$PM_{2.5}$ predictions for urban monitoring sites in Budapest using statistical fusion of CAMS air quality models

Adrienn Varga-Balogh, Ádám Leelőssy and Róbert Mészáros

Eötvös Loránd University
Institute of Geography and Earth Sciences
Department of Meteorology
Budapest, Hungary

vargabaloghadrienn@gmail.com

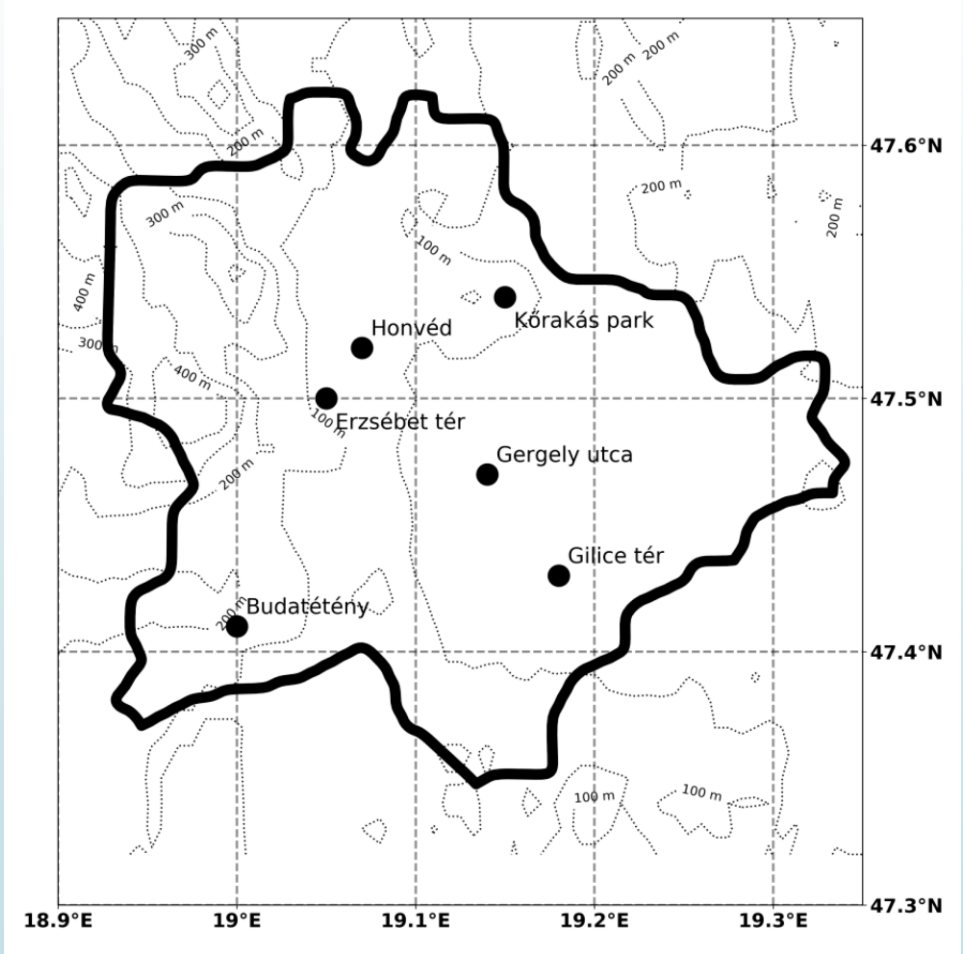
ELTE
EÖTVÖS LORÁND
UNIVERSITY

Study area and data

- Budapest

Study area and data

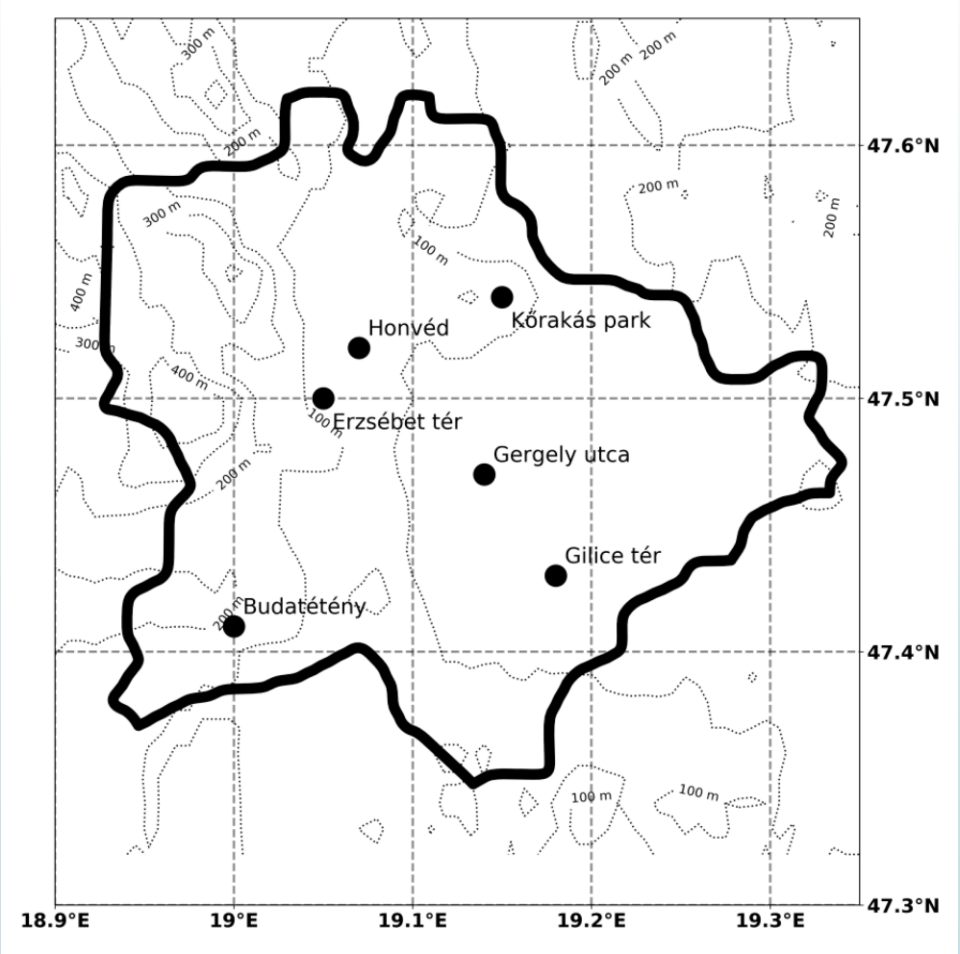
- Budapest
- Hungarian Air Quality Network



Varga-Balogh et al., Atmosphere 2020, 11(6), 669

Study area and data

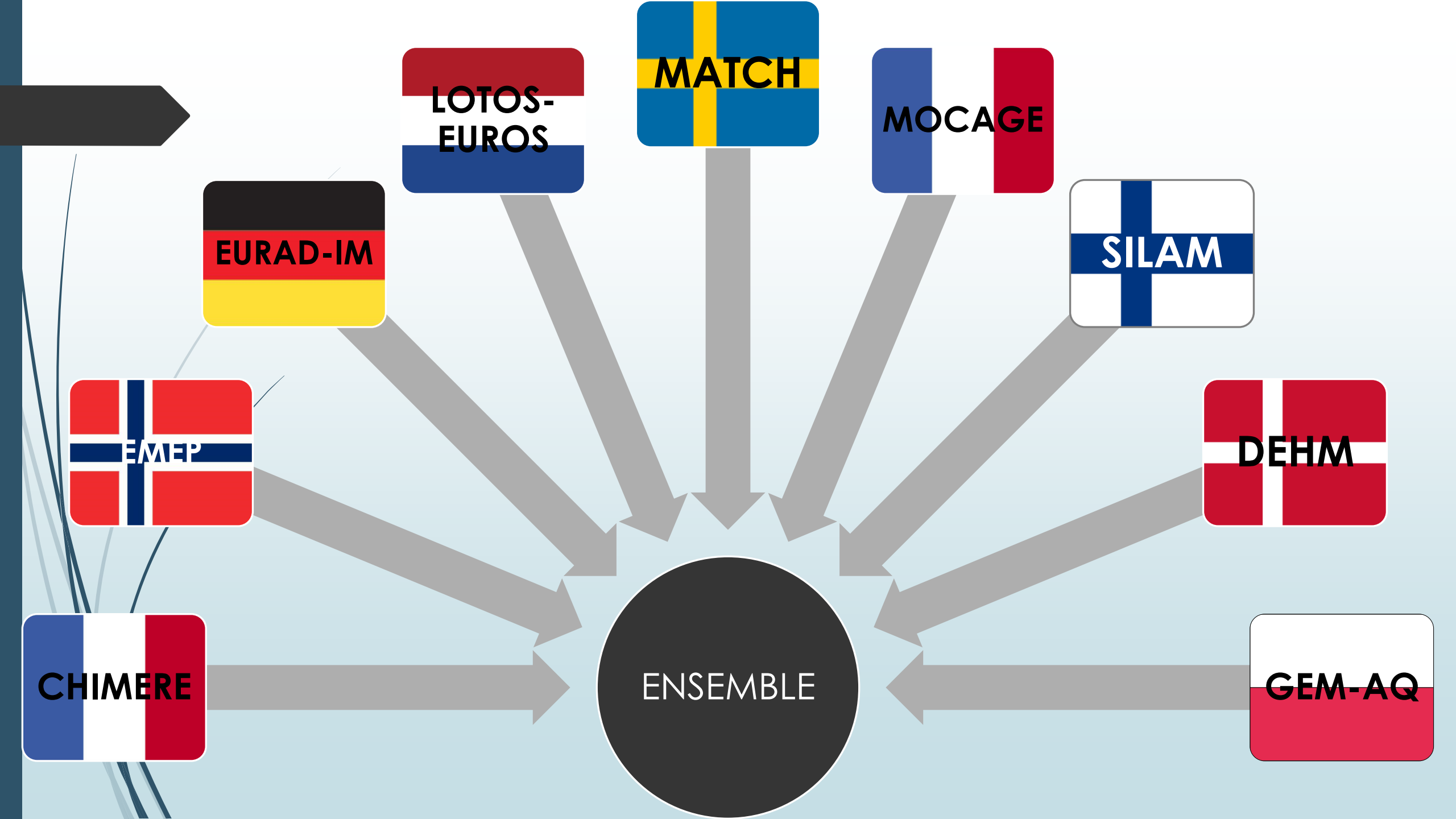
- Budapest
- Hungarian Air Quality Network
  - 6 stations



Varga-Balogh et al., Atmosphere 2020, 11(6), 669

Study area and data

- Budapest
- Hungarian Air Quality Network
  - 6 stations
- Copernicus Atmosphere Monitoring Service (CAMS) numerical air quality models


LOTOS-EUROS
MATCH
MOCAGE
EURAD-IM
SILAM
EMEP
DEHM
CHIMERE
ENSEMBLE
GEM-AQ

Study area and data

- Budapest
- Hungarian Air Quality Network
  - 6 stations
- Copernicus Atmosphere Monitoring Service (CAMS) numerical air quality models
- Winters of 2018–19, 2019–20, 2020–21, 2021–22

Fusion method

- 5 of 6 measurement sites were taken into consideration for cross-validation
  - Model forecasts were fitted to the measurements
  - Optimal combination of models (simplified from Sofiev et al. 2017)

Sofiev et al. 2017: Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

Fusion method

- 5 of 6 measurement sites were taken into consideration for cross-validation
  - Model forecasts were fitted to the measurements
  - Optimal combination of models (simplified from Sofiev et al. 2017)

$$cost\ function = \sum_{\substack{obs \\ sites}} RMSE(measurements, forecasts) +$$
$$+ weights\ deviation\ from\ homogen\ weights +$$
$$+ weights\ deviation\ in\ consecutive\ time\ steps$$

$$forecast = const + \sum_{models} weight_{model} \cdot predicted\ conc_{model}$$

Sofiev et al. 2017: Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

Fusion method

- 5 of 6 measurement sites were taken into consideration for cross-validation
  - Model forecasts were fitted to the measurements
  - Optimal combination of models (simplified from Sofiev et al. 2017)

$$cost\ function = \sum_{\substack{obs \\ sites}} RMSE(measurements, forecasts) + \\ + weights\ deviation\ from\ homogen\ weights + \\ + weights\ deviation\ in\ consecutive\ time\ steps$$

$$forecast = const + \sum_{models} weight_{model} \cdot predicted\ conc_{model}$$

Sofiev et al. 2017: Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

Fusion method

- 5 of 6 measurement sites were taken into consideration for cross-validation
  - Model forecasts were fitted to the measurements
  - Optimal combination of models (simplified from Sofiev et al. 2017)

$$cost\ function = \sum_{\substack{obs \\ sites}} RMSE(measurements, forecasts) +$$
$$+ weights\ deviation\ from\ homogen\ weights +$$
$$+ weights\ deviation\ in\ consecutive\ time\ steps$$

$$forecast = const + \sum_{models} weight_{model} \cdot predicted\ conc_{model}$$

Sofiev et al. 2017: Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

Fusion method

- 5 of 6 measurement sites were taken into consideration for cross-validation
  - Model forecasts were fitted to the measurements
  - Optimal combination of models (simplified from Sofiev et al. 2017)

$$cost\ function = \sum_{\substack{obs \\ sites}} RMSE(measurements, forecasts) +$$
$$+ \cancel{weights\ deviation\ from\ homogen\ weights} +$$
$$+ weights\ deviation\ in\ consecutive\ time\ steps$$

$$forecast = const + \sum_{models} weight_{model} \cdot predicted\ conc_{model}$$

Sofiev et al. 2017: Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

Fusion method

- 5 of 6 measurement sites were taken into consideration for cross-validation
  - Model forecasts were fitted to the measurements
  - Optimal combination of models (simplified from Sofiev et al. 2017)

$$cost\ function = \sum_{\substack{obs \\ sites}} RMSE(measurements, forecasts) + \\ + weights\ deviation\ from\ homogen\ weights + \\ + weights\ deviation\ in\ consecutive\ time\ steps$$

$$forecast = const + \sum_{models} weight_{model} \cdot predicted\ conc_{model}$$

- constant member and weights are fitted on a 10-day training period
- Model-weigths were evaluated on the residual measuring site

Sofiev et al. 2017: Multi-model ensemble simulations of olive pollen distribution in Europe in 2014

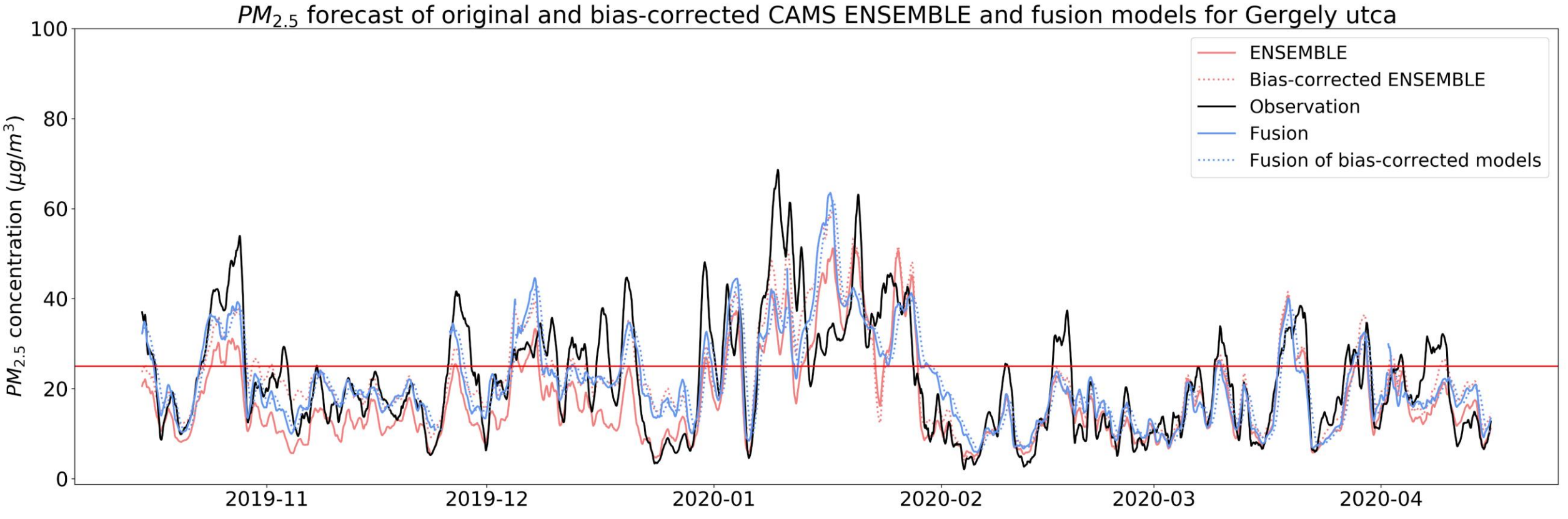
Method

- Uncorrected (original) model forecast

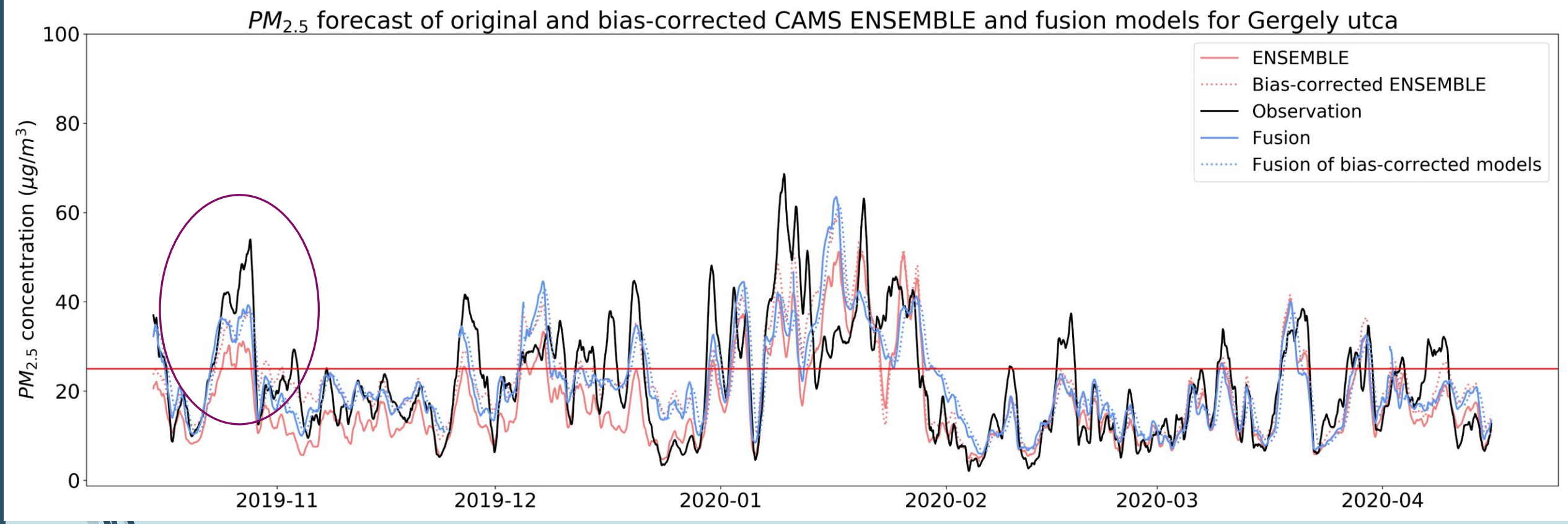
Method

- Uncorrected (original) model forecast
- BIAS-corrected dataset
  - 10-day

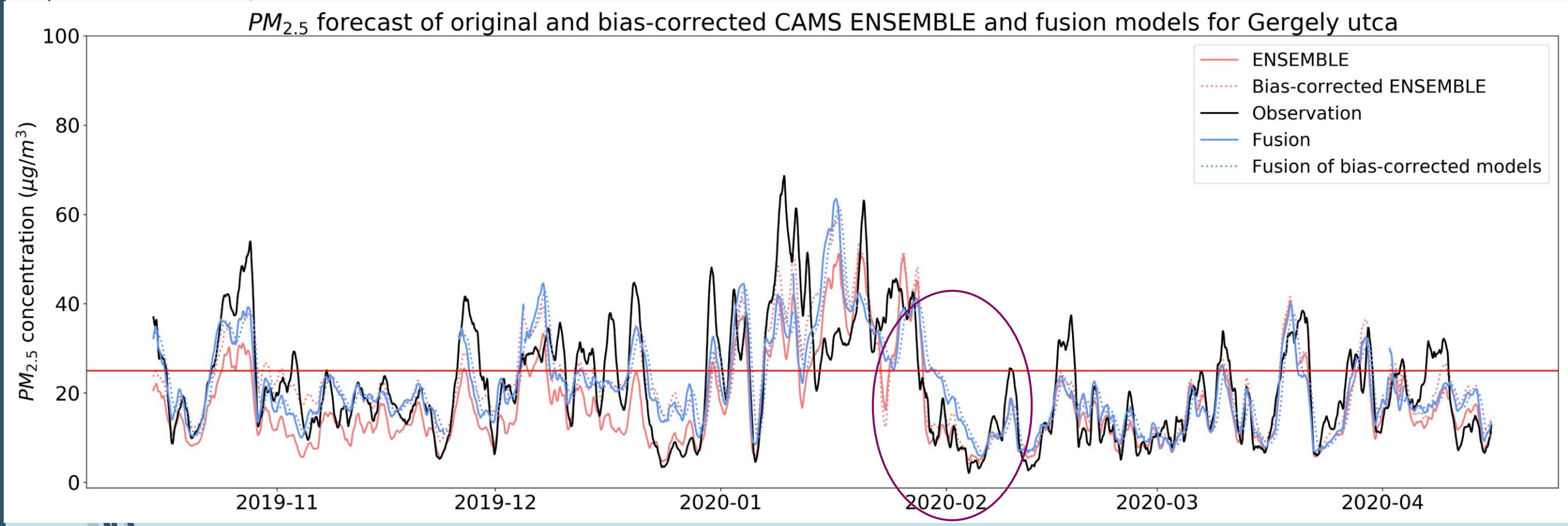
Results


$PM_{2.5}$ forecast of original and bias-corrected CAMS ENSEMBLE and fusion models for Gergely utca
$PM_{2.5}$ concentration ($\mu g/m^3$)
100
80
60
40
20
0
2019-11
2019-12
2020-01
2020-02
2020-03
2020-04
ENSEMBLE
Bias-corrected ENSEMBLE
Observation
Fusion
Fusion of bias-corrected models

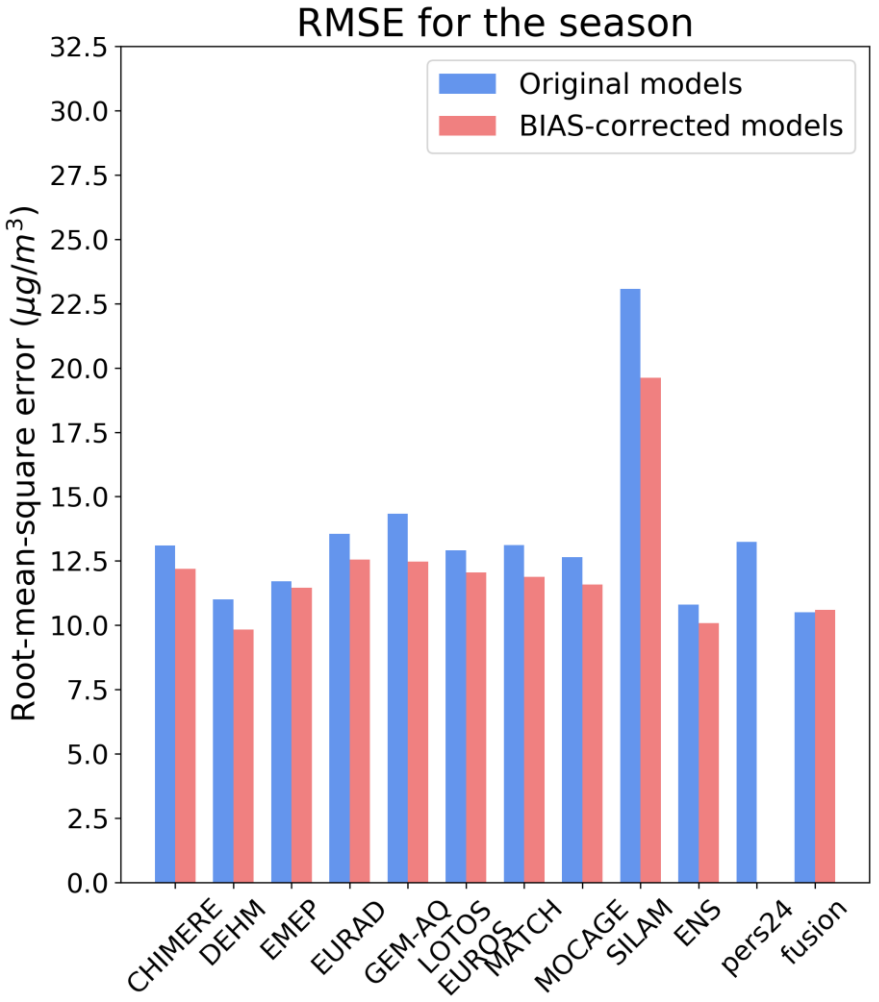
Results

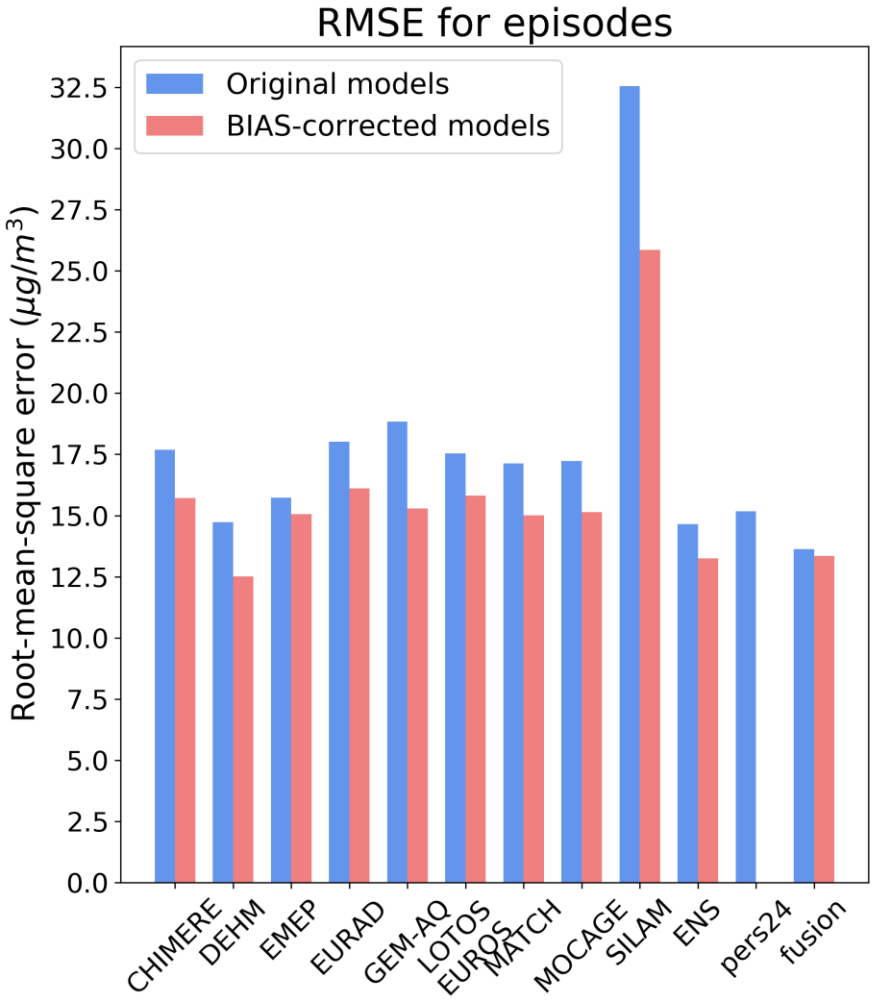

$PM_{2.5}$ forecast of original and bias-corrected CAMS ENSEMBLE and fusion models for Gergely utca
$PM_{2.5}$ concentration ($\mu g/m^3$)
100
80
60
40
20
0
2019-11
2019-12
2020-01
2020-02
2020-03
2020-04
ENSEMBLE
Bias-corrected ENSEMBLE
Observation
Fusion
Fusion of bias-corrected models

Results

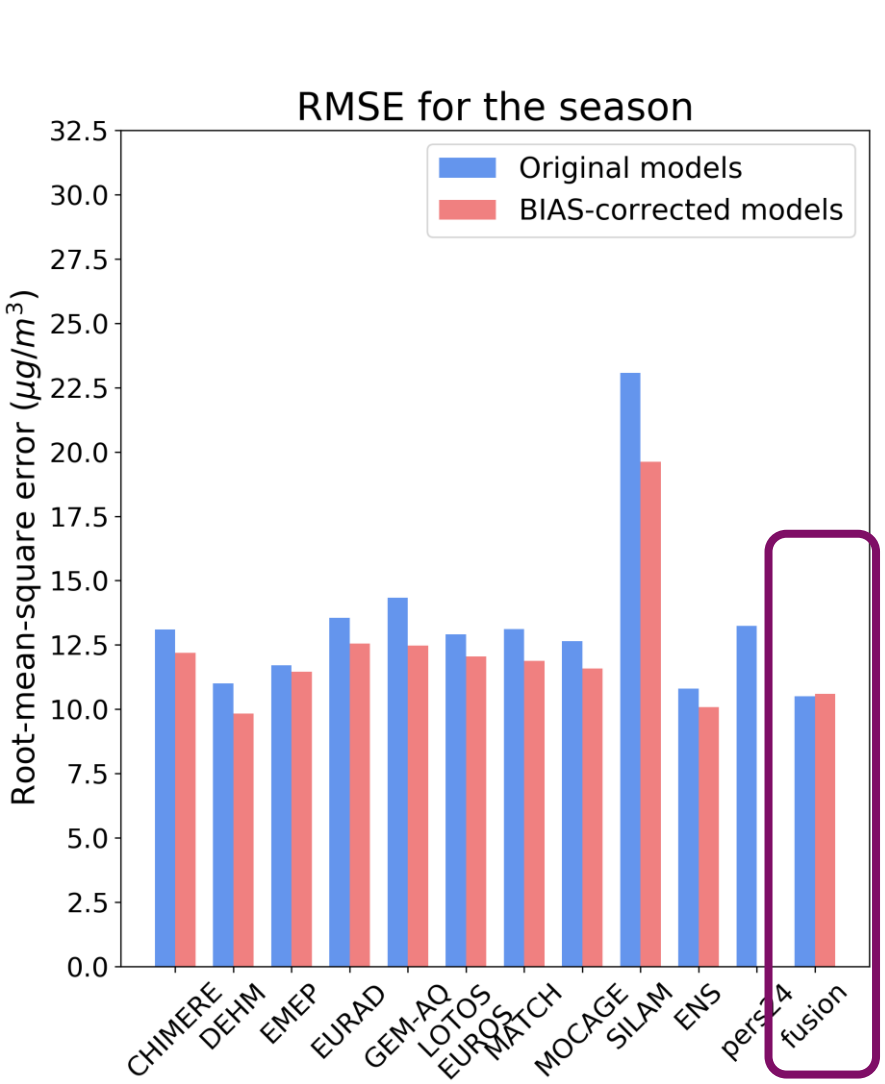

$PM_{2.5}$ forecast of original and bias-corrected CAMS ENSEMBLE and fusion models for Gergely utca
$PM_{2.5}$ concentration ($\mu g/m^3$)
100
80
60
40
20
0
2019-11
2019-12
2020-01
2020-02
2020-03
2020-04
ENSEMBLE
Bias-corrected ENSEMBLE
Observation
Fusion
Fusion of bias-corrected models

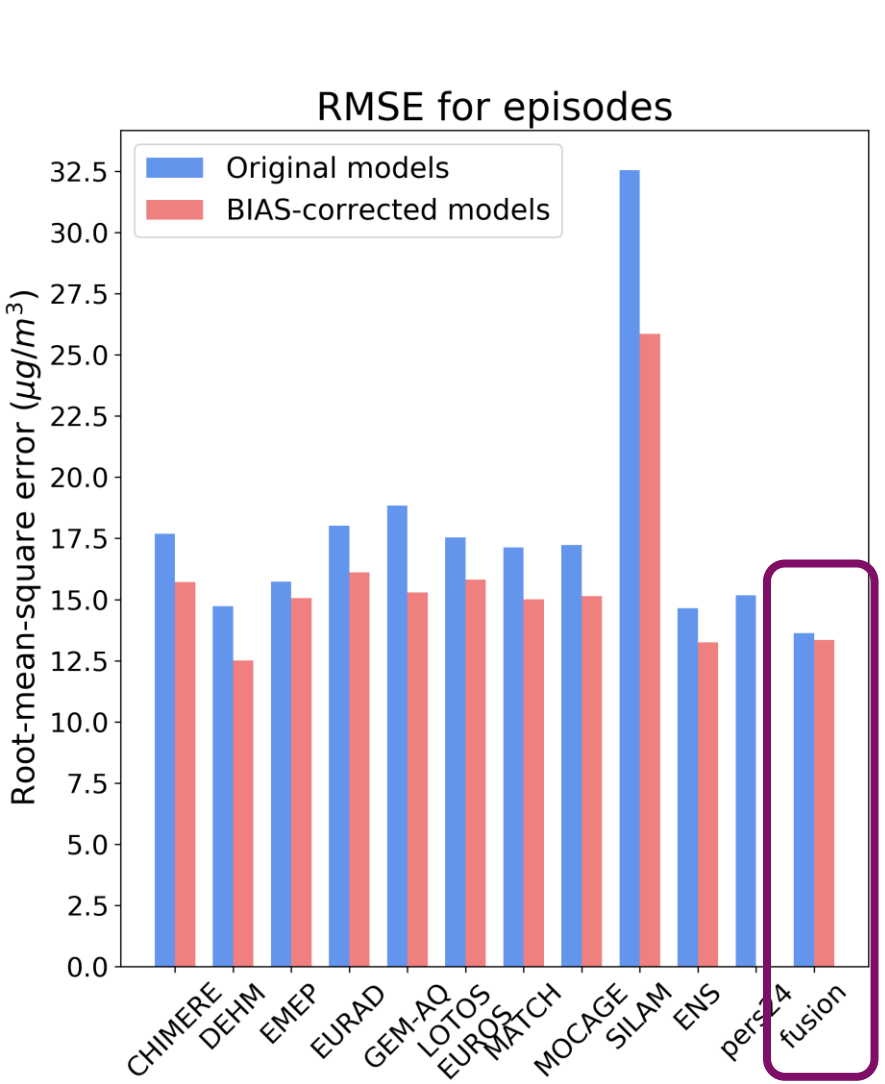
Results


RMSE for the season
Original models
BIAS-corrected models
Root-mean-square error ($\mu g/m^3$)
32.5
30.0
27.5
25.0
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

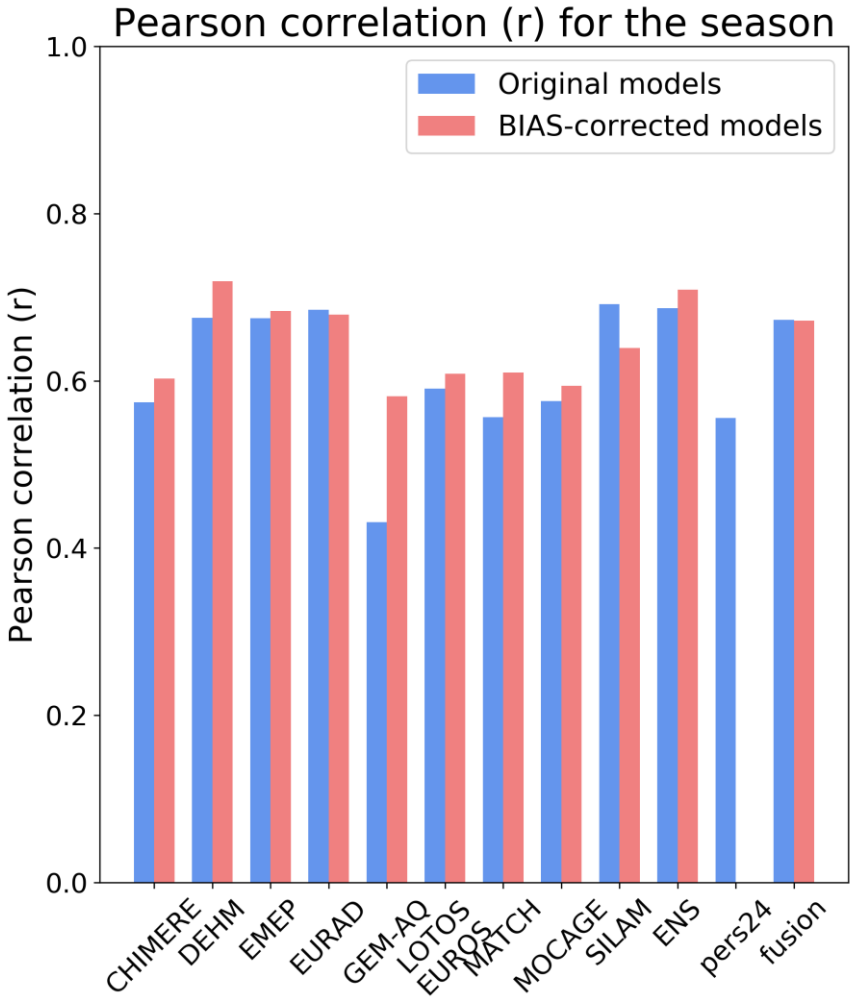

RMSE for episodes
Original models
BIAS-corrected models
Root-mean-square error ($\mu g/m^3$)
32.5
30.0
27.5
25.0
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

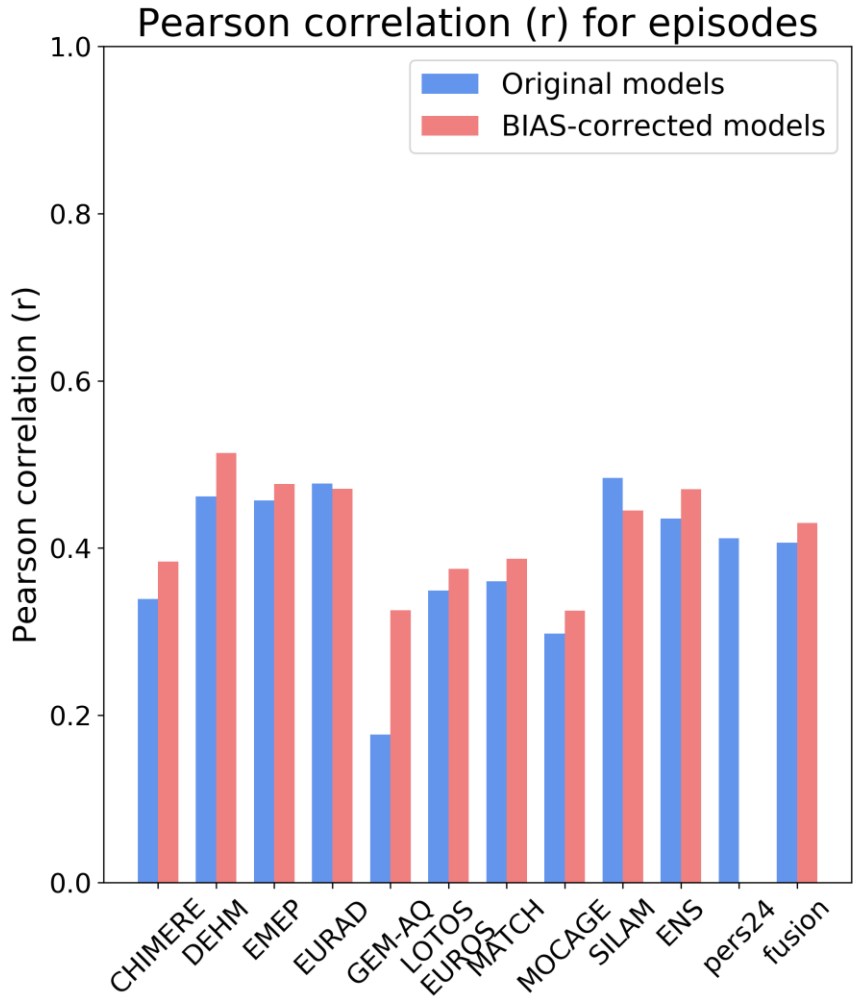
Results


RMSE for the season
Original models
BIAS-corrected models
Root-mean-square error ($\mu g/m^3$)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
25.0
27.5
30.0
32.5
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

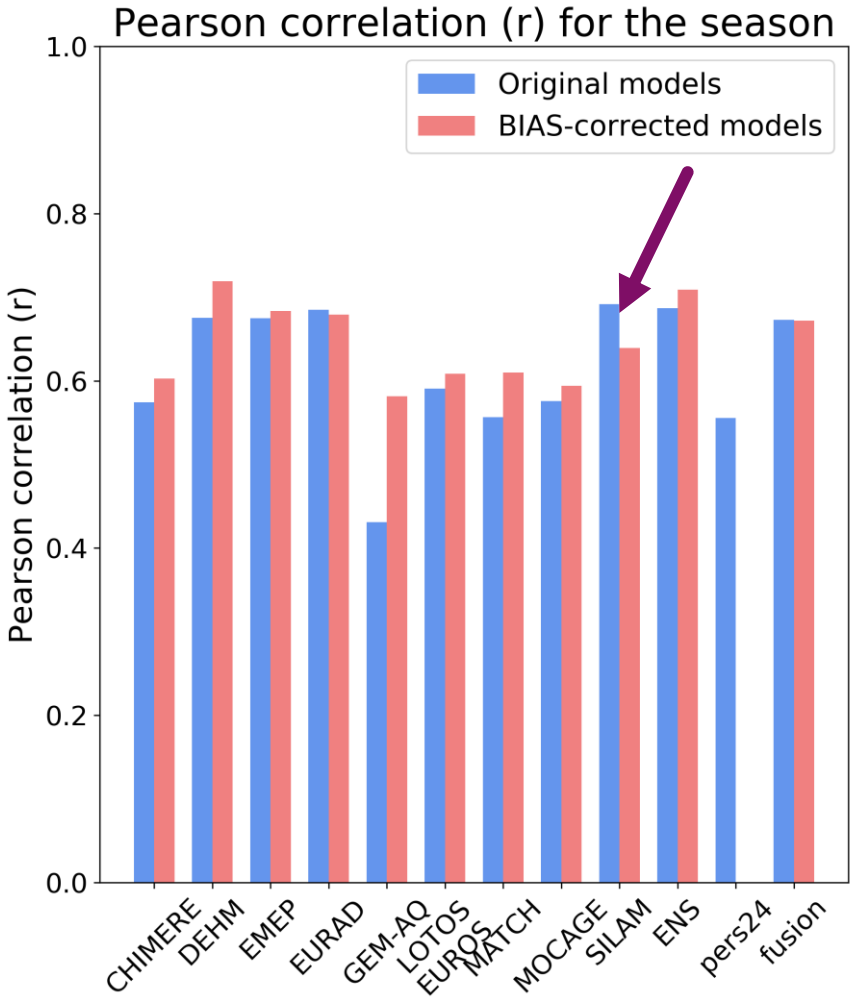

RMSE for episodes
Original models
BIAS-corrected models
Root-mean-square error ($\mu g/m^3$)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
25.0
27.5
30.0
32.5
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

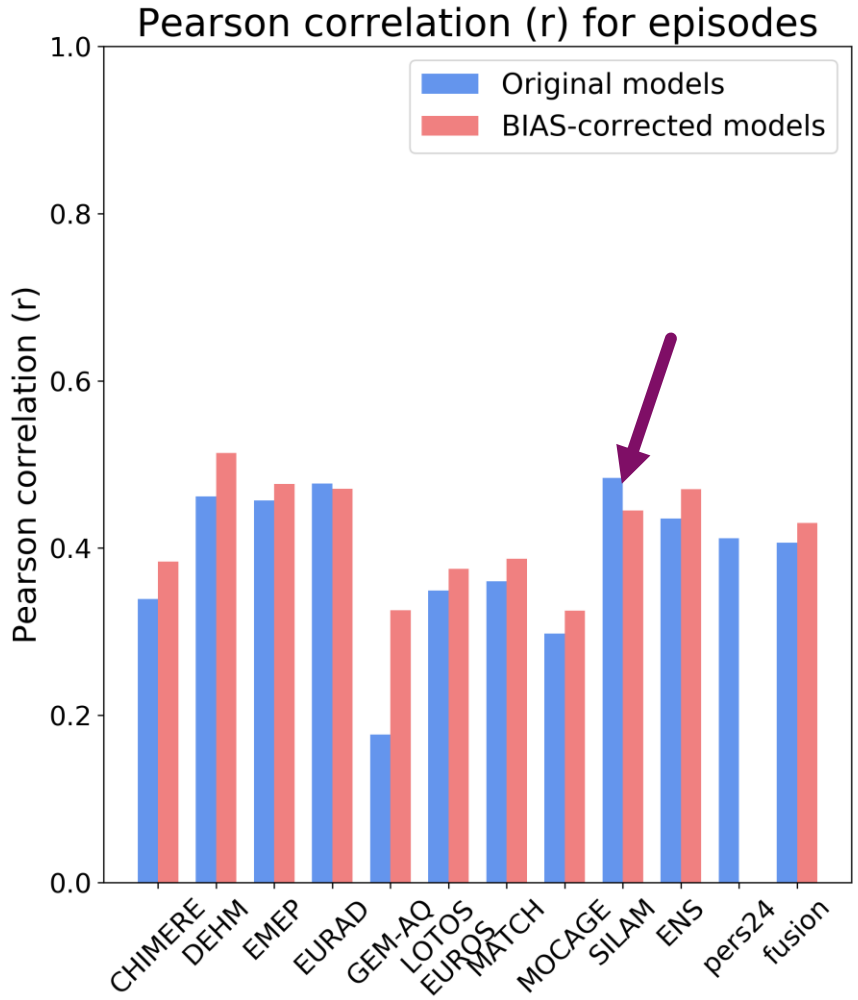
Results


Pearson correlation (r) for the season
Original models
BIAS-corrected models
Pearson correlation (r)
1.0
0.8
0.6
0.4
0.2
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

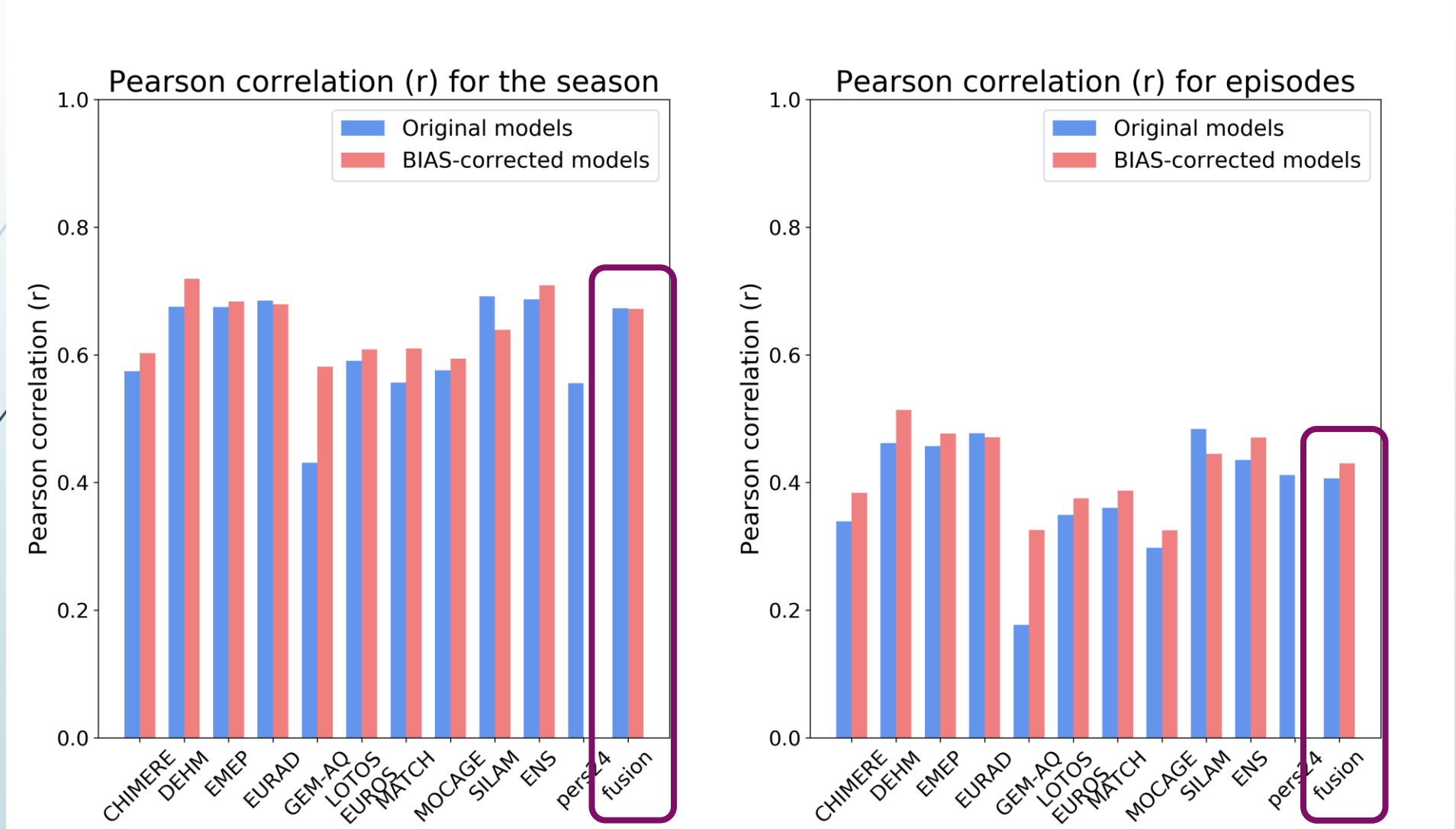

Pearson correlation (r) for episodes
Original models
BIAS-corrected models
Pearson correlation (r)
1.0
0.8
0.6
0.4
0.2
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

Results

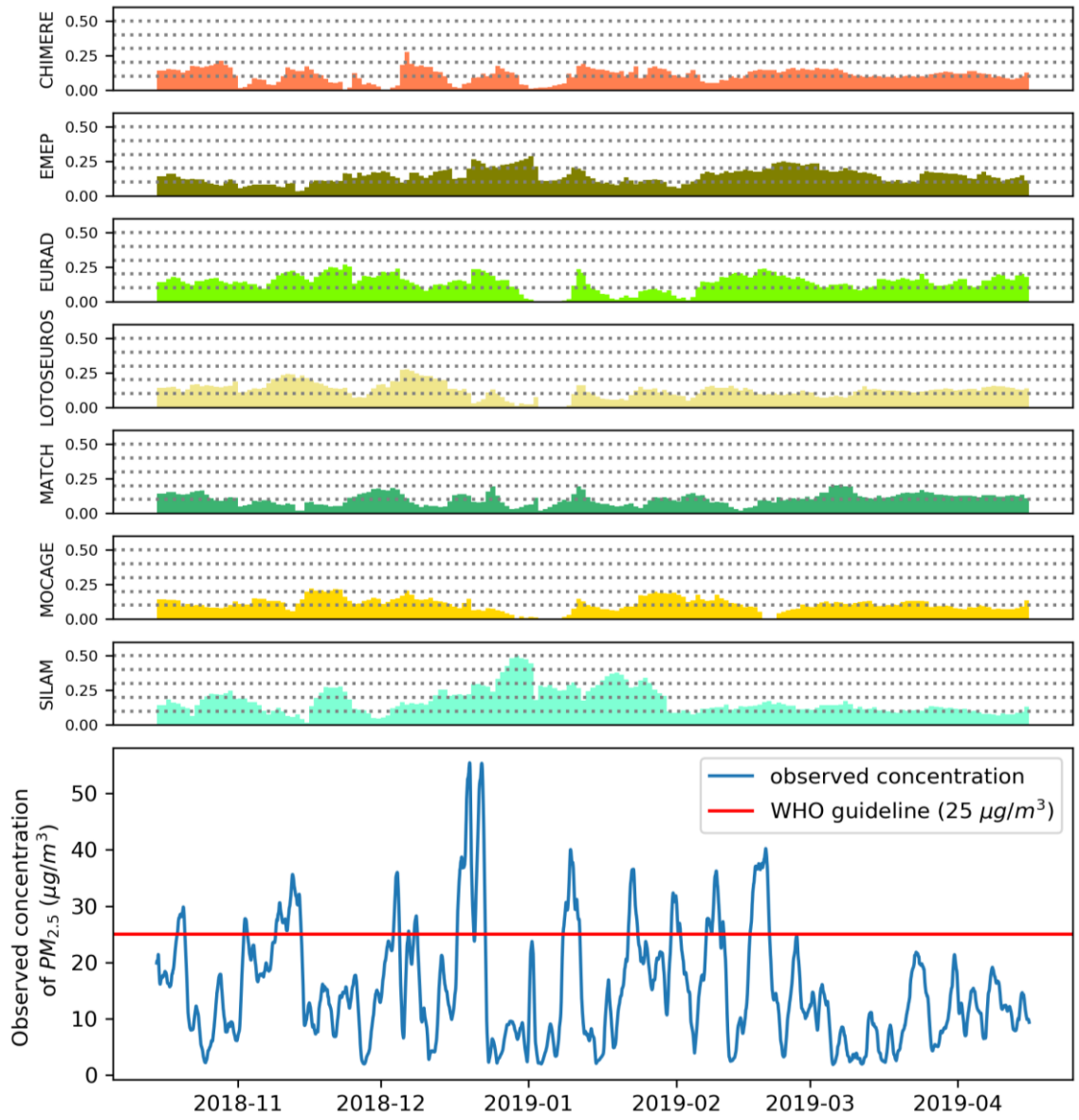

Pearson correlation (r) for the season
Original models
BIAS-corrected models
Pearson correlation (r)
1.0
0.8
0.6
0.4
0.2
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion


Pearson correlation (r) for episodes
Original models
BIAS-corrected models
Pearson correlation (r)
1.0
0.8
0.6
0.4
0.2
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

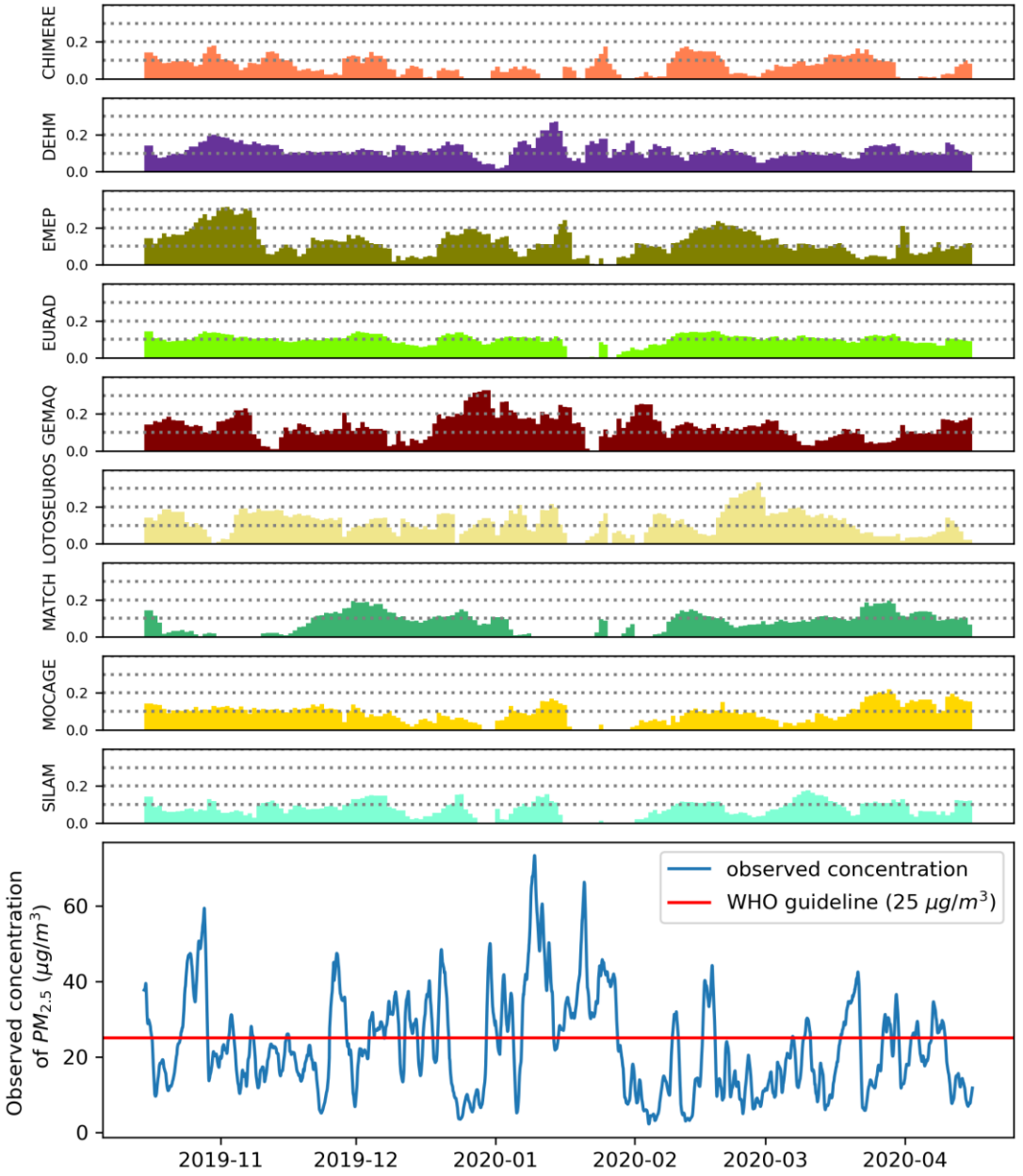
Results


Pearson correlation (r) for the season
Original models
BIAS-corrected models
Pearson correlation (r)
1.0
0.8
0.6
0.4
0.2
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion
Pearson correlation (r) for episodes
Original models
BIAS-corrected models
Pearson correlation (r)
1.0
0.8
0.6
0.4
0.2
0.0
CHIMERE
DEHM
EMEP
EURAD
GEM-AQ
LOTOS
EUROS
MATCH
MOCAGE
SILAM
ENS
pers24
fusion

2018-2019

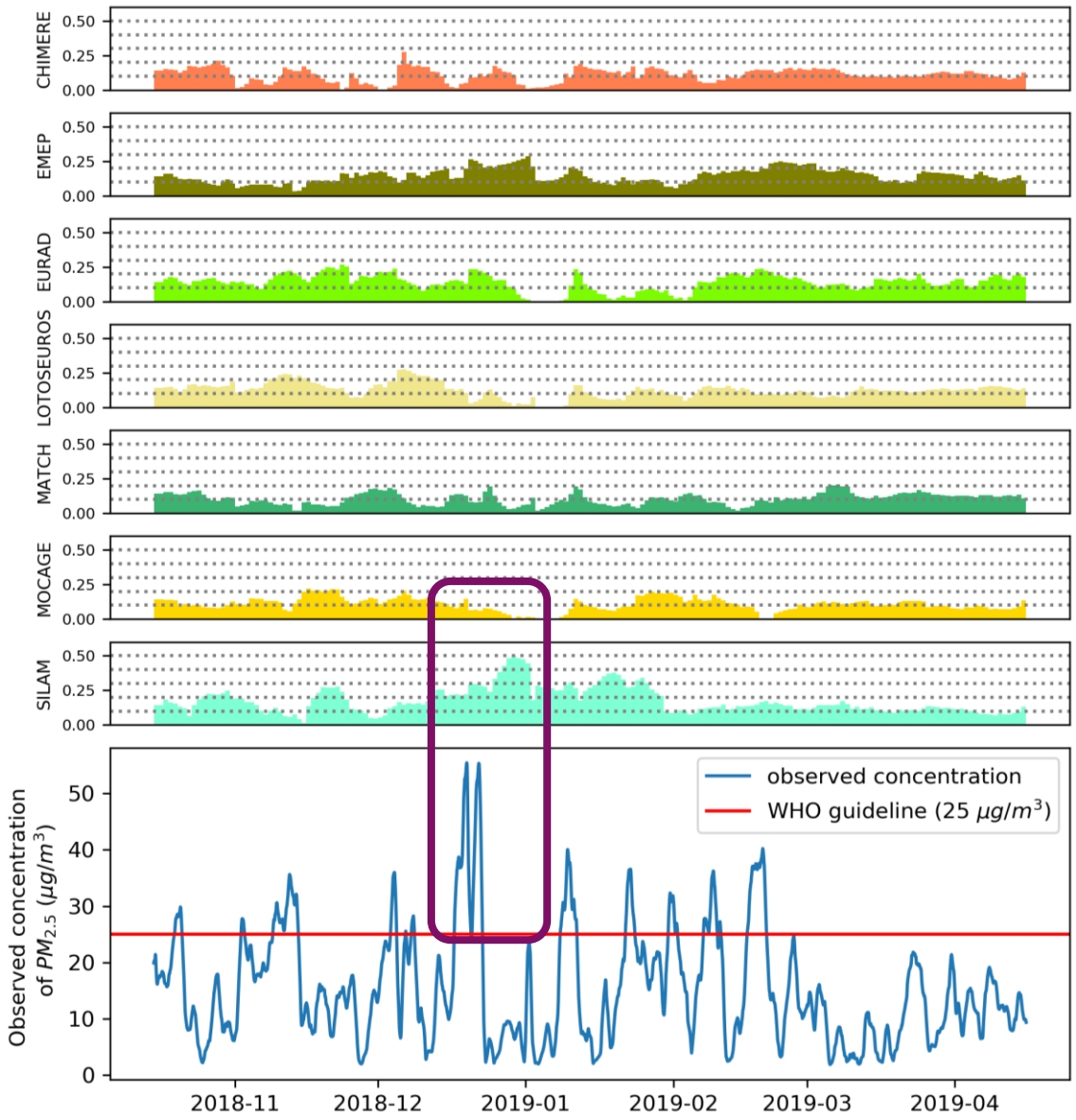


2019-2020

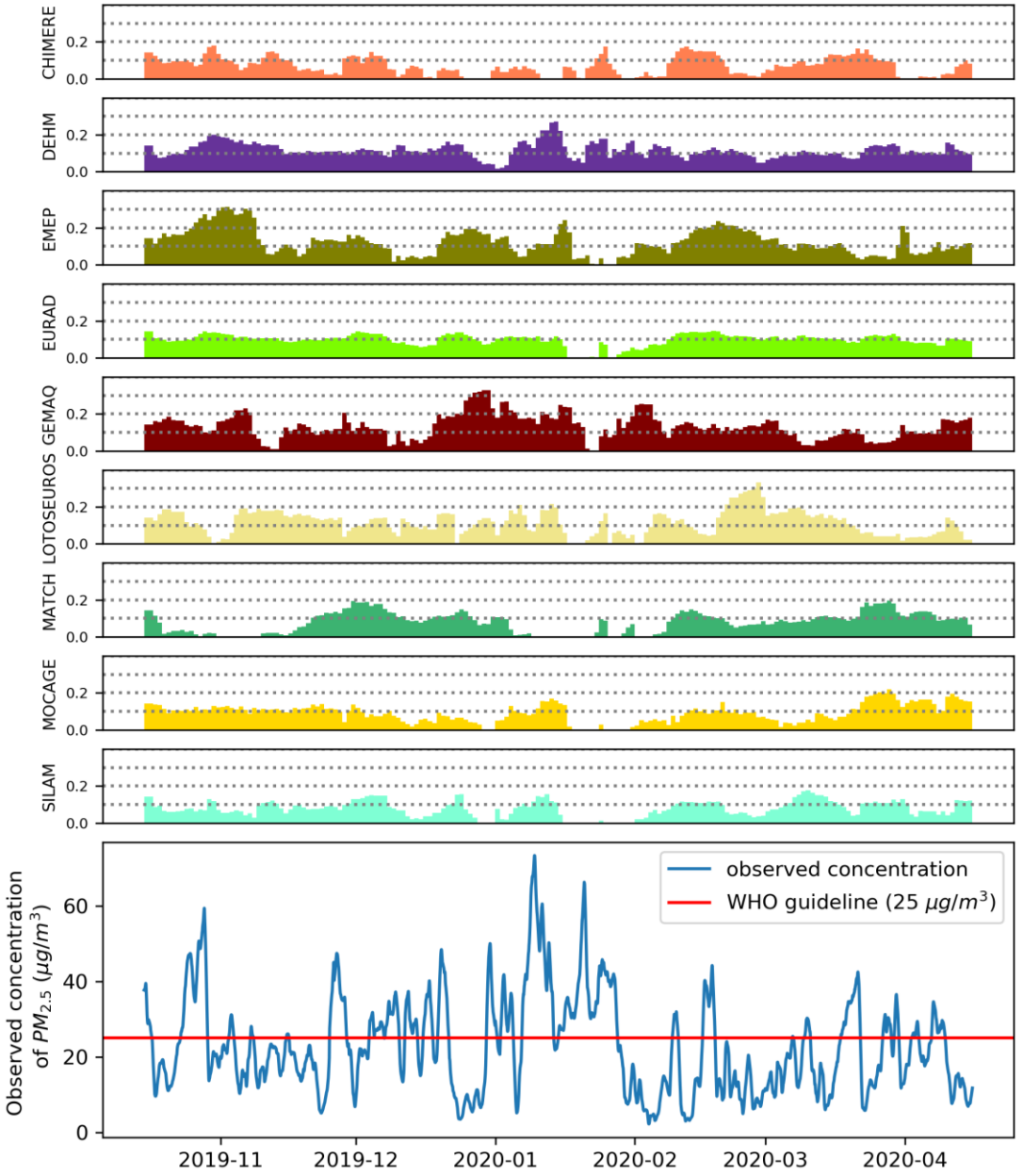


Varga-Balogh et al., Atmosphere 2020, 11(6), 669

2018-2019

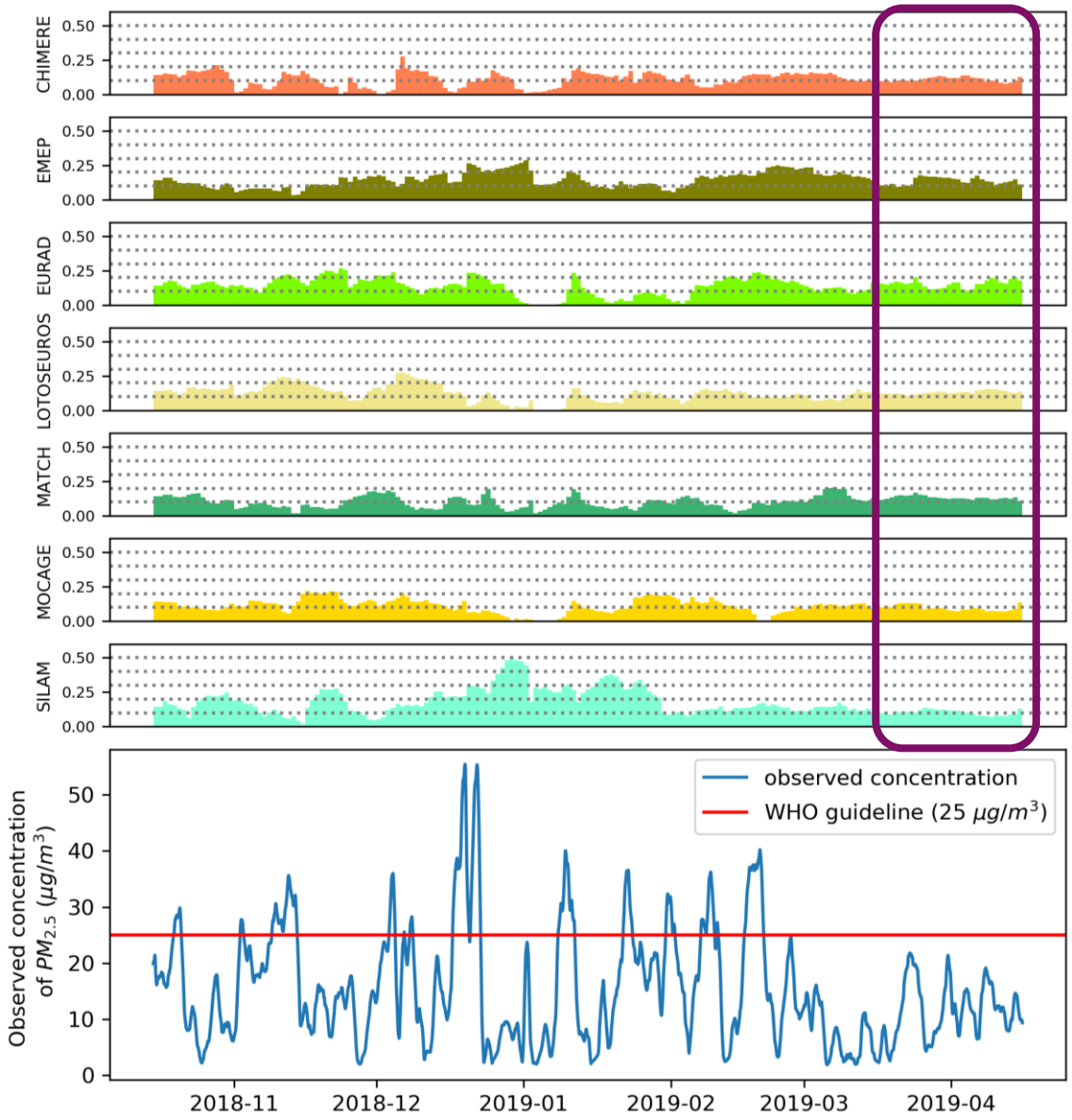


2019-2020

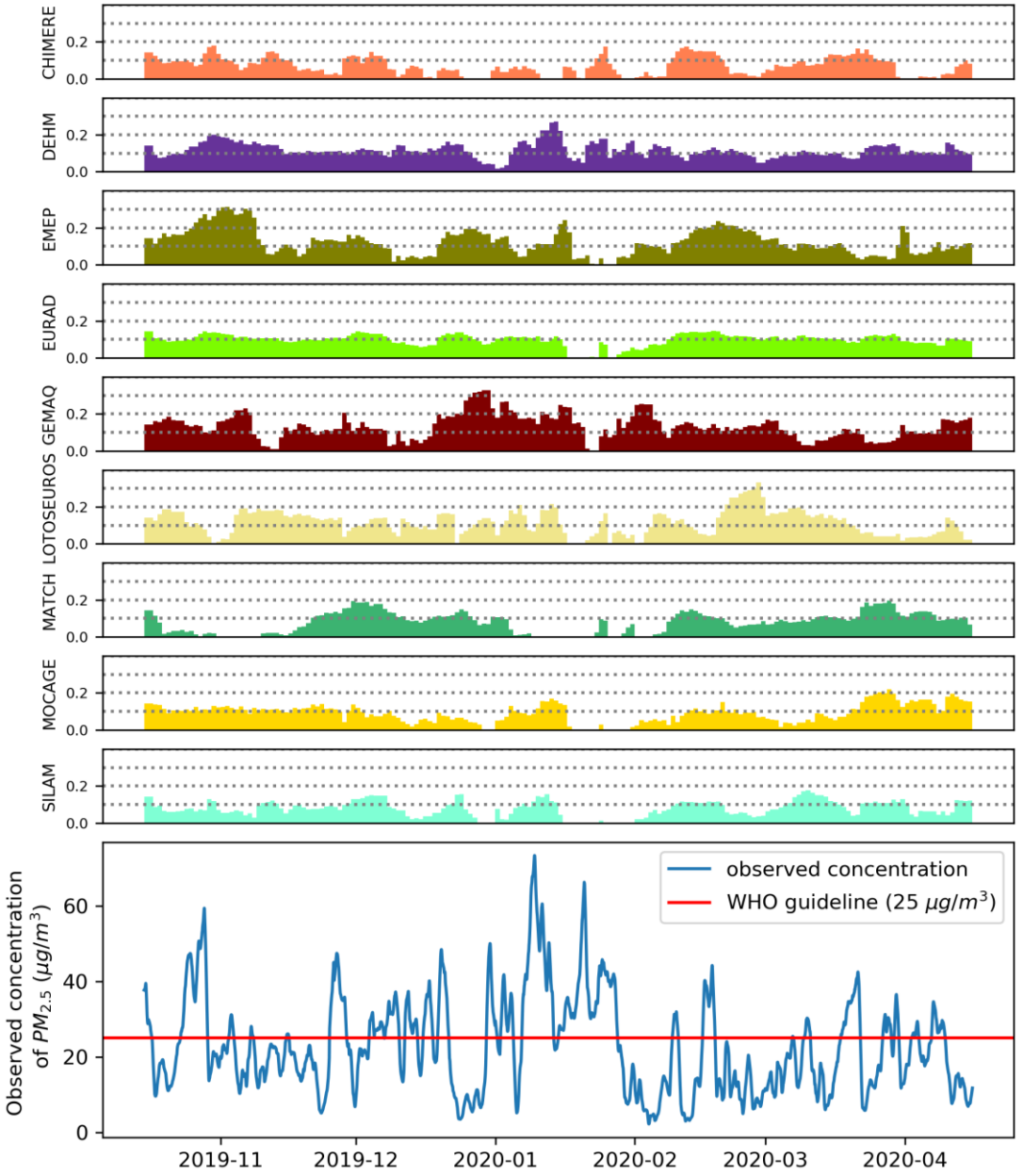


Varga-Balogh et al., Atmosphere 2020, 11(6), 669

2018-2019



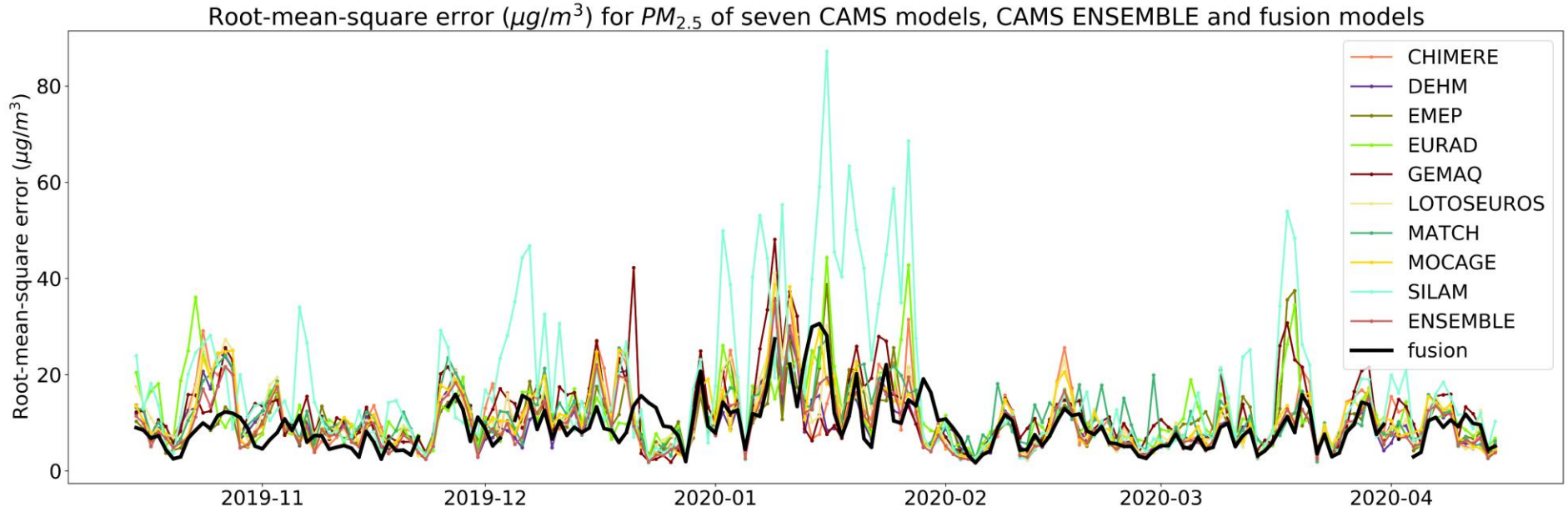
2019-2020

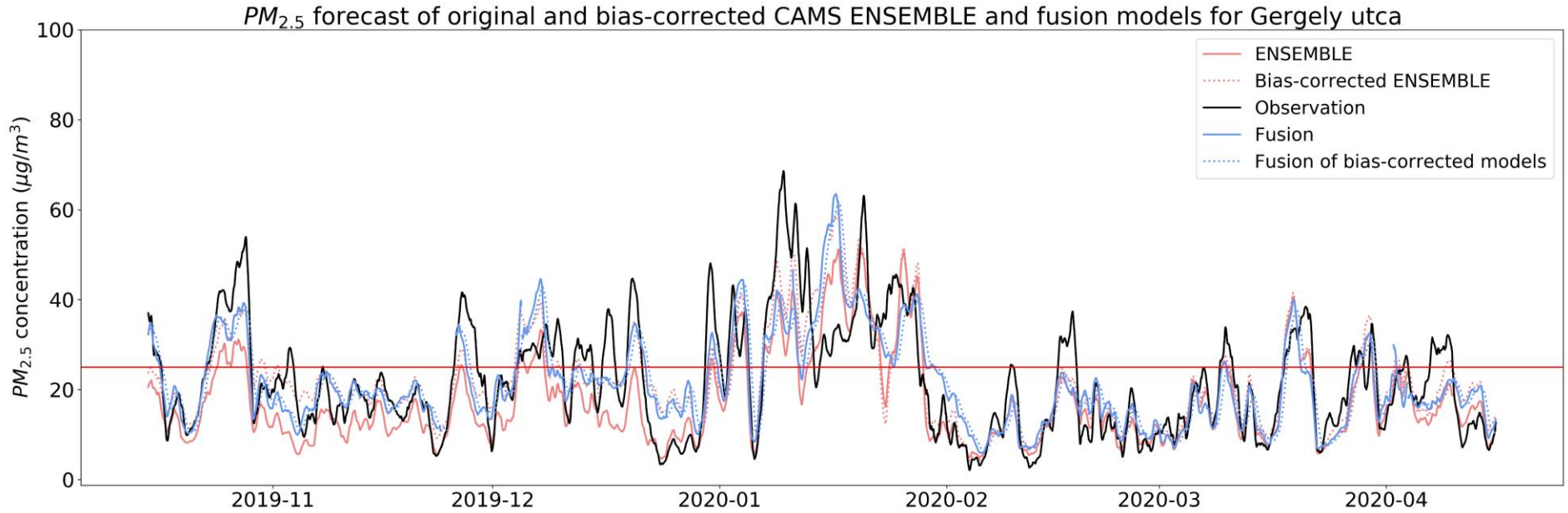


Varga-Balogh et al., Atmosphere 2020, 11(6), 669

Conclusion

- The CAMS ENSEMBLE was better than individual models in terms of bias, RMSE and Pearson correlation (r).
- Bias-corrected models mostly performed better than the uncorrected models, especially ENSEMBLE forecast improved for all winters with bias-correction.
- Fusion model performs nearly as ENSEMBLE forecast, however in winter stagnation events, it performs better than CAMS and CAMS ENSEMBLE models.
- Model weights were found to be strongly weather-dependent and variable among winters with many and no stagnation events.





Thank you for your attention

vargabaloghadrienn@gmail.com