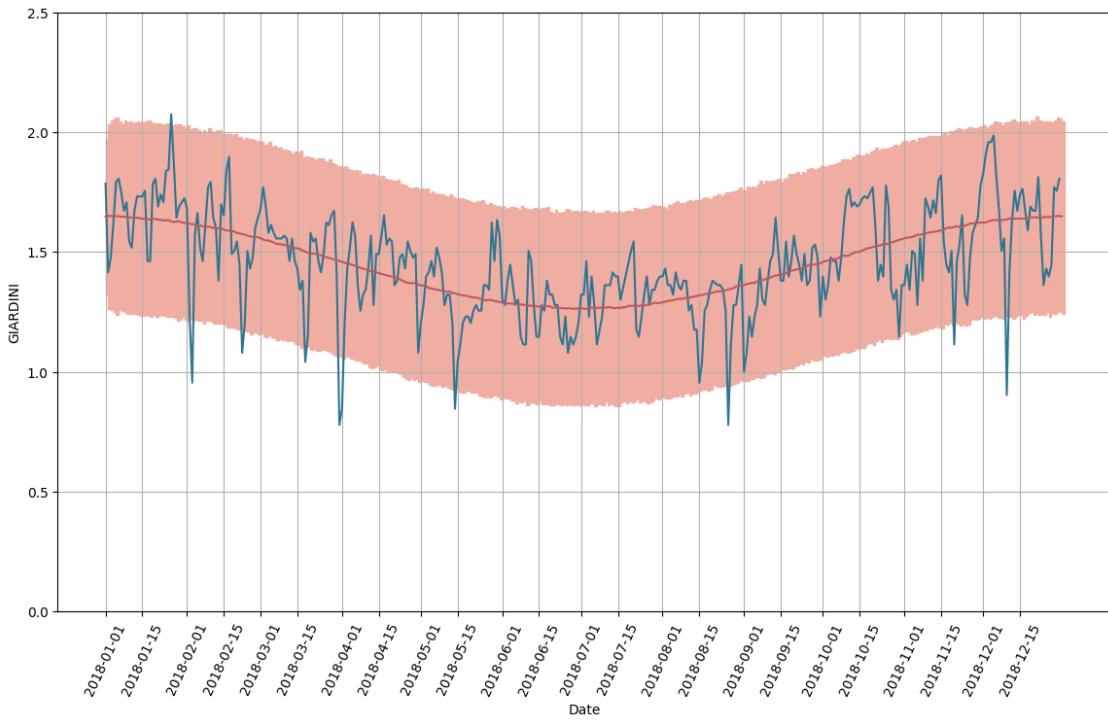


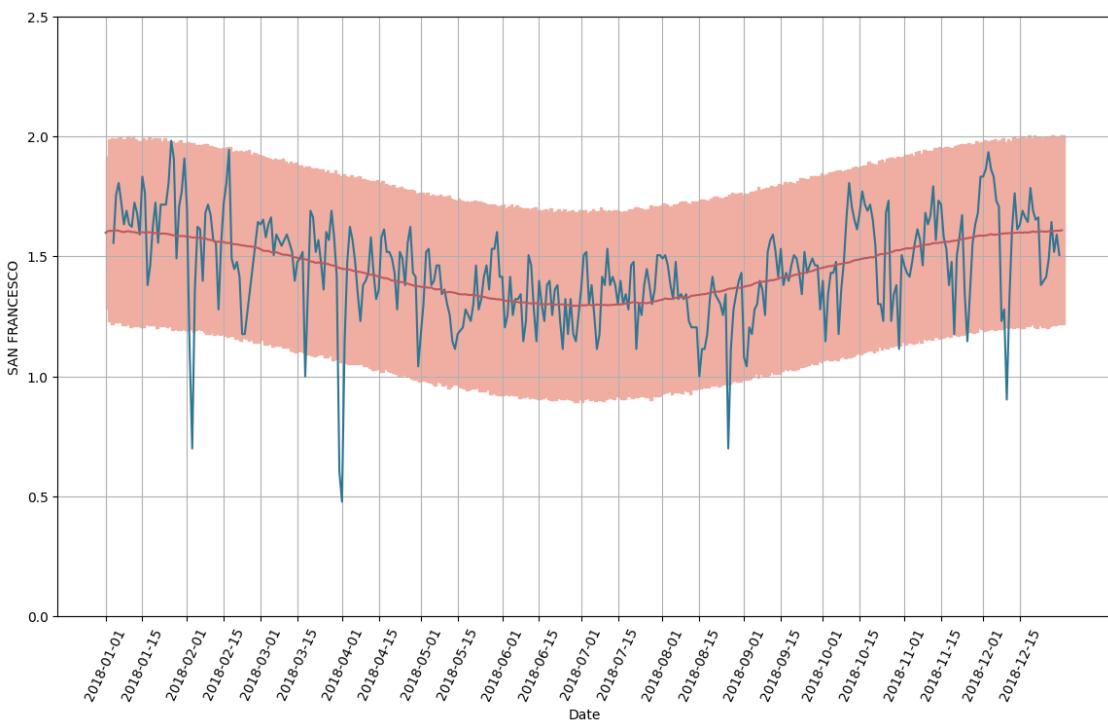
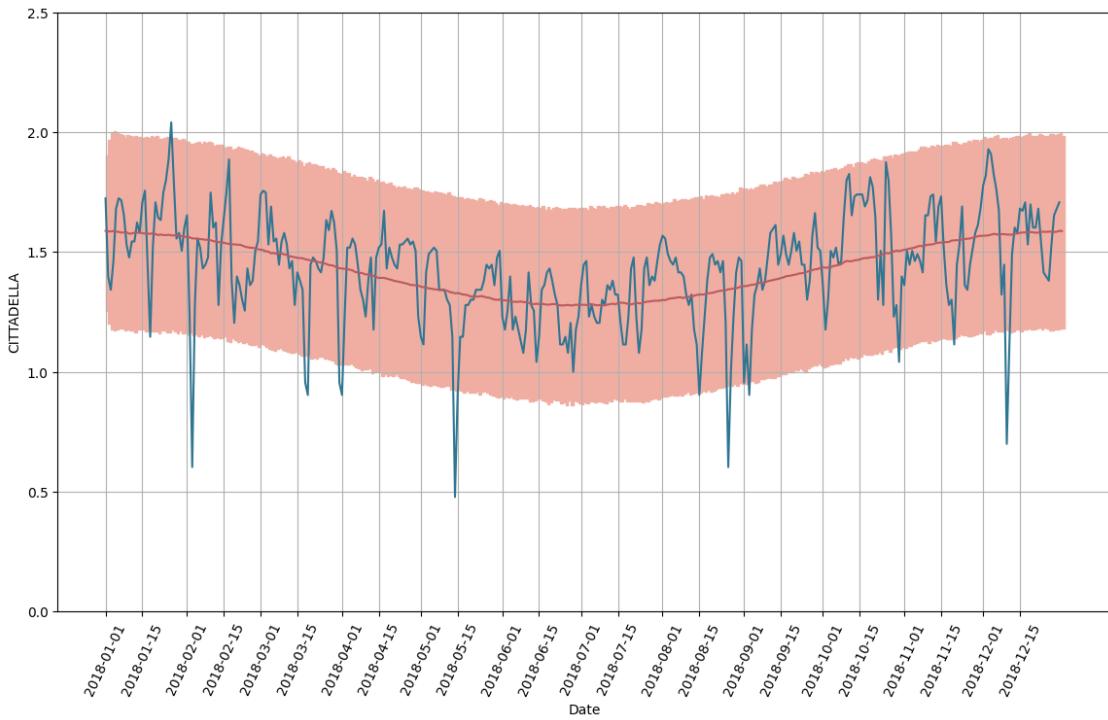


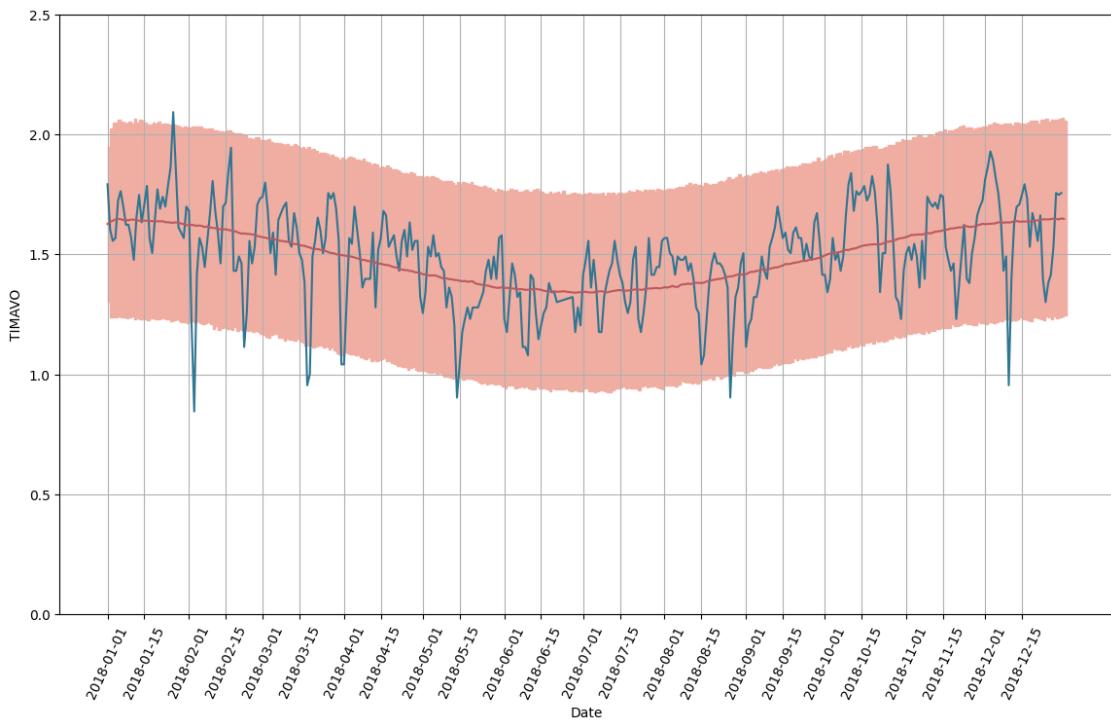
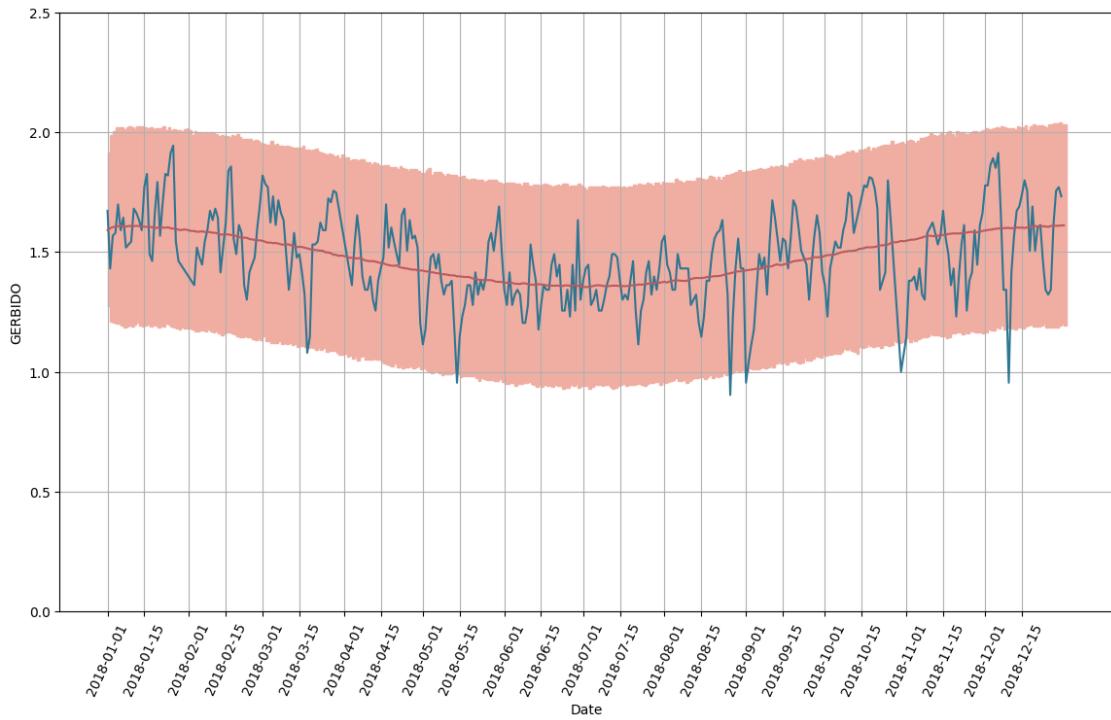












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