



*Supplement of*

**Evaluation of the offline-coupled GFSv15–FV3–CMAQv5.0.2 in support of the next-generation National Air Quality Forecast Capability over the contiguous United States**

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## Supplement

Table S1. Datasets used in this study

Database	Parameter	Data frequency	Number of sites / resolution
CASTNET	T2, RH2, WS10, WD10, Precipitation	Hourly	Up to 90 sites
METAR	T2, RH2, WS10, WD10, Precipitation	Hourly	Up to 1900 sites
AirNow	O <sub>3</sub> , PM <sub>2.5</sub>	Hourly	Up to 1100 sites
AQS	PM <sub>2.5</sub> speciation	Daily	Up to 280 sites
CCPA	Precipitation	Hourly	0.125 degree
GPCP	Precipitation	Monthly	2.5 degree
MODIS_MOD04	Aerosol Optical depth	Monthly	1 degree

Table S2. Monthly performance statistics of meteorological variables

Datasets	Variable	Period	CASTNET						METAR						
			Mean Obs.	Mean Sim.	MB	RMSE	NMB, %	NME, %	Corr	Mean Obs.	Mean Sim.	MB	RMSE	NMB, %	NME, %
T2, °C	Jan	-1.8	-2.2	-0.4	2.5	-23.2	102.1	0.96	1.3	1.1	-0.1	2.4	-11.5	144.5	0.97
	Feb	-0.6	-1.2	-0.6	2.6	-88.8	308.4	0.97	2.5	2.2	-0.2	2.6	-10.2	77.5	0.97
	Mar	3.5	2.7	-0.7	2.4	-20.6	53.2	0.97	6.2	5.8	-0.4	2.3	-6.2	28.2	0.97
	Apr	11.2	10.7	-0.5	2.3	-4.5	16.0	0.96	13.5	13.1	-0.3	2.3	-2.4	12.7	0.96
	May	15.0	14.7	-0.3	2.3	-2.1	11.7	0.96	17.5	17.2	-0.4	2.3	-2.2	9.7	0.96
	Jun	19.8	19.5	-0.3	2.4	-1.7	9.2	0.94	21.9	21.4	-0.5	2.4	-2.1	8.3	0.94
	Jul	22.9	22.9	-0.1	2.5	-0.2	8.2	0.91	24.6	24.4	-0.3	2.3	-1.1	7.1	0.92
	Aug	21.8	21.6	-0.2	2.4	-0.7	8.4	0.93	23.6	23.5	-0.1	2.3	-0.5	7.3	0.93
	Sept	19.5	19.2	-0.3	2.3	-1.7	9.0	0.95	21.7	21.6	-0.1	2.2	-0.6	7.5	0.95
	Oct	11.1	11.0	-0.2	2.7	-1.6	16.7	0.95	13.4	13.5	0.1	2.3	0.6	12.9	0.97
	Nov	4.0	3.8	-0.2	2.8	-4.9	48.5	0.94	6.2	6.5	0.2	2.5	3.8	29.4	0.96
	Dec	2.0	1.8	-0.3	2.8	-12.6	97.6	0.94	4.3	4.4	0.1	2.5	2.4	43.5	0.96
RH2, %	Jan	68.6	70.9	2.3	14.4	3.3	15.3	0.73	72.7	72.3	-0.4	13.1	-0.6	13.6	0.76
	Feb	69.3	74.0	4.6	14.3	6.7	14.8	0.76	74.1	75.6	1.5	14.0	2.0	13.9	0.75
	Mar	63.1	69.1	6.0	15.9	9.6	18.5	0.77	66.6	70.0	3.4	14.7	5.1	16.8	0.77
	Apr	59.9	63.3	3.4	13.3	5.7	16.4	0.85	66.0	68.9	2.9	13.8	4.4	15.9	0.82
	May	65.0	65.6	0.7	13.0	1.0	14.9	0.85	69.5	71.3	1.8	13.0	2.6	14.1	0.82
	Jun	56.4	55.6	-0.8	12.2	-1.4	15.9	0.88	66.4	68.0	1.6	13.7	2.5	15.6	0.82
	Jul	55.0	52.7	-2.3	12.4	-4.2	16.8	0.88	66.6	67.1	0.5	12.9	0.8	14.7	0.84
	Aug	53.7	51.6	-2.0	12.0	-3.8	16.4	0.89	68.0	66.8	-1.1	12.7	-1.7	14.1	0.85
	Sept	58.3	56.0	-2.3	11.7	-3.9	14.7	0.89	68.3	66.9	-1.4	12.3	-2.0	13.6	0.85
	Oct	56.5	54.4	-2.1	12.6	-3.7	16.2	0.89	67.8	65.6	-2.2	13.2	-3.2	14.5	0.85

	Nov	62.4	62.6	0.2	14.5	0.3	17.3	0.82	70.1	68.6	-1.5	14.1	-2.1	15.4	0.77
	Dec	69.3	71.1	1.9	14.3	2.7	15.1	0.75	87.8	88.0	0.2	9.5	0.2	8.0	0.60
WS10, m s <sup>-1</sup>	Jan	2.6	3.0	0.4	2.0	15.5	55.2	0.61	3.4	3.8	0.3	2.0	9.9	42.5	0.73
	Feb	2.7	3.4	0.6	2.2	22.8	56.9	0.57	3.5	3.8	0.3	2.0	8.2	42.6	0.71
	Mar	2.7	3.2	0.5	1.9	17.0	51.6	0.63	3.6	3.9	0.3	1.9	8.2	41.0	0.72
	Apr	2.9	3.6	0.7	2.2	24.9	57.3	0.58	3.8	4.2	0.4	2.1	11.0	41.3	0.71
	May	2.7	3.3	0.7	2.1	24.7	58.0	0.59	3.4	3.8	0.4	2.0	12.4	45.7	0.66
	Jun	2.6	3.2	0.6	2.1	23.0	60.6	0.51	3.1	3.5	0.5	2.0	14.8	49.3	0.63
	Jul	2.4	3.0	0.6	1.9	25.8	61.5	0.49	2.7	3.2	0.4	1.9	16.2	52.2	0.62
	Aug	2.3	2.8	0.6	1.8	24.8	60.6	0.52	2.6	3.1	0.5	1.9	20.6	57.0	0.59
	Sept	2.6	3.2	0.6	2.0	24.7	58.2	0.59	3.8	4.0	0.2	1.7	5.1	34.3	0.65
	Oct	2.7	3.2	0.5	2.2	20.6	59.7	0.53	4.1	4.3	0.2	1.9	5.1	33.0	0.69
	Nov	2.4	2.8	0.4	2.0	15.3	58.0	0.58	4.0	4.1	0.1	1.8	2.6	32.3	0.70
	Dec	2.4	2.8	0.4	1.9	18.7	58.2	0.57	3.1	3.6	0.4	1.9	14.4	45.8	0.70
Precip, mm hr <sup>-1</sup>	Jan	1.0	0.6	-0.5	1.6	-43.2	87.1	0.24	1.3	0.8	-0.6	2.9	-44.3	75.9	0.21
	Feb	1.0	0.6	-0.4	1.7	-41.7	86.5	0.25	1.3	0.6	-0.6	4.5	-48.9	78.4	0.11
	Mar	1.1	0.6	-0.5	1.7	-46.0	83.4	0.28	1.6	0.6	-1.0	12.5	-60.5	83.4	0.04
	Apr	1.1	0.5	-0.6	1.9	-54.2	88.4	0.28	1.7	0.8	-0.9	3.5	-51.0	85.2	0.18
	May	1.2	0.5	-0.7	2.3	-55.6	88.8	0.15	2.0	0.7	-1.2	4.9	-63.2	87.3	0.10
	Jun	2.0	0.5	-1.5	4.2	-74.5	93.0	0.09	2.4	0.7	-1.7	5.7	-70.7	89.7	0.07
	Jul	2.2	0.4	-1.8	4.8	-82.4	95.8	0.04	2.8	0.7	-2.1	7.3	-76.1	93.3	0.04
	Aug	2.3	0.5	-1.8	5.2	-77.2	93.1	0.17	2.7	0.6	-2.1	9.7	-77.3	92.1	0.03
	Sept	1.3	0.5	-0.8	2.4	-60.5	86.8	0.18	2.3	0.7	-1.6	13.7	-70.2	89.9	0.03
	Oct	1.5	0.7	-0.8	2.7	-52.4	88.0	0.25	1.9	0.9	-0.9	6.7	-49.9	82.8	0.10
	Nov	1.1	0.5	-0.5	1.9	-49.8	82.7	0.28	1.3	0.6	-0.7	6.1	-50.6	77.7	0.07
	Dec	1.0	0.6	-0.4	1.5	-44.2	83.7	0.32	1.4	0.8	-0.6	2.7	-40.4	77.7	0.18

Table S3. Summary of forecasting skills of air quality forecasting systems

Reference	Region	Model System	Period	Pollutant	Performance
Moran et al., 2018	Canada/North America	GEM-MACH	2010	O <sub>3</sub>	NMB=1.4%, R=0.76
				PM <sub>2.5</sub>	NMB=-0.6%, R=0.58
Russell et al., 2019	Canada	GEM-MACH	Aug-Sept 2013	O <sub>3</sub>	MB=5.7 to 10.9 ppb, RMSE=9.7 to 16.0 ppb, Corr=0.50 to 0.74
				PM <sub>2.5</sub>	MB=3.2 to 5.5 µg m <sup>-3</sup> , RMSE=5.7 to 8.8 µg m <sup>-3</sup> , Corr=0.20 to 0.47
Struzewska et al., 2016	Poland	GEM-AQ	Nov 2011 to Sep 2013	O <sub>3</sub>	MB=12.8 to 25.6 µg m <sup>-3</sup> , RMSE=24.6 to 28.7 µg m <sup>-3</sup> , Corr=0.48 to 0.62
				PM <sub>2.5</sub>	MB=-9.6 to -1.86 µg m <sup>-3</sup> , RMSE=24.8 to 34.1 µg m <sup>-3</sup> , Corr=0.48 to 0.58
D'Allura et al., 2018	Italy	WRF/RAMS-FARM	2015	O <sub>3</sub>	FAR=36.1%, POD= 71.2%, threshold=83 µg m <sup>-3</sup>
				PM <sub>10</sub>	FAR=20.0%, POD= 27.3%, threshold=33 µg m <sup>-3</sup>
Podrascanin, 2019	Serbia	WRF/Chem	August 2016	O <sub>3</sub>	MB=1.6 to 9.3 µg m <sup>-3</sup> , NMB=3.0 to 17.2%, Corr=0.45 to 0.50
				PM <sub>10</sub>	MB=-15.2 to -14.3 µg m <sup>-3</sup> , NMB=-74.0 to -56.1%, Corr=-0.01 to 0.18
Stortini et al., 2020	Italy	CHIMERE	October 2019	O <sub>3</sub>	MB=11.0 to 16.9 µg m <sup>-3</sup> , RMSE=19.3 to 28.0 µg m <sup>-3</sup> , Corr=0.63 to 0.78
				PM <sub>10</sub>	MB=-8.2 to -4.9 µg m <sup>-3</sup> , RMSE=11.4 to 13.0 µg m <sup>-3</sup> , Corr=0.72 to 0.76, FAR=43-44%, POD= 6-22%

Lyu et al., 2017	China	WRF-CMAQ	2014-2016	PM <sub>2.5</sub>	NME=49%, RMSE=32.2 $\mu\text{g m}^{-3}$ , R <sup>2</sup> =0.46
Zhou et al., 2017	China	WRF/Chem	2014-2015	MDA8 O <sub>3</sub>	MB=18.9 ppb, NMB=77%, RMSE=27.9 ppb, Corr=0.63
				PM <sub>2.5</sub>	MB=-12.0 $\mu\text{g m}^{-3}$ , NMB=-9%, RMSE=35.8 $\mu\text{g m}^{-3}$ , Corr=0.67
Peng et al., 2018	China	WRF/Chem	6 to 16 October 2014	O <sub>3</sub>	MB=-31.0 $\mu\text{g m}^{-3}$ , RMSE=50.8 $\mu\text{g m}^{-3}$ , Corr=0.46
				PM <sub>2.5</sub>	MB=-34.1 $\mu\text{g m}^{-3}$ , RMSE=92.1 $\mu\text{g m}^{-3}$ , Corr=0.74
Ha et al., 2020	Korea	WRF/Chem	May 2016	PM <sub>2.5</sub>	MAE=12.8, FAR=59.0%, Overall_Accuracy=59.7%, High_Pollution_Accuracy=35.6%
Kang et al., 2010	CONUS	NAM-CMAQ	2008	MDA8 O <sub>3</sub>	HR=~47% for cat 2, ~31% for cat 3, FAR=~68% at cat 3
				PM <sub>2.5</sub>	HR=~46% for cat 2, ~21% for cat3, FAR=~91% at cat 3
Zhang et al., 2016	Southeastern US	WRF/Chem-MADRID	2012-2014 (May–September)	MDA8 O <sub>3</sub>	NMB= 0.0 to 17.0 %, NME= 22.0 to 27.0 %, Corr= 0.5
				PM <sub>2.5</sub>	NMB= -4.0 to 15.0 %, NME= 36.0 to 40.0 %, Corr= 0.3 to 0.4
			2012-2014 (December-February)	MDA8 O <sub>3</sub>	NMB= -17.7 to -9.1 %, NME= 19.6 to 24.6 %, Corr= 0.0 to 0.2
				PM <sub>2.5</sub>	NMB= 0.8 to 8.3 %, NME= 42.6 to 47.2 %, Corr= 0.3 to 0.4
Lee et al., 2017	CONUS	NAM-CMAQ	May and Jul 2014	PM <sub>2.5</sub>	MB=-2.7 to -1.6 $\mu\text{g m}^{-3}$ , NME=-35 to -20%, RMSE=4.5 to 8.8 $\mu\text{g m}^{-3}$ , Corr=0.22 to 0.33
			Jan 2015	PM <sub>2.5</sub>	MB=1.3 to 3.7 $\mu\text{g m}^{-3}$ , NME=13 to 38%, RMSE=6.5 to 12.6 $\mu\text{g m}^{-3}$ , Corr=0.37 to 0.38
This work	CONUS	FV3GFS-CMAQ	2019	MDA8 O <sub>3</sub>	MB=0.4 ppb, NMB=1.0%, Corr=0.73. FAR=41.4 % and HR=45.8% at cat 2.
				PM <sub>2.5</sub>	MB=2.3 $\mu\text{g m}^{-3}$ , NMB=30.0%, Corr=0.41. FAR=70.3% and HR=57.6% for cat 2.

FAR: False Alarm Ratio; POD: Probability of Detection; HR: Hit Rate.

Figure S1. Site locations within CONUS of (a) CASTNET and (b) METAR. (c) Ten regions within CONUS for regional analysis

Figure S2. Spatial distribution of MBs for forecasted seasonal mean T2 by GFSv15-CMAQv5.0.2 against observations from METAR

Figure S3. Monthly accumulated precipitation for four seasons by (left column) the GFSv15-CMAQv5.0.2 prediction, (middle column) the CCPA observation, and (right column) the GPCP observation

Figure S4. Time series of observed and predicted hourly precipitation at two CASTNET sites at site GRS420 in

Tennessee during (a) Jan, (b) July, (c) Aug, and (d) Nov.

Figure S5. Spatial distribution of annual area emissions

Figure S6. Time series of daily maximum 8-hr O<sub>3</sub> in 10 regions within CONUS

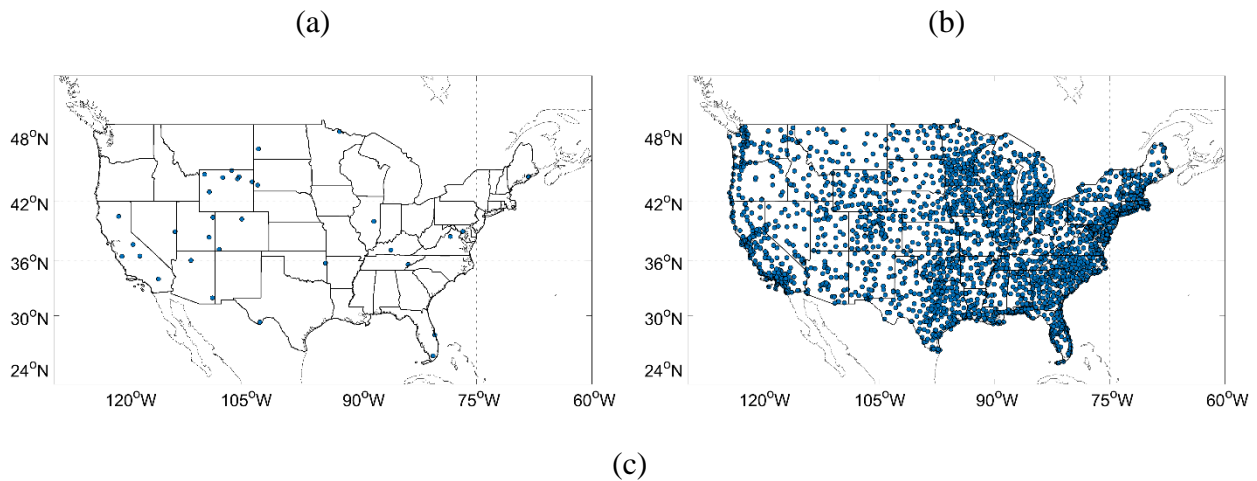
Figure S7. Diurnal O<sub>3</sub> in: (a) O<sub>3</sub> season for regions 1 to 5; (b) Non-O<sub>3</sub> season for regions 1 to 5; (c) O<sub>3</sub> season for regions 6 to 10; (d) non-O<sub>3</sub> season for regions 6 to 10

Figure S8. Time series of 24-h avg PM<sub>2.5</sub> in 10 regions within CONUS for regions 6 to 10; (d) Non-O<sub>3</sub> season for region 6 to 10. Solid curves are observed values and dash curves are predicted values

Figure S9. Annual performance for 10 regions in predicting meteorological variables of temperature at 2-m (T2), relative humidity at 2-m (RH2), precipitation, and wind speed at 10-m (WS10)

Figure S10. Difference of VOC emissions from pt\_oilgas sector in 2016 NEI comparing to the emissions used in

Figure S11. (a) Monthly variation of domain-wide surface emissions, and (b) diurnal emissions of fine mode PM



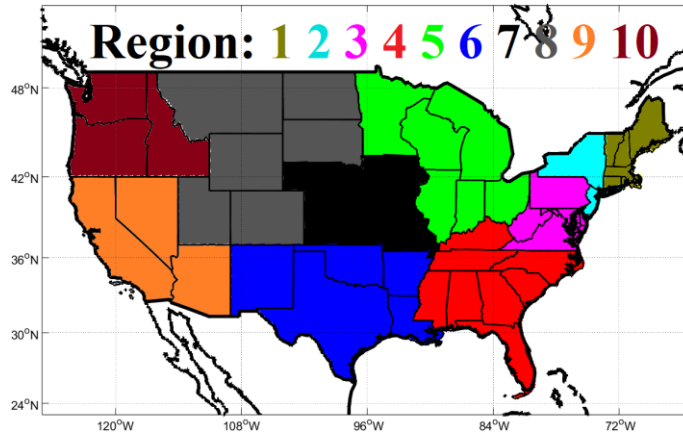


Figure S1. Site locations within CONUS of (a) CASTNET and (b) METAR. (c) Ten regions within CONUS for regional analysis: (Region 1) Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont; (Region 2) New Jersey, and New York; (Region 3) Delaware, Washington D.C, Maryland, Pennsylvania, Virginia, and West Virginia; (Region 4) Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee; (Region 5) Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin; (Region 6) Arkansas, Louisiana, New Mexico, Oklahoma, and Texas; (Region 7) Iowa, Kansas, Missouri, and Nebraska; (Region 8) Colorado, Montana, North Dakota, South Dakota, Utah, and Wyoming; (Region 9) Arizona, California, and Nevada; and (Region 10) Idaho, Oregon, and Washington

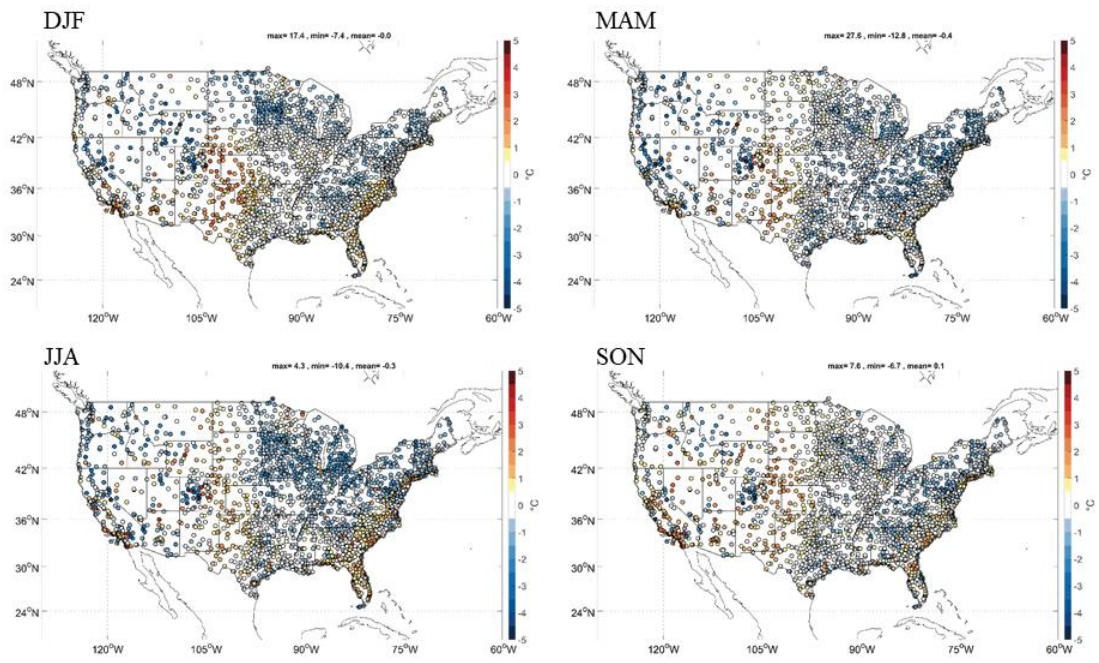


Figure S2. Spatial distribution of MBs for forecasted seasonal mean T2 by GFSv15-CMAQv5.0.2 against observations from METAR

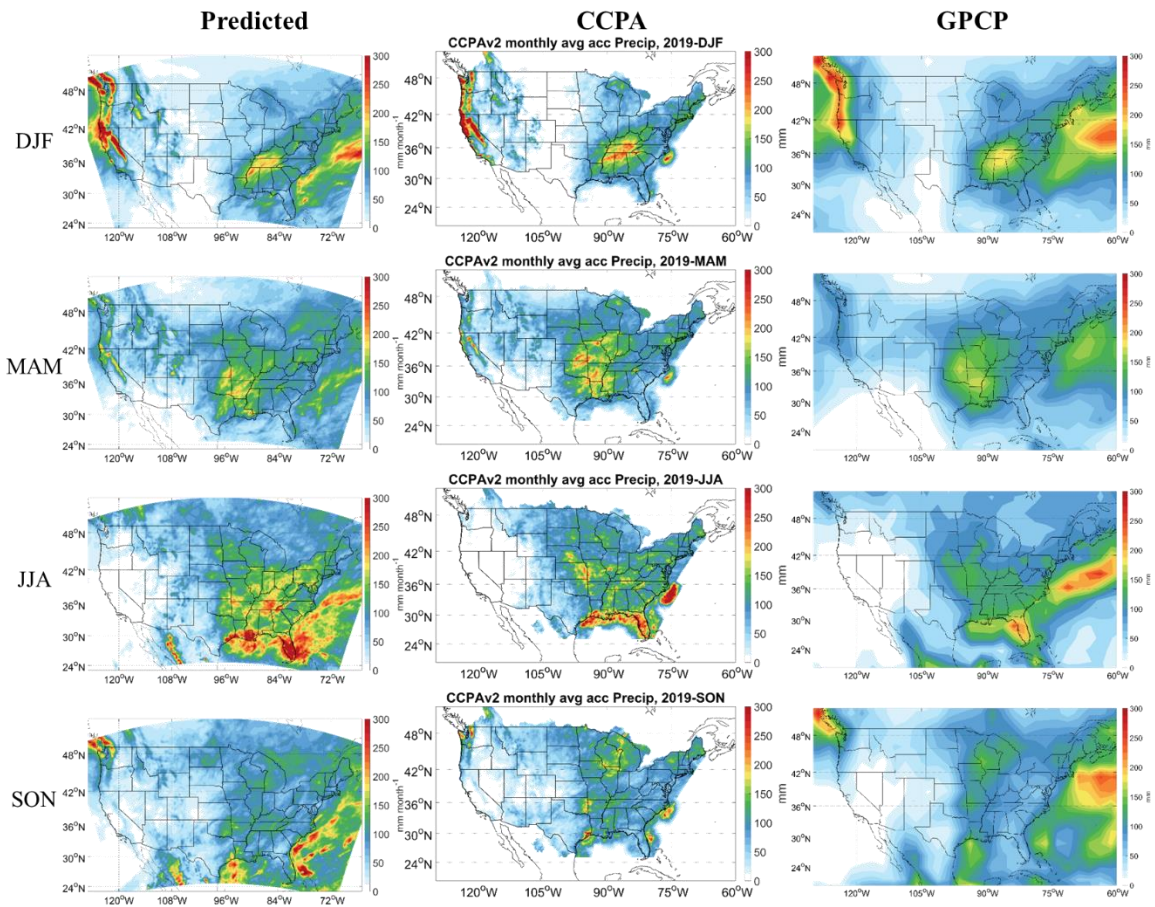


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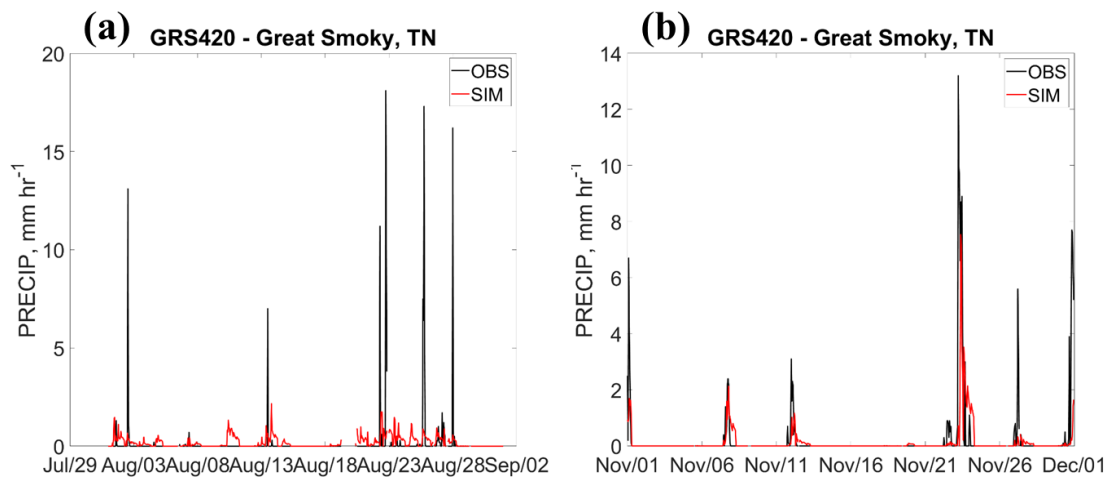


Figure S4. Time series of observed and predicted hourly precipitation at two CASTNET sites at site GRS420 in



Tennessee during (a) Jan, (b) July, (c) Aug, and (d) Nov.

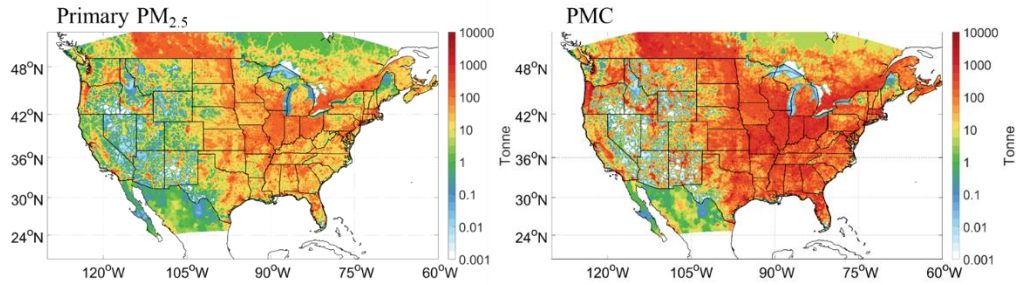


Figure S5. Spatial distribution of annual area emissions in anthropogenic sectors for primary PM<sub>2.5</sub>, and coarse mode PM (PMC)

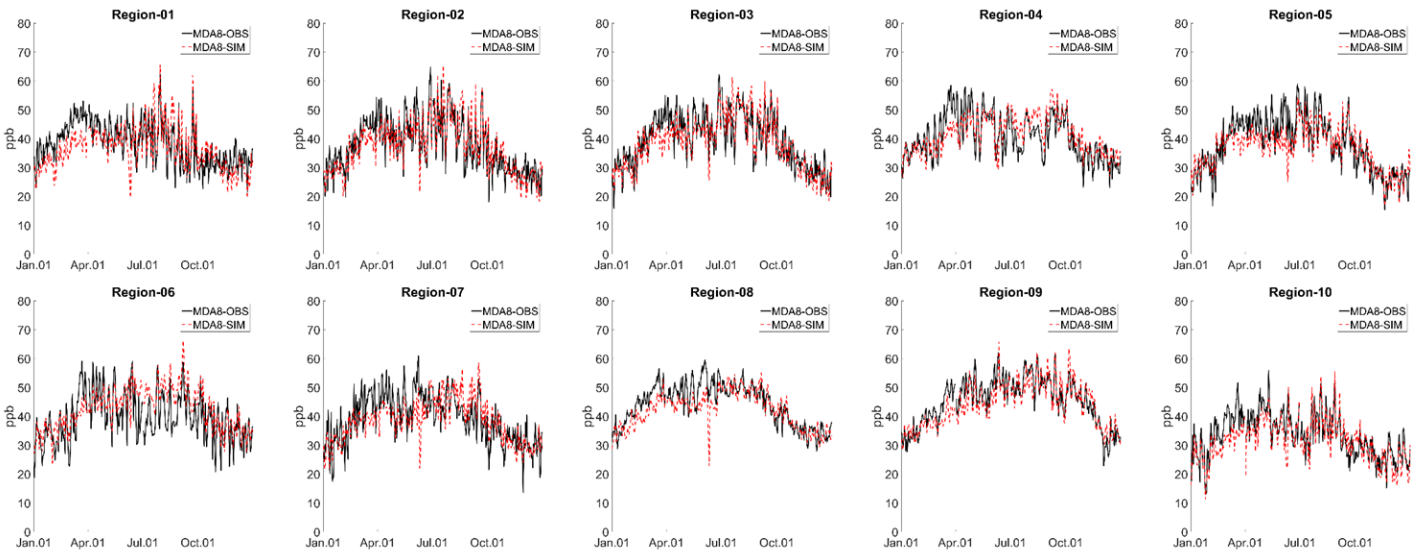


Figure S6. Time series of daily maximum 8-hr O<sub>3</sub> in 10 regions within CONUS

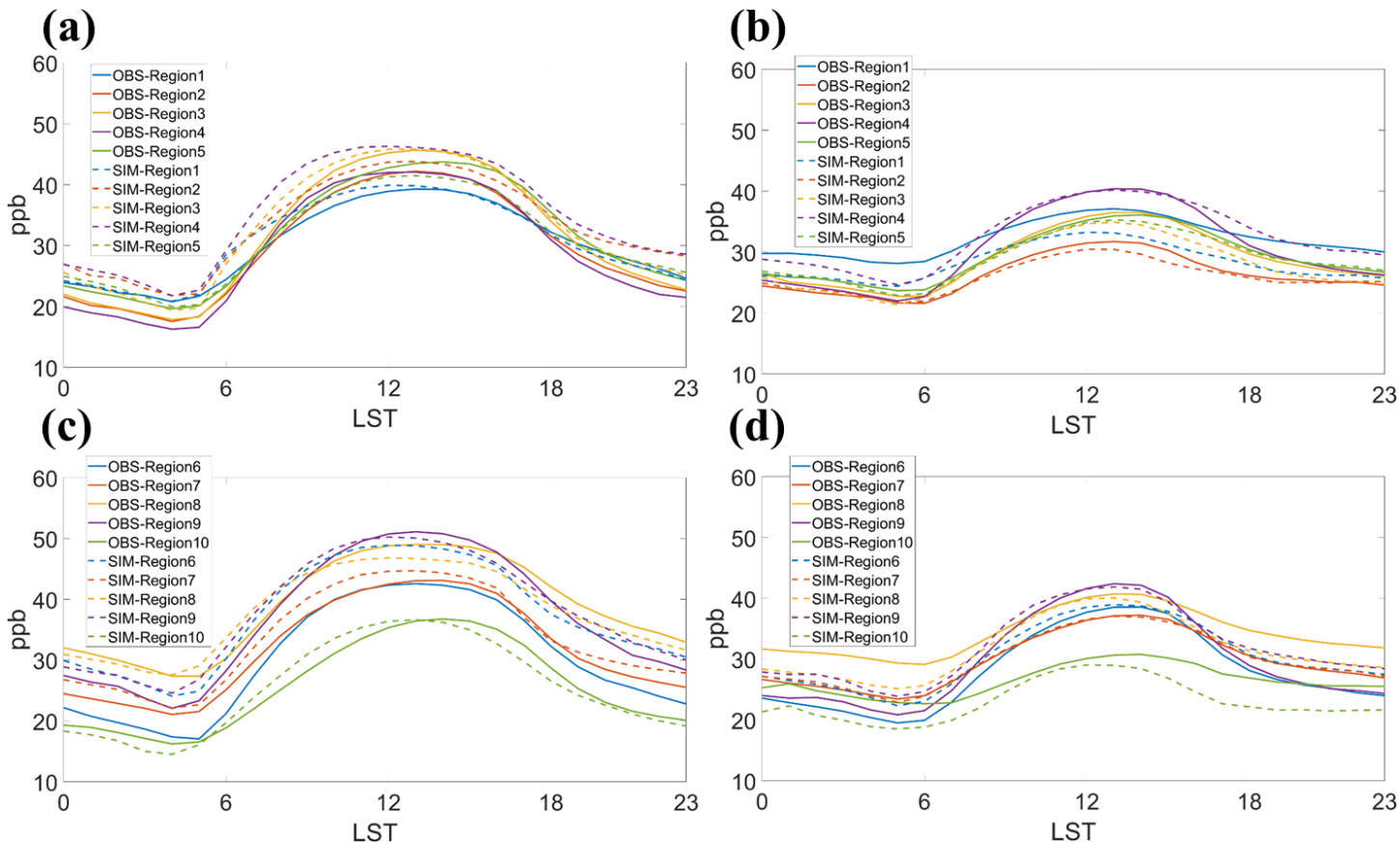


Figure S7. Diurnal O<sub>3</sub> in: (a) O<sub>3</sub> season for regions 1 to 5; (b) Non-O<sub>3</sub> season for regions 1 to 5; (c) O<sub>3</sub> season for regions 6 to 10; (d) non-O<sub>3</sub> season for regions 6 to 10

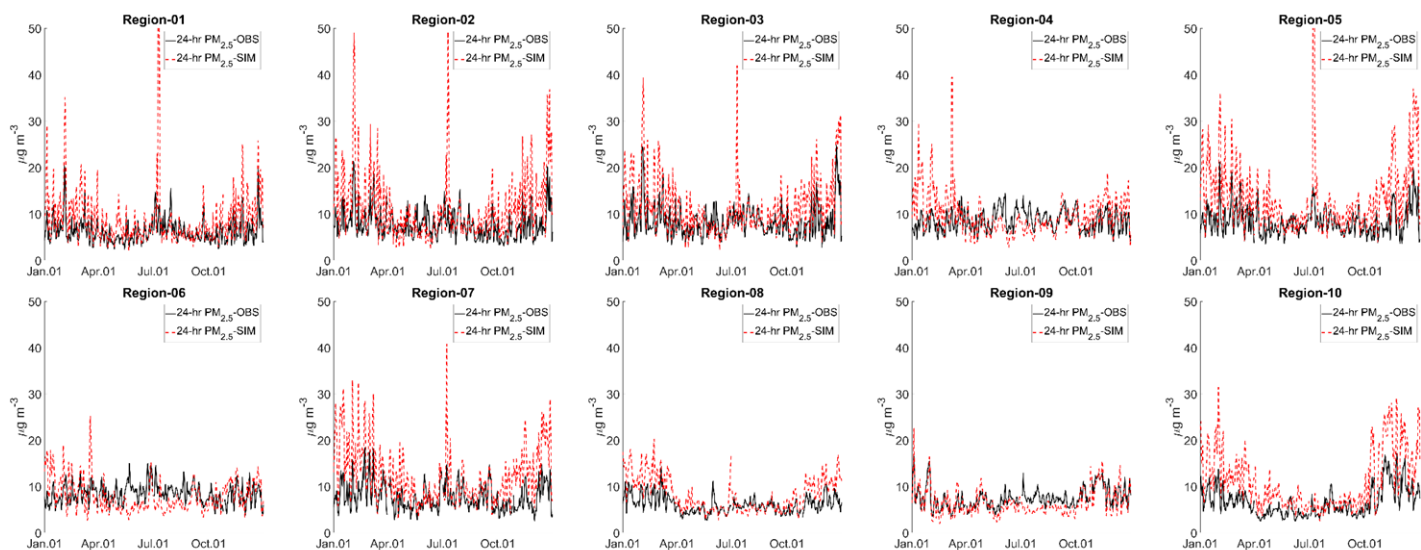


Figure S8. Time series of 24-h avg PM<sub>2.5</sub> in 10 regions within CONUS for regions 6 to 10; (d) Non-O<sub>3</sub> season

for region 6 to 10. Solid curves are observed values and dash curves are predicted values

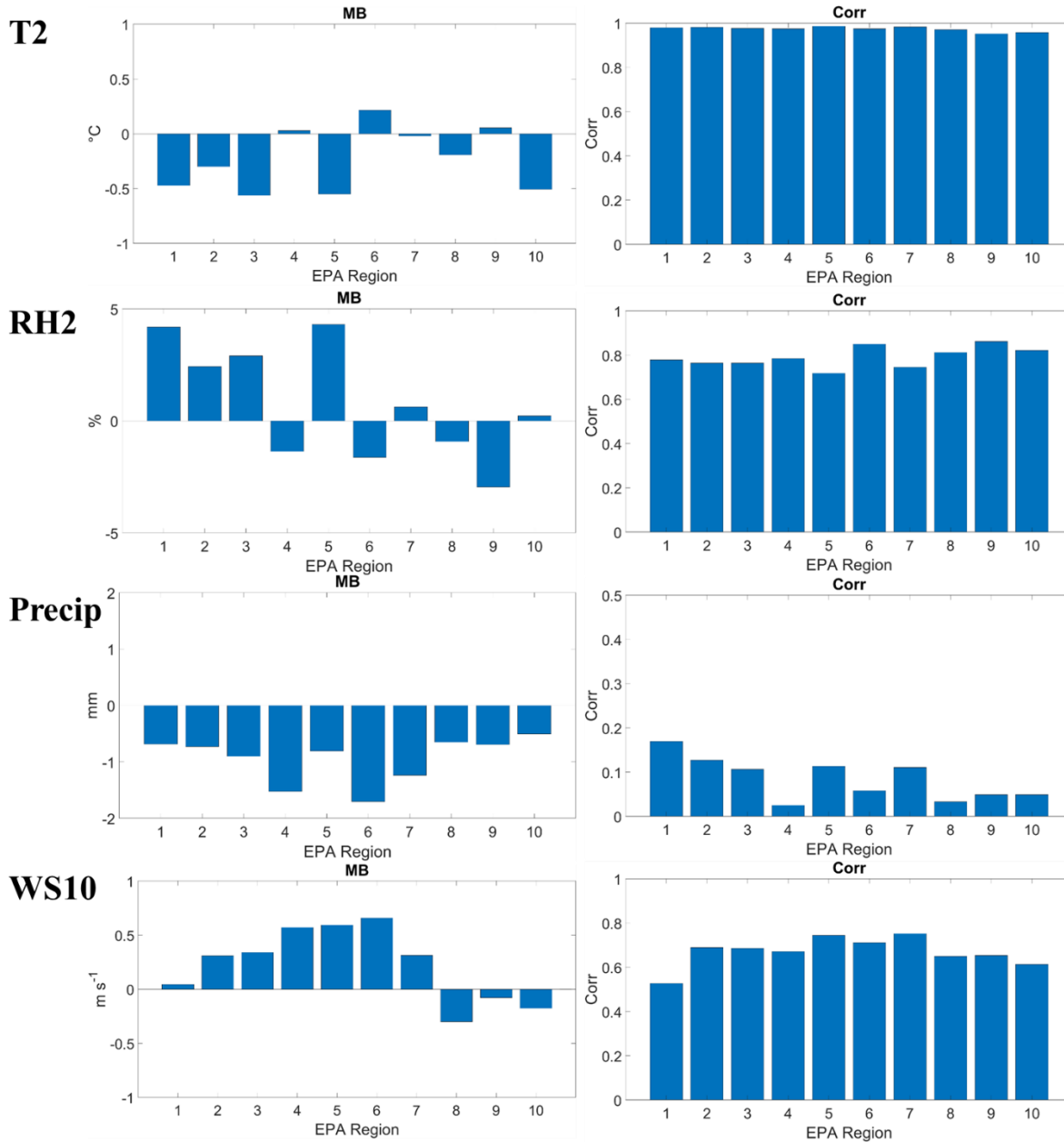


Figure S9. Annual performance for 10 regions in predicting meteorological variables of temperature at 2-m (T2), relative humidity at 2-m (RH2), precipitation, and wind speed at 10-m (WS10)

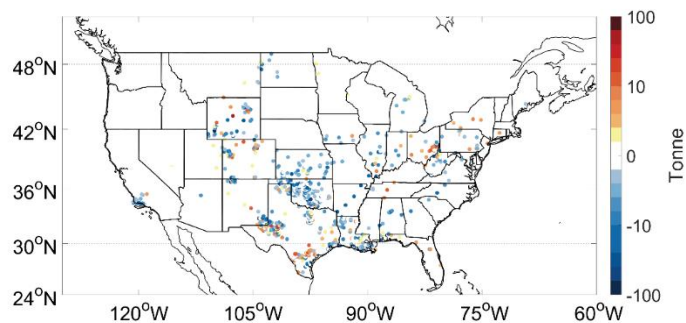


Figure S10. Difference of VOC emissions from pt\_oilgas sector in 2016 NEI comparing to the emissions used in this study

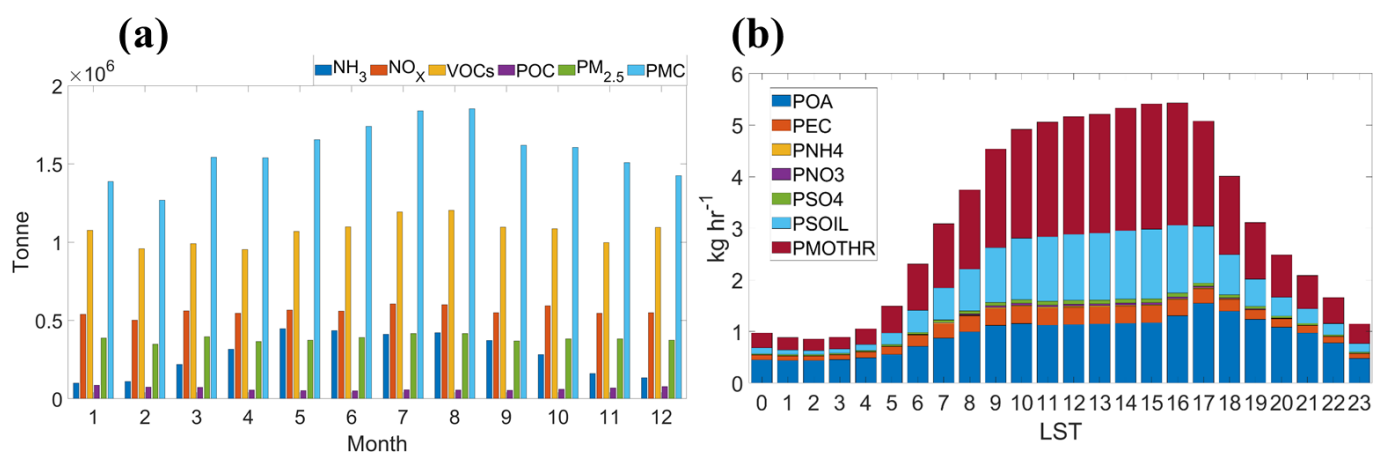


Figure S11. (a) Monthly variation of domain-wide surface emissions, and (b) diurnal emissions of fine mode PM

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