

1 *Supplement of*

2

3 **Constraints on NO_x emission in Thailand using GEMS satellite data**

4

5

6 Thongsame et al.

7

8 *Correspondence to:* Worapop Thongsame (t.worapop@gmail.com)

9

10

11

12

13

14

15

16

17

18

19

20

21

22

23

24

25

26

27

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

43

44

45 **S1 The impact of the hyperparameter on IFDMB**

46

47 In this section, we evaluate the impact of C_1 and C_2 parameters on the IFDMB performance.
48 IFDMB with fixed diurnal update is applied to four different sets of $[C_1, C_2]$ parameters, and we
49 evaluate IFDMB solution as a function of iteration for each. The four $[C_1, C_2]$ parameters are
50 $[2 \times 10^{15}, 1]$, $[2 \times 10^{15}, 10]$, $[1 \times 10^{14}, 1]$, and $[1 \times 10^{14}, 10]$. We find that iteration five is the optimal
51 iteration for $[2 \times 10^{15}, 1]$ and $[2 \times 10^{15}, 10]$, and iteration two is optimal for $[1 \times 10^{14}, 1]$ and $[1 \times 10^{14}, 10]$.
52 All four parameters produce similar spatial patterns in model performance (Table S1). The
53 IFDMB with fixed diurnal update significantly reduces both NMB and NRMSE relative to GEMS
54 observations across Thailand, particularly in the Bangkok Metropolitan Region.

55

56 Increasing C_1 from 1×10^{14} to 2×10^{15} molecules cm^{-2} suppresses the influence of satellite
57 constraints, resulting in higher NMB and NRMSE values for the $[2 \times 10^{15}, 1]$ and $[2 \times 10^{15}, 10]$
58 cases, especially in Central and East Thailand (Figs. S1 and S2). This is attributed to smaller
59 emission updates under high C_1 . Even though the σ_o in these regions is low (on the order of 0.5
60 $- 0.2 \times 10^{13}$ molecules cm^{-2}), the corresponding NO_2 VCDs are also relatively low, which leads to
61 a small $J_{\text{prediction}}$ compared to the $J_{\text{parameter}}$. This causes the solution to remain close to the
62 prior emissions. However, a larger C_1 value helps prevent overfitting in rural North Thailand,
63 where σ_o is much higher.

64

65 Increasing C_2 from 1 to 10 $\text{mol km}^{-2} \text{hr}^{-1}$ has minimal impact in the $[1 \times 10^{14}, 1]$ and $[1 \times 10^{14}, 10]$
66 cases. While the percentage change in emissions is relatively larger in $[1 \times 10^{14}, 10]$, the
67 improvements in NMB and NRMSE are comparable: $[1 \times 10^{14}, 1]$ reduces NMB by 66% and
68 NRMSE by 62%, whereas $[1 \times 10^{14}, 10]$ achieves 47% and 48% reductions, respectively (Table
69 S1). This is because the larger emission adjustments occur in low-emission areas, thus
70 contributing little to the overall NO_2 VCD improvements. In contrast, the effect of increasing C_2 is
71 more pronounced in the $[2 \times 10^{15}, 1]$ and $[2 \times 10^{15}, 10]$ cases. A higher C_2 value (10 $\text{mol km}^{-2} \text{hr}^{-1}$)
72 allows emissions in Central and East Thailand to be more effectively constrained by GEMS data
73 compared to $C_2 = 1$ (Figs. S1 and S2). Consequently, NMB and NRMSE improve significantly in
74 $[2 \times 10^{15}, 1]$ with $\sim 30\%$ reduction. The $[2 \times 10^{15}, 10]$ yields reductions of approximately 47% in both
75 metrics.

76

77 The parameter C_1 notably influences the relative errors between the Bangkok Metropolitan
78 Region and North Thailand. A low C_1 value (1×10^{14} molecules cm^{-2}) permits large adjustments
79 even in high error areas (Fig. S3) in GEMS like North Thailand. This greatly decreases NMB
80 and RMSE in the Bangkok Metropolitan Region, but also excessively increases bias and error in
81 North Thailand (Figs. S1 and S2). In contrast, a high C_1 (2×10^{15} molecules cm^{-2}) constrains
82 adjustments in the North, preventing over-correction and lowering bias and error in that region.
83 However, it also limits the improvement in the Bangkok Metropolitan Region.

84

85 The second parameter, C_2 , primarily affects adjustments for smaller emission sources (such as
86 rural areas). Using a smaller C_2 limits the changes in rural emissions (Fig. S3), keeping those
87 values closer to the prior and yielding lower bias and error against TROPOMI. In contrast, a
88 larger C_2 allows greater adjustments for low-emission areas, which led to higher bias and error

89 in rural North due to overfitting to the GEMS data. Overall, the adjustable parameters $[C_1, C_2]$ in
 90 IFDDB offer flexibility to manage the mismatch between GEMS and TROPOMI in the North by
 91 moderating the influence of emission updates in high-error regions and balancing between prior
 92 and posterior estimates.

93

94 **Table S1: Monthly statistical evaluation between WRF-Chem and GEMS NO₂ VCD of**
 95 **IFDDB for each $[C_1, C_2]$ parameters: $[1 \times 10^{14}, 1]$, $[2 \times 10^{15}, 1]$, $[1 \times 10^{14}, 10]$, and $[2 \times 10^{15}, 10]$.**

96

	$[1 \times 10^{14}, 1]$			$[2 \times 10^{15}, 1]$			$[1 \times 10^{14}, 10]$			$[2 \times 10^{15}, 10]$		
	MB	RMSE	<i>R</i>	MB	RMSE	<i>R</i>	MB	RMSE	<i>R</i>	MB	RMSE	<i>R</i>
All hour	28.78	58.01	0.83	58.95	106.51	0.67	31.90	56.25	0.84	44.12	78.38	0.80
8 AM	182.35	238.83	0.74	239.49	320.79	0.56	184.21	235.57	0.75	207.88	266.08	0.72
9 AM	137.07	186.46	0.81	191.50	268.58	0.69	142.48	187.51	0.80	163.54	215.74	0.81
10 AM	68.16	116.39	0.80	109.21	179.89	0.69	74.24	117.91	0.78	89.83	142.27	0.79
11 AM	22.23	67.94	0.77	51.59	112.94	0.63	26.71	67.61	0.77	38.56	87.41	0.75
12 PM	-3.62	50.73	0.72	19.85	84.19	0.55	-0.24	48.86	0.73	9.10	66.10	0.69
2 PM	-6.81	56.53	0.65	16.52	90.37	0.48	-4.75	53.50	0.68	5.78	73.10	0.61
3 PM	2.28	59.95	0.66	27.87	98.65	0.51	5.07	58.27	0.69	15.69	78.92	0.63

97

98

99

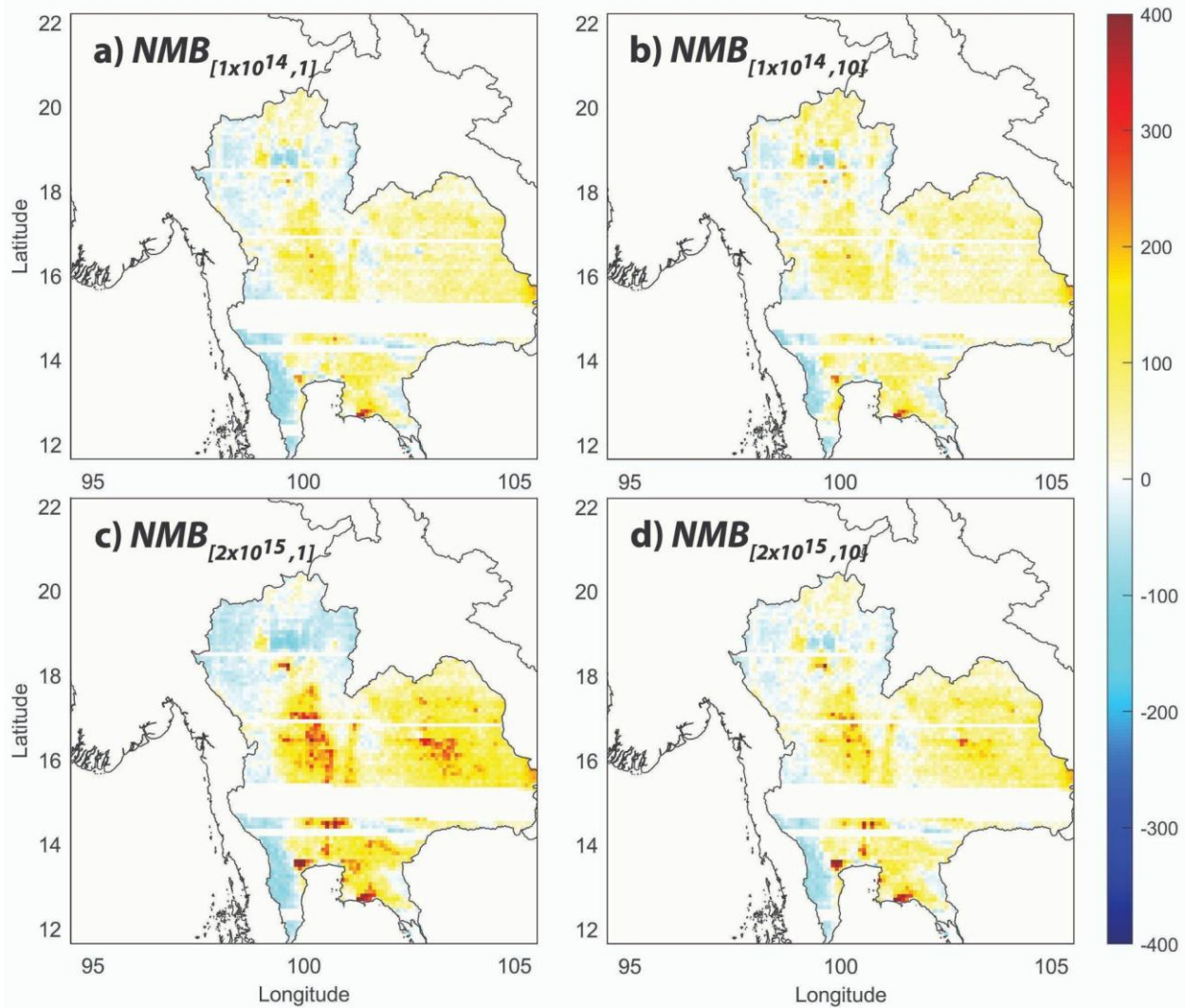
100

101

102

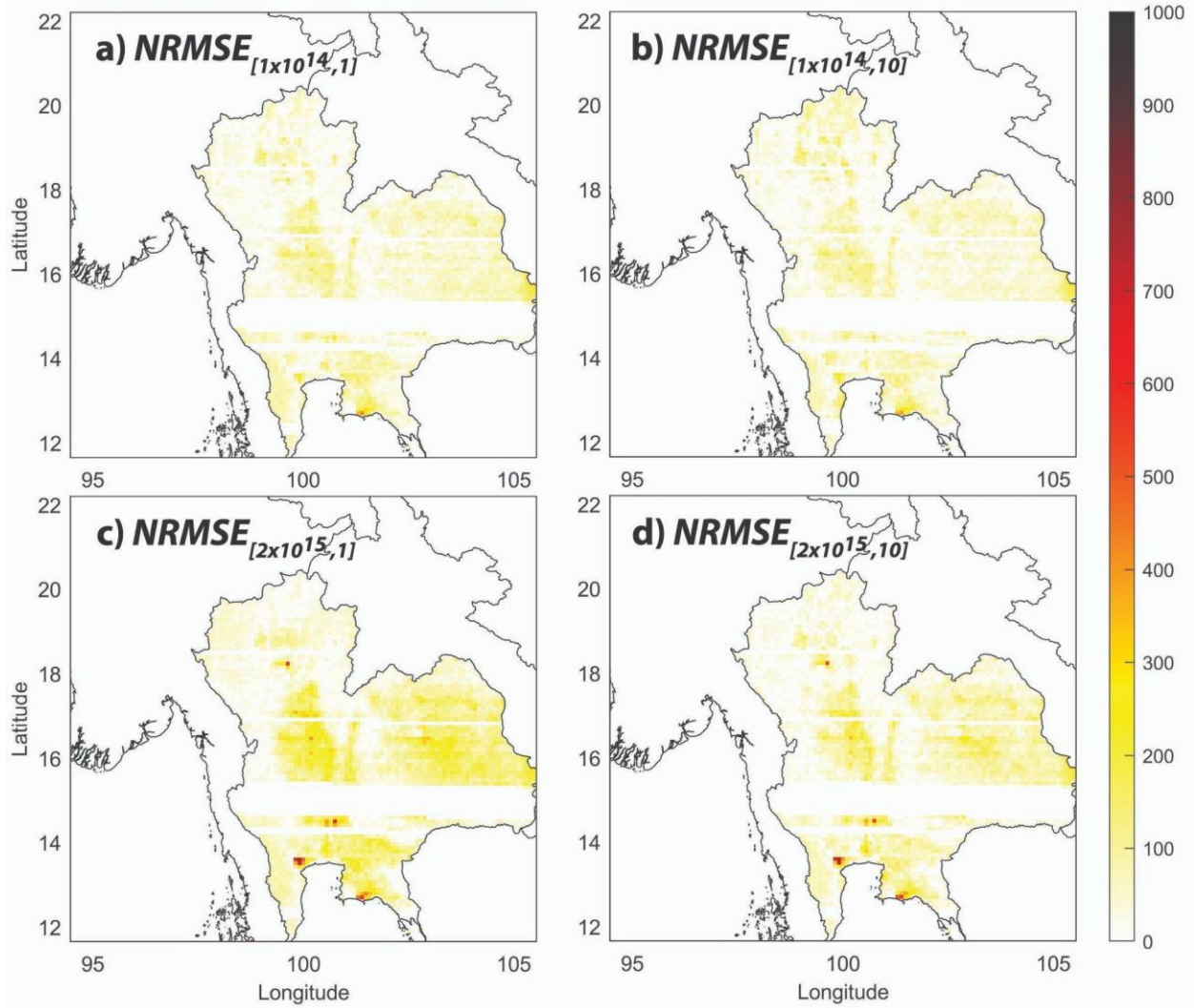
103

104



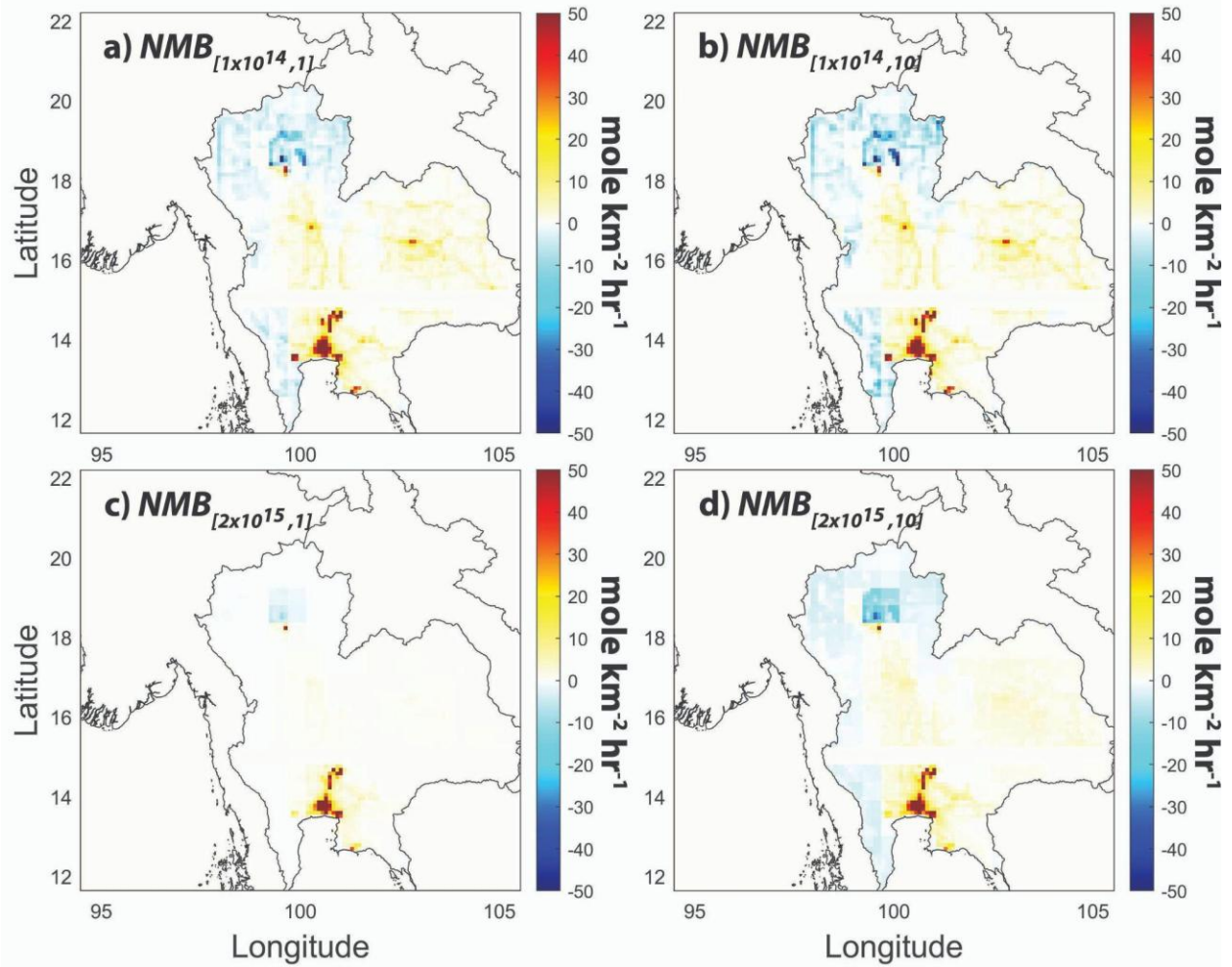
105
 106
 107
 108
 109

Figure S1: Normalized Mean Bias (NMB) of hourly NO₂ VCD between WRF-Chem and GEMS of IFDMB for September 2023 using $[C_1, C_2]$: (a) $[1 \times 10^{14}, 1]$, (b) $[1 \times 10^{14}, 10]$, (c) $[2 \times 10^{15}, 1]$, and (d) $[2 \times 10^{15}, 10]$.



110
 111
 112
 113
 114
 115
 116
 117
 118
 119
 120
 121
 122
 123

Figure S2: Normalized Root Mean Square (NRMSE) of hourly NO₂ VCD between WRF-Chem and GEMS of IFDMB for September 2023 using $[C_1, C_2]$: (a) $[1 \times 10^{14}, 1]$, (b) $[1 \times 10^{14}, 10]$, (c) $[2 \times 10^{15}, 1]$, and (d) $[2 \times 10^{15}, 10]$.



124
 125
 126
 127
 128
 129
 130
 131
 132
 133
 134
 135
 136
 137
 138
 139
 140
 141
 142

Figure S3: The emission changes from prior for IFDMB with different $[C_1, C_2]$ values: (a) changes from $[1 \times 10^{14}, 1]$, (b) changes from $[1 \times 10^{14}, 10]$, (c) changes from $[2 \times 10^{15}, 1]$, and (d) changes from $[2 \times 10^{15}, 10]$.

143 **S2 The comparison between GEMS DVCF and GEMS DOAS**

144

145 The retrieval algorithm impacts the NO₂ VCDs from the GEMS satellite. Yang et al. (2023) use
146 the Direct Vertical Column Fitting (DVCF) algorithm, whereas GEMS version 3 relies on the
147 DOAS algorithm. The two products also differ in their prior models. The DVCF algorithm (Huang
148 et al., 2022; Yang et al., 2014) finds the modeled radiance spectra (I_{TOA}) that match the satellite
149 measured spectra (I_m) by minimizing the cost function as shown in Eq (S1).

150

$$151 \ln I_m(\lambda) - \ln I_{TOA}(\lambda) = V \int_0^\infty \frac{\partial \ln I_{TOA}(\lambda)}{\partial \tau_z} S_z \sigma(\lambda, T_z) dz - \sum_{i=1}^m \xi_i \sigma_i(\lambda, T_i) +$$
$$152 \sum_{k=0}^{n-1} \frac{\partial \ln I_{TOA}(\lambda)}{\partial R} \Delta R_k (\lambda - \lambda_0)^k + \varepsilon \quad (S1)$$

153

154 where λ is the wavelength and V is the NO₂ vertical column. S_z is the shape factor derived from
155 the normalized vertical profile at the altitude (z). A more detailed explanation of the algorithm is
156 in Yang et al. (2014).

157

158 The prior model used in GEMS DVCF is GEOS-CF using the HTAP inventory, while that in
159 GEMS DOAS is GEOS-Chem using the ASIA-AQv3 inventory. These differences contribute to
160 variations in the slant columns, vertical columns, and averaging kernels between GEMS DVCF
161 and GEMS DOAS.

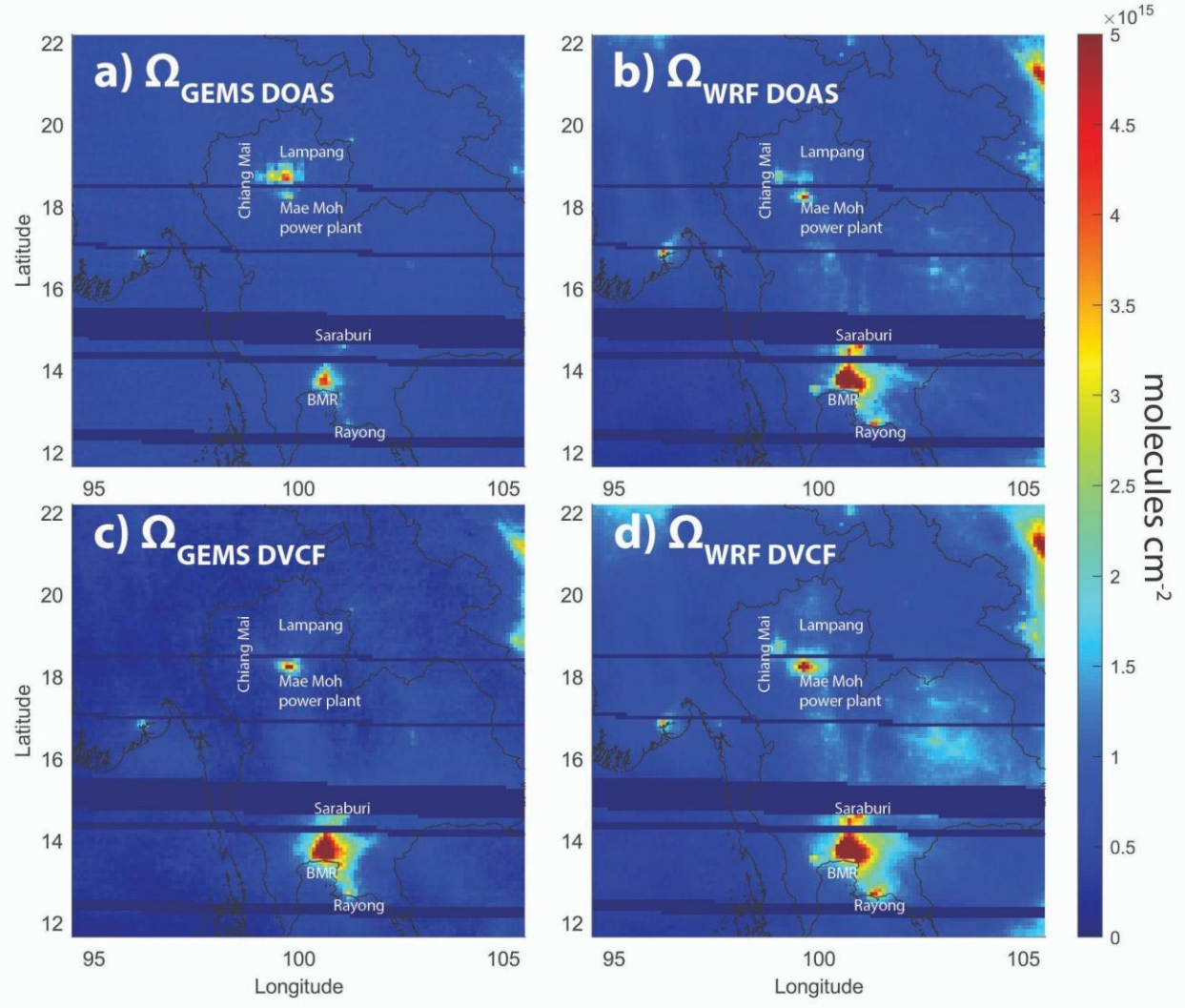
162

163 Because the averaging kernels differ between GEMS DVCF and GEMS DOAS, direct
164 comparison is not feasible; therefore, we assess the relative NO₂ distributions instead. GEMS
165 DVCF has relatively higher NO₂ over the Bangkok Metropolitan Region compared to North
166 Thailand, while GEMS DOAS has higher NO₂ levels in the North (Fig. S4). Notably, GEMS
167 DOAS has a large NO₂ signal over Lampang due to the high NO_x emissions in ASIA-AQv3. This
168 high NO₂ is absent in both GEMS DOAS and TROPOMI. The uncertainties in ASIA-AQv3 lead
169 to high retrieval error in GEMS DOAS in Lampang. Furthermore, both GEMS ACX and GEMS
170 v3 exhibit artificial striping, implying that the stripes originate from the instrument itself rather
171 than the retrieval algorithm.

172

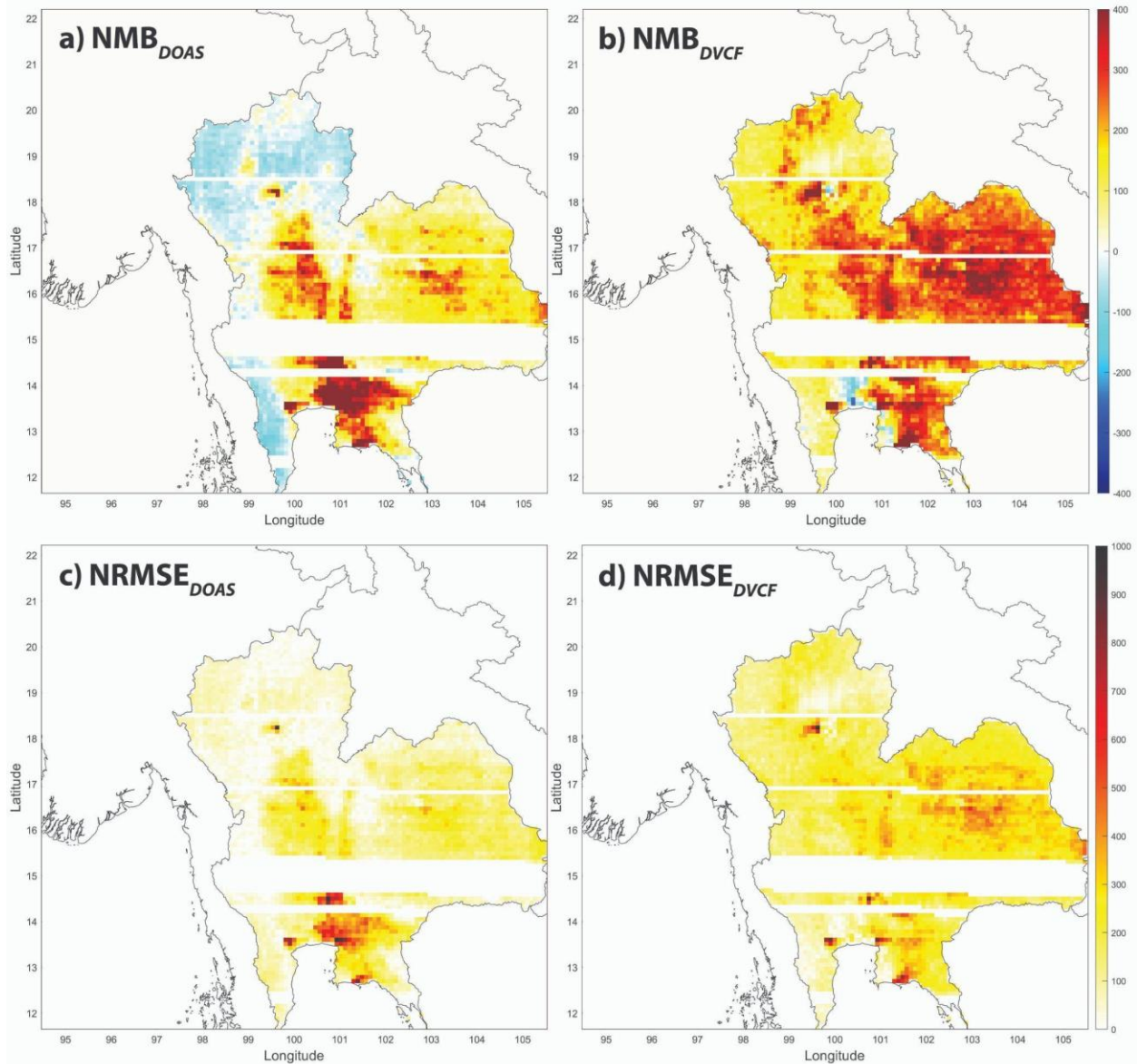
173 We also compare the magnitude of NO₂ columns between the two retrievals using the baseline
174 WRF-Chem simulation as a reference. When compared with GEMS DOAS, the baseline
175 simulation generally overestimates NO₂ VCDs across Thailand, with an NMB of 84 and an
176 NRMSE of 152 (Fig. S5). The model notably overestimates NO₂ in the Bangkok Metropolitan
177 Region but underestimates it in North and West Thailand. For GEMS DVCF, we normalize the
178 bias and error using the retrieval error from GEMS DOAS, as there is no error provided in
179 GEMS DVCF. The baseline simulation overestimates NO₂ VCDs across most of the domain,
180 with an NMB of 198 and NRMSE of 216, except in the western Bangkok Metropolitan Region
181 (Fig. S5). This suggests that the CAMS-GLOB-ANT inventory overestimates NO_x emissions in
182 Thailand when compared with GEMS DOAS. In contrast, CAMS-GLOB-ANT tends to
183 underestimate NO_x emissions in North Thailand relative to GEMS DOAS. Although GEMS
184 DVCF shows good agreement with CAMS-GLOB-ANT over major NO_x sources such as
185 Bangkok, Rayong, and the Mae Moh power plant, it yields much lower NO₂ VCDs in small cities

186 and background regions compared to these urban and industrial areas. Additionally, GEMS
 187 DVCF shows a broader spatial spread of NO₂ over the Bangkok Metropolitan Region than
 188 TROPOMI. Considering these characteristics, we adopt the GEMS DOAS product for this study.
 189



190
 191 **Figure S4: Monthly average tropospheric NO₂ VCD in September 2023 from GEMS DOAS**
 192 **(a) and GEMS DVCF (c), the baseline simulation applying the averaging kernel from**
 193 **GEMS DOAS (b) and GEMS DVCF (d). High NO₂ VCDs are observed over urban areas**
 194 **such as Chiang Mai, Lampang, and the Bangkok Metropolitan Region (BMR), as well as**
 195 **over the Mae Moh power plant and industrial zones in Saraburi and Rayong.**

196
 197
 198
 199



200
 201 **Figure S5: Normalized Mean Bias (NMB) of NO₂ VCD between the baseline simulation and**
 202 **GEMS DOAS (a) and GEMS DVCF (b). Normalized Root Mean Square Error (NRMSE) of**
 203 **NO₂ VCD between the baseline simulation and GEMS DOAS (c) and GEMS DVCF (d).**

204
 205
 206
 207
 208
 209
 210
 211
 212
 213

214 **S3 Uncertainty in GEMS DOAS due to ASIA-AQv3 Emission Inventory**

215

216 According to the GEMS DOAS team (private communication), the operational GEMS version 3
217 uses the ASIA-AQv3 anthropogenic emissions inventory as input for its prior GEOS-Chem
218 model. This prior is used to derive key retrieval parameters, including air mass factors, shape
219 factors, and averaging kernels. In our study period (September 2023), biomass burning in
220 Thailand is minimal (late wet season), so anthropogenic emissions are the dominant source of
221 NO₂. Consequently, the ASIA-AQv3 inventory can exert a significant influence on the retrieved
222 GEMS NO₂ VCDs over Thailand during this time.

223

224 We discovered that the ASIA-AQv3 inventory contains an anomalously high NO_x point source in
225 Lampang. The magnitude of this single source in ASIA-AQv3 is significantly larger than the NO_x
226 emissions allocated to known major sources like the Mae Moh power plant or even the Bangkok
227 Metropolitan Region, within the same inventory. This large Lampang emission does not appear
228 in the CAMS or the HTAP global inventories (Fig. S6), and there are no known large power
229 plants or industrial facilities in Lampang city that would justify such a high emission. Notably, the
230 total NO_x emissions for Thailand in ASIA-AQv3 are of the same order as those in CAMS and
231 HTAP, implying that the Lampang point source significantly contributes to total NO_x emissions
232 in Thailand. In other inventories, by contrast, the Bangkok Metropolitan Region and the Mae
233 Moh power plant are the main NO_x contributors. This suggests that ASIA-AQv3's Lampang
234 point source might be too high for NO_x emissions in Thailand.

235

236 Our inversion results indicate that ASIA-AQv3 indirectly affects the top-down emission
237 estimates. The IFDMB posterior NO_x emissions for North Thailand appear to be influenced by
238 the Lampang point source (Fig. S7). Because our WRF-Chem model and GEMS data are
239 aggregated onto a coarse grid (~81 × 81 km²), any extreme point source signal in the GEMS
240 observations tends to be spatially spread out over the surrounding area. As a result, the
241 influence of the Lampang point source can be seen in the posterior emission field over a broad
242 area of North Thailand. However, since we did not use ASIA-AQv3 directly to adjust the
243 emissions, the posterior emissions do not simply replicate the ASIA-AQv3 spatial pattern.

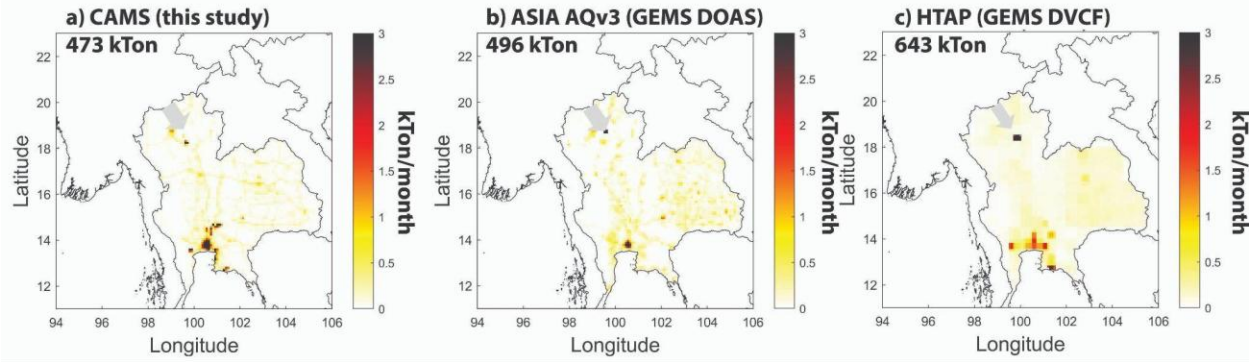
244

245 Furthermore, the GEMS retrieval reported high RMSE for NO₂ VCDs in the area around this
246 Lampang point source. In future applications of GEMS data, we recommend filtering the satellite
247 data not only by the standard quality flags but also by excluding data points with abnormally
248 high errors. This is because the RMSE (order of 10¹³) in GEMS version 3 is relatively low
249 compared to the NO₂ VCDs (order of 10¹⁵). Consequently, the weighting by σ in the cost
250 function is insufficient to handle this uncertainty. Applying such an error filter would help remove
251 spurious signals and improve the robustness of emission updates derived from GEMS satellite
252 observations.

253

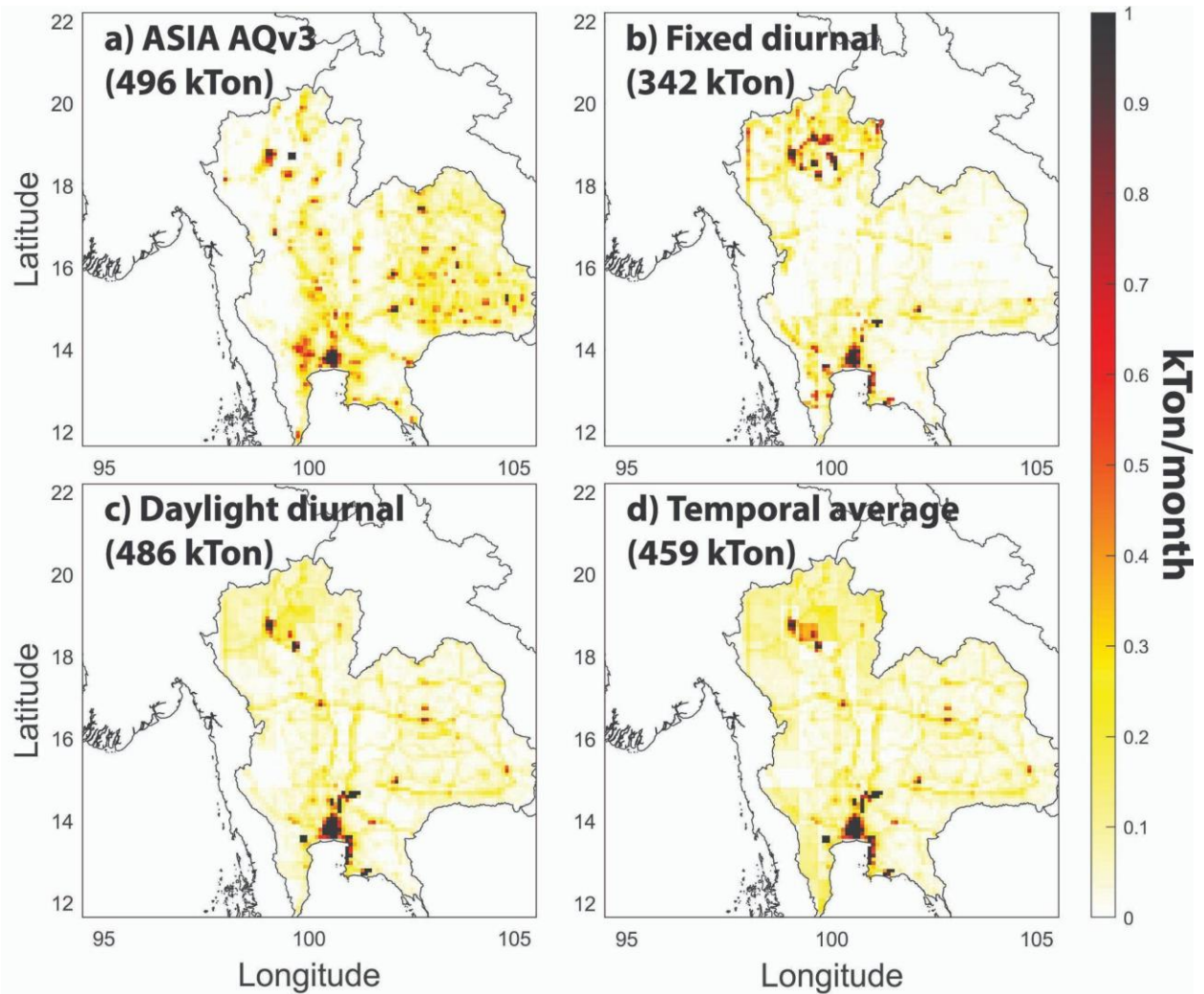
254

255



256
257
258
259
260
261
262

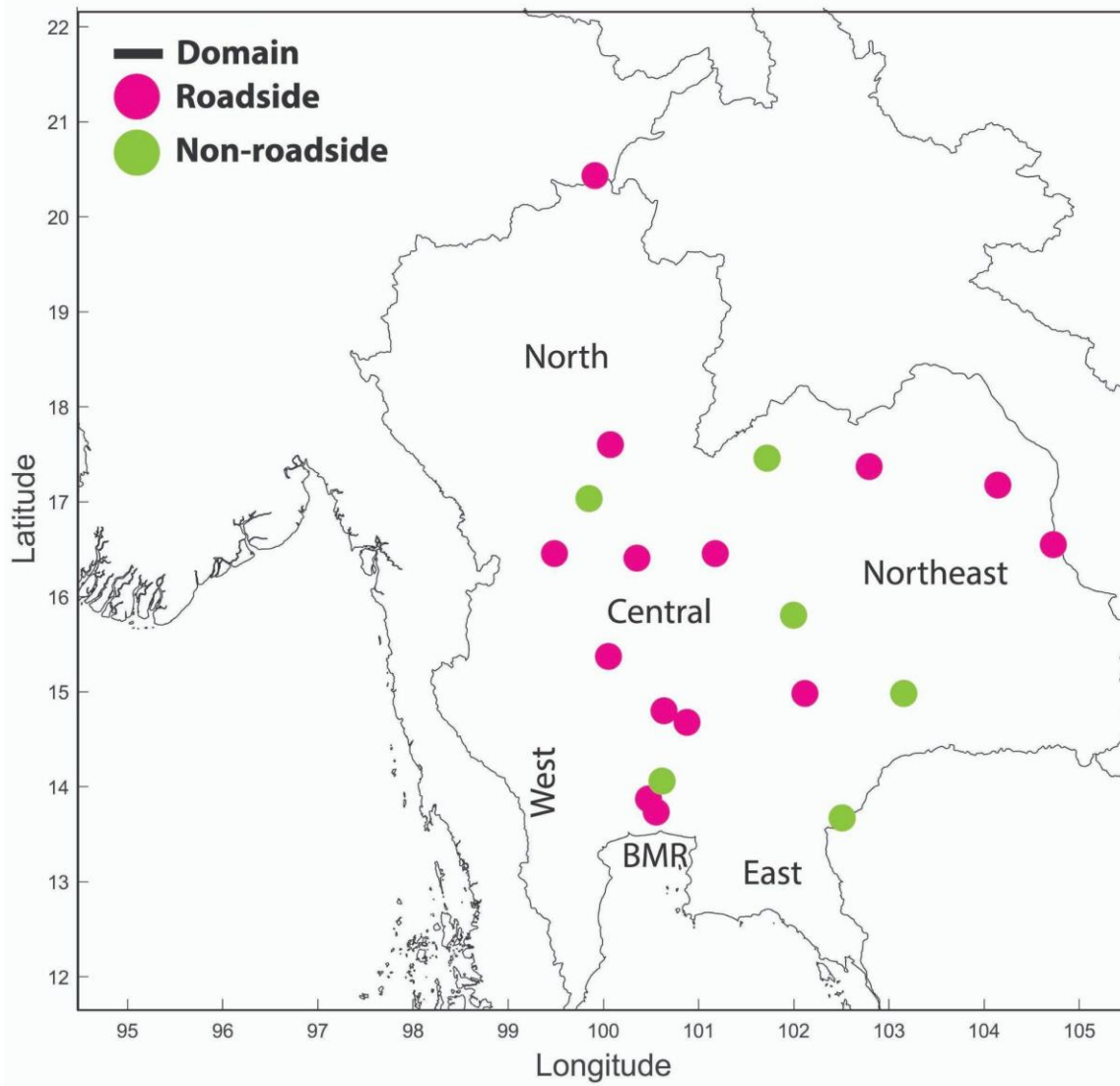
Figure S6: The comparison of NO_x emissions during September 2023 from three different inventories: a) CAMS, b) ASIA AQv3, and c) HTAP. The arrow points to the high NO₂ VCDs in GEMS DOAS.



263
264
265

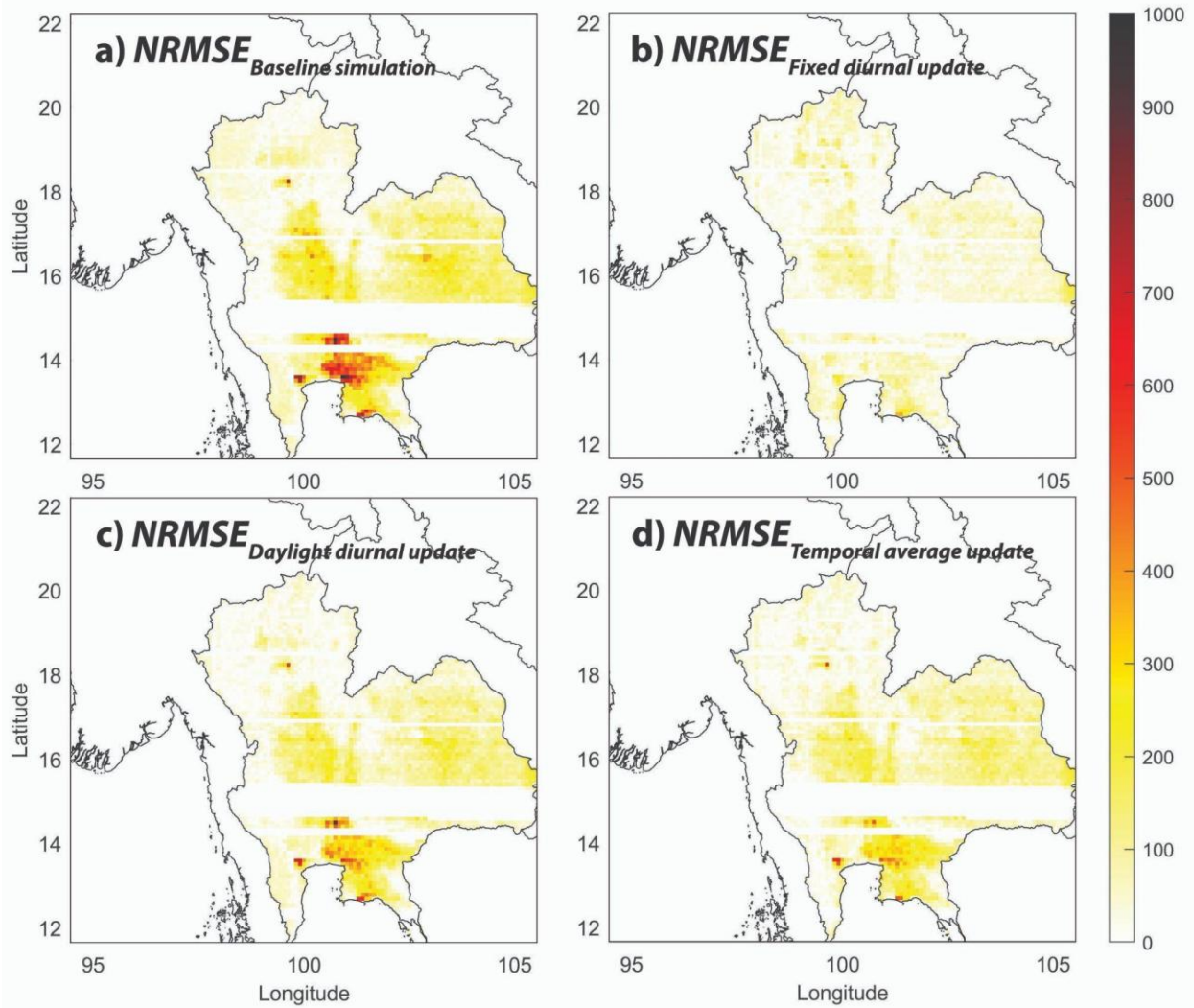
Figure S7: The comparison of NO_x emissions between ASIA AQv3 and our posterior emissions in September 2023.

266
267
268
269
270
271
272
273
274
275
276
277
278
279
280
281
282
283
284
285
286
287
288
289
290
291
292
293
294
295
296
297
298
299
300
301
302
303
304
305
306
307
308
309

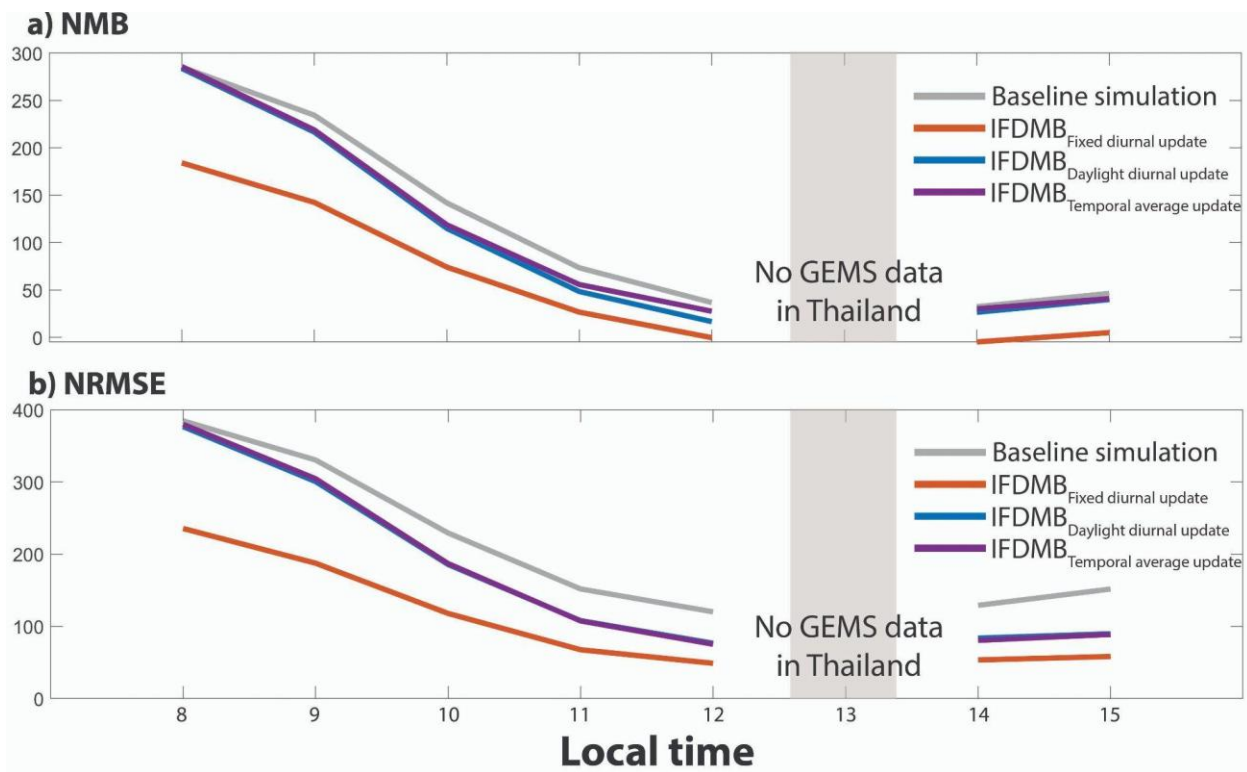


311
312 **Figure S8: Model domain and location of PCD stations, classified as roadside (pink) and**
313 **non-roadside (green). BMR is the Bangkok Metropolitan Region.**

314
315
316

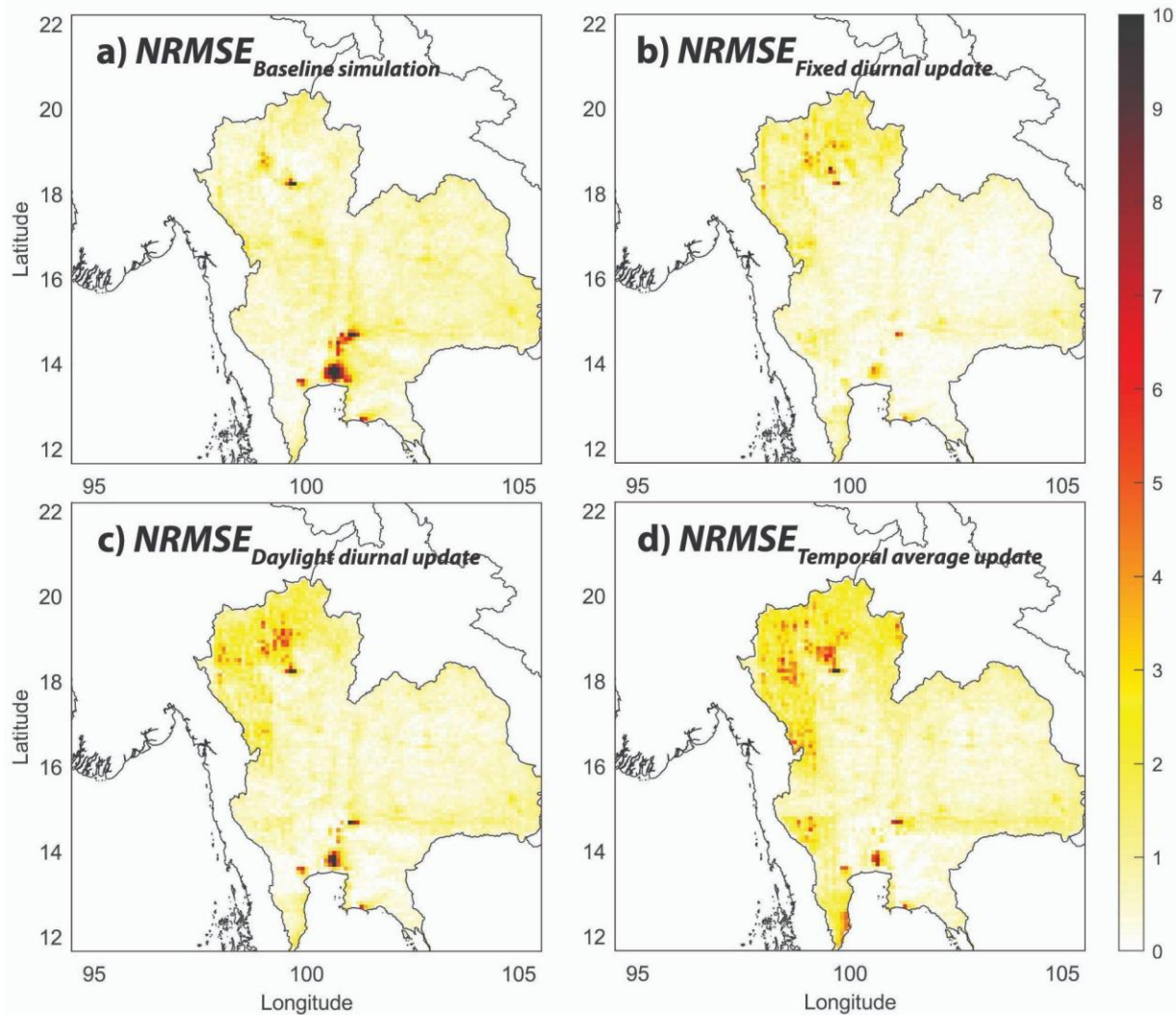


317
 318 **Figure S9: Normalized Root Mean Square (NRMSE) of NO₂ VCD between WRF-Chem and**
 319 **GEMS of IFDMB for September 2023 using (a) prior emissions, and emissions updated by**
 320 **(b) fixed diurnal, (c) daylight diurnal, and (d) temporal average update schemes.**
 321



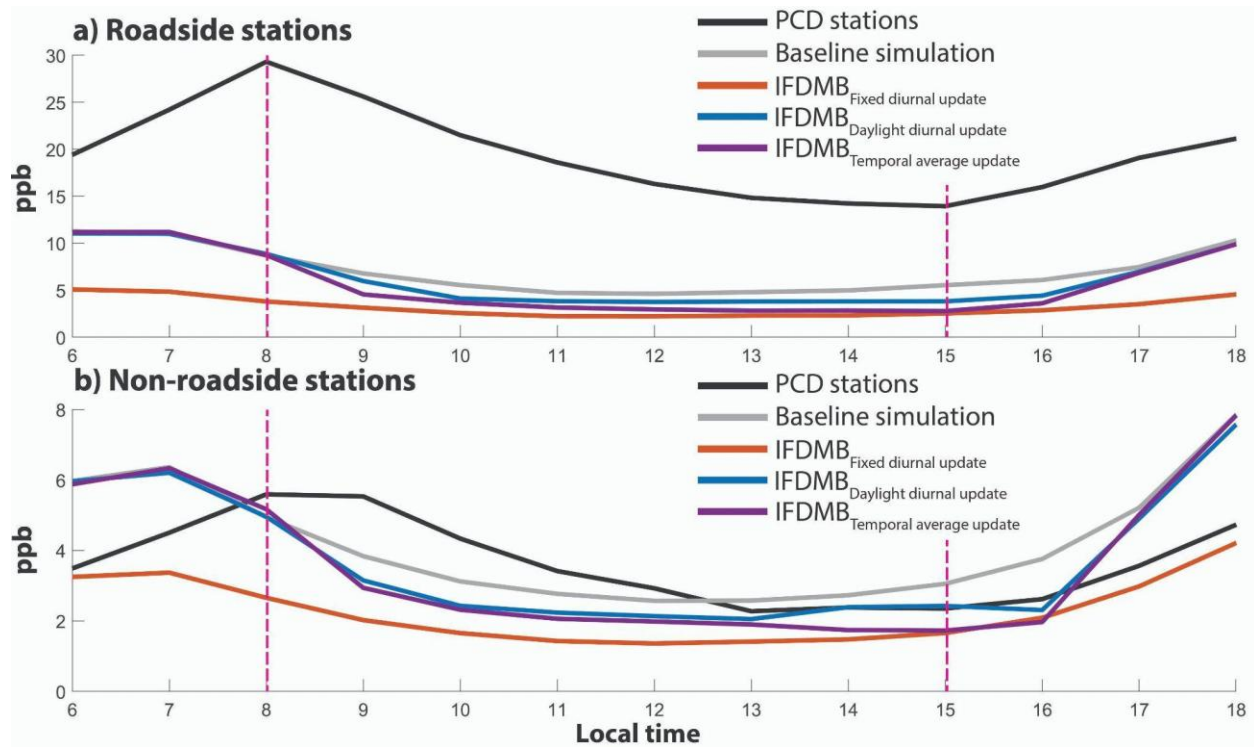
322
323
324

Figure S10: Monthly statistical evaluation between WRF-Chem and GEMS NO₂ VCD of each hour averaged from Thailand grid cells.



325
 326 **Figure S11: NRMSE of NO₂ VCD between WRF-Chem and GEMS of IFDDB for September**
 327 **2023 using (a) prior emissions, and emissions updated by (b) fixed diurnal, (c) daylight**
 328 **diurnal, and (d) temporal average update schemes.**

329
 330
 331



332
 333
 334
 335
 336
 337
 338
 339
 340
 341
 342
 343
 344
 345
 346
 347
 348
 349
 350
 351
 352
 353
 354
 355
 356
 357

Figure S12: The monthly average diurnal profile of surface NO_x mixing ratios from PCD stations (black) and WRF-Chem: the baseline simulation (gray), IFDMB with fixed diurnal update (orange), IFDMB with daylight diurnal update (blue), and IFDMB with temporal average update (purple). PCD stations are classified into roadside stations (a) and non-roadside stations (b). The pink lines mark the GEMS overpass times in Thailand from 08:00 - 15:00 local time.

358
359
360
361
362
363

Supplement table

Table S2: Monthly statistical evaluation between TROPOMI NO₂ VCD and WRF-Chem for IFDMB with different update schemes for Thailand and BMR.

Thailand	NMB (unitless)	NRMSE (unitless)	R
Baseline simulation	0.80	1.21	0.79
IFDMB _{Fixed diurnal}	0.60	0.86	0.61
IFDMB _{Daylight diurnal}	0.84	1.19	0.63
IFDMB _{Temporal average}	1.05	1.41	0.47

BMR	NMB (unitless)	NRMSE (unitless)	R
Baseline simulation	3.46	5.26	0.90
IFDMB _{Fixed diurnal}	0.59	1.25	0.93
IFDMB _{Daylight diurnal}	1.58	3.22	0.88
IFDMB _{Temporal average}	0.66	2.05	0.82

364
365
366
367
368
369
370
371
372
373
374
375
376
377
378
379
380
381
382
383
384
385

386 **References**

387

388 Huang, X., Yang, K., Kondragunta, S., Wei, Z., Valin, L., Szykman, J., and Goldberg, M.: NO₂
389 retrievals from NOAA-20 OMPS: Algorithm, evaluation, and observations of drastic changes
390 during COVID-19, *Atmos. Environ.*, 290, 119367,
391 <https://doi.org/10.1016/j.atmosenv.2022.119367>, 2022.

392 Yang, K., Carn, S. A., Ge, C., Wang, J., and Dickerson, R. R.: Advancing measurements of
393 tropospheric NO₂ from space: New algorithm and first global results from OMPS, *Geophys. Res.*
394 *Let.*, 41, 4777–4786, <https://doi.org/10.1002/2014GL060136>, 2014.

395 Yang, K., Kondragunta, S., and Wei, Z.: The NO₂ Algorithm for GeoXO-ACX and Application to
396 GEMS and TEMPO, <https://doi.org/10.22541/essoar.170365312.22362491/v1>, 2023.

397

398