

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=1250, burnin=1000)
```

17:17:02 - 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

17:35:25 - cmdstanpy - INFO - CmdStan done processing.

17:35:25 - 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][3] 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 -0.687949, 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 -1.7316, 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][2] 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 -24.4747, 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 -4.71381, 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][2] 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][30] 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 -0.939195, 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 -1.2321, 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][1] 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][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: normal_lpdf: Scale parameter is -0.780896, 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 -0.675852, 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][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][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][1] 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[1][9] 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][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 -0.00272799, 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 -0.00711351, but must be
positive! (in '/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/code.stan', line 143, column 4 to column 61)
Consider re-running with show_console=True if the above output is unclear!

```

```

/home/br1/PythonProjects/PythonStats/git_bayesian_copie/ARIMA/NoCovariates/fit_arima.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]],'Samples':inference_data.posterior.w.values[:, :, i].reshape(catene*samples_per_chain)})
)

```

Tempo di computazione: 18:23

```
[5]: res = az.loo(ritorno['inference_data'], var_name="log_lik", 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 5000 posterior samples and 17148 observations log-likelihood
matrix.
```

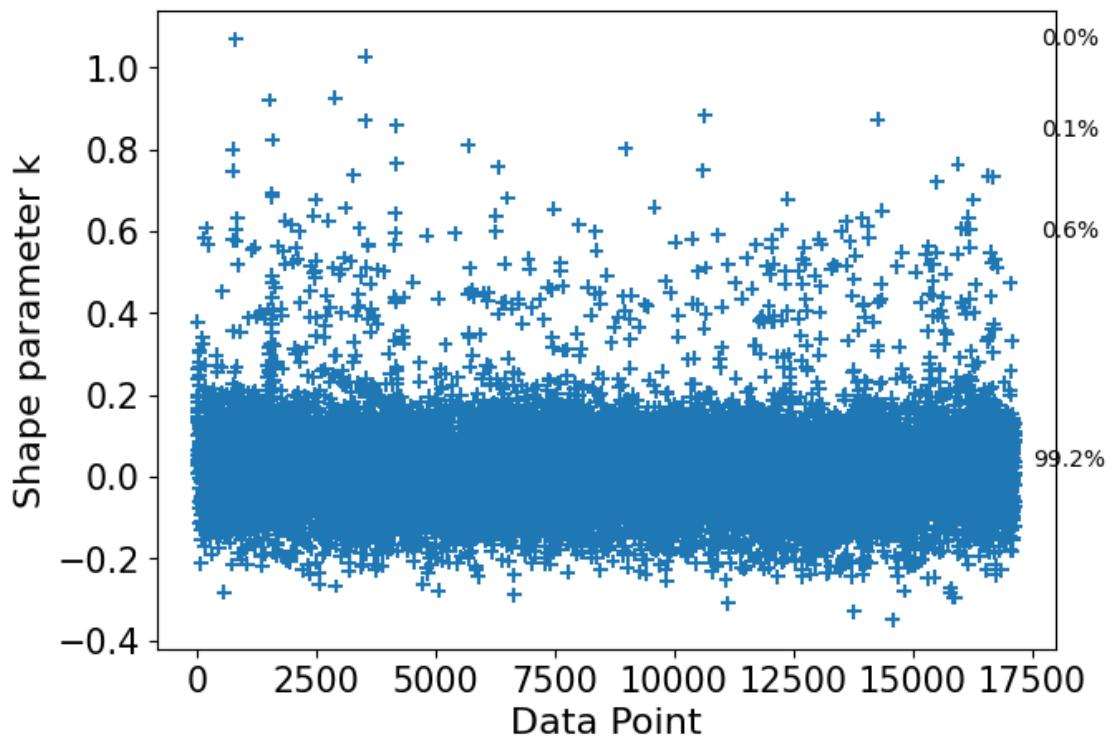
	Estimate	SE
elpd_loo	7287.64	154.66
p_loo	313.24	-

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

```
Pareto k diagnostic values:
```

		Count	Pct.
(-Inf, 0.5]	(good)	17017	99.2%
(0.5, 0.7]	(ok)	110	0.6%
(0.7, 1]	(bad)	19	0.1%
(1, Inf)	(very bad)	2	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_liik")
res
```

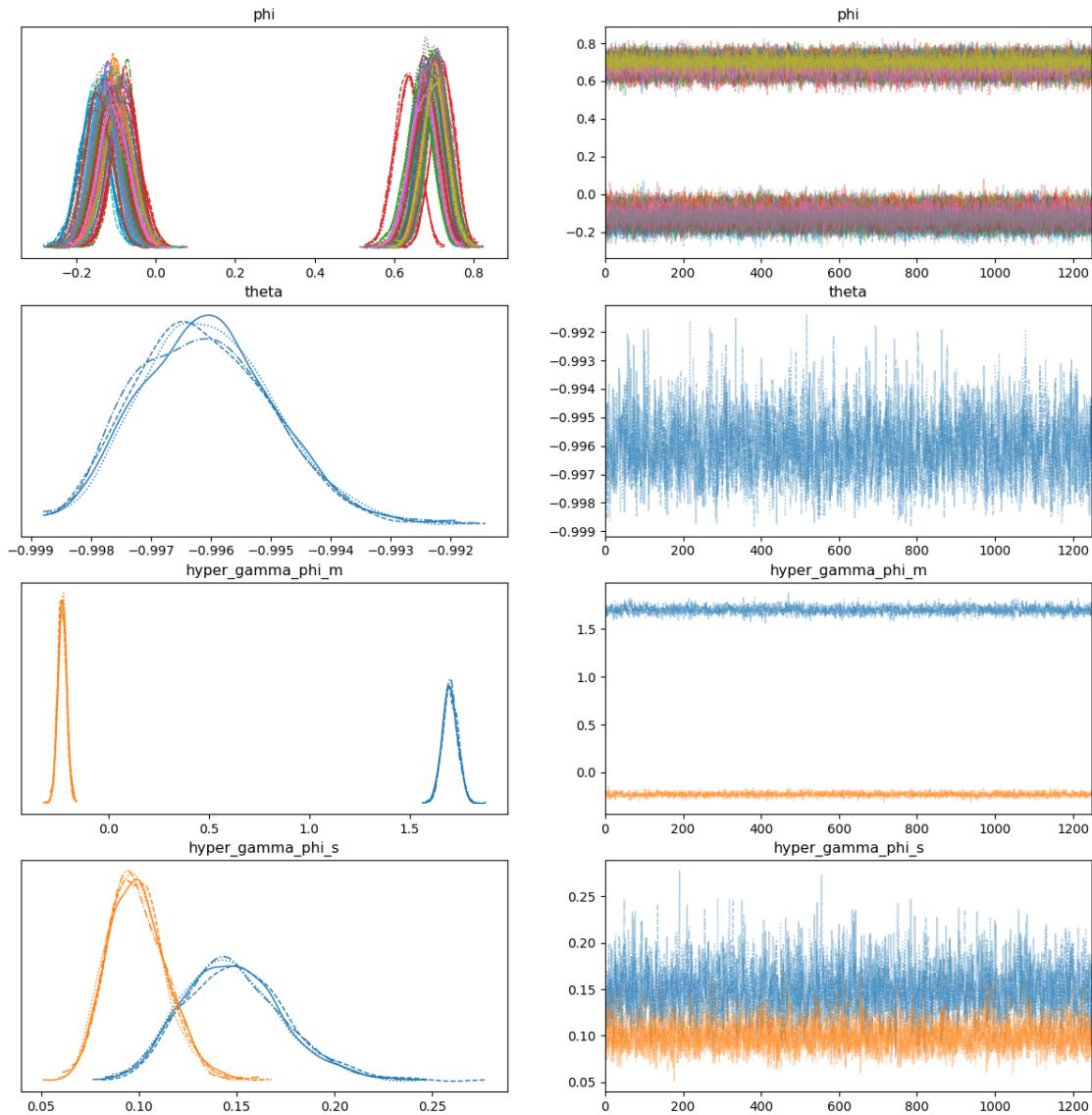
```
/home/br1/PythonProjects/PythonStats/.venv/lib/python3.10/site-
packages/arviz/stats/stats.py:1645: UserWarning: For one or more samples the
posterior variance of the log predictive densities exceeds 0.4. This could be
indication of WAIC starting to fail.
See http://arxiv.org/abs/1507.04544 for details
warnings.warn(
```

[7]: Computed from 5000 posterior samples and 17148 observations log-likelihood matrix.

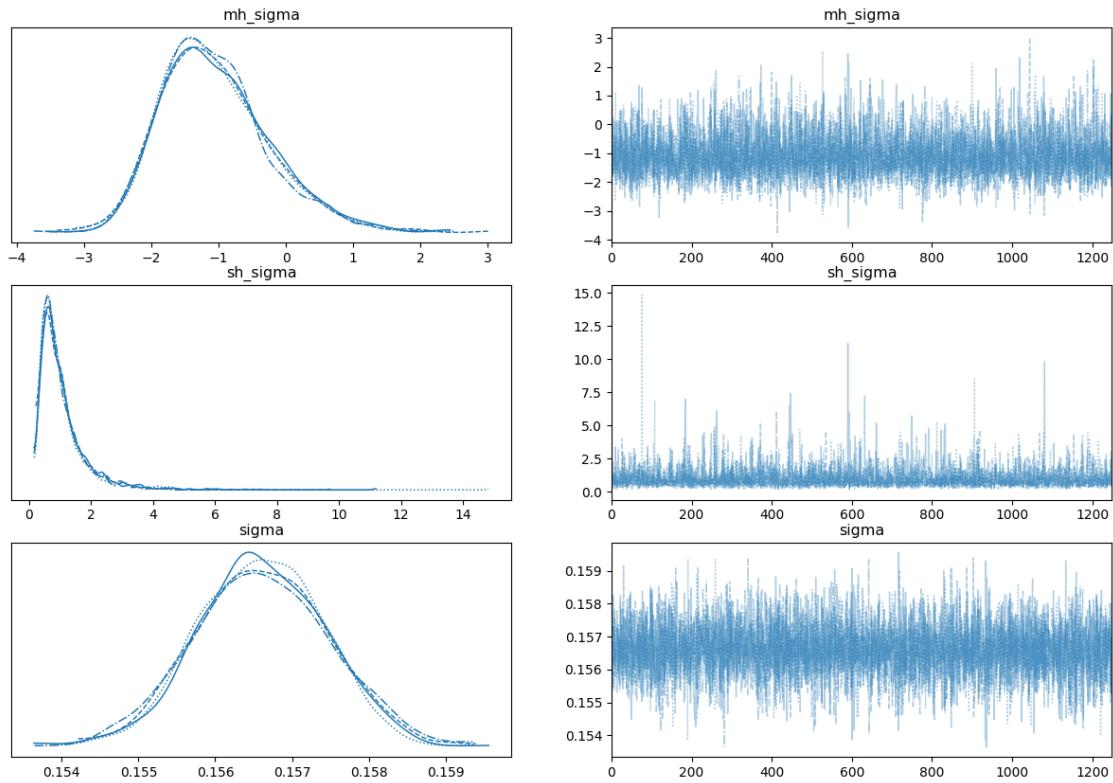
	Estimate	SE
elpd_waic	7301.79	154.50
p_waic	299.09	-

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

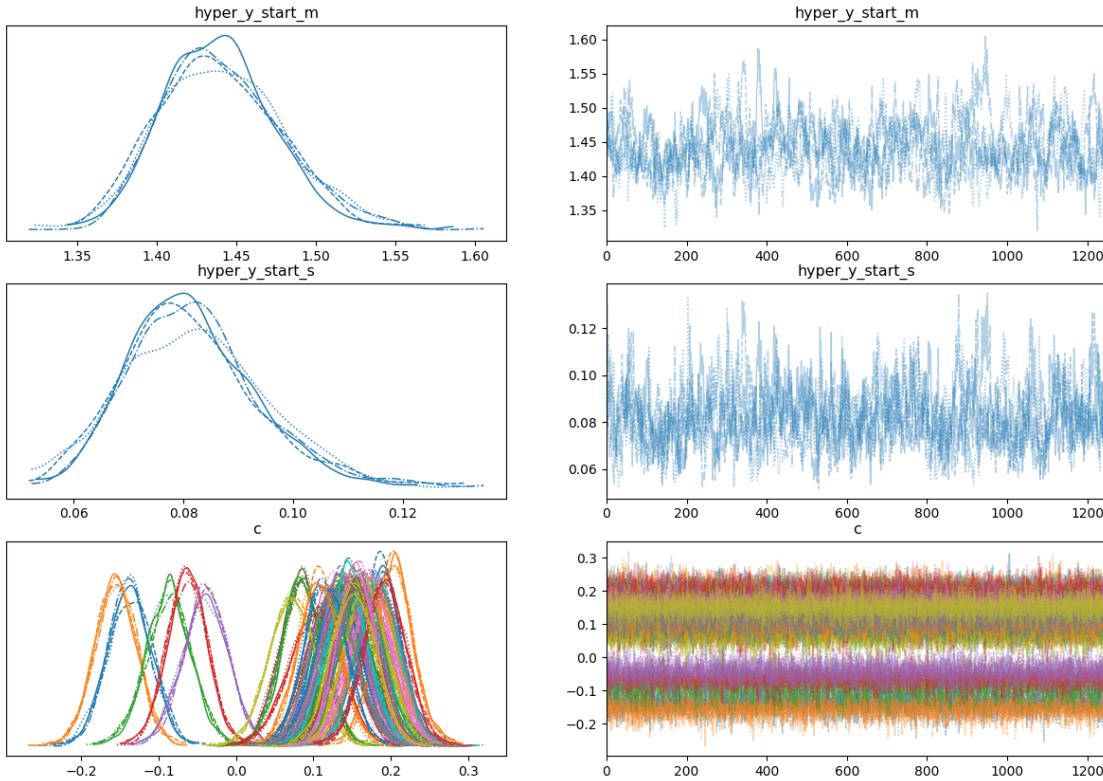
```
[8]: plt_aux = az.plot_trace(ritorno['inference_data'],  
    var_names=['phi','theta','hyper_gamma_phi_m','hyper_gamma_phi_s'],  
    divergences=True, figsize=(15,15))
```



```
[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	ess_tail	r_hat
y_start[0, 0]	1.428	0.090	1.261	1.599	0.002	0.002	1424.0		
y_start[0, 1]	1.426	0.086	1.273	1.597	0.003	0.002	1028.0		
y_start[0, 2]	1.428	0.091	1.256	1.601	0.003	0.002	1207.0		
y_start[0, 3]	1.430	0.091	1.255	1.598	0.002	0.002	1439.0		
y_start[0, 4]	1.436	0.094	1.262	1.609	0.003	0.002	1339.0		
...			
y_start[2, 44]	1.451	0.054	1.354	1.559	0.002	0.001	981.0		
y_start[2, 45]	1.447	0.056	1.342	1.551	0.002	0.001	888.0		
y_start[2, 46]	1.443	0.054	1.348	1.550	0.002	0.001	918.0		
y_start[2, 47]	1.459	0.056	1.357	1.567	0.002	0.001	826.0		
y_start[2, 48]	1.465	0.055	1.359	1.566	0.002	0.001	968.0		
...			

```
y_start[2, 44]    1643.0    1.0
y_start[2, 45]    1248.0    1.0
y_start[2, 46]    1881.0    1.0
y_start[2, 47]    1179.0    1.0
y_start[2, 48]    1494.0    1.0
```

[147 rows x 9 columns]

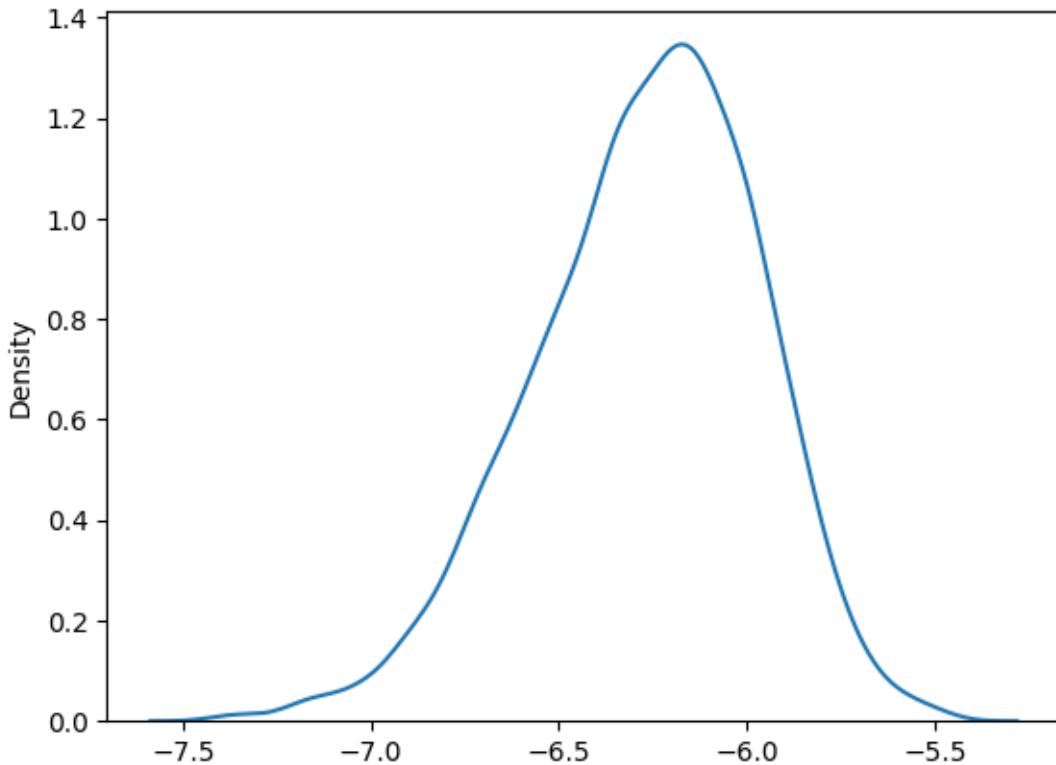
```
[12]: az.summary(ritorno['inference_data'], var_names=['hyper_y_start_m', ↴'hyper_y_start_s'])
```

```
mean      sd   hdi_3%   hdi_97%  mcse_mean  mcse_sd  ess_bulk \
hyper_y_start_m 1.441  0.038   1.374   1.514     0.003   0.002   226.0
hyper_y_start_s 0.082  0.013   0.059   0.106     0.001   0.000   359.0

ess_tail  r_hat
hyper_y_start_m    404.0   1.01
hyper_y_start_s    907.0   1.01
```

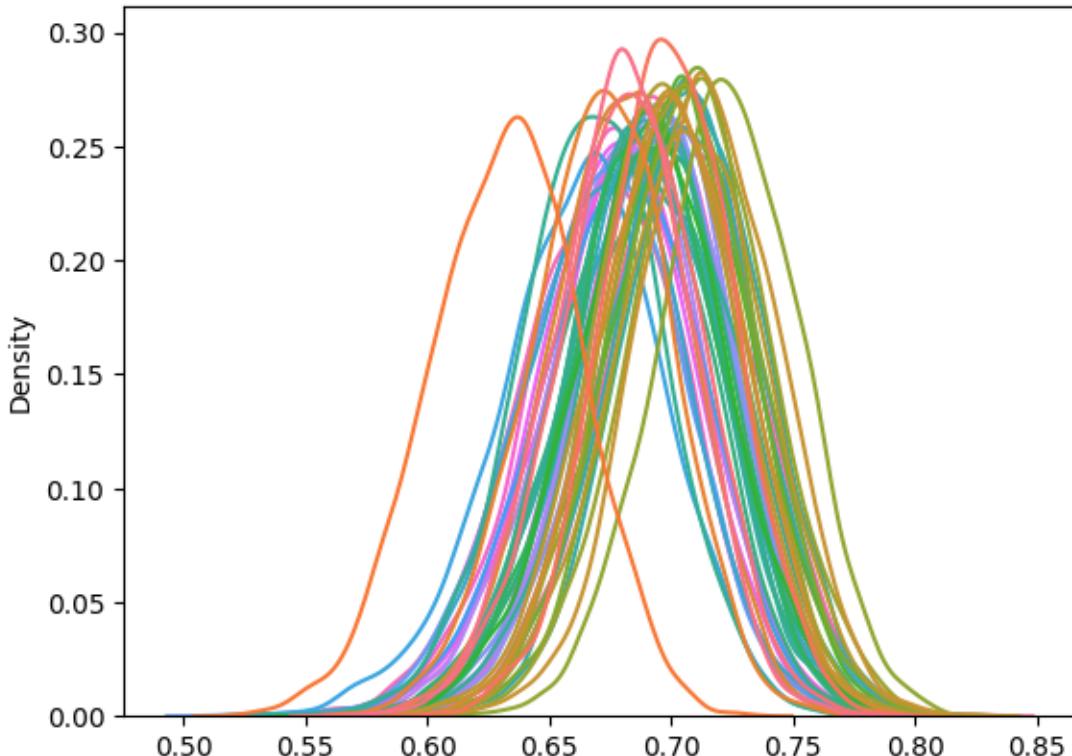
```
[13]: aux_shape = ritorno['inference_data'].posterior.gamma_th.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.gamma_th.values.
             ↴reshape((aux_shape[0]*aux_shape[1])), legend=False)
```

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



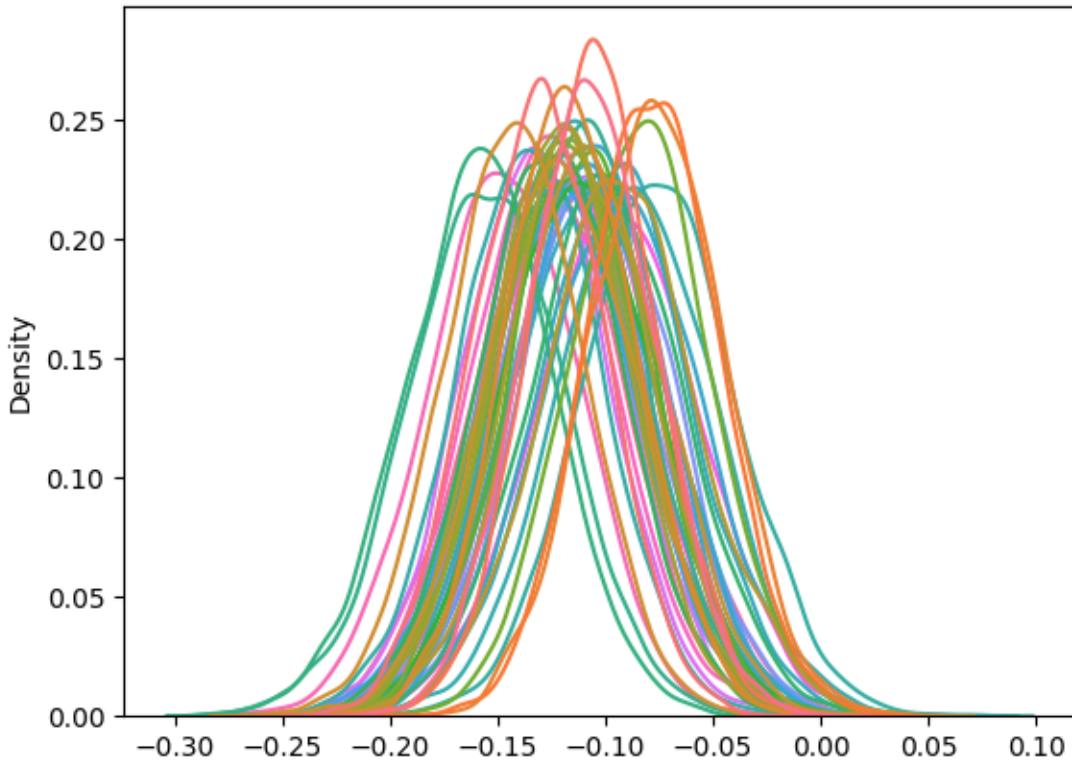
```
[14]: aux_shape = ritorno['inference_data'].posterior.phi.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.phi.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2],aux_shape[3]))[:,0,:,:],  
            legend=False)
```

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



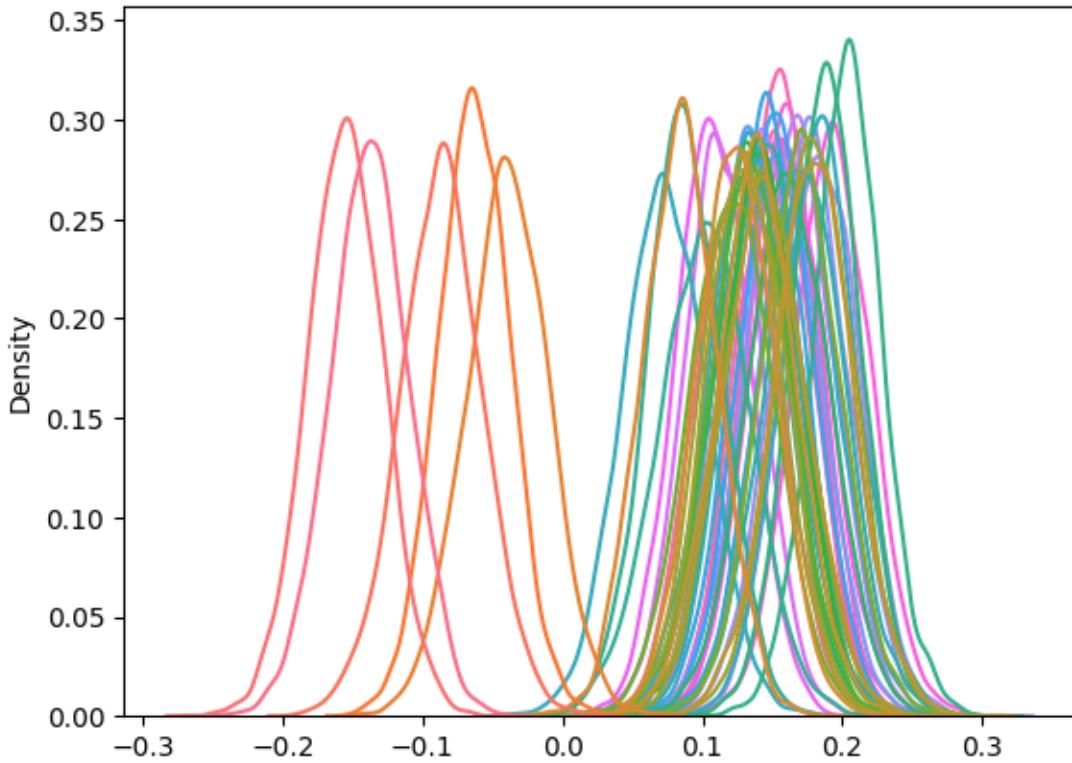
```
[15]: aux_shape = ritorno['inference_data'].posterior.phi.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.phi.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2],aux_shape[3]))[:,1,:,:],  
            legend=False)
```

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



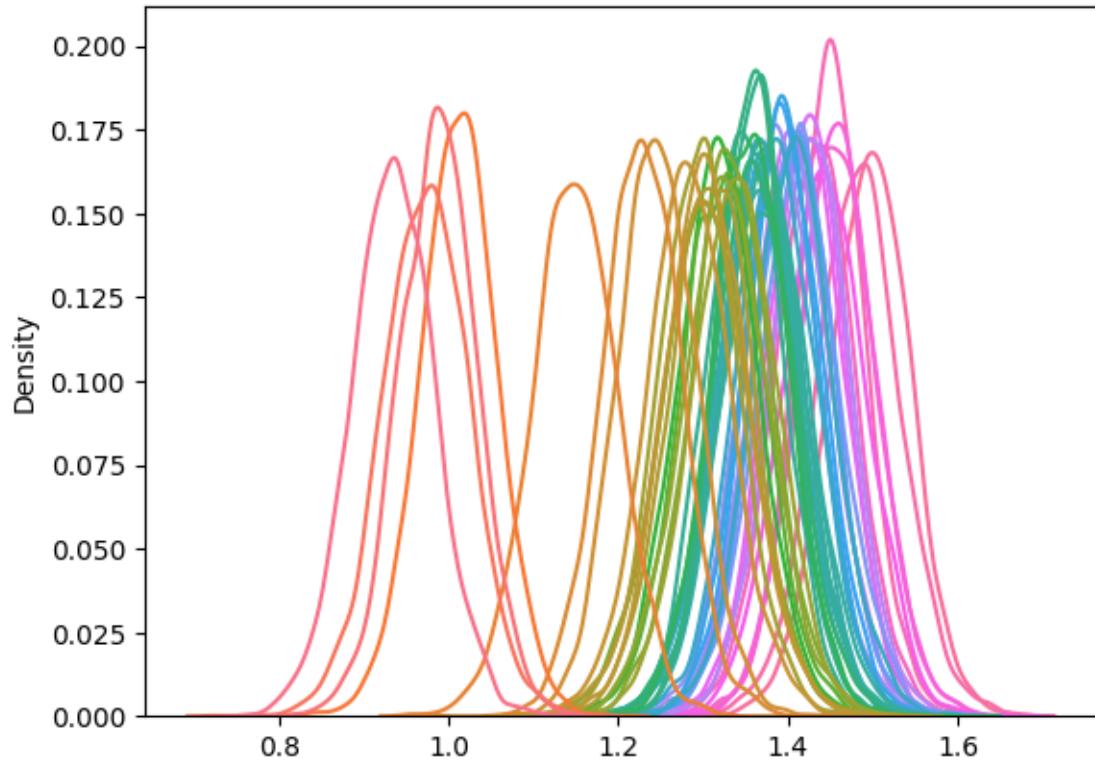
```
[16]: aux_shape = ritorno['inference_data'].posterior.c.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.c.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

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



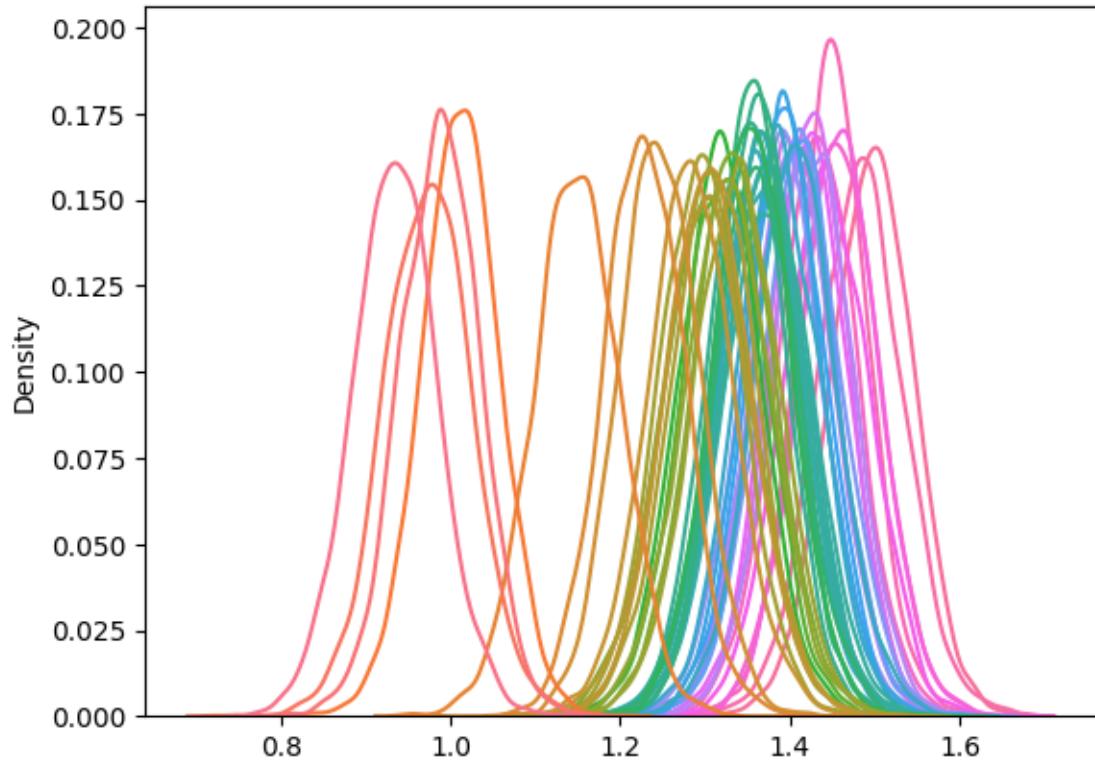
```
[17]: aux_shape = ritorno['inference_data'].posterior.annual_mean.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.annual_mean.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

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



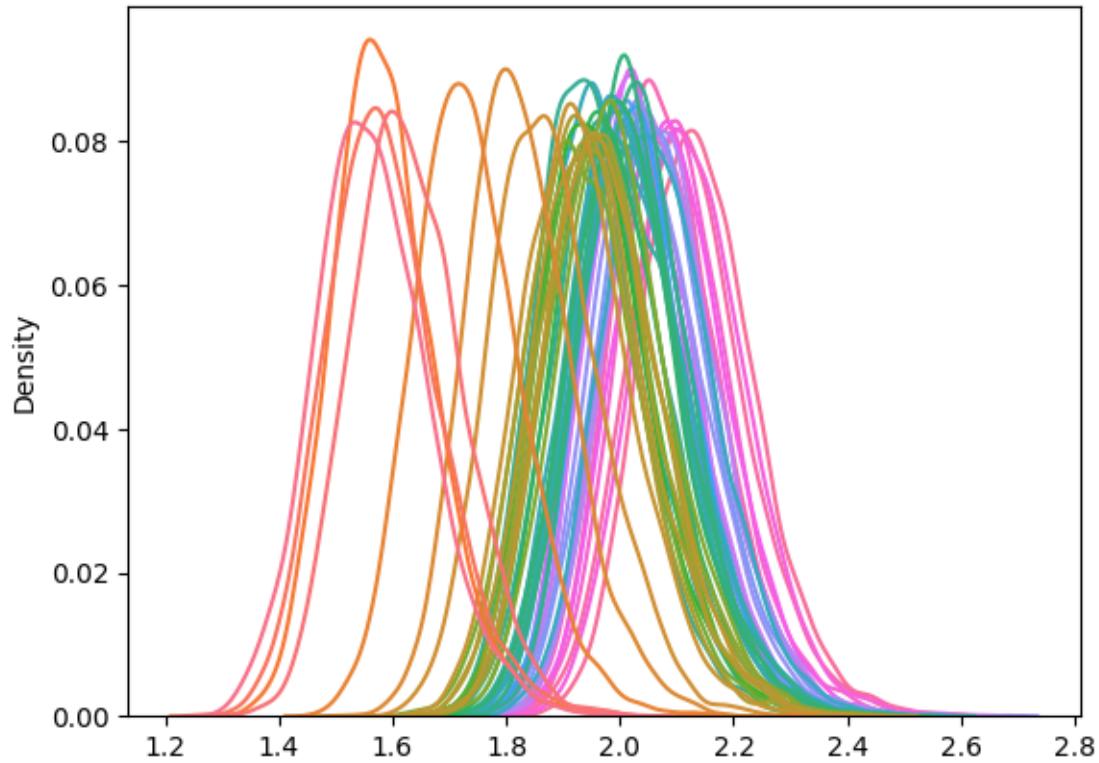
```
[18]: aux_shape = ritorno['inference_data'].posterior.annual_median.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.annual_median.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

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



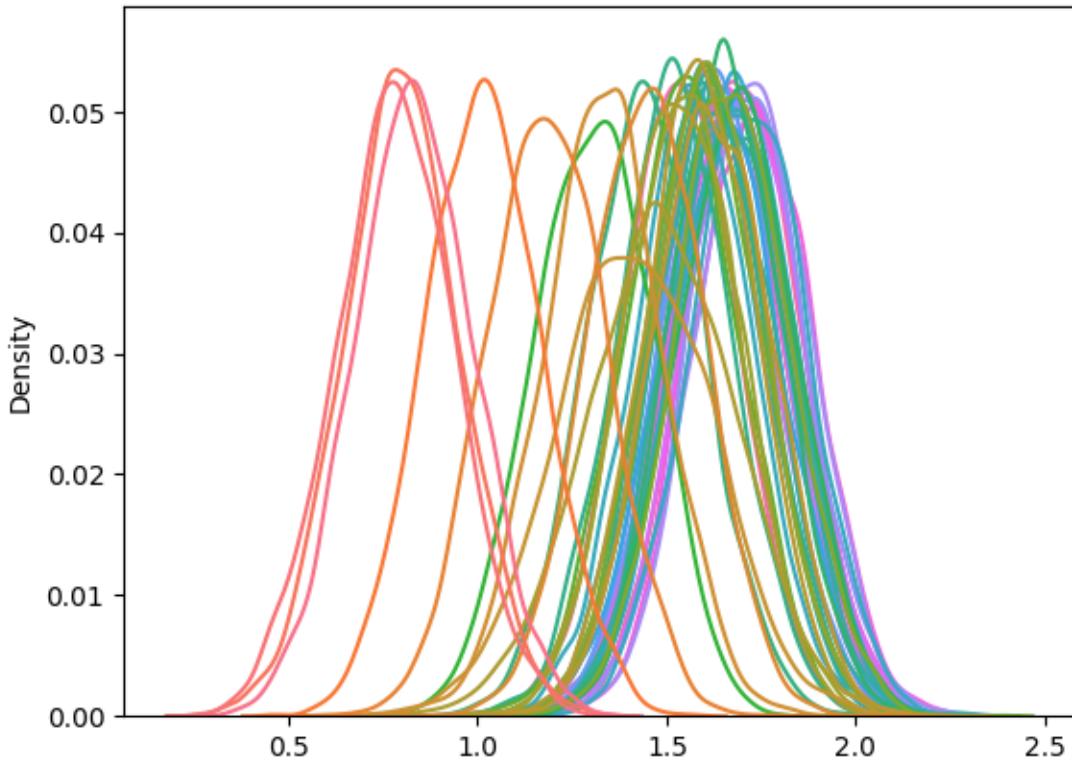
```
[19]: aux_shape = ritorno['inference_data'].posterior.annual_max.values.shape
sns.kdeplot(ritorno['inference_data'].posterior.annual_max.values.
             .reshape((aux_shape[0]*aux_shape[1],aux_shape[2])), legend=False)
```

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



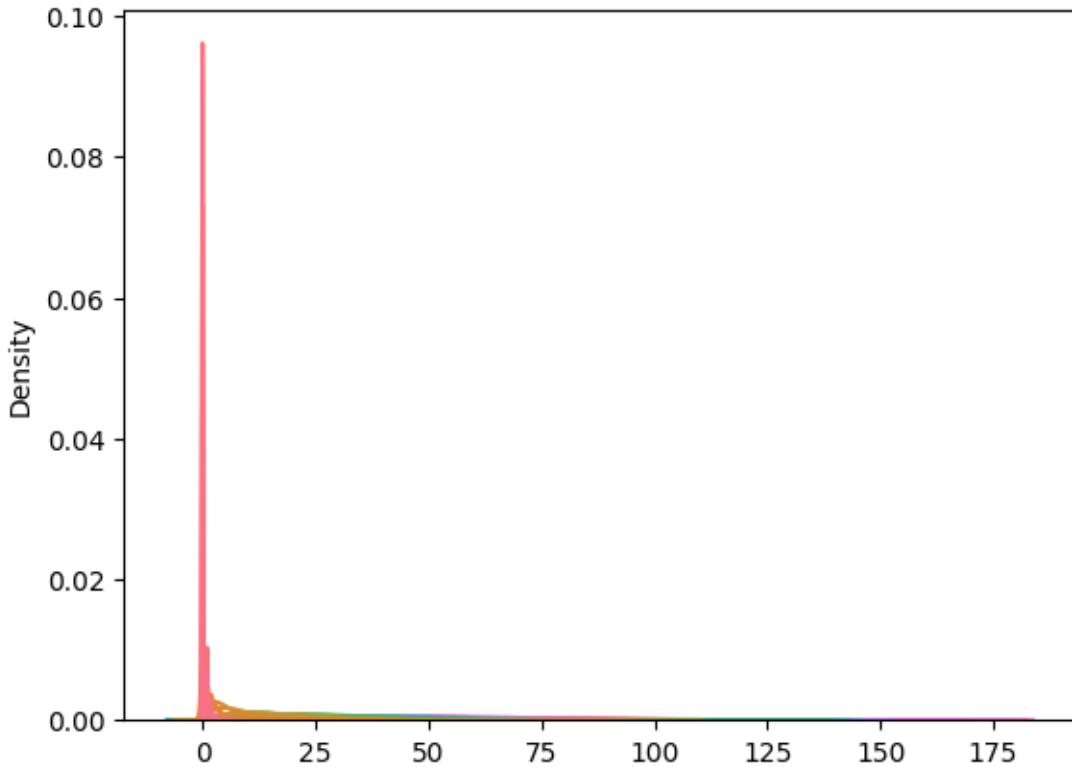
```
[20]: valori_31_dic = []
for dizionario in ritorno['missing']:
    if dizionario['Data'] == '2018-12-31':
        valori_31_dic.append(dizionario['Samples'])

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)
```

	CASTELLUCCIO	SAVIGNANO DI RIGO	CORTE BRUGNATELLA	FEBBIO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.119200	0.130600	0.170800	0.306400	
std	0.422643	0.415184	0.533371	0.680156	
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	6.000000	6.000000	9.000000	6.000000	
	SAN LEO	VERUCCHIO	BADIA	GIARDINI MARGHERITA	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	1.583400	4.804800	7.843600	13.554000	
std	2.001861	3.975507	5.518299	8.352906	
min	0.000000	0.000000	0.000000	0.000000	

25%	0.000000	2.000000	4.000000	8.000000
50%	1.000000	4.000000	7.000000	12.000000
75%	2.000000	7.000000	11.000000	18.000000
max	24.000000	42.000000	42.000000	75.000000

	SAN PIETRO CAPOFIUME	MARECCHIA	PARCO BERTOZZI	LUGAGNANO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	15.655600	15.800600	17.107800	17.855200	
std	9.705845	9.337059	10.243806	9.912491	
min	0.000000	0.000000	0.000000	0.000000	
25%	9.000000	9.000000	10.000000	11.000000	
50%	14.000000	14.000000	15.000000	16.000000	
75%	21.000000	20.250000	22.000000	23.000000	
max	82.000000	90.000000	88.000000	83.000000	

	DELTA CERVIA	DE AMICIS	SAN LAZZARO	PARCO RESISTENZA	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	17.867400	17.951600	18.928600	19.46160	
std	9.684223	9.433147	10.543004	10.36772	
min	0.000000	0.000000	0.000000	0.00000	
25%	11.000000	11.000000	11.000000	12.00000	
50%	16.000000	16.000000	17.000000	18.00000	
75%	23.000000	23.000000	24.000000	25.00000	
max	92.000000	78.000000	86.000000	84.00000	

	FRANCHINI-ANGELONI	GHERARDI	VIA CHIARINI	SAVIGNANO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	21.112200	21.216200	21.463000	23.671600	
std	11.518565	11.860742	11.379584	11.679479	
min	0.000000	0.000000	1.000000	0.000000	
25%	13.000000	13.000000	13.000000	15.000000	
50%	19.000000	19.000000	20.000000	22.000000	
75%	27.000000	27.000000	27.000000	30.000000	
max	104.000000	121.000000	95.000000	90.000000	

	GAVELLO	BESENZONE	VILLA FULVIA	ROMA	PORTA SAN FELICE	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	23.673800	24.549600	28.082400	28.478600	29.057200	
std	11.559901	13.067857	13.089594	13.462979	13.000359	
min	1.000000	0.000000	1.000000	1.000000	1.000000	
25%	15.000000	15.000000	19.000000	19.000000	20.000000	
50%	22.000000	22.000000	26.000000	27.000000	27.000000	
75%	30.000000	31.000000	35.000000	36.000000	37.000000	
max	93.000000	95.000000	101.000000	132.000000	129.000000	

	CAORLE	CASTELLARANO	PARCO MONTECUCCO	ZALAMELLA	CENTO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	

mean	29.496600	29.690800	30.348400	30.654000	30.750400
std	14.558213	12.144146	14.083433	14.440166	14.005246
min	1.000000	1.000000	0.000000	0.000000	0.000000
25%	19.000000	21.000000	20.000000	20.000000	21.000000
50%	27.000000	28.000000	28.000000	29.000000	29.000000
75%	38.000000	37.000000	38.000000	39.000000	39.000000
max	132.000000	95.000000	113.000000	135.000000	110.000000

	PARCO EDILCARANI	BOGOLESE	SARAGAT	PARADIGNA	MALCANTONE	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	31.862400	32.414000	34.823600	36.049800	36.40740	
std	12.495227	14.122114	14.769946	15.517109	15.62687	
min	3.000000	3.000000	1.000000	1.000000	3.00000	
25%	23.000000	22.000000	24.000000	25.000000	25.00000	
50%	30.000000	30.000000	33.000000	34.000000	34.00000	
75%	39.000000	41.000000	44.000000	45.000000	45.00000	
max	97.000000	126.000000	106.000000	137.000000	144.00000	

	S. LAZZARO	REMESINA	S. ROCCO	CENO	ISONZO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	36.717600	37.258400	38.640600	41.682000	42.197200	
std	15.295524	15.270752	15.793585	16.954432	16.223247	
min	2.000000	3.000000	3.000000	3.000000	3.000000	
25%	26.000000	26.000000	27.000000	30.000000	30.000000	
50%	35.000000	35.000000	37.000000	40.000000	41.000000	
75%	46.000000	46.000000	48.000000	51.250000	52.000000	
max	144.000000	117.000000	126.000000	132.000000	124.000000	

	PARCO FERRARI	CITTADELLA	GIORDANI-FARNESE	SAN FRANCESCO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	
mean	42.662200	46.169400	46.499200	50.950200	
std	16.549878	17.223322	17.256279	17.201375	
min	5.000000	6.000000	5.000000	8.000000	
25%	31.000000	34.000000	34.000000	39.000000	
50%	41.000000	45.000000	45.000000	49.000000	
75%	52.000000	56.000000	57.000000	61.000000	
max	131.000000	137.000000	137.000000	157.000000	

	FLAMINIA	MONTEBELLO	GIARDINI	GERBIDO	TIMAVO
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	51.843400	55.108200	60.897800	63.058000	70.958800
std	19.372205	19.523666	19.522161	22.329388	22.126125
min	6.000000	7.000000	11.000000	8.000000	8.000000
25%	38.000000	42.000000	47.000000	47.000000	55.000000
50%	50.000000	53.000000	59.000000	61.000000	69.000000
75%	63.000000	67.000000	73.000000	76.000000	85.000000
max	158.000000	173.000000	168.000000	170.000000	170.000000

```
[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)
```

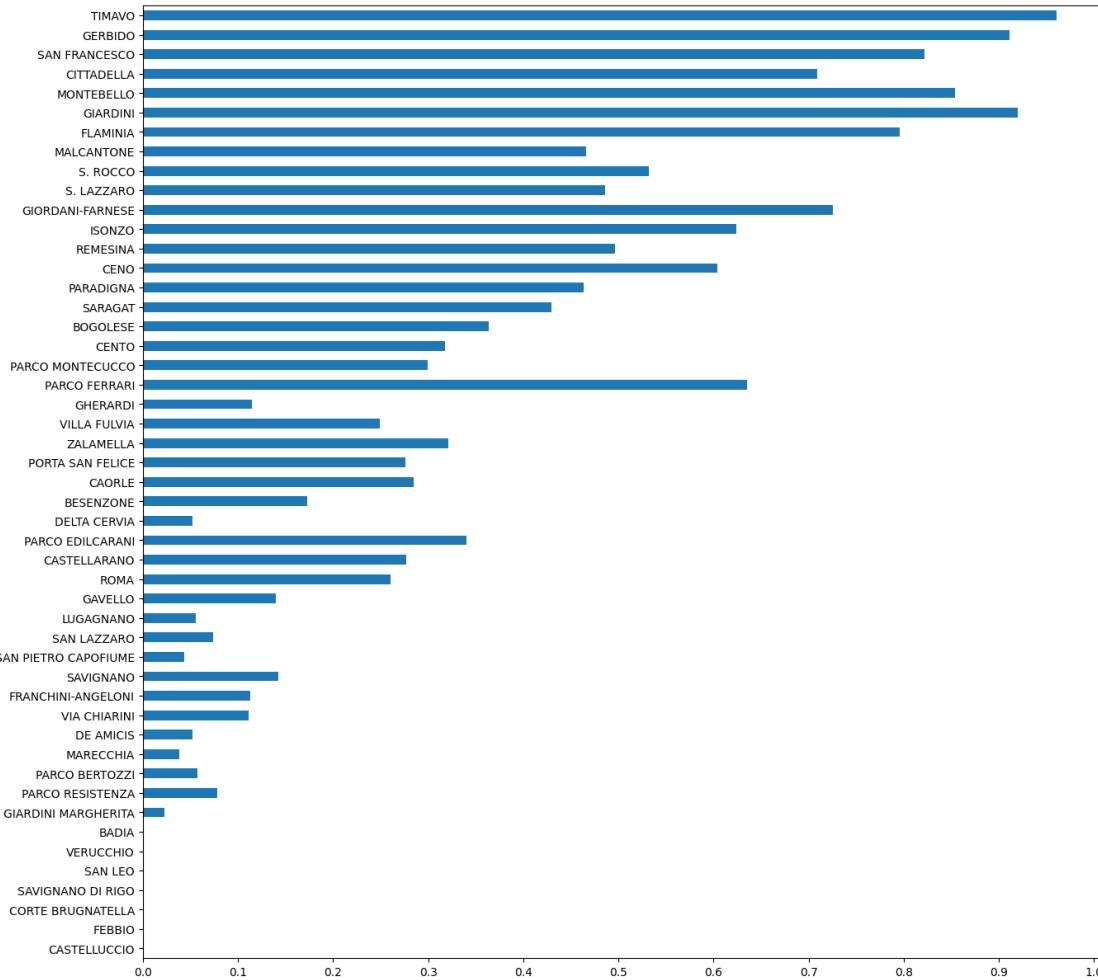
	CASTELLUCCIO	FEBBIO	CORTE BRUGNATELLA	SAVIGNANO DI RIGO	SAN LEO	\
count	5000.0	5000.0	5000.0	5000.0	5000.0	
mean	0.0	0.0	0.0	0.0	0.0	
std	0.0	0.0	0.0	0.0	0.0	
min	0.0	0.0	0.0	0.0	0.0	
25%	0.0	0.0	0.0	0.0	0.0	
50%	0.0	0.0	0.0	0.0	0.0	
75%	0.0	0.0	0.0	0.0	0.0	
max	0.0	0.0	0.0	0.0	0.0	
	VERUCCHIO	BADIA	GIARDINI MARGHERITA	MARECCHIA	\	
count	5000.000000	5000.000000	5000.000000	5000.000000		
mean	0.000400	0.00100	0.022600	0.038200		
std	0.019998	0.03161	0.148639	0.191698		
min	0.000000	0.00000	0.000000	0.000000		
25%	0.000000	0.00000	0.000000	0.000000		
50%	0.000000	0.00000	0.000000	0.000000		
75%	0.000000	0.00000	0.000000	0.000000		
max	1.000000	1.00000	1.000000	1.000000		
	SAN PIETRO CAPOFIUME	DE AMICIS	DELTA CERVIA	LUGAGNANO	\	
count	5000.000000	5000.000000	5000.000000	5000.000000		
mean	0.043400	0.051800	0.052600	0.056000		
std	0.203776	0.221645	0.223256	0.229945		
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	VIA CHIARINI	\	
count	5000.000000	5000.000000	5000.000000	5000.000000		
mean	0.057200	0.074000	0.078400	0.111200		
std	0.232248	0.261797	0.268827	0.314411		
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		

	FRANCHINI-ANGELONI	GHERARDI	GAVELLO	SAVIGNANO	BESENZONE	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.113000	0.114800	0.140000	0.142600	0.173200	
std	0.316624	0.318812	0.347022	0.349699	0.378458	
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	
	VILLA FULVIA	ROMA	PORTA SAN FELICE	CASTELLARANO	CAORLE	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.248800	0.260400	0.276000	0.276800	0.28500	
std	0.432361	0.438897	0.447061	0.447462	0.45146	
min	0.000000	0.000000	0.000000	0.000000	0.00000	
25%	0.000000	0.000000	0.000000	0.000000	0.00000	
50%	0.000000	0.000000	0.000000	0.000000	0.00000	
75%	0.000000	1.000000	1.000000	1.000000	1.00000	
max	1.000000	1.000000	1.000000	1.000000	1.00000	
	PARCO MONTECUCCO	CENTO	ZALAMELLA	PARCO EDILCARANI		\
count	5000.000000	5000.000000	5000.000000	5000.000000		
mean	0.299800	0.317400	0.320800	0.340400		
std	0.458216	0.465511	0.466831	0.473891		
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		
	BOGOLESE	SARAGAT	PARADIGNA	MALCANTONE	S. LAZZARO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.363400	0.42940	0.463600	0.46640	0.485800	
std	0.481027	0.49504	0.498723	0.49892	0.499848	
min	0.000000	0.00000	0.000000	0.00000	0.000000	
25%	0.000000	0.00000	0.000000	0.00000	0.000000	
50%	0.000000	0.00000	0.000000	0.00000	0.000000	
75%	1.000000	1.00000	1.000000	1.00000	1.000000	
max	1.000000	1.00000	1.000000	1.00000	1.000000	
	REMESINA	S. ROCCO	CENO	ISONZO	PARCO FERRARI	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.496000	0.531800	0.604000	0.624000	0.635000	
std	0.500034	0.499038	0.489113	0.484428	0.481478	
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	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	
	CITTADELLA	GIORDANI-FARNESE	FLAMINIA	SAN FRANCESCO	MONTEBELLO	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.709200	0.725200	0.796000	0.821600	0.853600	
std	0.454177	0.446458	0.403009	0.382887	0.353542	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	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	
	GERBIDO	GIARDINI	TIMAVO			
count	5000.000000	5000.000000	5000.000000			
mean	0.910800	0.92000	0.960600			
std	0.285061	0.27132	0.194564			
min	0.000000	0.00000	0.000000			
25%	1.000000	1.00000	1.000000			
50%	1.000000	1.00000	1.000000			
75%	1.000000	1.00000	1.000000			
max	1.000000	1.00000	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]:      CASTELLUCCIO BOGOLESE CENTO PARCO MONTECUCCO PARCO FERRARI \
count      5000.0   5000.0  5000.0      5000.0   5000.0
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
```

	VILLA	FULVIA	ZALAMELLA	PORTA	SAN FELICE	S. LAZZARO	BESENZONE	\
count	5000.0	5000.0		5000.0	5000.0	5000.0	5000.0	
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	

	DELTA	CERVIA	PARCO	EDILCARANI	CASTELLARANO	GAVELLO	SARAGAT	\
count	5000.0		5000.0		5000.0	5000.0	5000.0	
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 LAZZARO	LUGAGNANO	SAVIGNANO	FEBBIO	CORTE BRUGNATELLA	\	
count	5000.0	5000.0	5000.0	5000.0		5000.0	
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	

	SAVIGNANO DI RIGO	SAN LEO	VERUCCHIO	BADIA	SAN PIETRO CAPOFIUME	\	
count	5000.0	5000.0	5000.0	5000.0		5000.0	
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	

	GIARDINI MARGHERITA	PARCO BERTOZZI	MARECCHIA	DE AMICIS	\
count	5000.0	5000.0	5000.0	5000.0	
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

	VIA CHIARINI	FRANCHINI-ANGELONI	PARCO RESISTENZA	REMESINA	\
count	5000.0	5000.0	5000.0	5000.0	5000.0
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

	ISONZO	S. ROCCO	CAORLE	PARADIGNA	GHERARDI	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.000200	0.000200	0.000200	0.000200	0.000200	
std	0.014142	0.014142	0.014142	0.014142	0.014142	
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	CENO	GIORDANI-FARNESE	MALCANTONE	CITTADELLA	\
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.000200	0.000400	0.00060	0.00060	0.00060	
std	0.014142	0.019998	0.02449	0.02449	0.02449	
min	0.000000	0.000000	0.00000	0.00000	0.00000	
25%	0.000000	0.000000	0.00000	0.00000	0.00000	
50%	0.000000	0.000000	0.00000	0.00000	0.00000	
75%	0.000000	0.000000	0.00000	0.00000	0.00000	
max	1.000000	1.000000	1.00000	1.00000	1.00000	

	SAN FRANCESCO	GIARDINI	FLAMINIA	MONTEBELLO	GERBIDO	\
count	5000.00000	5000.000000	5000.000000	5000.000000	5000.000000	
mean	0.00100	0.001800	0.002200	0.002600	0.013400	
std	0.03161	0.042392	0.046857	0.050929	0.114992	
min	0.00000	0.000000	0.000000	0.000000	0.000000	
25%	0.00000	0.000000	0.000000	0.000000	0.000000	
50%	0.00000	0.000000	0.000000	0.000000	0.000000	
75%	0.00000	0.000000	0.000000	0.000000	0.000000	
max	1.00000	1.000000	1.000000	1.000000	1.000000	

TIMAVO
count 5000.000000
mean 0.014600

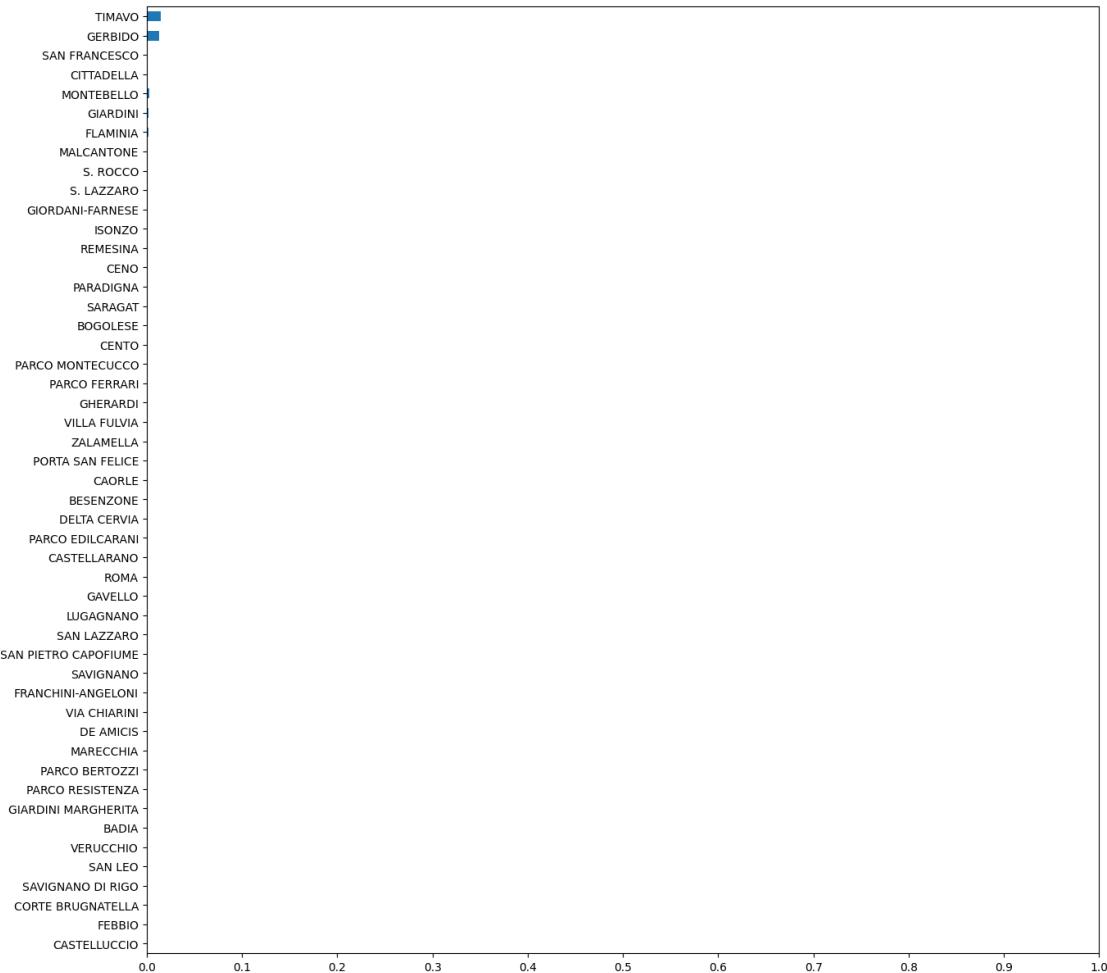
```

std      0.119957
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]: (5000, 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(mplt.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(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()

"""

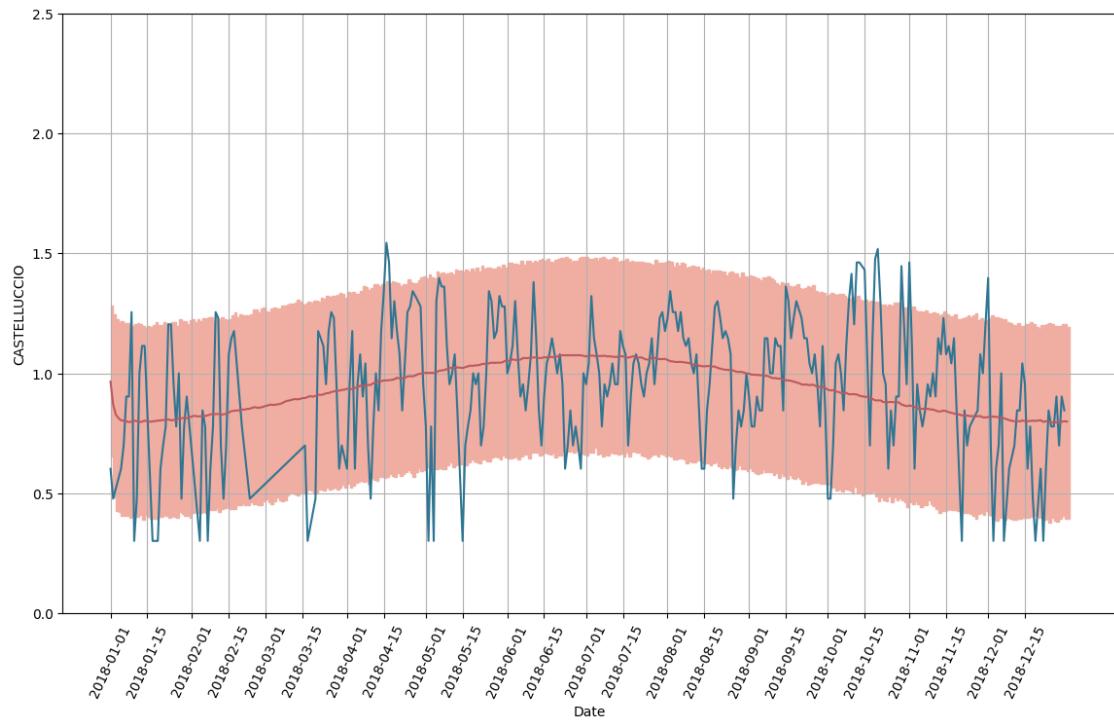
ax.get_legend().remove()
col_vals = np.linspace(1,255,num=len(df.columns))
index = 0
for line in ax.get_lines():
    if(index == len(ax.get_lines()) - 1):
        col_map = sns.dark_palette((230,90,65), input='husl', as_cmap=True)
        line.set_c(col_map(175))
        continue
    if(index == len(ax.get_lines())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

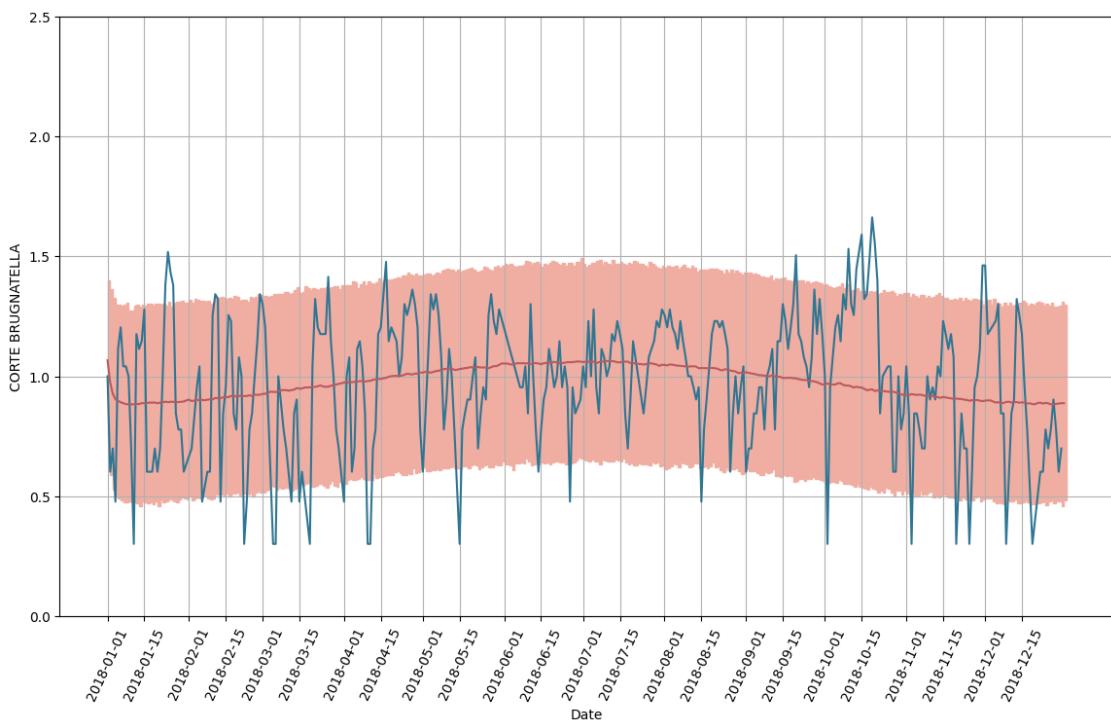
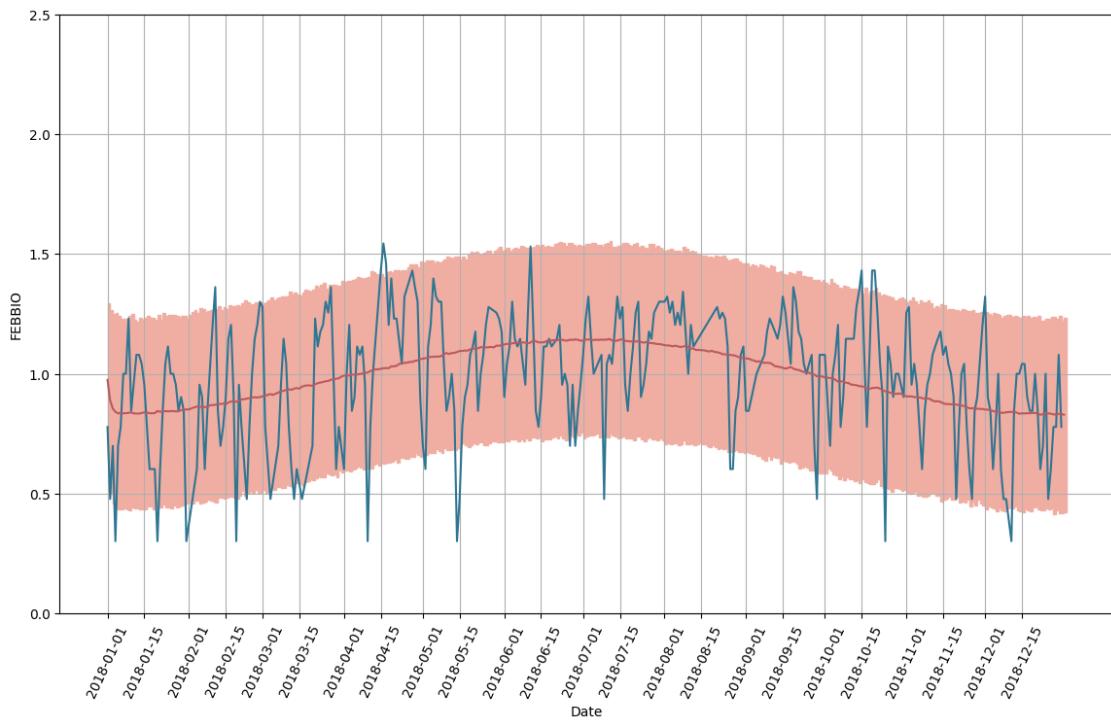
#line.set_c(col_map(int(np.round(col_vals[index]))))
line.set_c(col_map(220))
line.set_alpha(0.3)
index += 1
"""

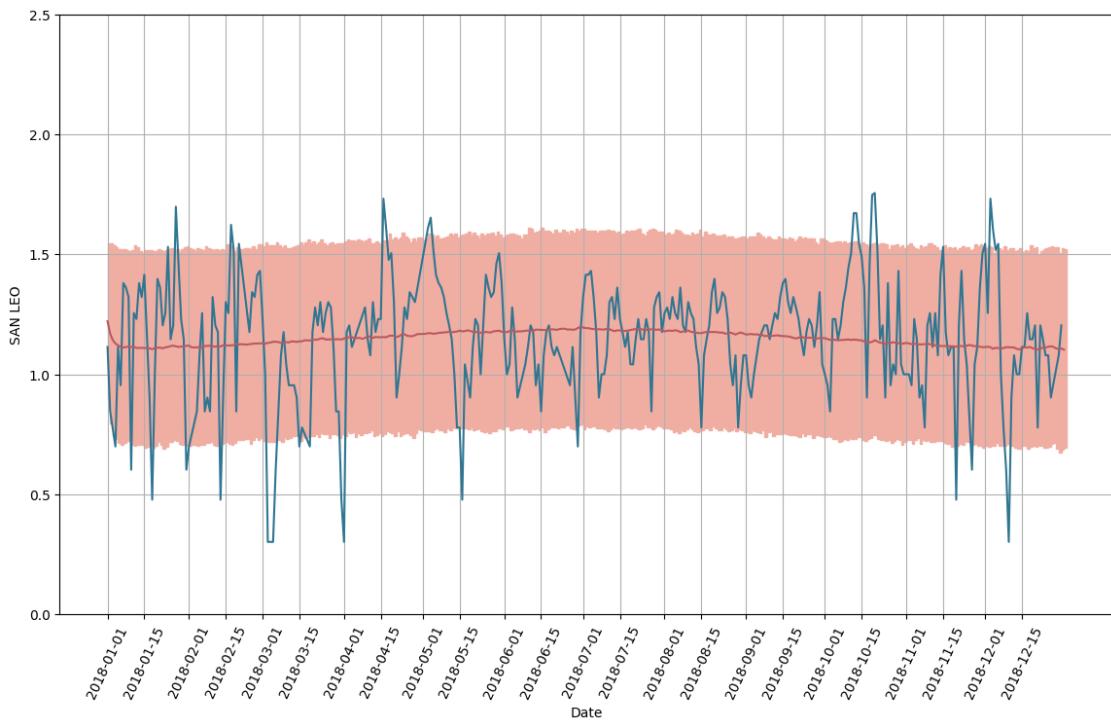
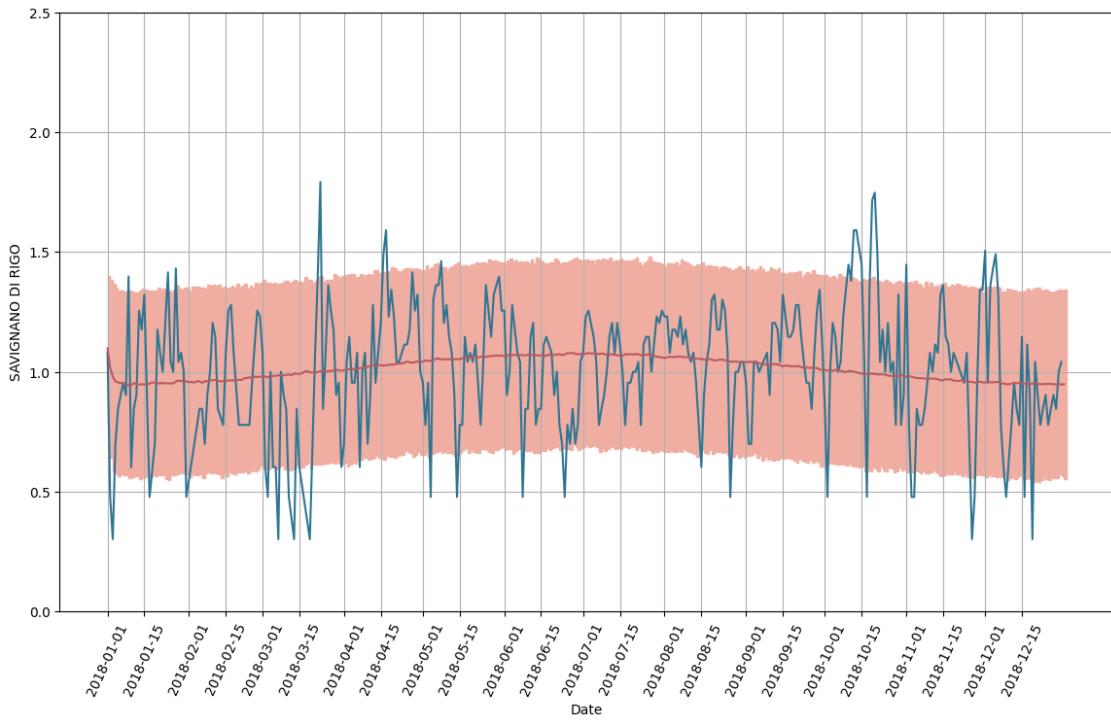
```

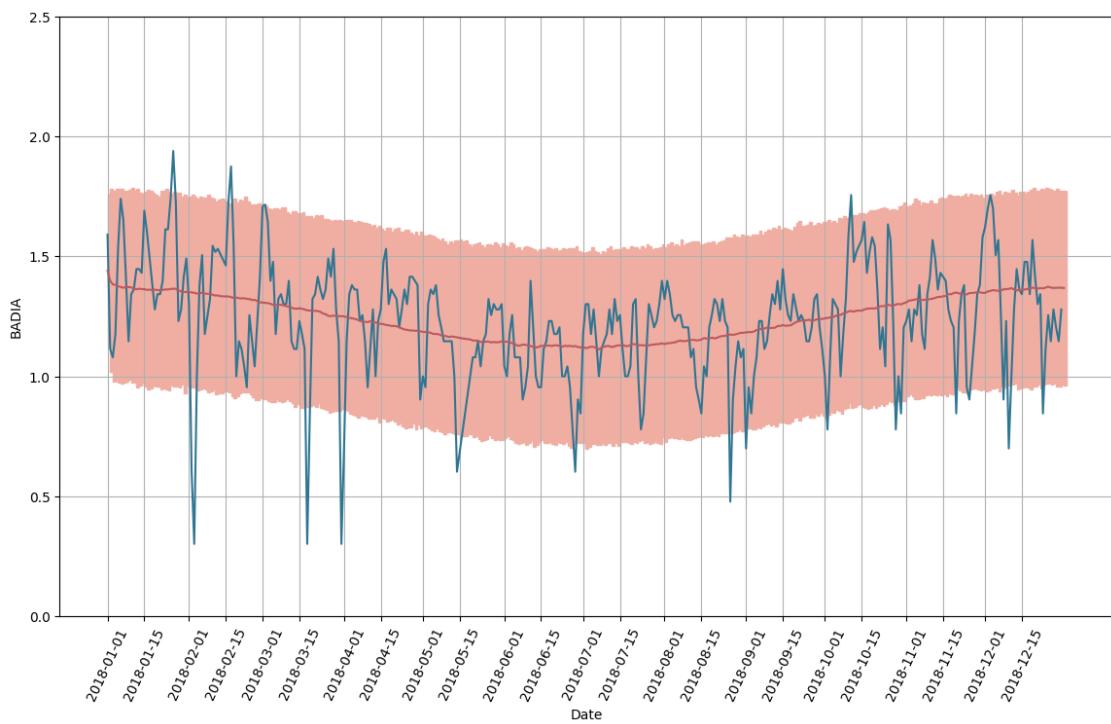
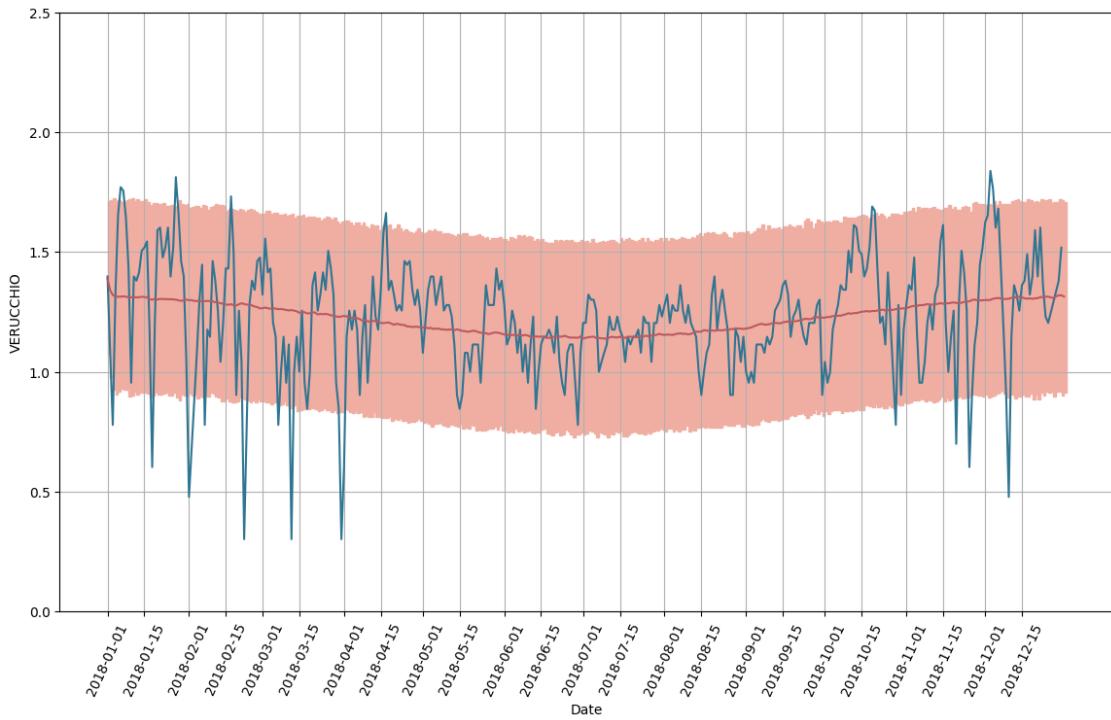
```
plt.show()
```

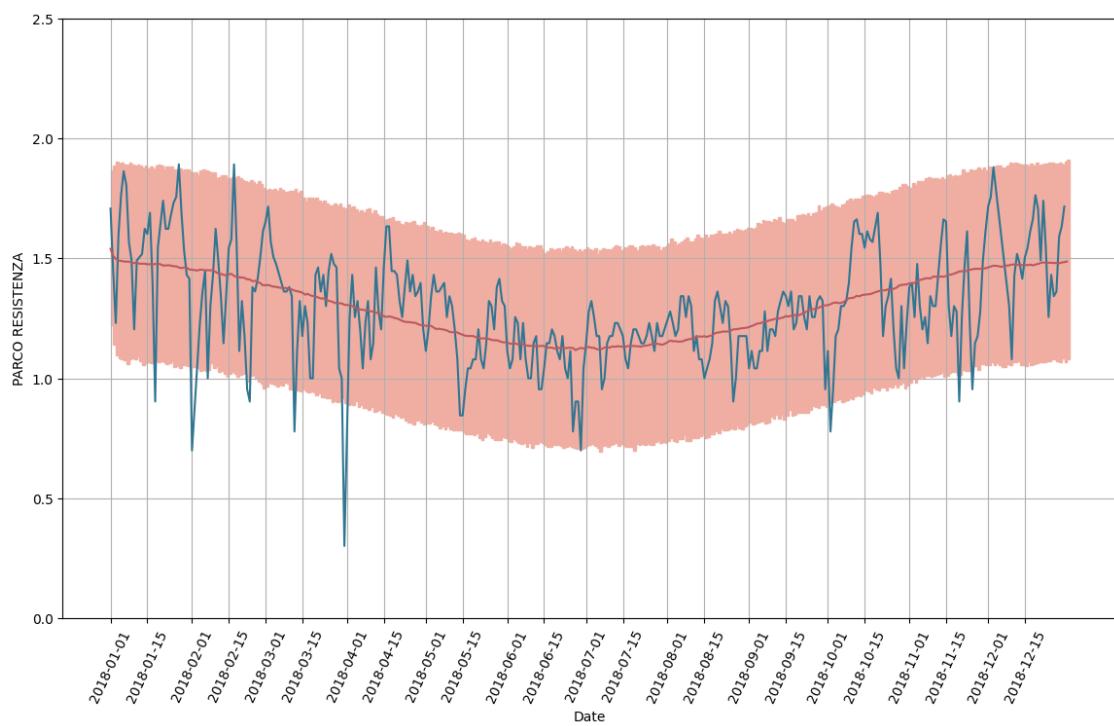
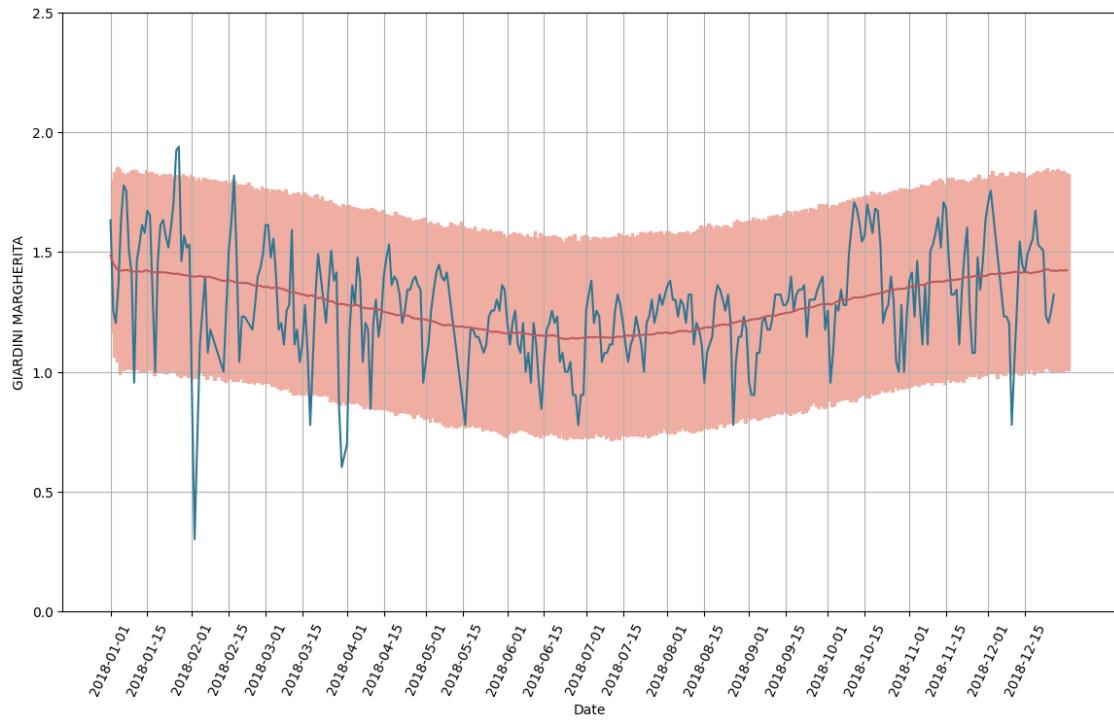
```
[31]: for stazione in df.columns:  
    f(stazione)
```

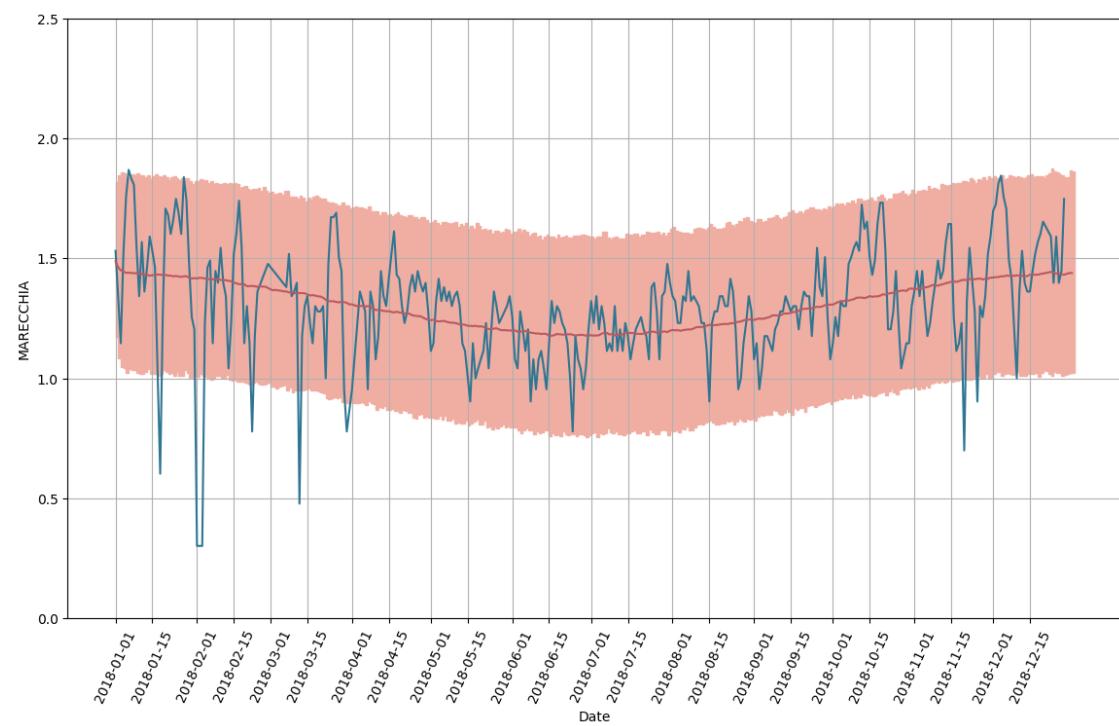
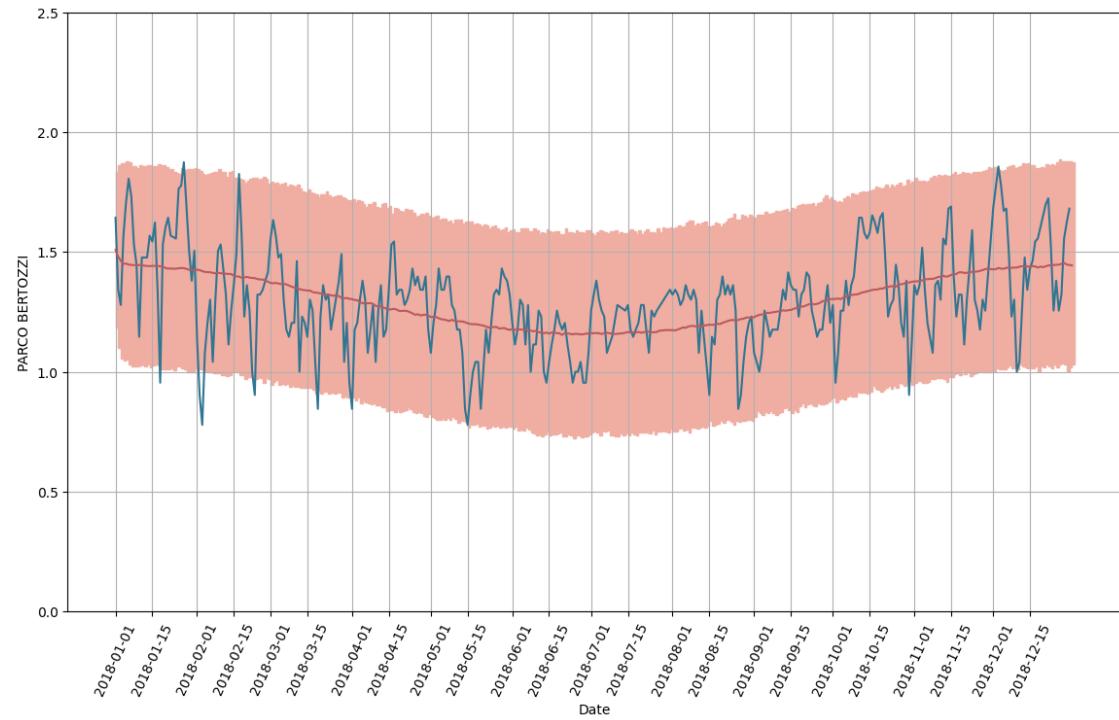


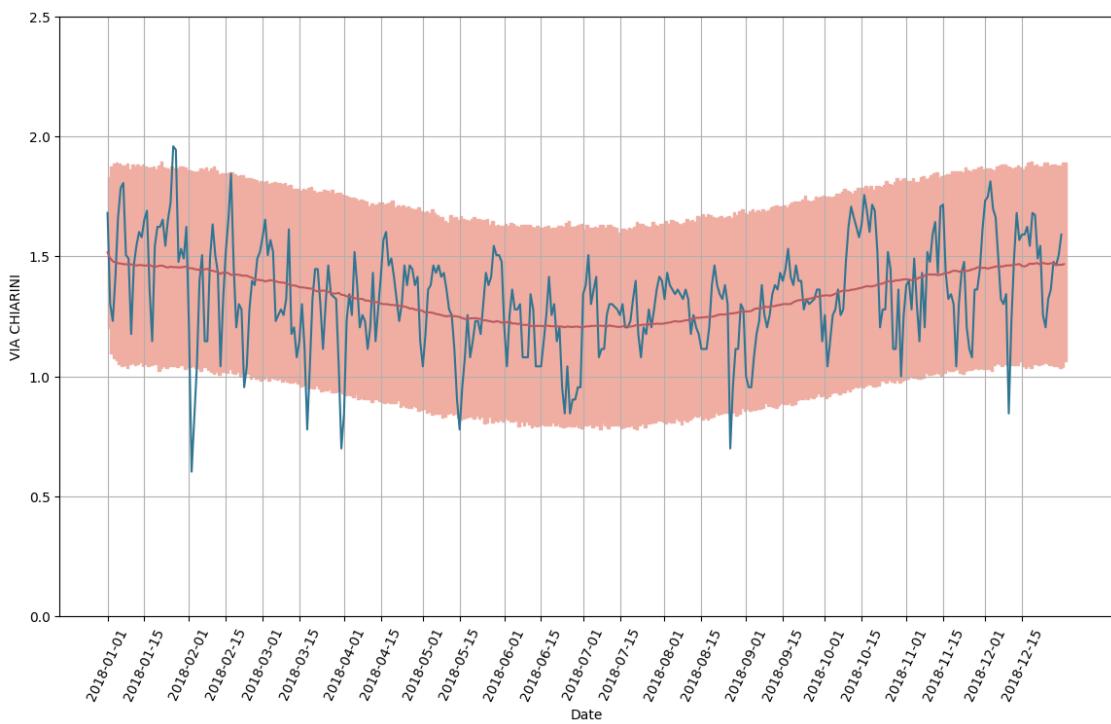
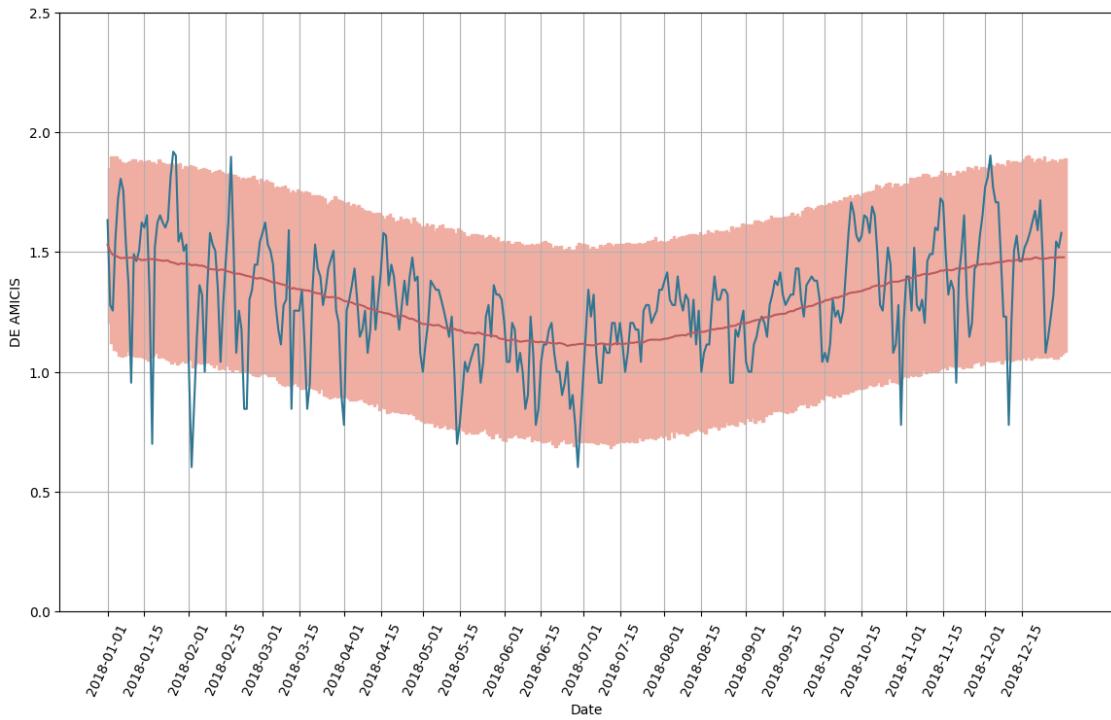


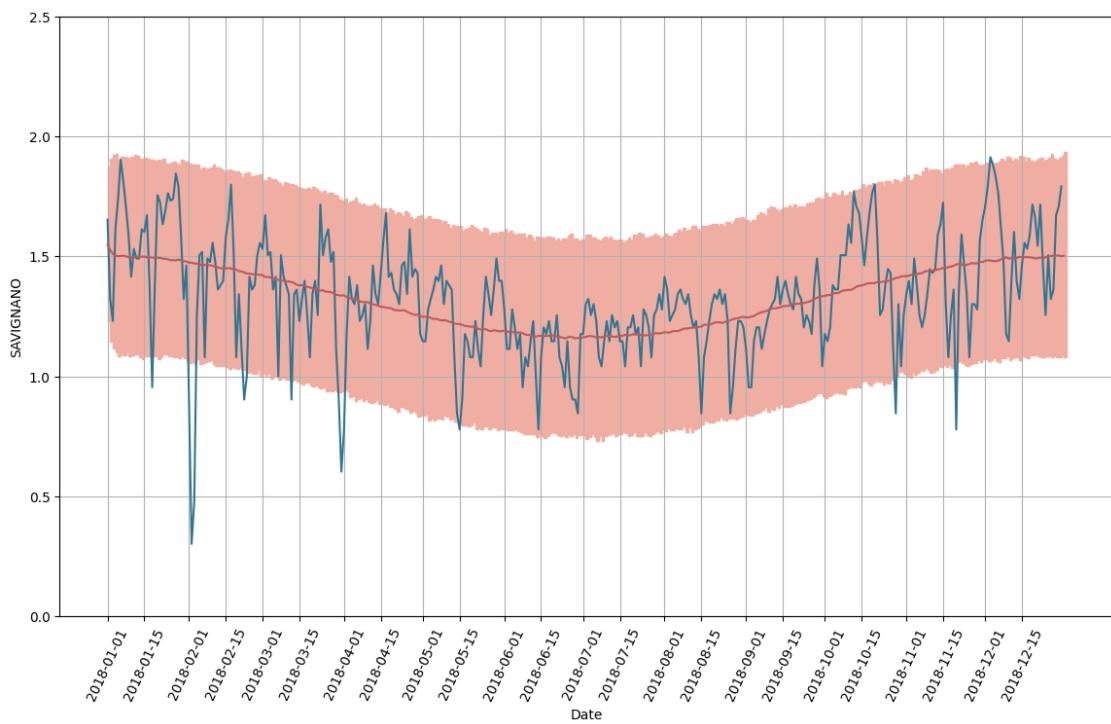
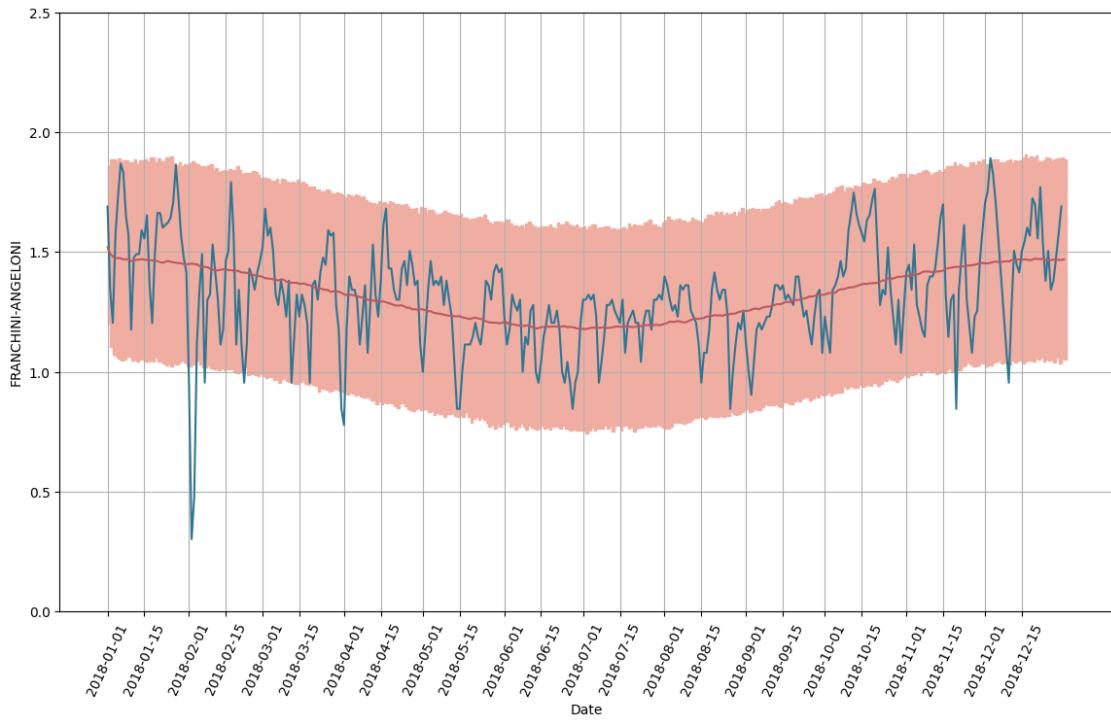


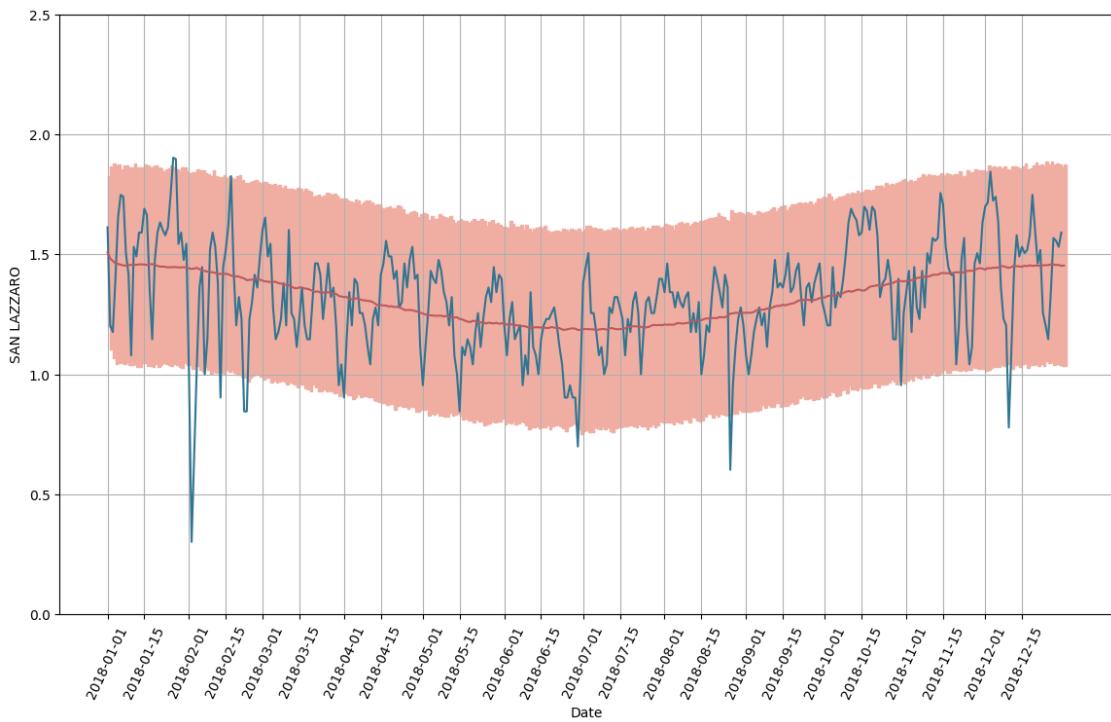
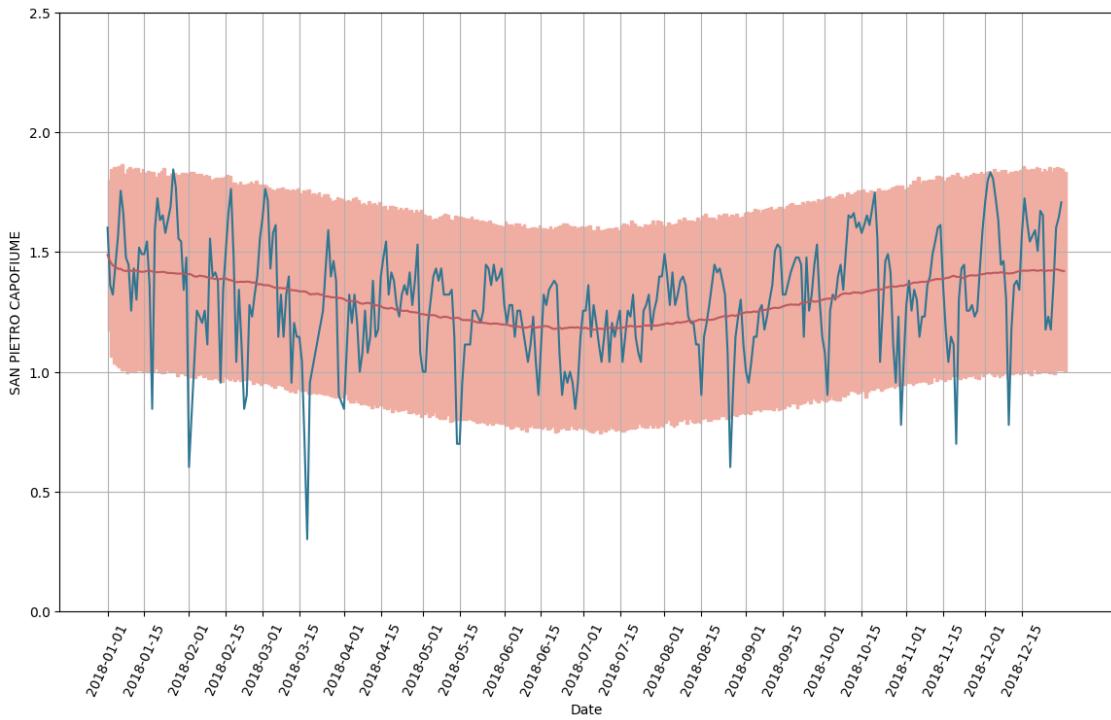


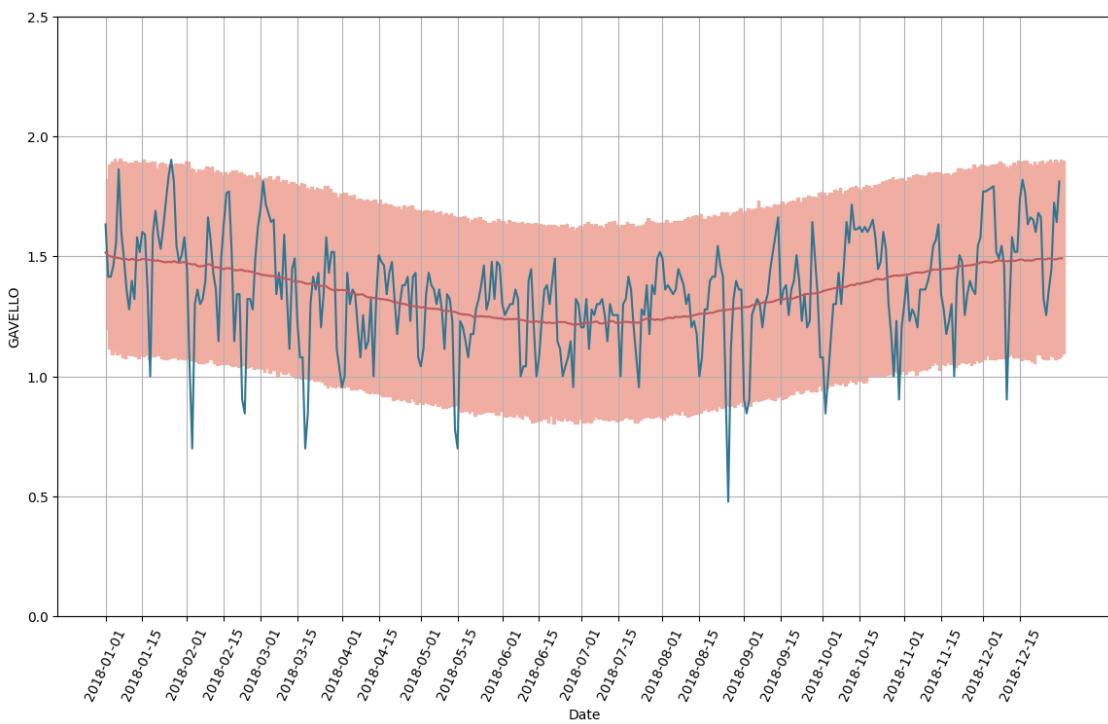
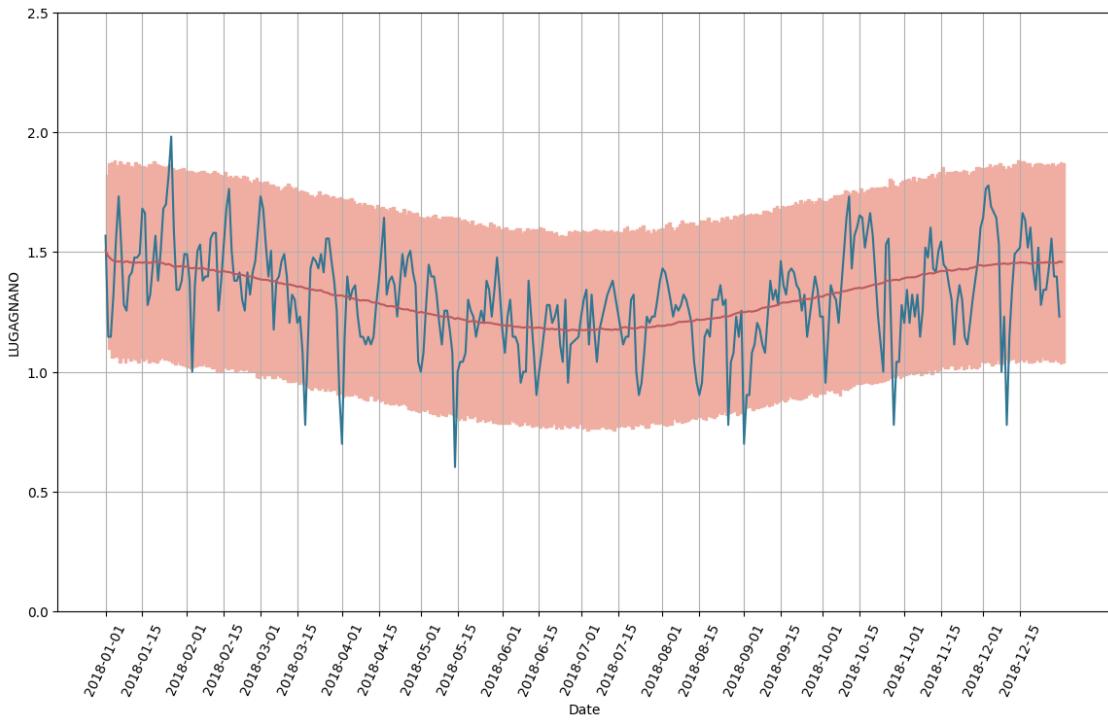


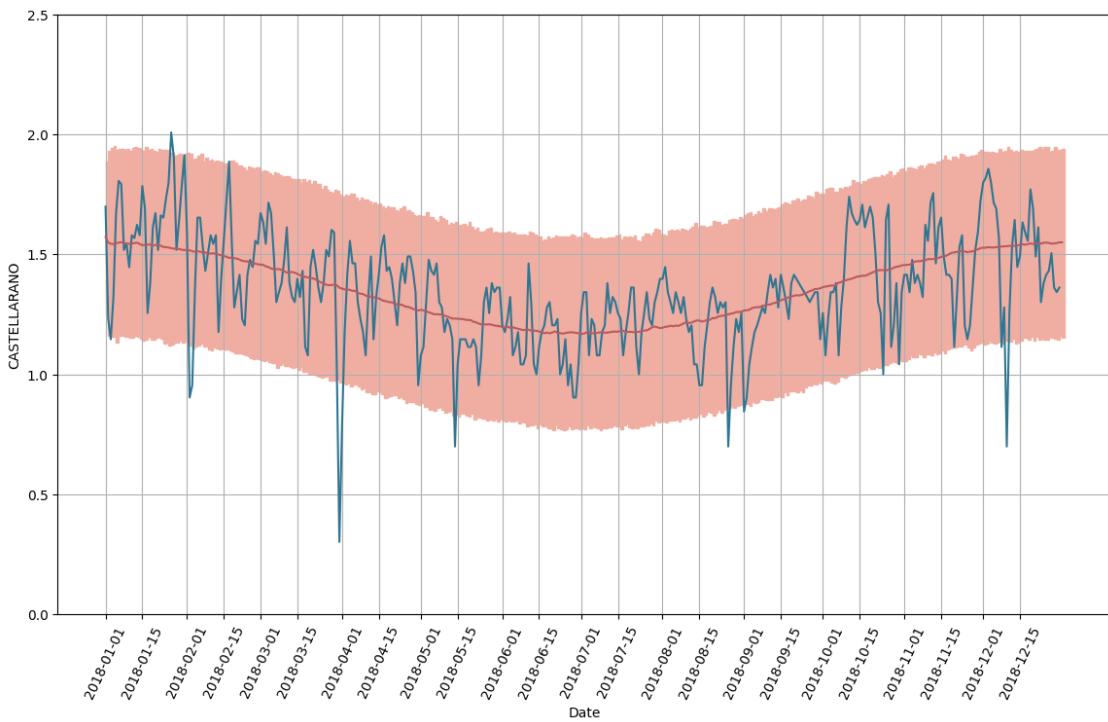
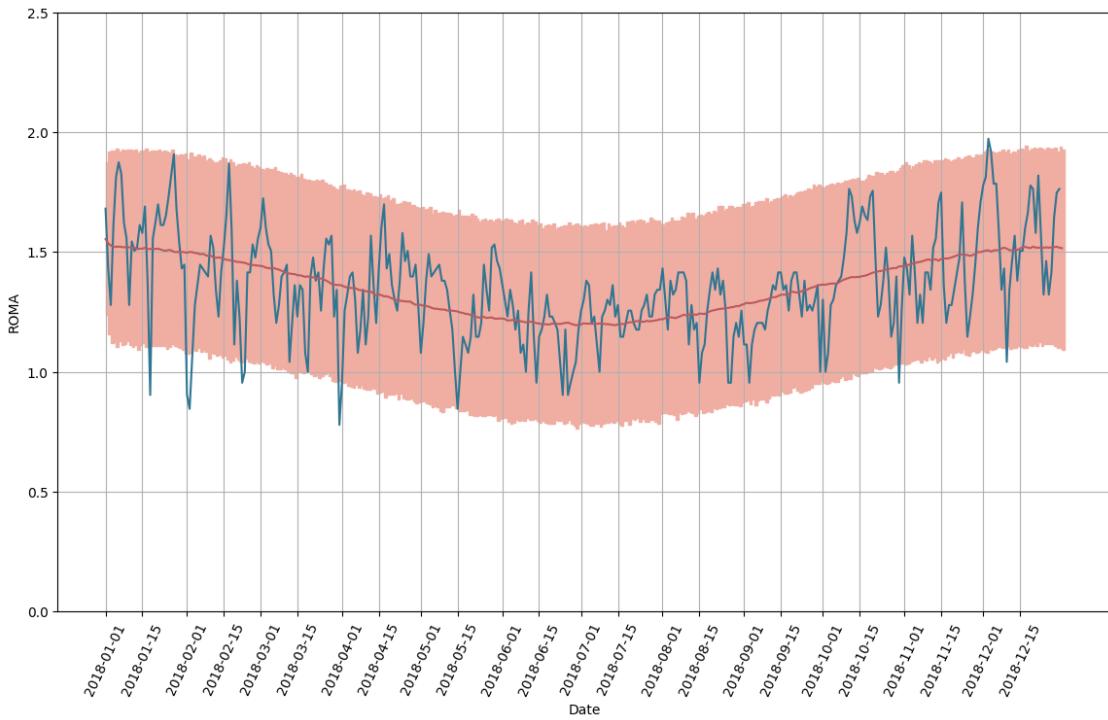


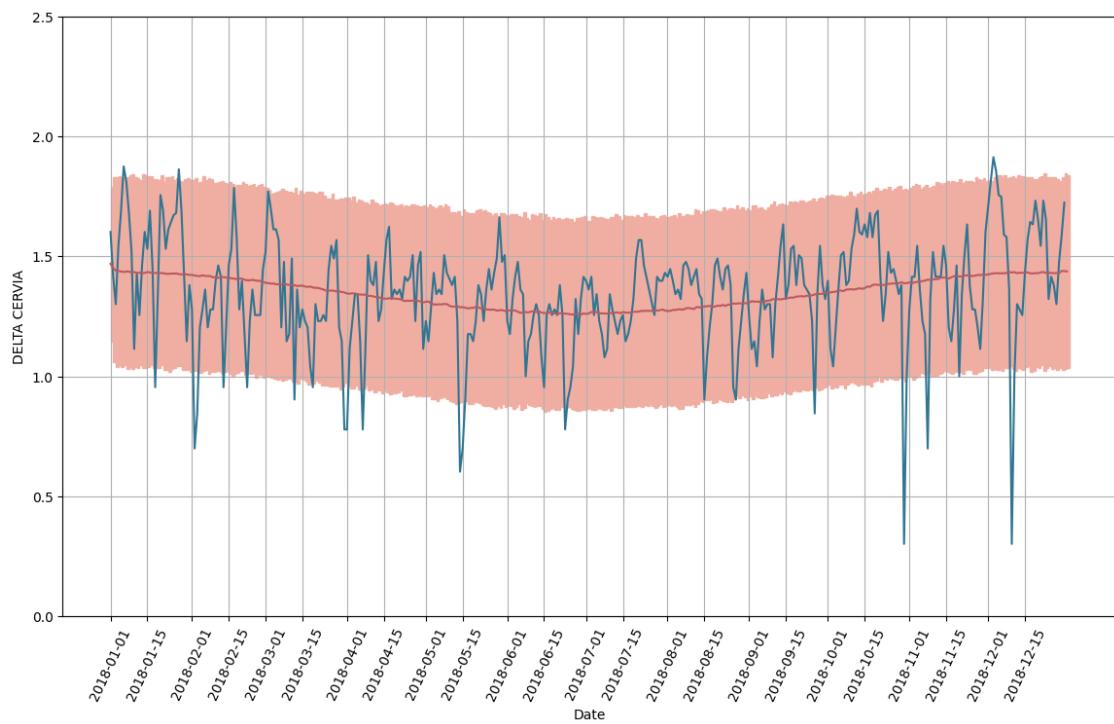
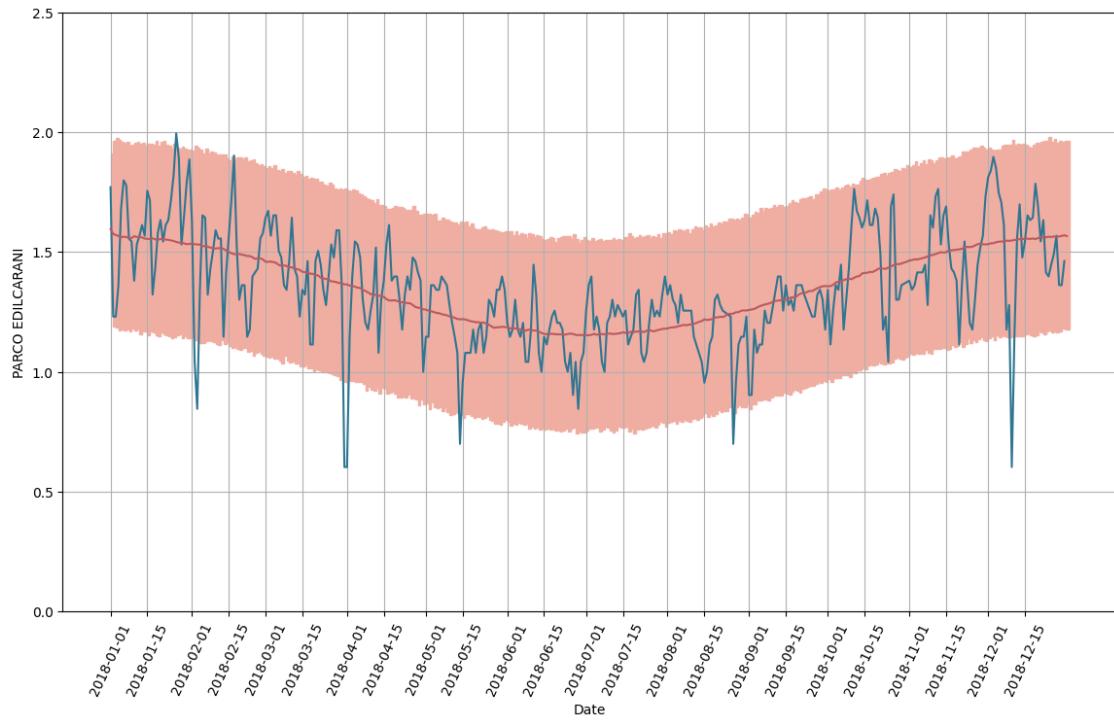


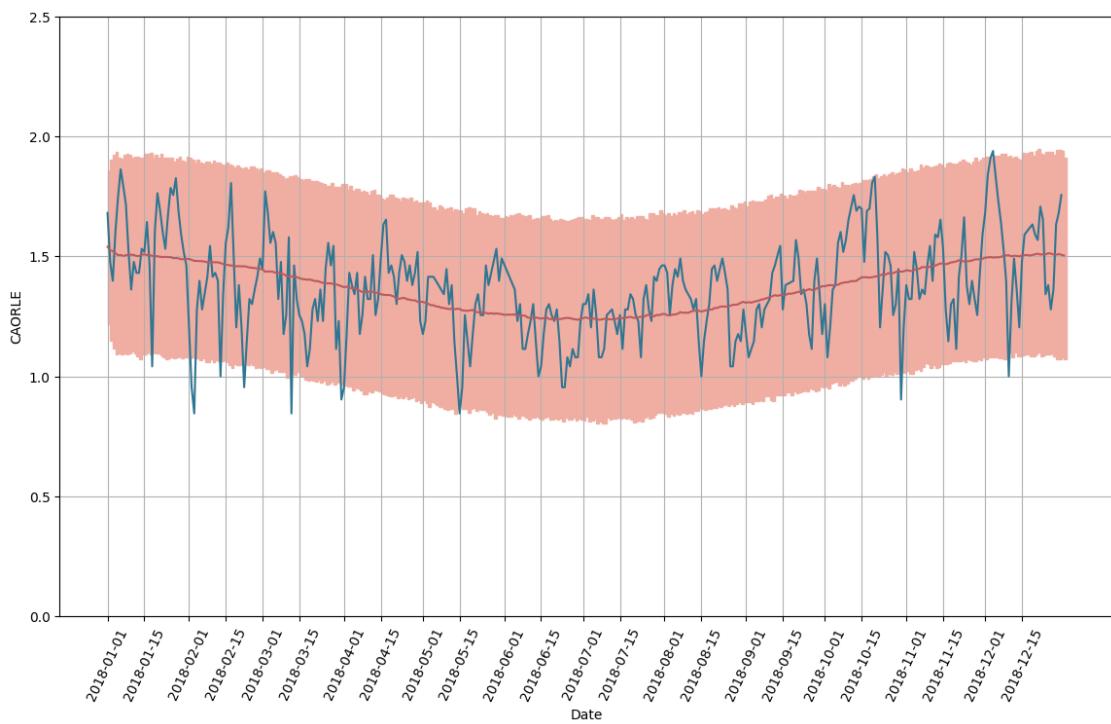
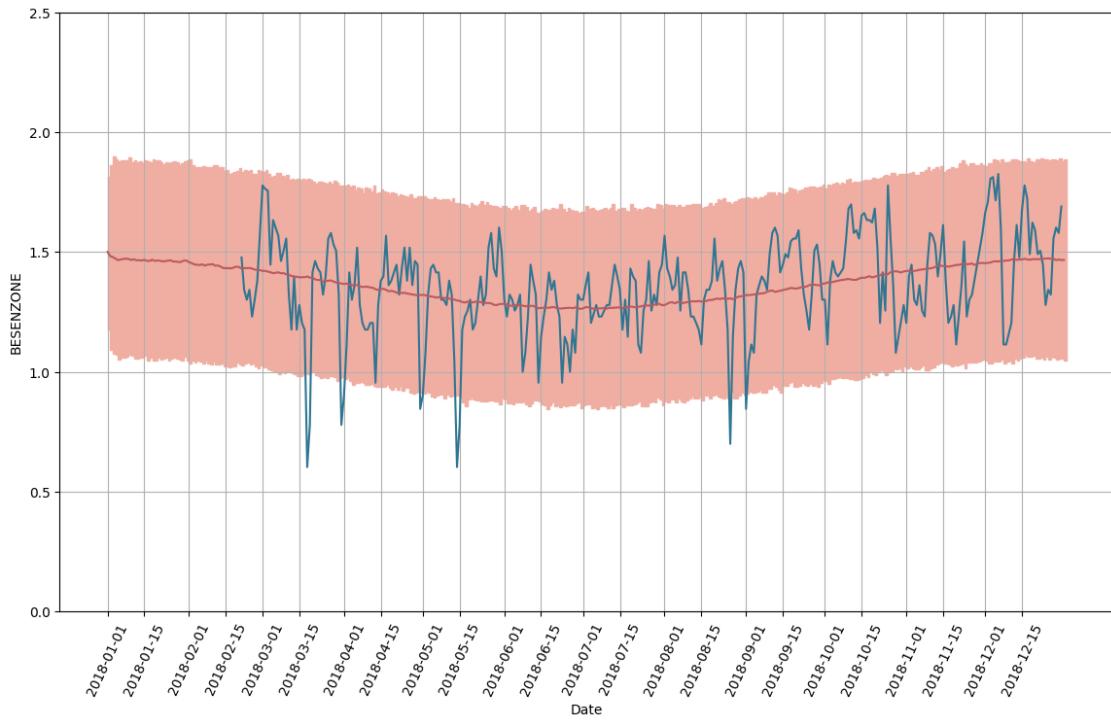


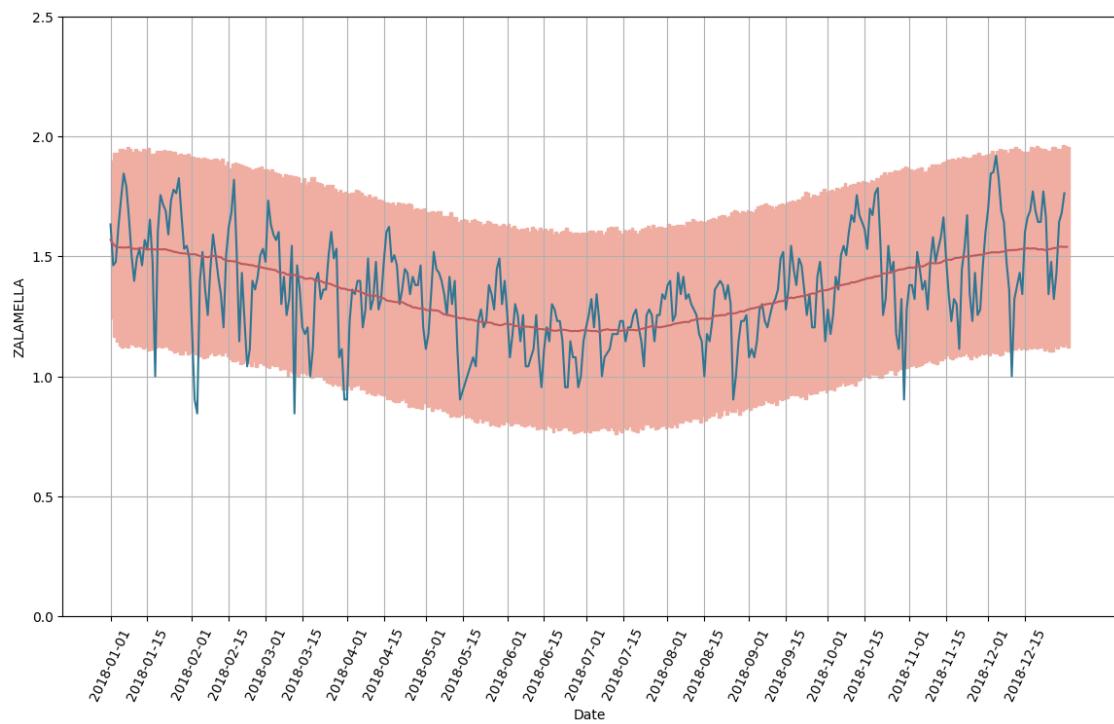
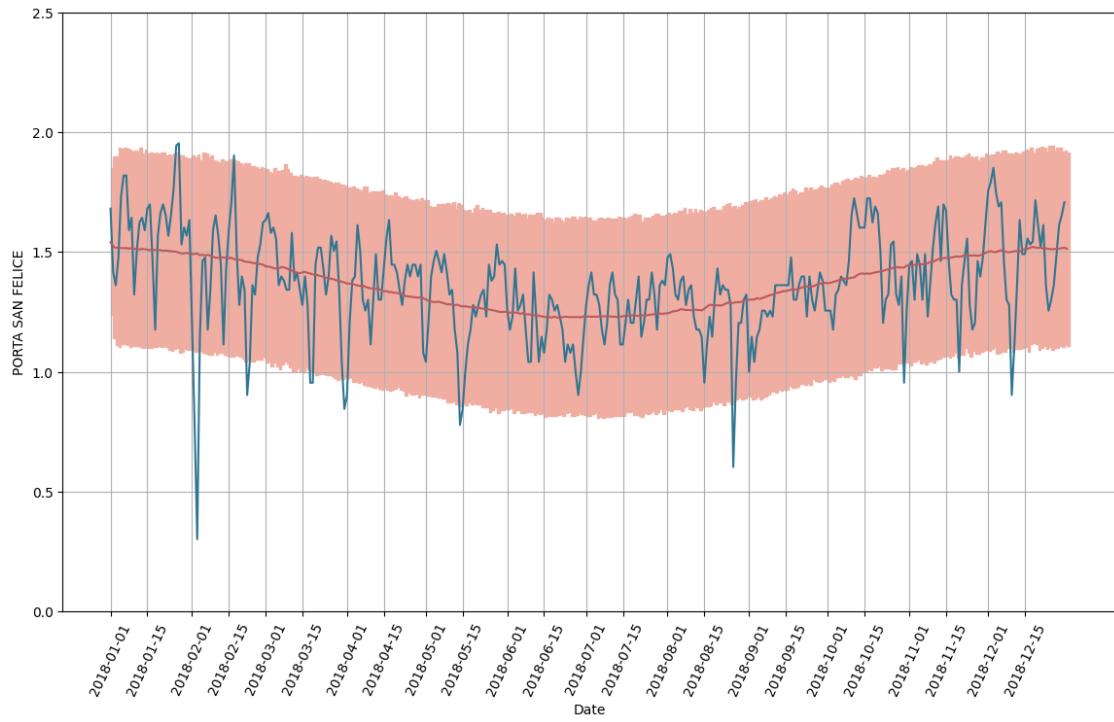


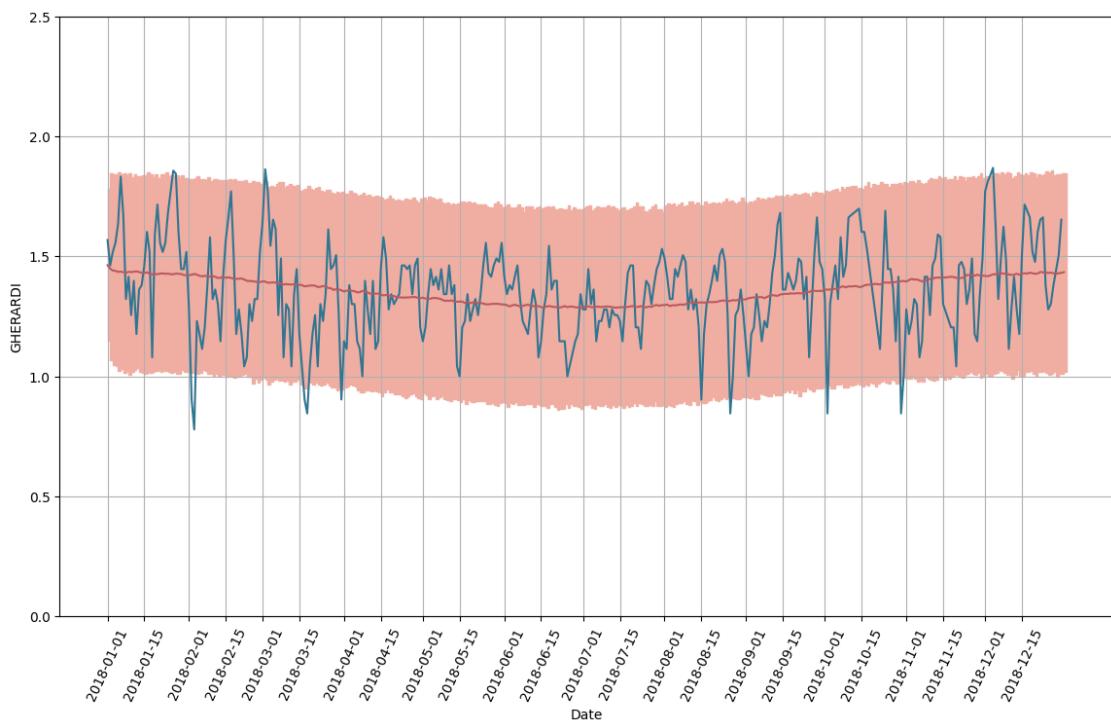
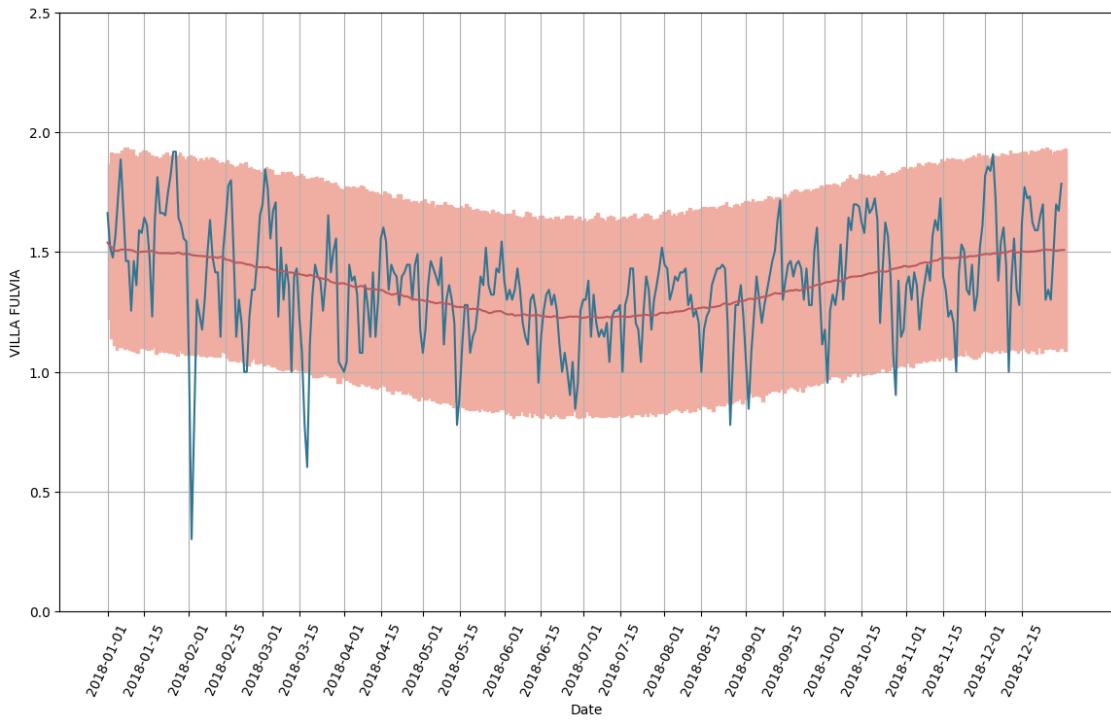


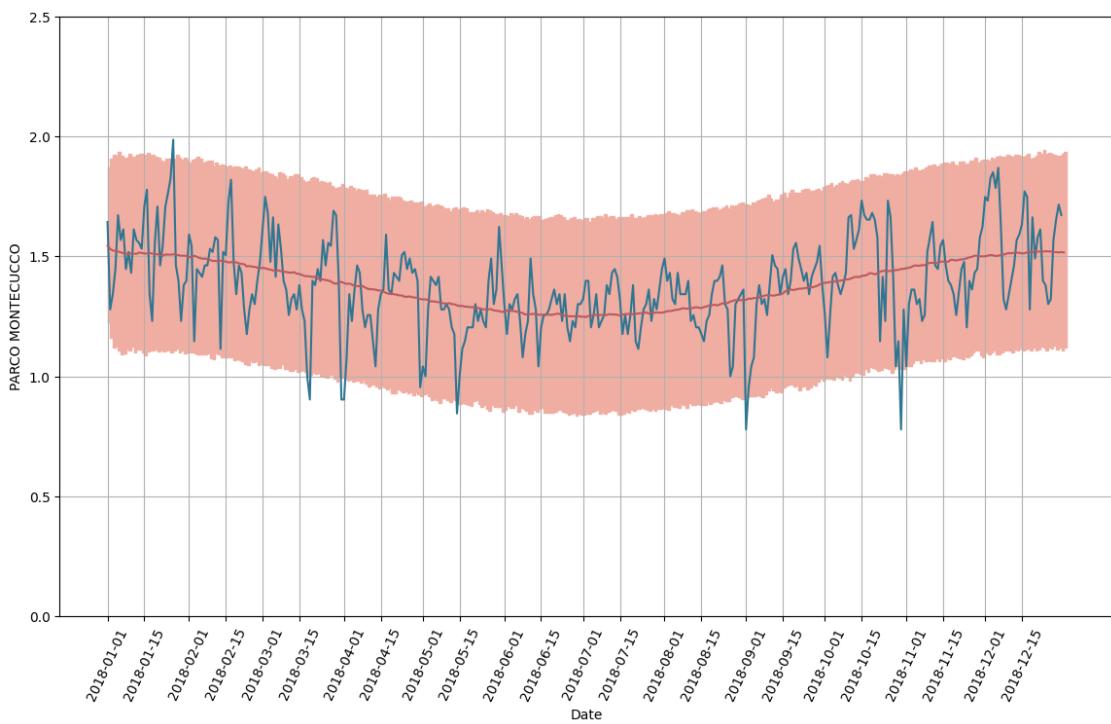
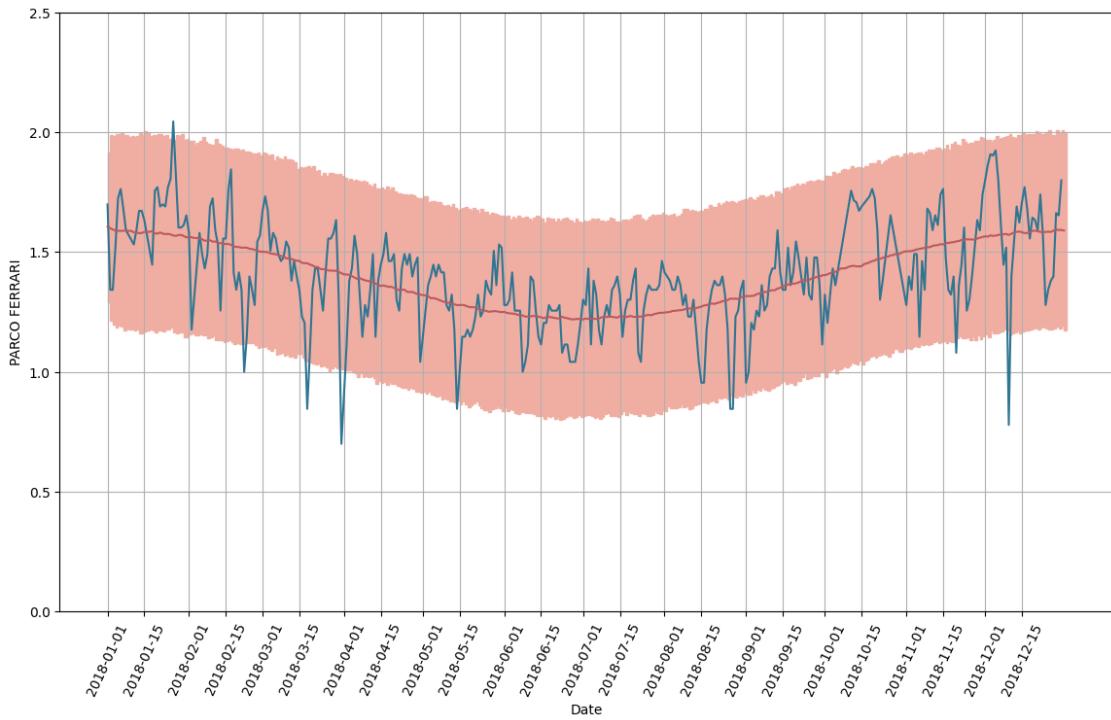


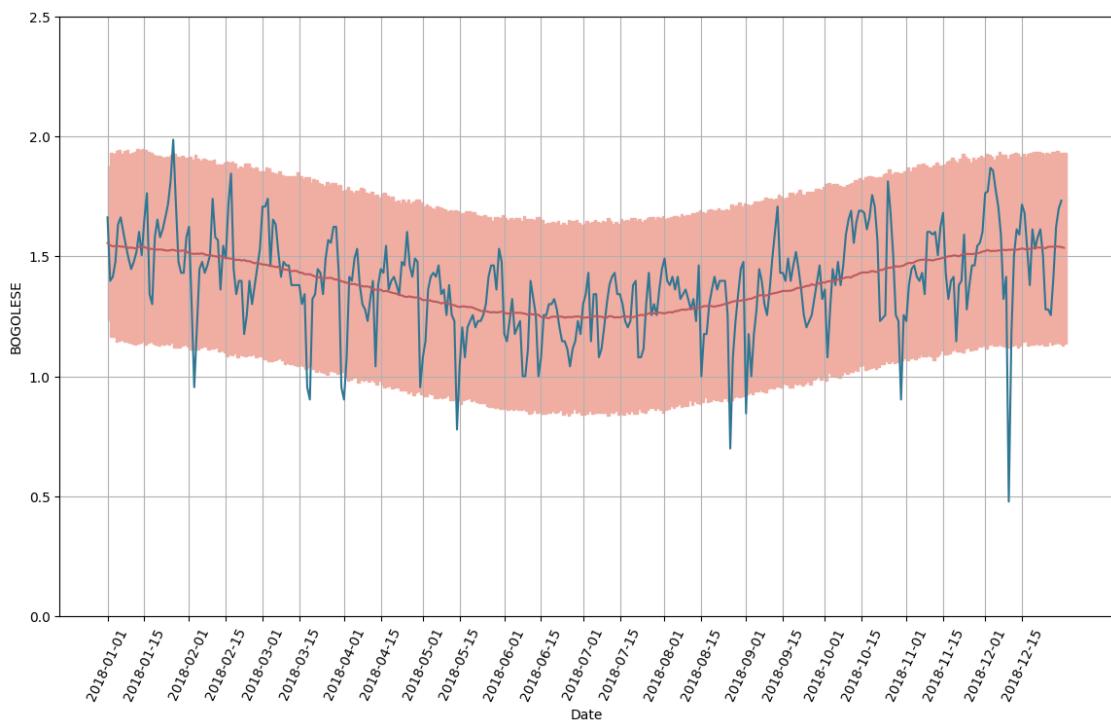
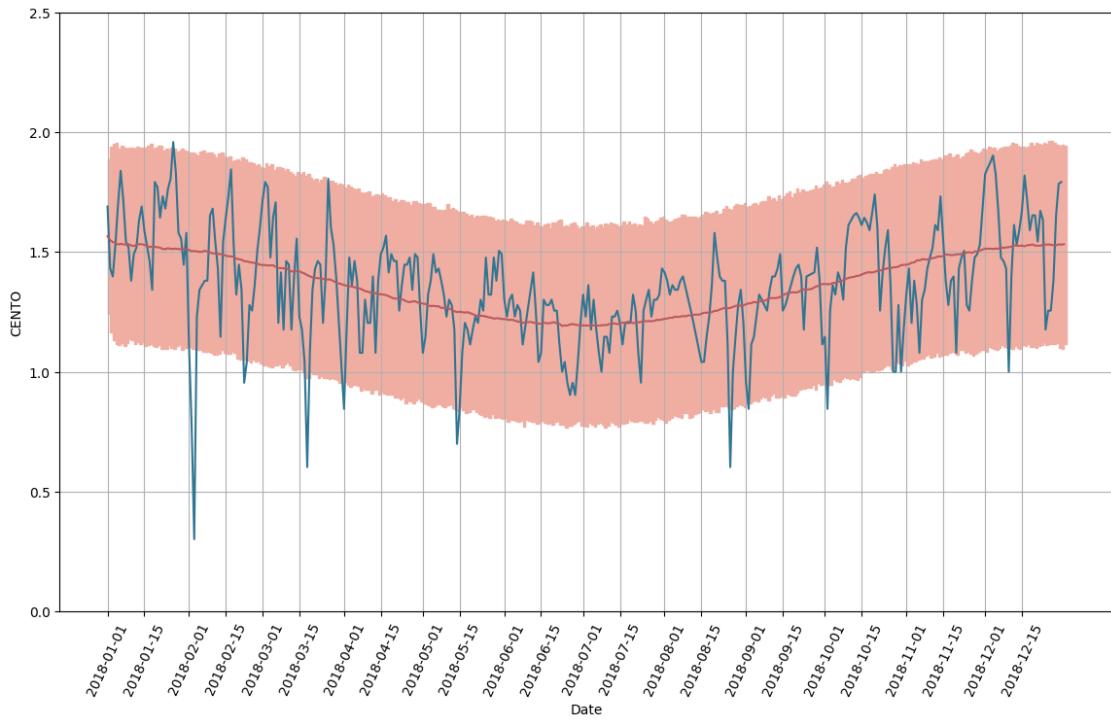


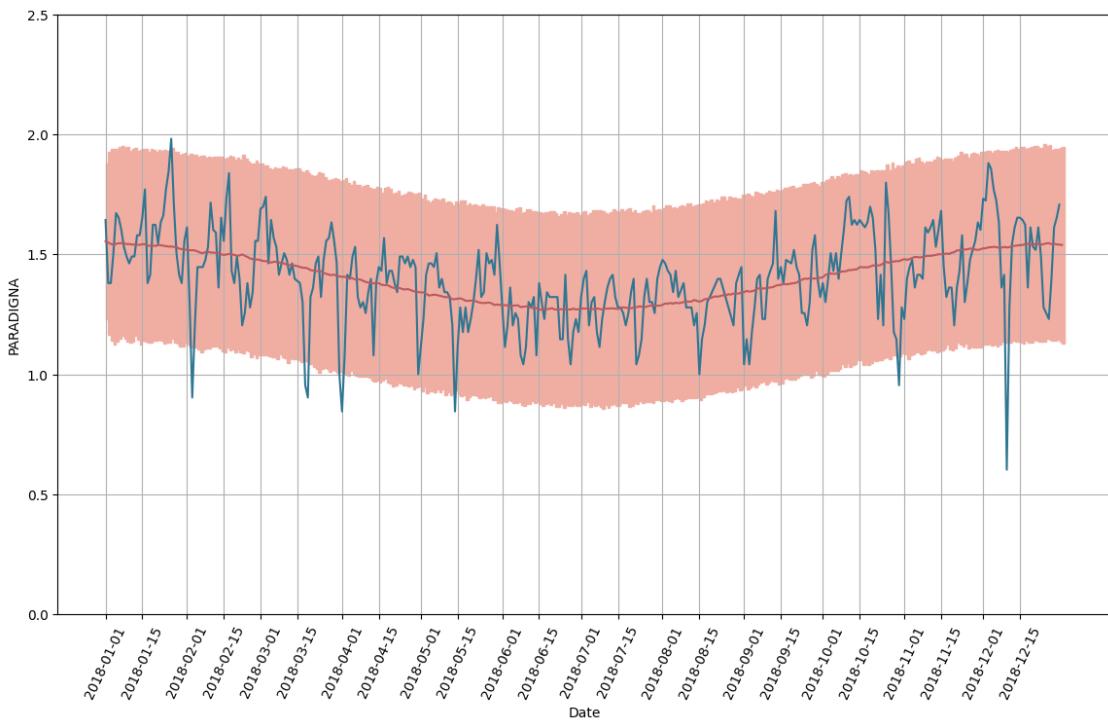
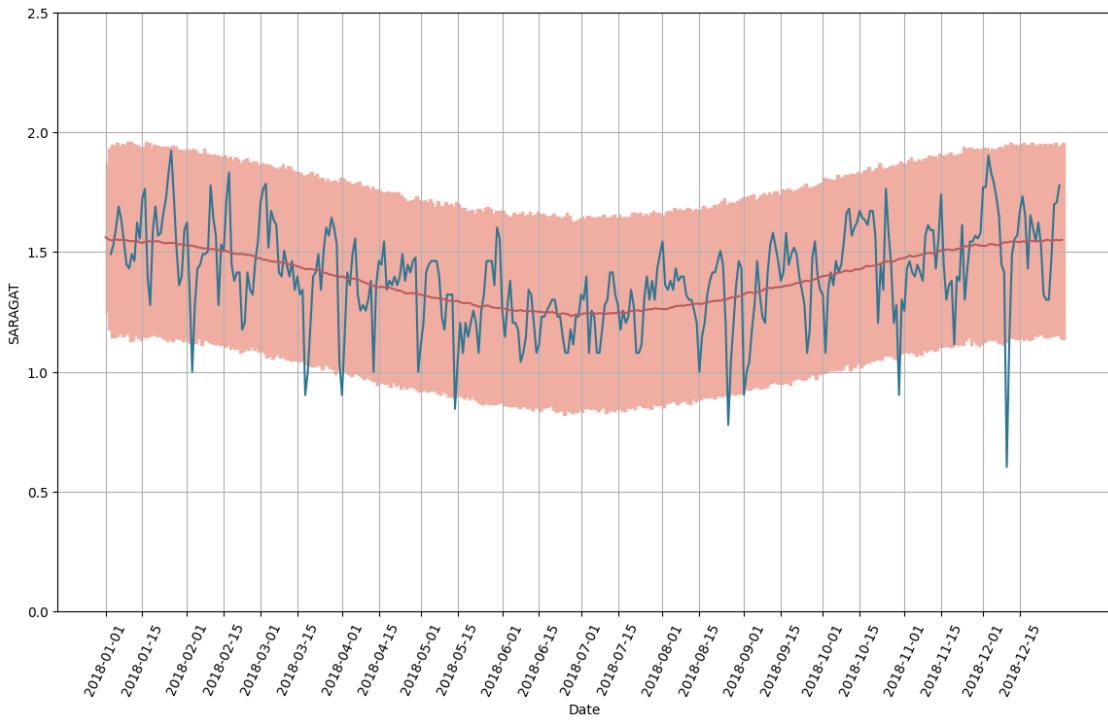


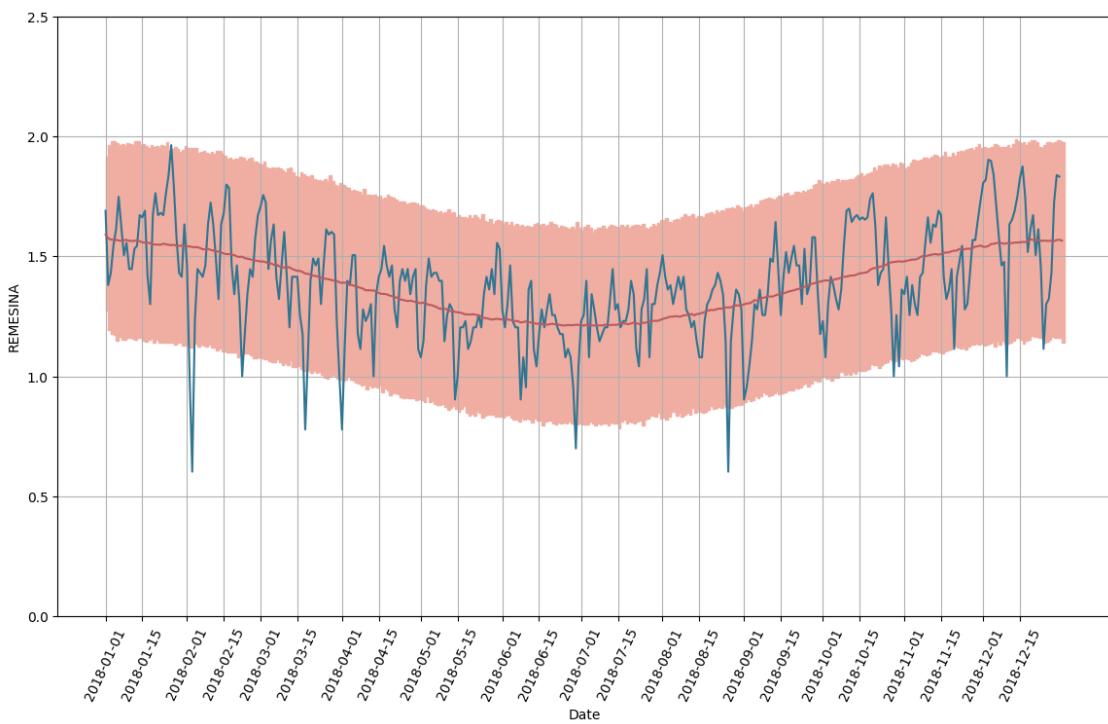
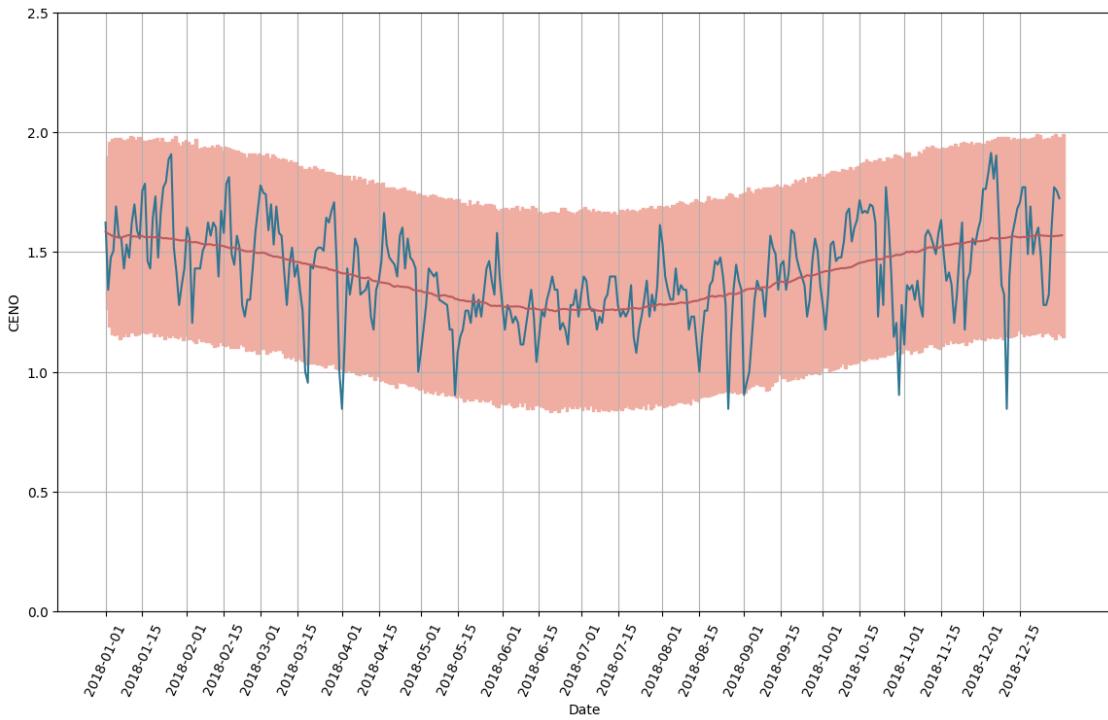


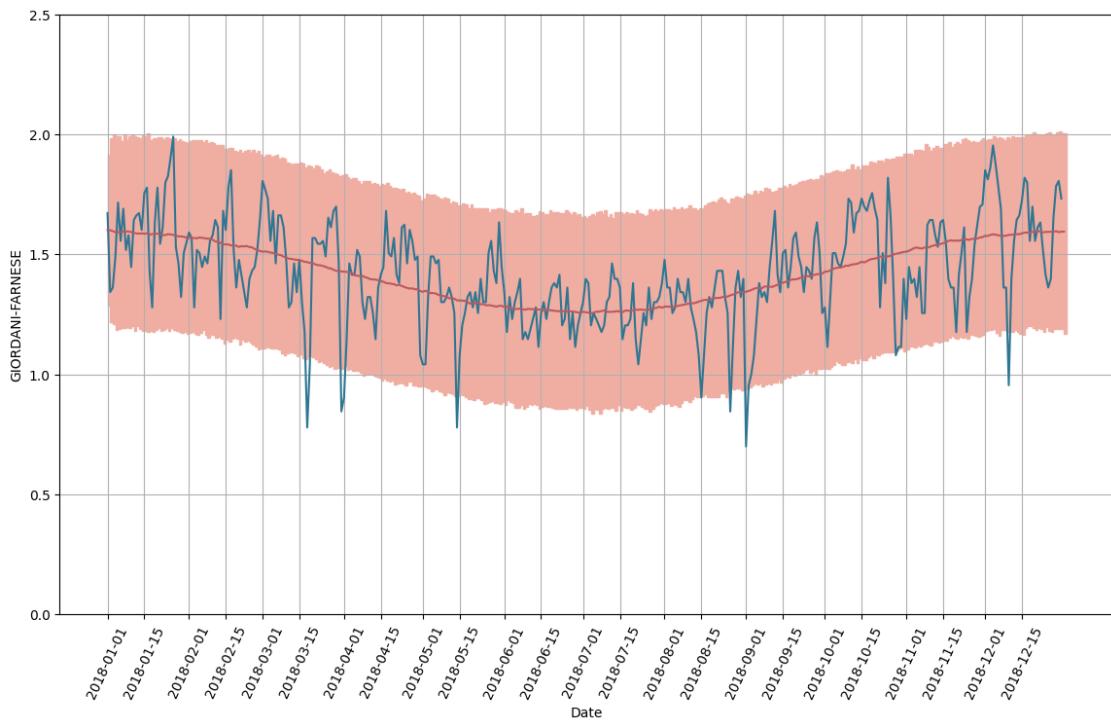
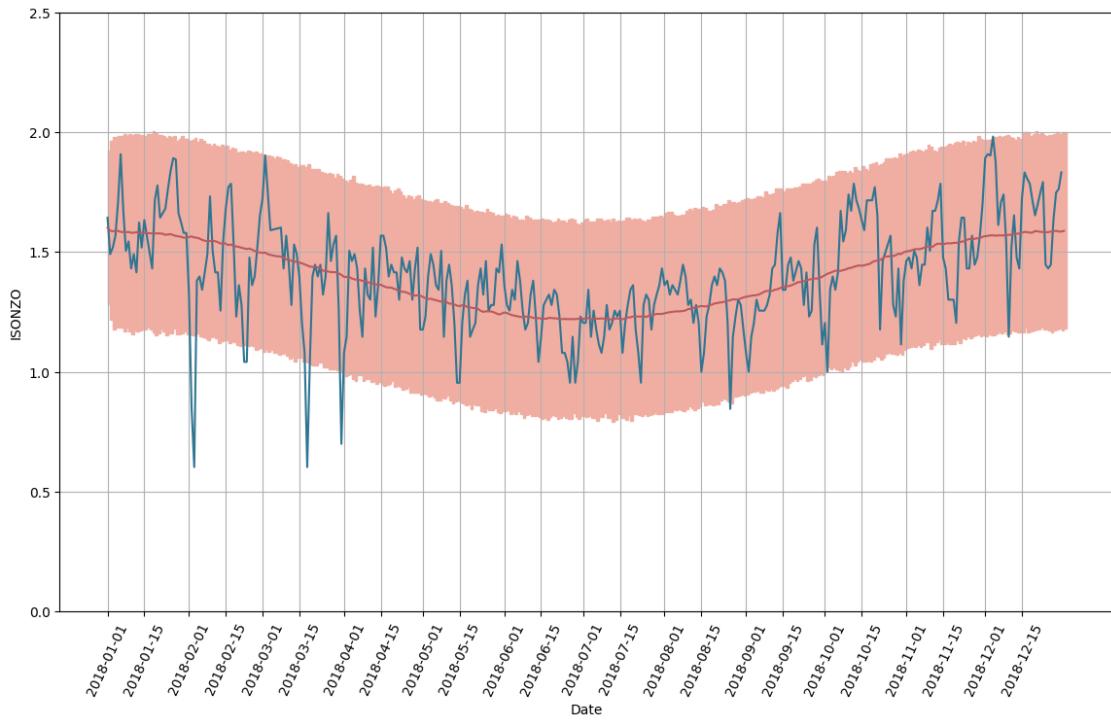


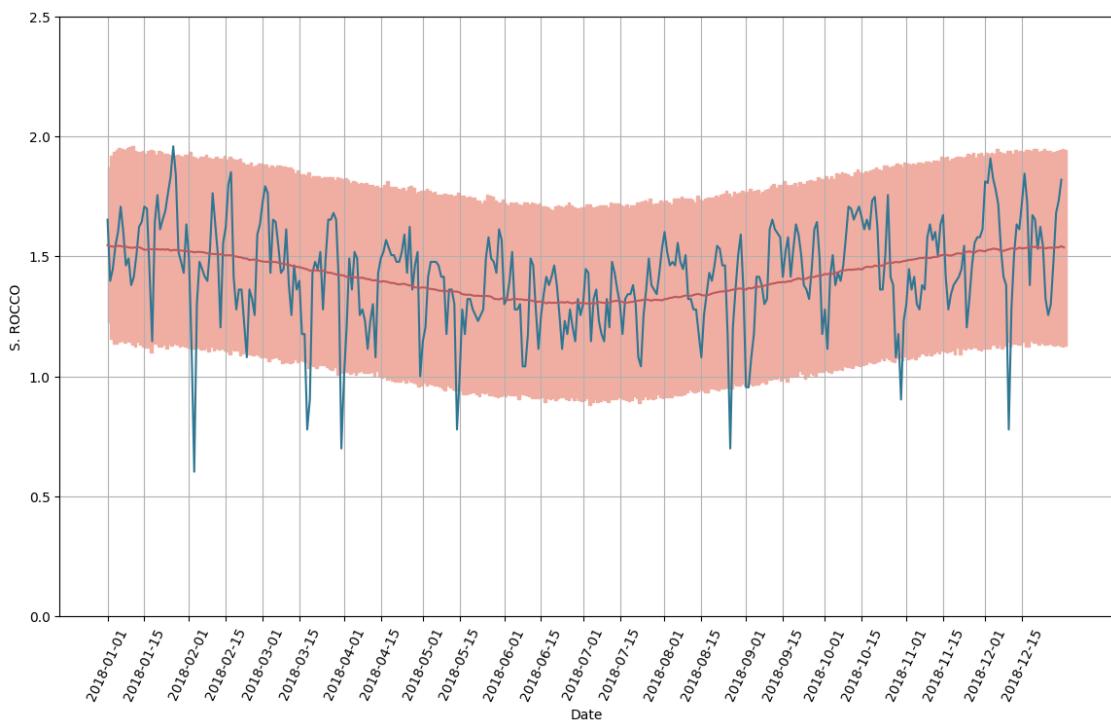
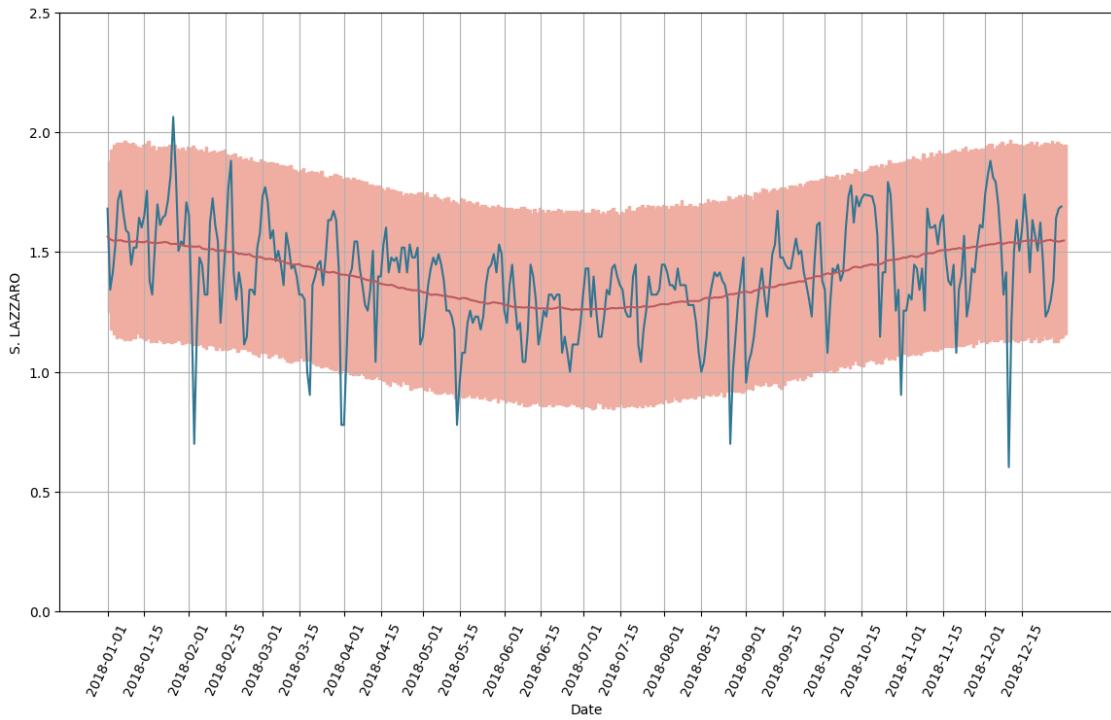


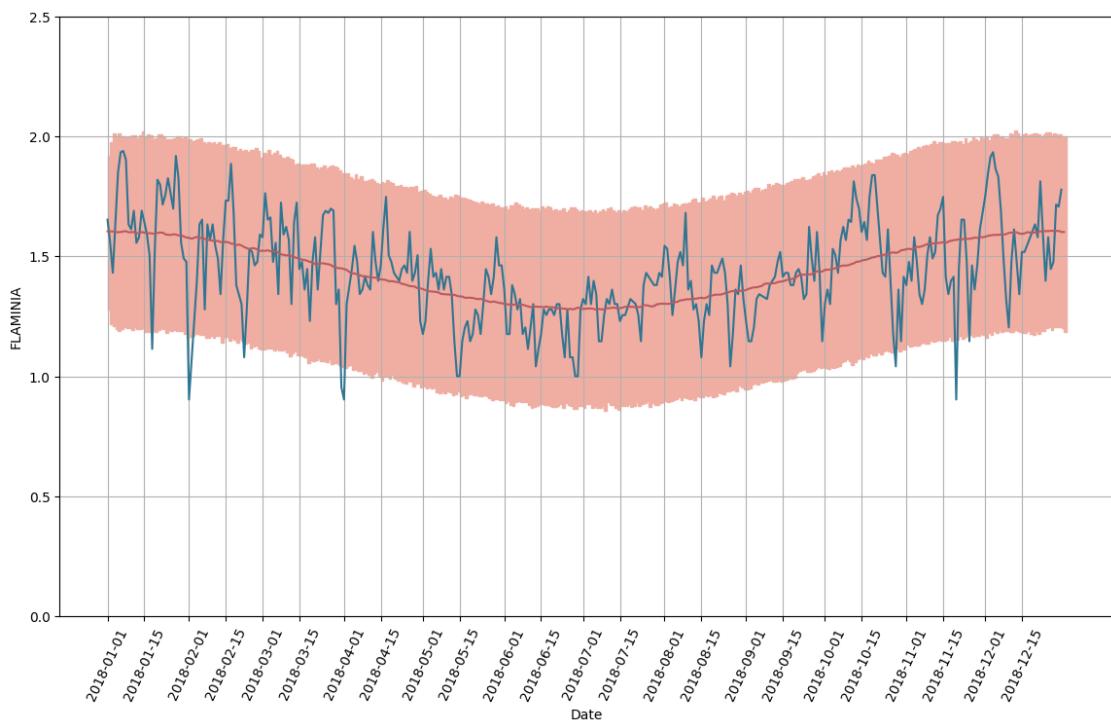
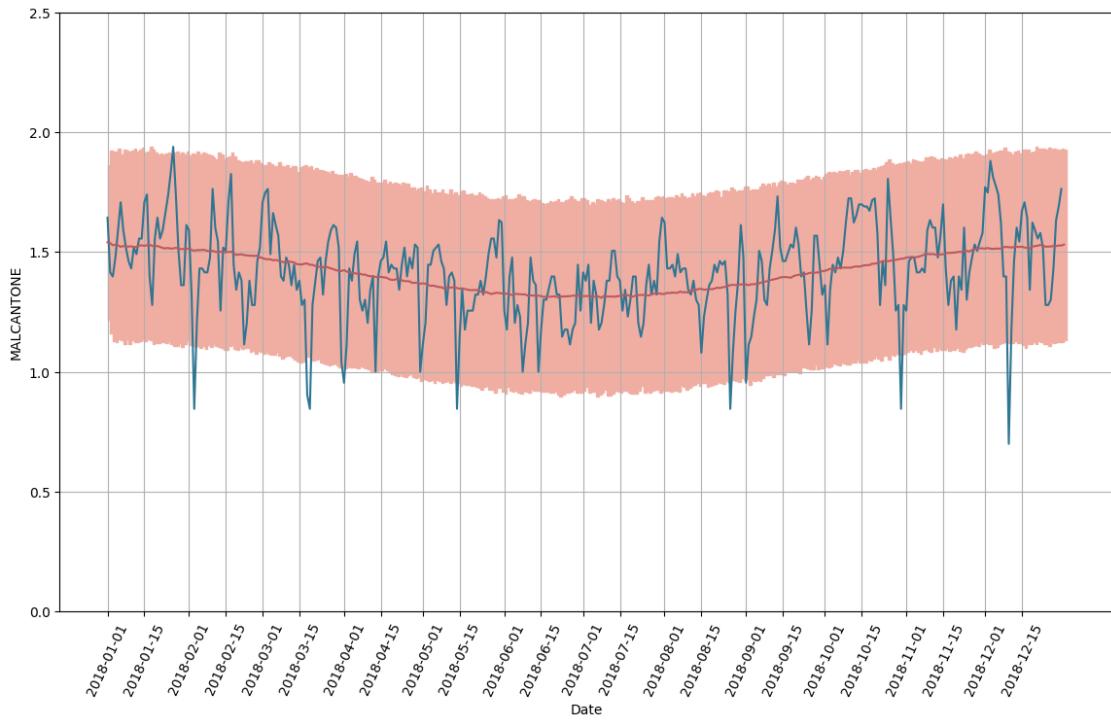


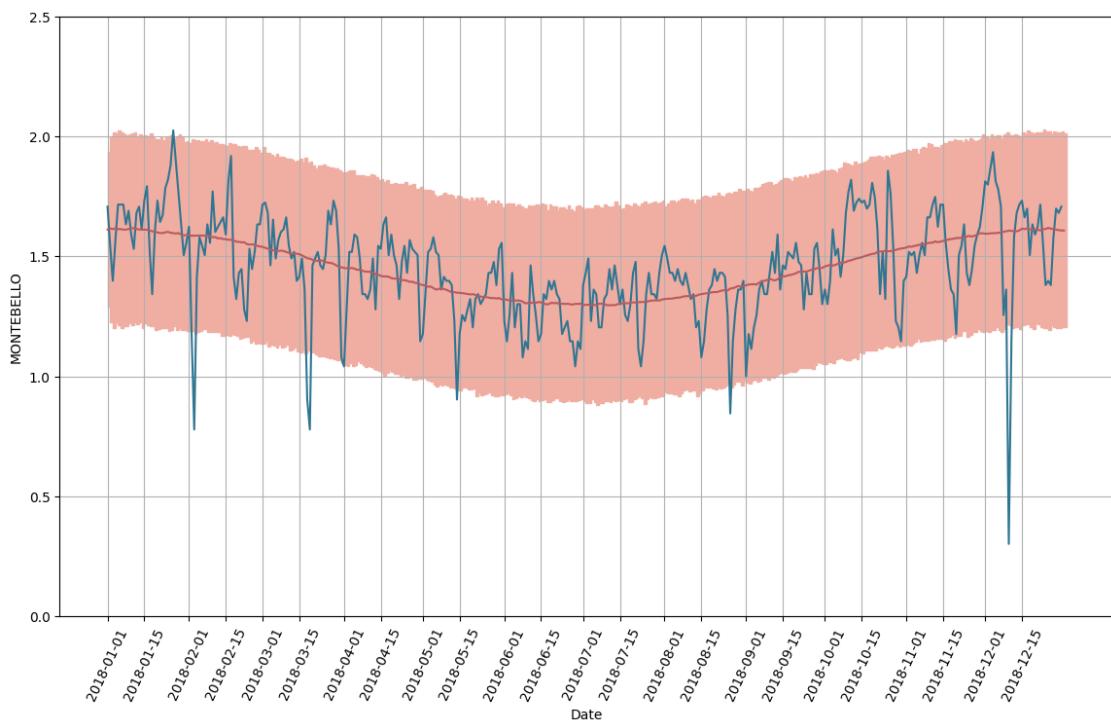
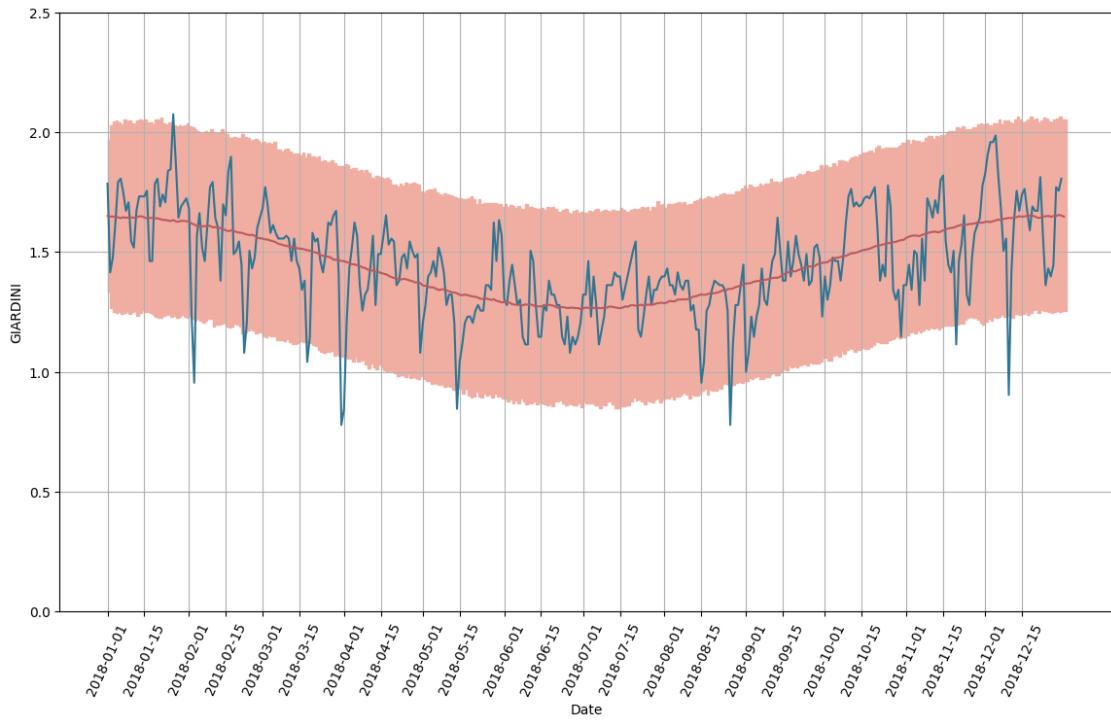


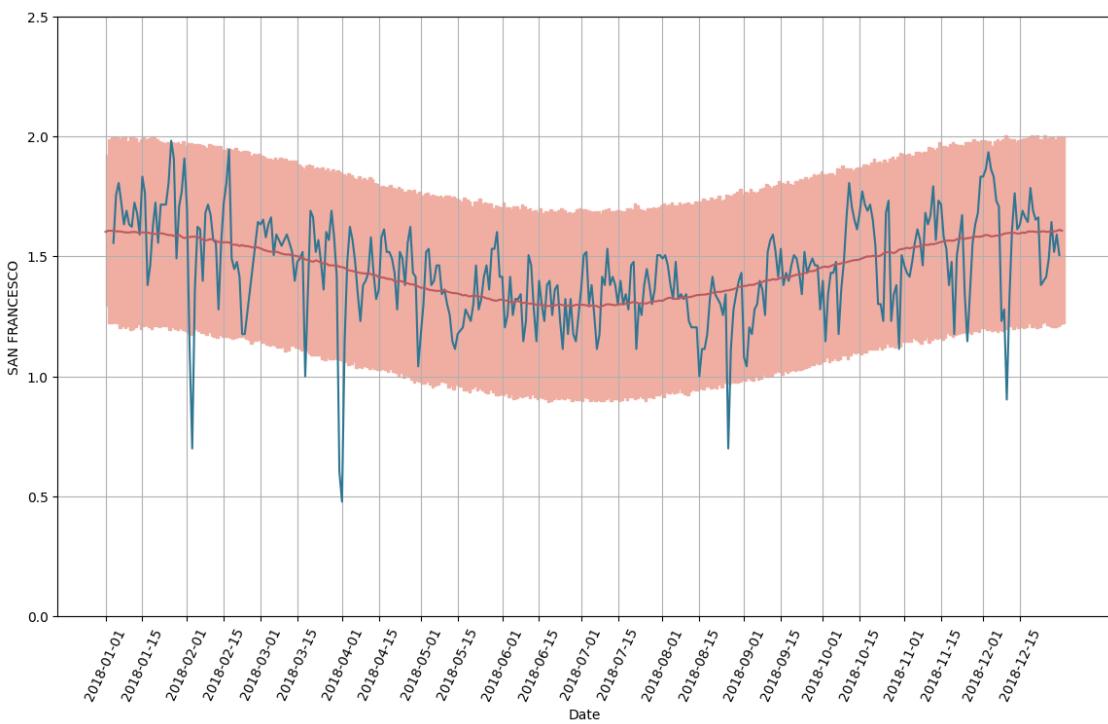
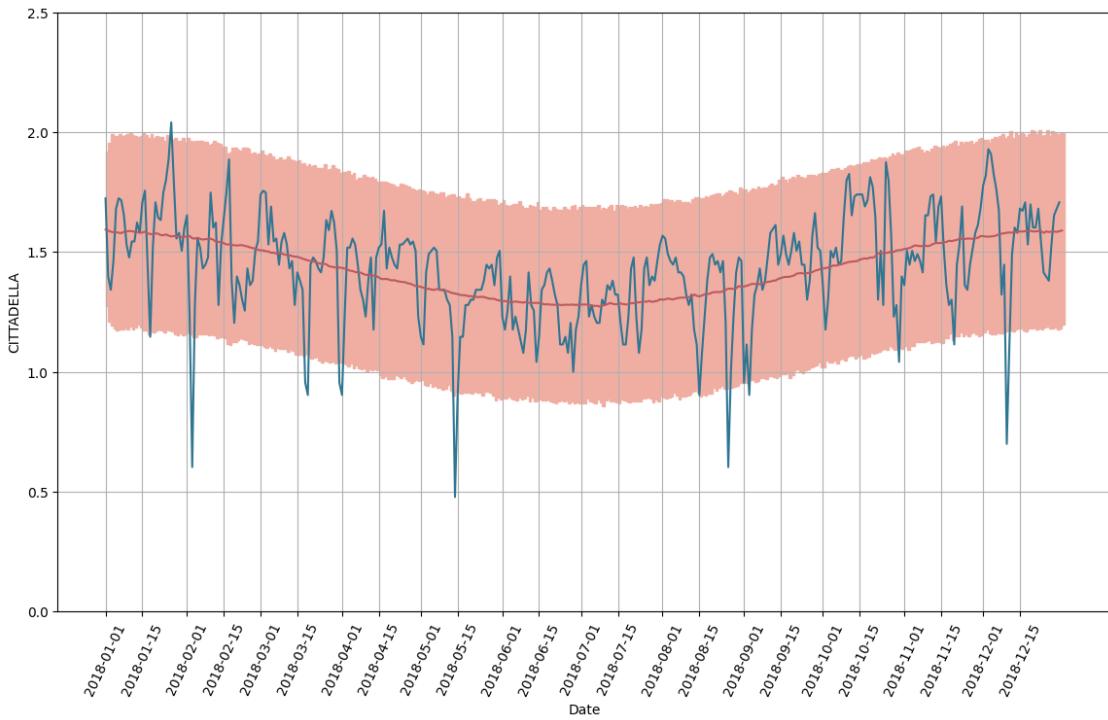


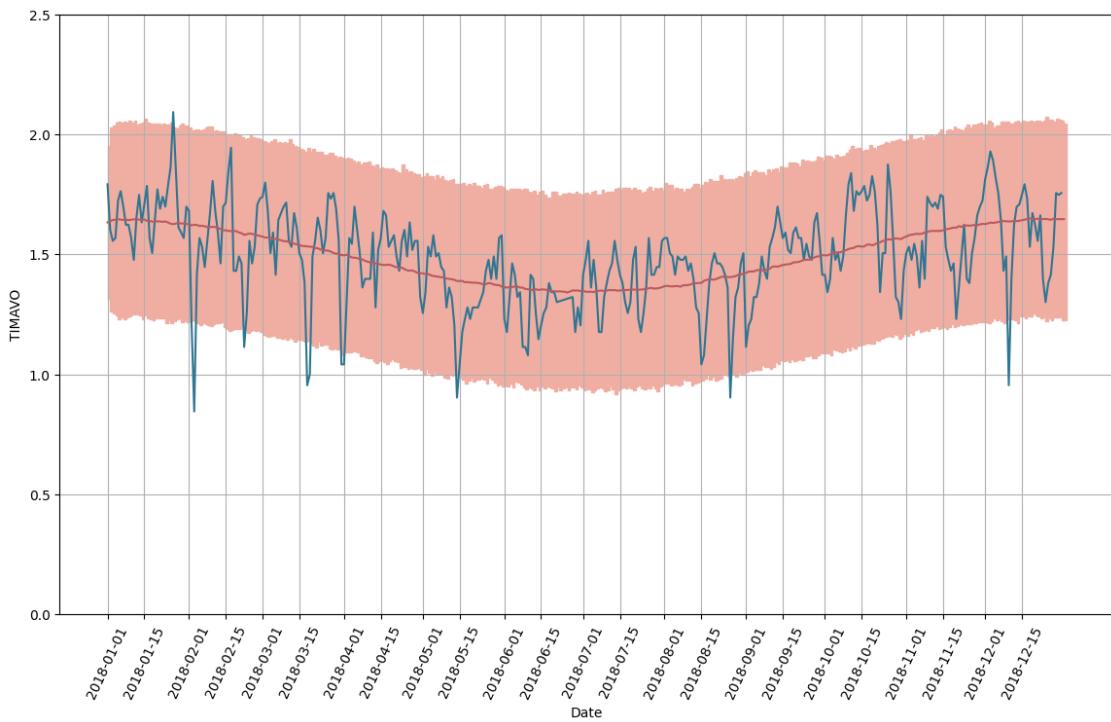
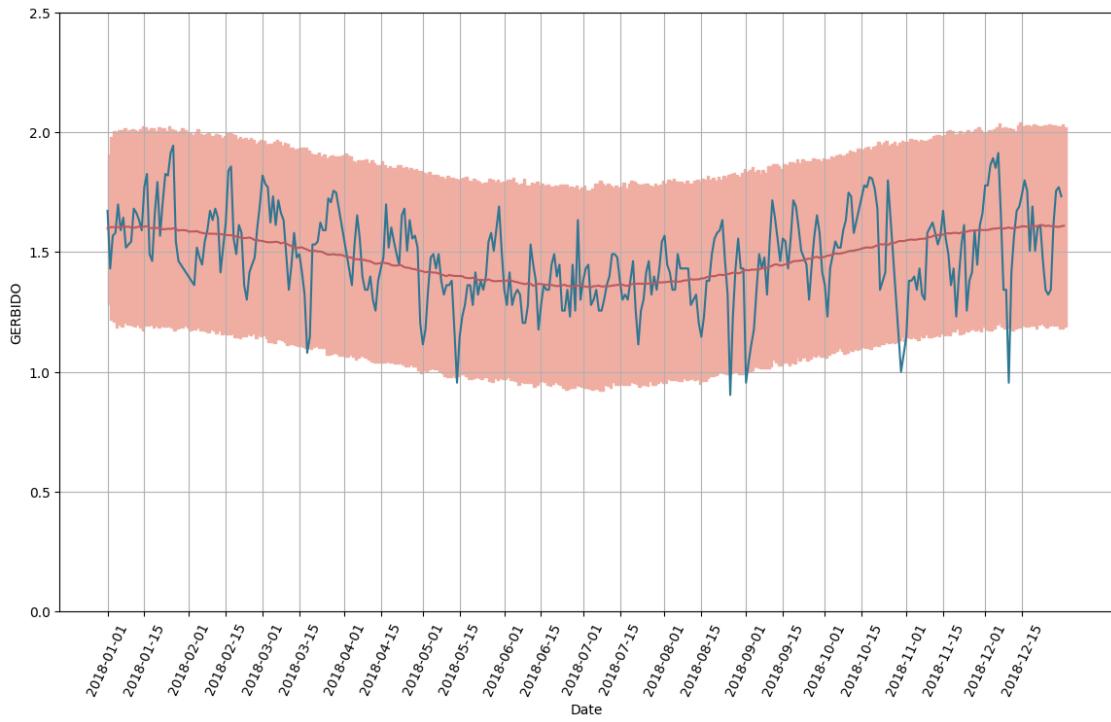












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