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2 **Estimation of CO₂ fluxes from Tokyo using a global**

3 **model and tower observation**

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Abstract

Quantifying emissions from megacities is important for reduction of greenhouse gases.

We used atmospheric carbon dioxide (CO₂) concentration data obtained at an altitude of around 250 m above the ground on TOKYO SKYTREE (TST; a 634-m-high freestanding broadcasting tower; 35.71°N, 139.81°E), which is located north of central Tokyo, Japan.

To use the TST observations for estimating net CO₂ fluxes from Tokyo, a global, high-resolution simulation of atmospheric CO₂ transport with CO₂ flux data from a global inverse analysis was performed. In the simulation, atmospheric CO₂ variations were well reproduced at remote sites around Japan. The application of tagged tracers in the simulation revealed that variations of CO₂ concentrations at TST were largely driven by fluxes in the southwest region of Tokyo, including the western Tokyo Bay area where huge power plants are located. Then, we performed a regression analysis of modeled and observed Tokyo-originated CO₂ concentrations, both of which were derived from the simulated background concentrations, while changing the minimum wind speed used in the analysis. The removal of low wind speeds altered the slope of the regression line, and excluding wind speeds below 7 m s⁻¹ resulted in a stabilized slope of 0.93 ± 0.08 . This stabilized regression indicated that the annual net CO₂ emission from Tokyo is 79.5 ± 6.6 Tg-C year⁻¹. Our findings demonstrate that analysis using a global high-resolution model with tagged tracers has the potential to monitor emissions changes in a megacity.

Keywords carbon dioxide; model simulation; East Asia

50 **1. Introduction**

51 The aim of the Paris Agreement in 2015 was to bring about large reductions in the
52 emissions of greenhouse gases (GHGs) to achieve the target of limiting global warming to
53 1.5/2.0 °C. The cause of the growth of atmospheric concentrations of carbon dioxide (CO₂),
54 one of the most important GHGs, is anthropogenic CO₂ emissions; 81%–91% of which are
55 from fossil-fuel combustion (IPCC, 2022). Urban areas account for 75% of global fossil-fuel
56 emissions; in addition, 55% of the global population lived in urban areas in 2018. This
57 proportion will increase to 60% by 2030, at which time one in three people are expected to
58 live in urban areas with a population of half a million or more (World Bank, 2010; UN
59 Population Division, 2018). So-called "bottom-up" approaches, in which the total emissions
60 from each source category are calculated by means of multiplying activity data by GHG
61 emission factors, are useful for estimating detailed GHG emissions data for different sectors
62 and fuel types. However, there are uncertainties in the assessment of data at an urban scale,
63 due to several factors such as the measurement technique used and data availability (Arioli
64 et al., 2020). Conversely, estimation methods using atmospheric GHG observations and
65 atmospheric transport models to estimate surface fluxes with quantifiable uncertainties are
66 referred to as "top-down" approaches (e.g., Turnbull et al., 2015). For assessing urban
67 emissions by means of a top-down approach, continuous observations of atmospheric GHG
68 concentrations at tall towers are useful because they capture representative signals from
69 emissions.

70 Tower GHG monitoring networks such as the Indianapolis Flux Experiment (INFLUX;
71 Lauvaux et al., 2016) are being deployed in some urban areas to assess urban GHG
72 emissions. Turnbull et al. (2015) estimated urban CO₂ emissions from Indianapolis using
73 flask sampling data from the INFLUX towers. The urban emissions were estimated from the
74 difference in CO₂ concentrations measured at upwind and downwind sides of the urban area.
75 Miles et al. (2021) also estimated urban CO₂ emissions using observation data from INFLUX
76 towers situated in different vegetation types. Although these multiple tower methods enable
77 estimation of urban emissions based on in situ observations, they are limited in that they
78 require data for a specific wind direction and assume an ideal condition that ignores vertical
79 or horizontal mixing, which would induce concentration changes at the boundaries of the
80 target area.

81 Tokyo, Japan, is one of the largest cities in the world, with a population of over 37
82 million as of 2018 (UN Population Division, 2018). Tokyo's main CO₂ emissions are from
83 power generation, automobiles, and industry (Long and Yoshida, 2018). Sun et al. (2021)
84 compared with the capitals of neighboring countries, and they showed that CO₂ emissions
85 from the Tokyo metropolitan area are slightly larger than those of Seoul (South Korea) and
86 half those of Beijing (China). However, the spatial distribution of emissions is centralized,
87 and 90% of CO₂ emissions are concentrated on 56% of the land area. The mean flux from
88 Tokyo is less than half that from Seoul. Especially along the shores of Tokyo Bay, there are
89 large point sources such as power plants and steel plants (Ohyama et al., 2023). In

90 residential areas, fossil-fuel CO₂ emissions come from household gas consumption and
91 traffic emissions (Hirano et al. 2015). Another important factor is inflow from East Asia,
92 where large emissions are produced. Shirai et al. (2012) analyzed aircraft CO₂ data over the
93 Tokyo area and showed a strong influence of fossil-fuel CO₂ from East Asia (mainly China)
94 in the free troposphere above 2 km over the surface. Therefore, it might be necessary to
95 consider the contribution from the strong emissions in East Asia when estimating Tokyo
96 emissions.

97 The National Institute for Environmental Studies (NIES) observes GHG concentrations
98 continuously at a height of around 250 m at TOKYO SKYTREE (TST; 35.71°N, 139.81°E),
99 a 634-m-high freestanding broadcasting tower. In this study, using the continuous TST
100 observation data, we estimated net CO₂ fluxes from the megacity area of Tokyo for two
101 years (2019 and 2020) in combination with a global high-resolution model simulation, which
102 can consistently simulate flows from out of the target area (i.e., there is no boundary
103 condition). To evaluate CO₂ fluxes from a local area, we performed a tagged tracer
104 simulation, in which independent tracers from different sources were simulated in the model.
105 We separated the atmospheric signals of the Tokyo local flux from those of other areas in
106 the tagged tracer simulation, and the contributions from different sectors and regions were
107 estimated quantitatively.

108

109 **2. Data and Method**

110 2.1 Observations

111 The atmospheric CO₂ concentrations at a height of approximately 250 m on TST have
112 been measured by NIES with a cavity ring-down spectrometer analyzer (G2401, Picarro Inc.)
113 since January 2017. CO₂ mole fractions were determined against three working standard
114 gases that were calibrated against the NIES 09 CO₂ standard scale (Machida et al. 2011). In
115 the target region, the nearly neutral mixing layer is maintained up to at least 250 m in summer
116 season even at night. Even in winter, a strongly stable layer can form aloft, which may result
117 in the mixed layer exceeding 200 m (Nakajima et al., 2018). Therefore, the observation height
118 may be included within the mixed layer.

119 Considering the inhomogeneity of CO₂ fluxes is important to analyze variations of CO₂
120 concentrations because strong point sources are scattered around the observation point.
121 Therefore, in addition to CO₂, we used ²²²Rn (hereinafter simply called Rn) data in the
122 analysis. Rn is a natural radioisotope with a half-life of 3.8 days and has a relatively
123 homogeneous flux field over land. Because Rn is produced by decay of ²²⁶Ra in soil, the land
124 surface is the dominant global source, and the flux is often assumed to be constant over land
125 (Jacob et al., 1997). To evaluate the effect of flux inhomogeneity, we performed a similar
126 analysis for both Rn and CO₂. Rn concentrations are observed at the same height on TST
127 as CO₂ concentrations with the electrostatic collection method developed by the National
128 Institute of Advanced Industrial Science and Technology and the Meteorological Research
129 Institute (MRI) of the Japan Meteorological Agency (Wada et al., 2010). Continuous

130 observations of Rn started in February 2018.

131

132 *2.2 Model simulation*

133 We simulated atmospheric CO₂ concentrations at TST from January 2019 to December
134 2020 using the Nonhydrostatic ICosahedral Atmospheric Model (NICAM: Tomita and Satoh,
135 2004; Satoh et al., 2008, 2014). NICAM has been developed as a global high-resolution
136 simulation (e.g., Kodama et al., 2021). The atmospheric tracer transport model version
137 named NICAM-based Transport Model (NICAM-TM: Niwa et al., 2011) has been developed
138 and used for CO₂ and other trace gas simulations by virtue of the perfect mass conservation
139 property of NICAM. The NICAM original icosahedron consists of 20 triangles to describe the
140 Earth, and this state is called as glevel-0. The “glevel-n” represents the grid division level.
141 By dividing each triangle into four small triangles, n increases by 1 and the horizontal model
142 resolution becomes higher. The shape of grid is hexagon, except that it is pentagon at only
143 twelve points inherited from the original icosahedron’s vertices. Because CO₂ is a long-lived
144 tracer and requires a long-term simulation, NICAM-TM has been used with a low horizontal
145 resolution of “glevel-5” or “glevel-6” (Niwa et al., 2012, 2021), corresponding to mean grid
146 intervals of ~223 and 112 km, respectively. NICAM is a general circulation model, and wind
147 velocities and directions modeled by NICAM were used for the wind analysis (Fig. S1).

148 We used NICAM-TM with the high resolution of glevel-9 (mean grid interval ~14 km)
149 for the atmospheric CO₂ transport simulation (Fig. 1a). This horizontal resolution is the

150 highest for our available computing resources to perform a two year-long integration. Ours
151 is the first study to use the high-resolution NICAM for CO₂ simulation, though several studies
152 of short-lived species or aerosols have already been performed (Ishijima et al., 2018; Goto
153 et al. 2020). As demonstrated by Ishijima et al. (2018), synoptic variations are better
154 simulated at a remote site by the high-resolution NICAM; however, that high-resolution
155 model has not yet been used for assessing emissions at a local scale such as Tokyo. Usually,
156 the glevel-9 of NICAM does not use a parameterization scheme for cumulus convection;
157 however, we applied the cumulus convection scheme of the Chikira–Sugiyama Scheme
158 (Chikira and Sugiyama, 2010) that has been used at lower resolutions for consistency with
159 inverse analysis simulations. In contrast to the conventional studies with the high-resolution
160 NICAM, we applied the nudging scheme with JRA-55 horizontal wind (Kobayashi et al.,
161 2015) to reproduce real atmospheric transport fields, which is the usual approach with
162 NICAM-TM. The numbers of the vertical layers are 40, and the center of the lowest layer is
163 at ~81 m. That of the second layer is at ~249 m, which roughly corresponds to the
164 observation altitude of TST, and that of the next layer is at 430m. A summary of the model
165 setup is provided in Table 1.

166 The locations of TST, remote sites around Japan, and the Tokyo area that we define
167 in this study are illustrated in Fig. 1. In this study, the Tokyo area is defined as the land within
168 50 km of the bay area of Tokyo (35.6°N, 139.8°E) to include point sources around Tokyo
169 Bay. In this study, “CO₂tk” denotes the Tokyo-originated CO₂ concentration. "Tokyo" in this

170 paper is different from Tokyo in terms of administrative divisions. This study focuses only on
171 the Tokyo area, but we used the global model to reproduce CO₂ concentration variations. In
172 fact, simulating atmospheric plumes in a scale comparable to or smaller than the horizontal
173 model grid is challenging (Skamarock, 2004; Frehlich & Sharman, 2008; Sato et al., 2018).
174 The global model was used to estimate CO₂ concentrations in a larger scale than the Tokyo
175 area. Especially, the model calculated CO₂ concentrations originated from out of the Tokyo
176 area, which this study defines as background concentrations (Sec. 2.5). Furthermore, in the
177 analysis of CO₂ concentration variations at TST, we used wind speed thresholds to select
178 well-mixed and highly representative data (Sec. 3.3).

179 To simulate atmospheric CO₂ concentrations comparable to observations from global
180 to regional scales, we used inversion fluxes in which non-fossil-fuel fluxes were optimized
181 by the NICAM-based Inverse Simulation for Monitoring CO₂ (NISMON-CO₂; Niwa, 2020;
182 Niwa et al., 2022) with globally distributed observations. Atmospheric simulations in
183 NISMON-CO₂ were performed by NICAM with glevel-5 (~223 km) resolution, and surface
184 fluxes were optimized on 1° × 1° grids through a grid conversion scheme. The 1° × 1°
185 inversion flux data thus produced were downscaled to the glevel-9 grids for the high-
186 resolution simulation of this study. For the inverse analysis of NISMON-CO₂, fossil-fuel
187 emissions were not optimized and other natural CO₂ fluxes were optimized. The Gridded
188 Fossil Emissions Dataset (GridFED; Jones et al., 2021), which was produced by scaling
189 data from the Emissions Database for Global Atmospheric Research (EDGAR; Janssens-

190 Maenhout et al., 2019), was used for the fixed fossil-fuel emissions in the inverse analysis.
191 The same data, but regridded to the glevel-9 grid data of GridFED, were used in this study.

192 To evaluate the dependency of the fossil-fuel emissions dataset on the results of the
193 analysis, we used additional fossil-fuel emissions data from the Open-source Data Inventory
194 for Anthropogenic Carbon dioxide (ODIAC; Oda et al., 2018). The inventory is produced
195 from information on emissions intensity and the locations of power plants and satellite-
196 observed nighttime lights. The monthly mean fossil-fuel emissions of GridFED and ODIAC
197 are both high around Tokyo Bay (Fig. 2a and b), but their distributions are slightly different
198 on the east coast of Tokyo Bay (Fig. 2c). In contrast, on the western coast of Tokyo Bay,
199 where strong emissions are present, the GridFED emissions are much larger than those of
200 ODIAC. Furthermore, ODIAC emissions are slightly stronger in the northern part of the
201 Tokyo area, where fossil-fuel emissions are relatively small. In the following analysis, unless
202 otherwise noted, the GridFED but not ODIAC is used for the fossil fuel emissions.

203 In addition, R_n , which has fluxes over almost all land surfaces, was also simulated and
204 compared with the observations. The R_n results were compared with those for CO_2 to
205 evaluate the influence of the flux inhomogeneity. In the model, the flux distribution of R_n is
206 set uniformly on the basis of latitude and whether the locality is land or ocean (Jacob et al.,
207 1997). Fluxes from $60^\circ N$ to $60^\circ S$ on land and over the ocean are 1.0 and 0.005 atoms cm^{-2}
208 s^{-1} , respectively; fluxes from $70^\circ N$ to $60^\circ N$ and $70^\circ S$ to $60^\circ S$ are 0.005 atoms $cm^{-2} s^{-1}$. The
209 other fluxes around the poles are zero.

210 Observed one-hourly mean CO₂ concentrations display large variability, which cannot
211 be correctly reproduced on brief timescales by the model. For a site such as TST, where
212 strong emissions occur nearby, it is typically difficult to reproduce short-term concentration
213 variations resulting from the large influence of small-scale turbulence. Because such model
214 errors can be reduced by increasing the mean interval (Turnbull et al., 2016), we applied 12-
215 h moving averages to both simulated and observed data.

216

217 *2.3 Pre-comparison in remote sites*

218 To test the model's basic performance in simulating variations of CO₂ concentrations,
219 we used data from Hateruma Island (HAT; 24.06°N, 123.78°E; Mukai et al., 2014; Tohjima
220 et al., 2020), in the Pacific Ocean southwest of the Japanese archipelago, and on
221 Minamitorishima Island (MNM; 24.29°N, 153.98°E; Watanabe et al., 2000), the easternmost
222 island belonging to Japan, where the influence of anthropogenic CO₂ emissions is very small
223 (Fig. 1b). HAT, like TST, is operated by the NIES/the Center for Global Environment
224 Research (CGER); MNM is operated by the Japan Meteorological Agency (JMA). Both HAT
225 and MNM observed CO₂ concentrations with a nondispersive infrared absorption
226 spectrometer analyzer during the target period. Comparisons of observed and calculated
227 total CO₂ concentrations (CO₂tot) at HAT and MNM for 2019–2020 are illustrated in Fig. 3a
228 and 3b, respectively. The correlation coefficients between the model simulation and the
229 observation are 0.823 and 0.941 at HAT and MNM, respectively, with almost no bias. The

230 good agreement between the model and the observations for both the remote sites suggests
231 that the inversion flux from NISMON-CO₂ was successfully downscaled to the high-
232 resolution NICAM (note that the observations at these two sites were used in the
233 optimization of NISMON-CO₂; Niwa, 2020).

234

235 *2.4 Tagged tracer*

236 In this high-resolution simulation of NICAM-TM, several “tagged CO₂ tracers” were
237 introduced. We separate flux data by source types and regions in the tagged tracer
238 simulation. Atmospheric CO₂ concentrations from fossil-fuel emissions (CO₂ff), terrestrial
239 biospheres (CO₂bio), and the ocean (CO₂ocn) were simulated separately. Moreover,
240 atmospheric CO₂ concentrations from East Asia (China, North and South Korea, and Taiwan,
241 but excluding Japan), Japan (including Tokyo), and Tokyo were also separately calculated;
242 the Tokyo tracer was further separated into tracers from four zones and a TST-neighbor
243 area to investigate local influences. The TST-neighbor consisted of the three NICAM grids
244 closest to TST, and the area overlapped with the four Tokyo local zones (Fig. 1c). CO₂tot
245 contains the atmospheric concentrations from all emissions (not only CO₂ff, CO₂bio, and
246 CO₂ocn, but also other sources such as biomass burning) and all regions. Although the
247 calculation in CO₂tot incorporates a sufficient spin-up period, calculation of the tagged
248 tracers has no spin-up time. However, the flux distribution is located only near the
249 observation point for tagged tracers, and the contribution of background variation caused by

250 Tokyo-originated flux relative to variations in CO₂ concentration is very small. Thus, the
 251 effect of the lack of spin-up time for tagged tracers can be ignored.

252 To quantify the contributions of CO₂ fluxes to variations of CO₂ concentrations at TST
 253 from different sectors and regions, we used the variance ratio (VR), which is calculated as
 254 the ratio of the CO₂ concentration variance of a tracer to that of another tracer over a 30
 255 day-period; for example, to evaluate the impact of fossil fuel at TST, the VR was calculated
 256 from the ratio of the variance of CO_{2ff} to the variance of CO_{2tot}.

257

258 *2.5 Estimation of Tokyo-originated CO₂*

259 Background_CO₂ concentration for estimation of urban emissions could be determined
 260 only by observations, such as the value at upwind site or the daily minimum value. However,
 261 those methods may have limitation in tracking continuous changes or need to limit wind
 262 directions. Our study used the global model with the tagged tracers to calculate the
 263 background concentrations, which does not require any wind direction limitation and enables
 264 us to track continuous changes (Sec. 3.1). The background CO₂ concentration of the Tokyo
 265 area was derived from the NICAM simulation (CO_{2bg}^{NICAM}), which is defined as the
 266 simulated total CO₂ (CO_{2tot}^{NICAM}) minus the simulated Tokyo-originated CO₂ concentration
 267 (CO_{2tk}^{NICAM}):

$$268 \quad CO_{2bg}^{NICAM} = CO_{2tot}^{NICAM} - CO_{2tk}^{NICAM}. \quad (\text{Eq. 1})$$

269 CO_{2tot}^{NICAM} is calculated from all fluxes, while CO_{2tk}^{NICAM} considers only the fluxes from

270 Tokyo region in the calculation of the tagged tracer. Because the fluxes other than fossil-
 271 fuel emissions are derived from the inverse simulation, CO₂ concentrations should be
 272 globally well reproduced in the model. In fact, this assumption was confirmed by the good
 273 agreement of CO₂tot between the model and the observations at the remote sites, where
 274 influences from fossil-fuel emissions are small (Section 2.3). Therefore, it is reasonable to
 275 also use CO₂bg^{NICAM} for the background value of the observations. Thus, the Tokyo-
 276 originated CO₂ concentrations of the observations (CO₂tk^{Obs}) can be estimated by
 277 subtracting CO₂bg^{NICAM} from observed total CO₂ (CO₂tot^{Obs}):

$$278 \quad CO_2tk^{Obs} = CO_2tot^{Obs} - CO_2bg^{NICAM}. \quad (\text{Eq. 2})$$

279 In this study, we compared CO₂tk^{Obs} and CO₂tk^{NICAM} using a standardized major axis
 280 linear regression, the slope of which is used to evaluate emissions. The slope of the linear
 281 regression is much less sensitive to outlier values than the ratio of the mean value or median
 282 value (Turnbull et al., 2015; Miller et al., 2012). Since both CO₂tk^{Obs} and CO₂tk^{NICAM} were
 283 defined using the same background concentration, the linear regression was calculated with
 284 the intercept fixed to zero.

285

286 **3. Results**

287 *3.1 Comparison between the model simulation and the observations*

288 The monthly VRs of CO₂ concentrations at TST are illustrated in Fig. 4. The VRs of
 289 CO₂ff of both GridFED and ODIAC were large, and their magnitudes were greater than 0.6

290 for all months (Fig. 4a). The VR of CO₂bio increased from late spring to autumn, but it was
291 much smaller than CO₂ff. The VR of CO₂ocn was negligible. The VR of CO₂ff was large in
292 winter, with small maxima also occurring in July. Suppression of vertical mixing and
293 increased fossil-fuel consumption might have caused the winter increment of CO₂ff in urban
294 areas (Moriwaki and Kanda, 2004; Xueref-Remy et al., 2018).

295 The VR of CO₂ concentrations from each region from which a tagged tracer was
296 simulated are shown in Fig. 4b. For CO₂ff, the annual mean VR of East Asia relative to all
297 regions was less than 0.03 at TST. In contrast, the value for the Tokyo area was 0.87; thus,
298 CO₂ emissions from the Tokyo area were dominant at TST. If the effect from areas outside
299 of Japan is strong near the surface, the boundary condition becomes important when a
300 regional model is used. Our study used a global model, which did not require boundary
301 conditions. In fact, previous studies have suggested that effects from East Asia on Japan
302 are large in terms of synoptic-scale variation (Tohjima et al., 2010) and that the influence of
303 CO₂ from East Asia cannot be ignored in the free troposphere over Tokyo (Shirai et al. 2012).
304 However, our results showed that the influence of areas outside Japan, such as China, was
305 very weak at TST in terms of short-term (daily-scale) variation.

306 When CO₂ff from the Tokyo area was divided into the contributions from the four zones,
307 VR of CO₂ff from ZSW (the southwest zone of the Tokyo area) to the whole Tokyo area was
308 0.4–0.9 and dominant. During summer, particularly strong VR was simulated from ZSW (Fig.
309 4c), where strong emissions from power plants and industrial areas occur south of TST

310 along Tokyo Bay (Fig. 2a).

311 The time-series of CO_2^{tot} at TST are illustrated in Fig. 5a. CO_2^{tot} in NICAM basically
312 reproduced the observations; however, the simulated values were sometimes larger than
313 the observations. Nevertheless, the frequency of large overestimations was small: fewer
314 than 3% of data were overestimated by more than 10%. Figure 5b shows the simulated and
315 observed time-series of CO_2^{tk} at TST. The fact that the variation of the difference of CO_2^{tk}
316 between the model and the observation was almost the same as that of the CO_2^{tot} difference
317 demonstrated the dominant contribution from the Tokyo area, as already indicated by the
318 VR results (Fig. 4b).

319 Around Tokyo Bay, the predominant wind directions are north and south (Fig. 5d)
320 because of the sea breeze (Yamato et al., 2017). The northern winds are further divided into
321 northwesterly winds blowing from inland and northeasterly winds blowing from the Pacific
322 side. Therefore, we defined three wind directions as follows: NE (azimuth degree 0–120°
323 clockwise from north; 30% of all period); S (120–270°; 41%); and NW (270–360°; 29%). S-
324 wind is the most frequent wind during summer because of the development of sea breezes
325 at that time of year under the weak pressure gradient associated with the Pacific anticyclone
326 (Yamato et al., 2017). In fact, southerly winds caused by the sea breeze transport an air mass
327 with large CO_2^{ff} . The frequency of S-wind carrying large CO_2^{ff} is high in summer and causes
328 the large VR of CO_2^{ff} in July (Fig. 4a). In particular, from late July to early August of 2019,
329 the observed CO_2^{tk} was higher than that in other months by approximately 20–30 ppm (Fig.

330 5b). This marked increase is well reproduced in the model calculation. During this period,
331 the wind direction was continuously from the south (Fig. 5d). The continuous southerly wind
332 carried air parcels from sources around Tokyo Bay and caused the large CO₂tk at TST. If
333 the background concentration was estimated only by using observational data, it would be
334 difficult to capture such changes. The CO₂ background concentration estimation method
335 using the observed daily minimum value would not be able to capture those continuous
336 changes. In background estimation using multiple tower observations, available data is
337 limited by the tower locations and wind direction because it is important to select sampling
338 locations corresponding to the upwind and downwind positions of the emission source. This
339 continuous elevation of CO₂ concentrations can be appropriately recognized as being
340 derived from the Tokyo area thanks to the tagged tracer in the model.

341

342 *3.2 Wind effect on CO₂*

343 As demonstrated in Fig. 2, fossil-fuel emissions in Tokyo are stronger in the southern
344 region, around Tokyo Bay, where many industrial areas and power plants are located. This
345 flux inhomogeneity induces remarkable variations of CO₂tk with changes of wind speed and
346 direction. Figs. 6a and 7a show the two-dimensional histogram in log-scale of the observed
347 CO₂tk versus wind speed and direction, respectively. The frequency of high observed CO₂tk
348 values gradually decreases with increasing wind speed; however, it is possible, although
349 infrequent, to observe large CO₂tk even at wind speeds higher than 10 m s⁻¹ (Fig. 6a).

350 Because of the existence of high emissions around Tokyo Bay, S-wind causes the observed
351 CO_2tk values to be larger than the values associated with other wind directions (Fig. 7a).
352 The difference between calculated and observed CO_2tk ($\Delta\text{CO}_2\text{tk}$) depends on wind velocity:
353 for low wind speeds, the model frequently simulated CO_2tk values larger than the
354 observations (Fig. 6b). $\Delta\text{CO}_2\text{tk}$ also depended on wind direction: under S-wind conditions,
355 when the observed CO_2tk was large, $\Delta\text{CO}_2\text{tk}$ was also large in comparison with the values
356 for other directions (Fig. 7d).

357 The $\Delta\text{CO}_2\text{tk}$ data were divided at the median wind speed of 5.5 m s^{-1} into the upper
358 50% and lower 50% of cases. In May to June and August to September, low wind speeds
359 dominated (53%–67%), but in other months, the frequency of high wind speeds was greater
360 (>52%). Under high-wind-speed conditions, the model generally reproduced observations
361 of CO_2tk (Fig. 7c, f). However, under low-wind-speed conditions, the model tended to
362 overestimate CO_2tk frequency (Fig. 7b). In particular, during southern winds, ΔCO_2 of
363 around 10 ppm was the most frequently observed value (Fig. 7e).

364 The VR of CO_2ff from the Tokyo area and the four Tokyo zones relative to total CO_2ff
365 calculated with respect to wind speed are illustrated in Fig. 8. The VR of the Tokyo area
366 decreased slightly with increasing wind speed, but the amount of decrease was very small.
367 The VR for areas outside of Tokyo was almost zero. In addition, the VR of TST-neighbor did
368 not show a clear change in response to wind speed. Even under high wind speeds, the VR
369 of TST-neighbor did not reach zero, thus the influence of TST-neighbor on TST persisted.

370 Changes of the VR of the other zones were small. To summarize, the impact of each region
371 varied slightly with wind speed, but the changes were not notably large, even under high-
372 wind conditions (wind speeds $\geq 10 \text{ m s}^{-1}$); thus, even in strong winds, the impact of
373 emissions from the Tokyo area remained important.

374

375 *3.3 Effects of wind speed limitation*

376 The seasonal changes of the slopes of the linear regression and the correlation
377 coefficients of CO_2tk between the model simulation and the observation (means of the data
378 shown in Fig. S2) for all, high ($>5.5 \text{ m s}^{-1}$), and low ($<5.5 \text{ m s}^{-1}$) wind speed conditions are
379 illustrated in Fig. 9. Under all wind conditions, the slope of the regression line showed
380 marked variations of approximately 1.2 to 1.8 (Fig. 9a). The slope of the regression line
381 approached 1 and the correlation coefficient increased in spring and autumn, albeit at
382 slightly different times. Because CO_2 emissions from GridFED for the Tokyo area were also
383 relatively low in spring and autumn, these seasonal variations of the regression slope and
384 correlation coefficient may be attributed to the seasonal changes in GridFED (Fig. S3).

385 The slope of the regression line was markedly different for different wind speeds: for
386 high wind speeds, the slope was stable at approximately 1 throughout the year (Fig. 9a).
387 However, the correlation coefficient did not show a clear trend between low and high wind
388 speeds. Overall, high wind speeds tended to have a higher correlation coefficient, but there
389 were cases in which low wind speeds had a higher coefficient (Fig. 9b).

390 To examine the effect of wind speeds, we performed a regression analysis with the
391 modeled and observed CO₂tk values and changed the wind-speed threshold below which
392 data were removed (Fig. 10a and b). The slope of the linear regression between observed
393 and modeled CO₂tk became small when the low wind speeds were removed (Fig. 10a). In
394 particular, the slope constantly decreased under low-wind-speed conditions, whereas the
395 correlation coefficient increased with lower wind speeds (Fig. 10b). The correlation
396 coefficient was greatest when results for wind speeds below 5.5 m s⁻¹ were removed.
397 Increasing the data-removal threshold resulted in the slope's becoming almost fixed. Over
398 a wind-speed threshold of 7.0 m s⁻¹, the slope remained nearly constant at 0.93.

399 The slopes of regression lines and correlation coefficients of CO₂tk between the
400 observation and the model for the three wind directions are illustrated in Fig. 10c and d. The
401 number of S-wind data was greater than the number of either the NE- or NW-wind data: the
402 proportions of data under S-, NE-, and NW-wind were 41%, 30%, and 29%, respectively, for
403 all wind speeds, and 38%, 24%, and 37%, respectively, for high wind speeds. The alterations
404 in slope for each wind direction were similar to that of all wind directions, i.e., removing low
405 wind speeds reduced the slope (Fig. 10c). Especially under a S-wind, the slope became
406 almost fixed and approximately 1 by removing low-wind-speed data. Thus, the simulation
407 under S-wind conditions reproduced observations that were affected by the smoothed
408 southern region by removing low-wind-speed data. However, the standard deviations under
409 NE- and NW-wind conditions were larger than those under S-wind conditions. For a NE- or

410 NW-wind, the slopes did not become stable, even if low-wind-speed data were removed,
411 and the reliability was low. In contrast, the correlation coefficients exhibited marked
412 differences with different wind directions (Fig. 10d). Correlation coefficients under NW- and
413 NE-wind conditions gradually decreased with fluctuations; however, the S-wind correlation
414 coefficient increased with rising wind threshold, even for low wind speeds, the same pattern
415 as for the all-wind-direction data.

416

417 *3.4 Comparison of fossil-fuel emissions between GridFED and ODIAC*

418 We mainly used GridFED for fossil-fuel emissions for the model simulation; however,
419 we also considered the ODIAC results, for comparison. A comparison of the flux distribution
420 between GridFED and ODIAC revealed that the GridFED emissions were much stronger
421 than those from ODIAC on the west coast of Tokyo Bay, but those from ODIAC were slightly
422 larger in the northern part of the Tokyo area (Fig. 2c). The larger emissions in GridFED made
423 a larger contribution to CO_2^{ff} than those of ODIAC during the summer months, when the S-
424 wind blew frequently; however, the VR of ODIAC was slightly larger from January to March,
425 when the northern winds were dominant (Fig. 4a).

426 Both the slope of the linear regression and the correlation coefficient between the
427 observed and modeled CO_2^{tk} were smaller for ODIAC than for GridFED, but the
428 dependency on wind speed was almost the same for both simulation cases (Fig. 10a and
429 b). The correlation coefficient between the model and the observations was greatest at a

430 threshold of 5.0 or 5.5 m s⁻¹.

431 For ODIAC, the dependencies on wind-speed threshold were similar to those of
432 GridFED for all wind directions (Fig. 10e and f). However, the magnitude of the S-wind
433 regression-line slope of ODIAC was particularly small, and the slopes for the other wind
434 directions were slightly larger than those of GridFED. The small slope was caused by the
435 weaker emissions of ODIAC than GridFED on the west coast of Tokyo Bay. In contrast, the
436 fact that the slopes of ODIAC under NE- and NW-wind conditions were slightly larger than
437 those of GridFED was the result of the slightly larger ODIAC emissions in the northern zones
438 of the Tokyo area (Fig. 2c).

439

440 *3.5 Comparison of wind dependency between CO₂ and Rn*

441 Although the reproducibility of the model was not necessarily determined drastically by
442 its horizontal resolution (Nassar et al., 2013), it is possible that the increasing correlation
443 coefficient and decreasing slope in Fig. 10 were caused by inadequate representation of
444 atmospheric transport or surface fluxes in the model. In particular, the latter possibility is
445 plausible because the CO₂ flux distribution in Tokyo is quite inhomogeneous. Although there
446 were differences in the flux distribution between GridFED and ODIAC, they were basically
447 similar, with strong fluxes at point sources around Tokyo Bay and weaker fluxes in other
448 areas. This similarity probably led to the result that the dependencies of the regression-line
449 slopes and correlation coefficients between the model and the observations were similar to

450 each other for the wind data. To investigate whether the changes in the regression slopes
451 and correlation coefficients resulted from insufficient model transport performance or from
452 the inhomogeneity of the CO₂ flux distribution, we analyzed Rn, which has a flux distribution
453 that differs from that of CO₂, and compared it with the CO₂ case using the same method as
454 before.

455 In the time-series of Rn concentrations, simulated Rn was sometimes larger than the
456 observed concentration (Fig. 5c), similarly to the simulated CO₂ concentrations; however,
457 the timing of large differences between calculations and observations for Rn differed from
458 that for CO₂. It is possible that the flux of Rn was overestimated in the model.

459 The seasonal variations in the slope of the linear regression and correlation coefficient
460 of Rn between the model and the observation (monthly means of the data shown in Fig. S4)
461 are illustrated in Fig. 11. The regression-line slope of Rn showed a more distinct seasonal
462 pattern compared to CO₂, and it increased notably from spring to summer. The difference
463 between the high and low wind speeds, separated using the threshold of 5.5 m s⁻¹, was
464 particularly large during this period, and a marked contrast observed, especially in June and
465 July. The correlation coefficient of Rn was larger than that of CO₂ because the flux
466 distribution of Rn was simpler than that of CO₂. Changes in the correlation coefficient, unlike
467 those of CO₂, show less clear seasonal variations. Similar to CO₂, data for high wind speeds
468 tended to have a higher correlation coefficient in general. Furthermore, the timing of changes
469 in the regression-line slope and the correlation coefficient did not necessarily align with each

470 other.

471 The slope of the regression line also decreased with increasing wind-speed threshold
472 (Fig. 10c), similar to CO_2tk , but the slope was greater than 1, even for a threshold wind
473 speed of 10 m s^{-1} . The correlation coefficient of Rn generally increased with increasing wind
474 speed (Fig. 10d), in contrast to CO_2 , which rose only under low-wind-speed conditions. If
475 the insufficient model transport performance were the only cause of the large overestimation
476 of CO_2tk and the relationship between CO_2tk and wind speed, the relationship between Rn
477 and wind speed should be the same as that between CO_2tk and wind speed. However, the
478 decrease in the regression-line slope and the rise in the correlation coefficient of Rn was
479 stronger than the patterns of CO_2tk for all wind directions.

480 In the same way as CO_2 , the regression-line slope and correlation coefficient of Rn
481 concentration were considered separately for each wind direction (Fig. 10c and d). Under
482 NW-wind conditions, increasing the wind speed threshold resulted in a decrease of the slope
483 and an increase of the correlation coefficient. Under S-wind, the slope decreased, but by a
484 smaller amount than for NW winds; in addition, the increase in correlation coefficient for S-
485 wind was gradual. The NE-wind showed a more obvious decrease in slope than the other
486 two wind directions. In addition, for the NE-wind, the correlation coefficient decreased with
487 rising wind-speed threshold, but with some variability. Unlike CO_2tk , under S-wind conditions,
488 the correlation coefficient of Rn did not increase under low-wind-speed conditions. The
489 regression slopes under S- and NW-wind conditions slowly fell, even under high-wind-speed

490 conditions, but they remained greater than 1. Thus, the Rn concentration in the model was
491 overestimated, even if the flux distribution was smoothed by removing low-wind-speed data,
492 as a result of overestimation of the fluxes provided to the model. One reason for the
493 overestimation may have been the covering of the surface with asphalt and thus prevention
494 of an Rn flux in the urban area, but it is also possible that the Rn flux input to the model was
495 too high. In contrast, the slope of CO₂tk under high wind speeds and S-wind conditions was
496 stable at approximately 1, and the model under high-wind-speed conditions reproduced the
497 observations. The comparison with Rn revealed that the changes of regression on CO₂tk
498 were mostly caused by flux inhomogeneity, but the insufficient flux inhomogeneity could be
499 smoothed by removing low-wind-speed data. This tendency was more pronounced under
500 S-wind conditions, which were strongly influenced by the coastal region with abundant
501 emissions.

502

503 *3.6 Estimation of net CO₂ flux from Tokyo*

504 To estimate the net CO₂ flux from Tokyo, we obtained an optimal slope to represent
505 the Tokyo area of 0.93 ± 0.08 by removing data with a threshold wind speed larger than 7
506 m s⁻¹. We selected this wind-speed because the slope became constant above this
507 threshold. The annual mean CO₂ fluxes in Tokyo area, within the circle of 50km radius, of
508 GridFED for fossil fuel and VISIT for the biosphere were 9.4 and -0.1 kg C m⁻² year⁻¹,
509 respectively. From this prior estimate of 9.3 kg C m⁻² year⁻¹, which is the sum of the fossil

510 fuel emission and the biosphere flux, the net CO₂ flux from Tokyo (which contains both land
511 and ocean areas) was corrected by dividing the optimal slope, yielding a value of 10.1 ± 0.8
512 kg C m⁻² year⁻¹. Multiplying the corrected flux value with the defined area, we obtained a
513 value of 79.5 ± 6.6 Tg C year⁻¹ for integrated net emissions from the Tokyo area. This flux
514 included both land and ocean components, and so the magnitude was smaller than that of
515 the land-only flux.

516 For ODIAC, when the same method as that for GridFED was applied, the optimal CO₂tk
517 slope was 0.74 ± 0.07 . The mean annual net CO₂ flux in the Tokyo area was 6.8 kg C m⁻²
518 year⁻¹ with ODIAC; thus, the net CO₂ flux from Tokyo corrected by the optimal slope was
519 9.1 ± 0.9 kg C m⁻² year⁻¹ (71.8 ± 6.8 Tg C year⁻¹), which was smaller by approximately 10%
520 than the value obtained with GridFED.

521

522 **4. Discussion and Conclusion**

523 *4.1 Insufficient representativeness of TST*

524 We applied TST to analyze emissions from the Tokyo area; however, the results
525 indicated that CO₂ concentration variations at TST were mainly affected by ZSW and not as
526 much by ZSE. Therefore, only using TST was not sufficient to investigate the influence of
527 the whole Tokyo area. Although the intensity of the flux on the east coast of Tokyo Bay was
528 approximately 70% of that of the west coast, the VR of ZSE (which includes the east coast
529 emissions) was lower than 0.1 and much smaller than the VR of ZSW (Fig. 8). This

530 difference was attributable to the less frequent easterly winds toward TST (Fig. 5d and Fig.
531 S1). Thus, further observations that can capture signals from the east coast of Tokyo Bay
532 are needed to evaluate the entirety of Tokyo emissions more accurately.

533

534 *4.2 Comparison with previous studies and original bottom-up modeling*

535 In the simulation of CO₂ using GridFED, although estimated CO₂tk was sometimes
536 overestimated, the overestimations were excluded under high-wind-speed conditions.
537 Removing low-wind-speed data induced an increment of the correlation coefficient between
538 simulation and observation, and the regression slope became stable. In contrast, the
539 regression slope of Rn continued to decrease under high-wind-speed conditions and did not
540 become stable. Thus, whether the regression slope became stable by excluding low wind
541 speeds depended on the flux distribution, and one of the causes of the CO₂tk overestimation
542 may have been the flux distribution in GridFED. Similar results were obtained with ODIAC.
543 By excluding the low-wind-speed data, the influence of flux inhomogeneity was smoothed,
544 and a stable regression line could be estimated for all seasons. Although removing low-
545 wind-speed data changed the impact from the TST vicinity, this removal did not always
546 eliminate local influences (Fig. 8). We estimated the net CO₂ flux from Tokyo to be $10.1 \pm$
547 $0.8 \text{ kg C m}^{-2} \text{ year}^{-1}$ ($79.5 \pm 6.6 \text{ Tg C year}^{-1}$) with GridFED, calculated by using the optimal
548 slope of the regression line.

549 The estimation obtained by using GridFED was consistent with those of previous

550 studies in an approximately similar target area: emissions of 75.8 Tg C year⁻¹ (Ohyama et
551 al., 2023) were calculated by an inversion analysis based on observations of ground-based
552 Fourier transform spectrometers around Tokyo, and a value of $70 \pm 21 \pm 6$ Tg C year⁻¹
553 (Babenhauserheide et al., 2020) was derived from a combination of Fourier transform
554 infrared and radiosonde meteorological observations around Tokyo. Comparing the flux
555 estimates for the Tokyo area obtained in the present and previous studies showed that our
556 result from GridFED was approximately 9% larger than that obtained with the original
557 GridFED (Fig. 12). Our value was also larger than those obtained in previous studies, but
558 the differences could not be discussed in detail because the target regions were not exactly
559 the same. The difference between our estimate obtained with ODIAC and the original
560 estimate was more notable—our estimate was approximately 1.4 times the original. This
561 difference was consistent with the fact that the two previous studies (Babenhauserheide et
562 al., 2020; Ohyama et al., 2023) have noted that their estimations were larger than those
563 obtained by using ODIAC. Therefore, it is likely that Tokyo-originated emissions inferred by
564 using bottom-up methods, especially ODIAC, were underestimated.

565 To summarize, we successfully estimated the net CO₂ flux from Tokyo, one of the
566 largest cities in the world, using observations at TST and the high-resolution NICAM with
567 tagged tracers. For future study, additional observation points on the east coast of Tokyo
568 Bay will be necessary to improve the estimate of emissions from the whole Tokyo area. By
569 performing a higher resolution calculation with a regional model and focusing on the urban

570 area, the reproducibility of CO₂ concentrations within the Tokyo area and the flux estimation
571 could be further improved.

572

573

574

Data Availability Statement

575 NICAM and NICAM-TM can be obtained by applying through the inquiry form on
576 [<https://nicam.jp/dokuwiki/doku.php>].

577 The flux data of NISMON-CO₂, GridFED, and ODIAC are available at
578 [<https://doi.org/10.17595/20201127.001>], [<https://doi.org/10.5281/zenodo.4277266>], and
579 [<https://doi.org/10.17595/20170411.001>], respectively.

580 The data of CO₂ and Rn observed at TST supporting the findings of this study are available
581 from NIES and MRI, respectively. Restrictions apply to the availability of these data, which
582 were used under license for the current study and are not publicly available. The data are
583 available from the authors upon reasonable request, subject to permission from NIES and
584 MRI, respectively.

585 The data for CO₂ observed at HAT are available from Mukai et al. (2014). The data for CO₂
586 observed at MNM were obtained from the World Data Centre for Greenhouse Gases
587 (<https://gaw.kishou.go.jp>).

588

589

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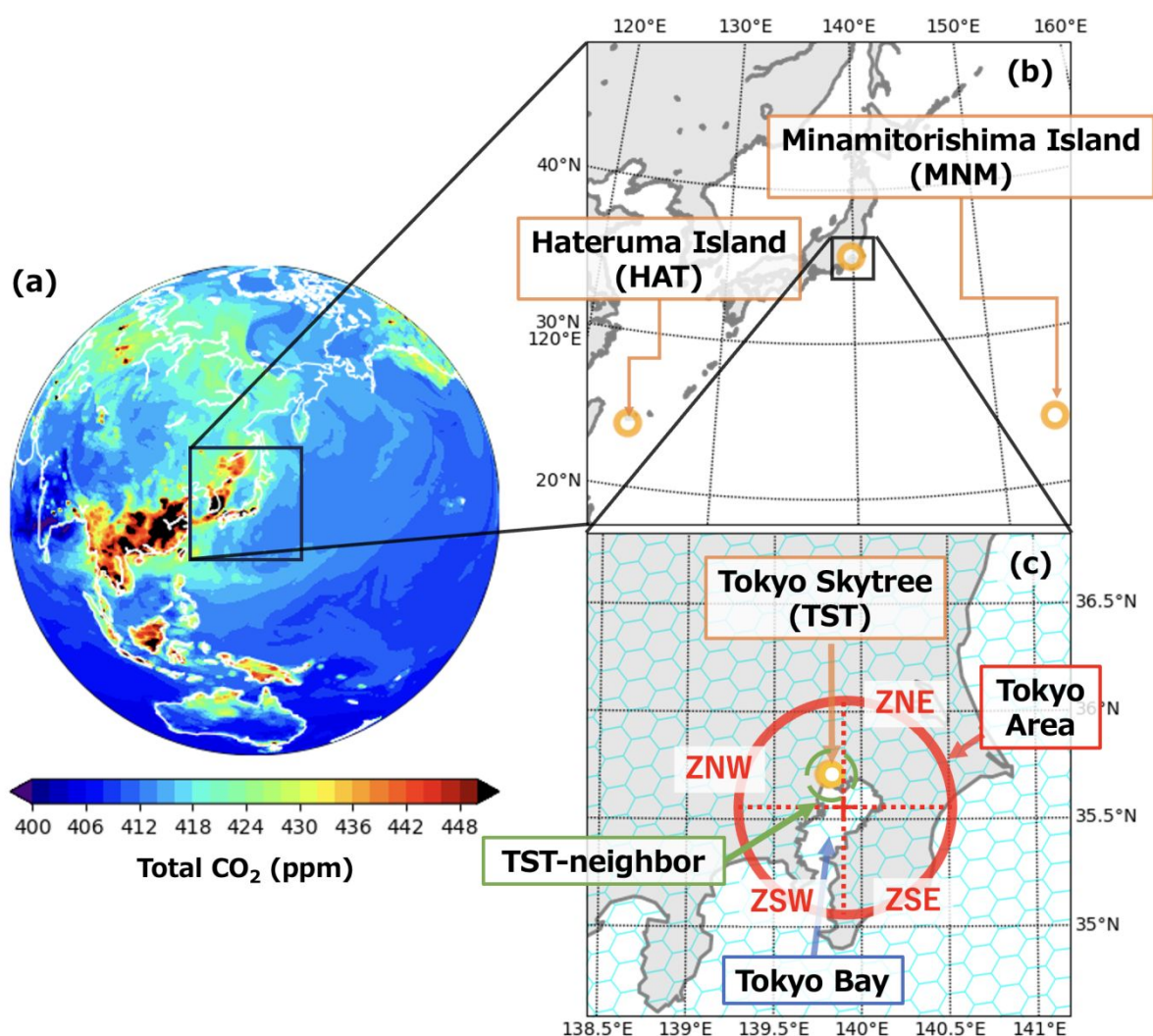
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List of Figures

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763

764 Fig. 1 An example of the NICAM global simulation with glevel-9 (~14 km) resolution for

765 January 15 2019 (a) and analysis regions and target sites (b, c). The red circle in (c)

766 with 50 km radius denotes the Tokyo area as defined in this study, which is separated

767 into four zones. The green circle in (c) around TST indicates TST-neighbor. The cyan

768 hexagons are NICAM grids.

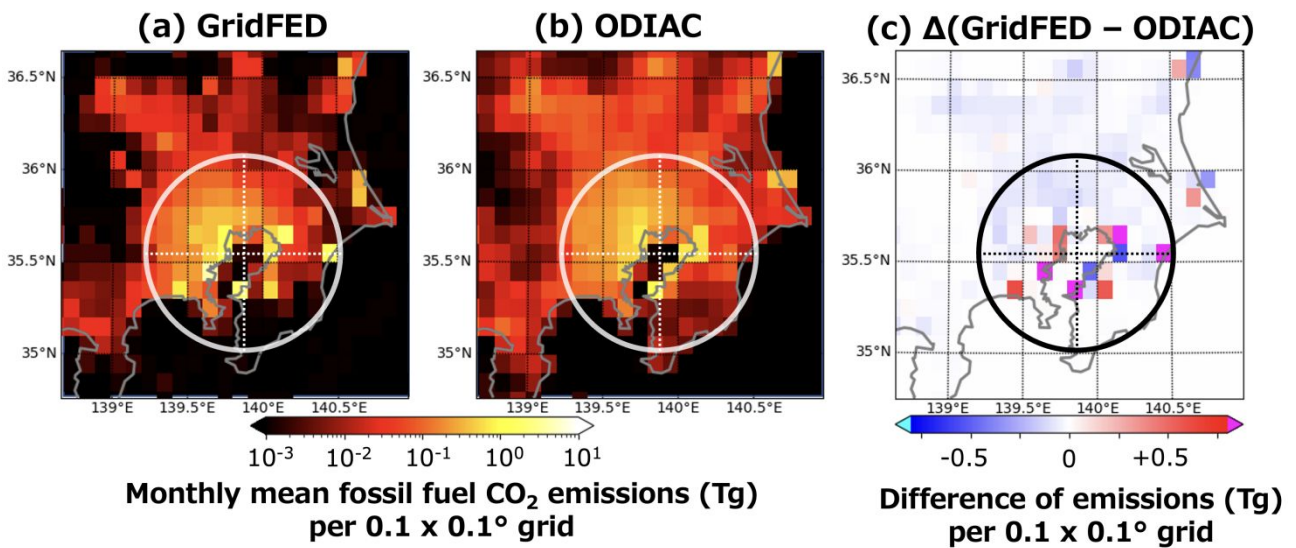
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775 Fig. 2 Distribution of monthly mean fossil-fuel emissions (Tg) per 0.1° grid of (a) GridFED,

776 (b) ODIAC, and (c) the difference between ODIAC and GridFED. ODIAC is averaged

777 from a 0.1 km grid to a 0.1° grid. The circle marks the Tokyo region as shown in Fig. 1c.

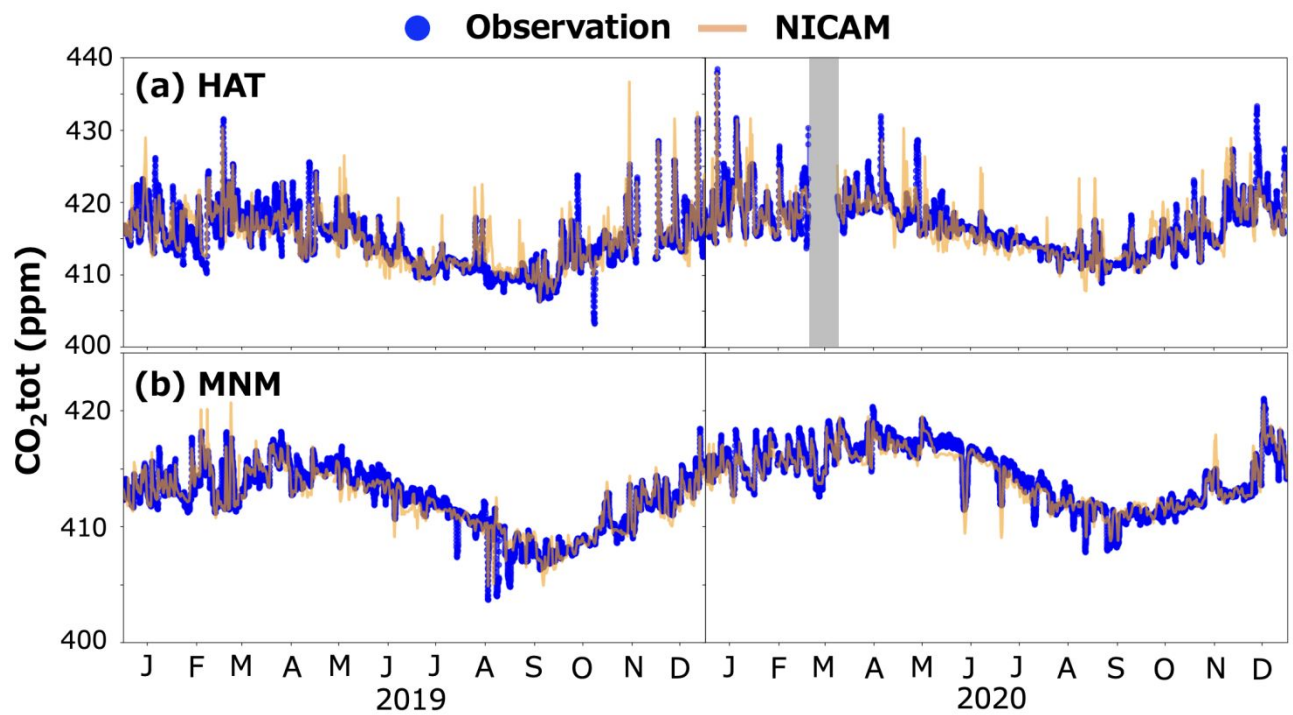
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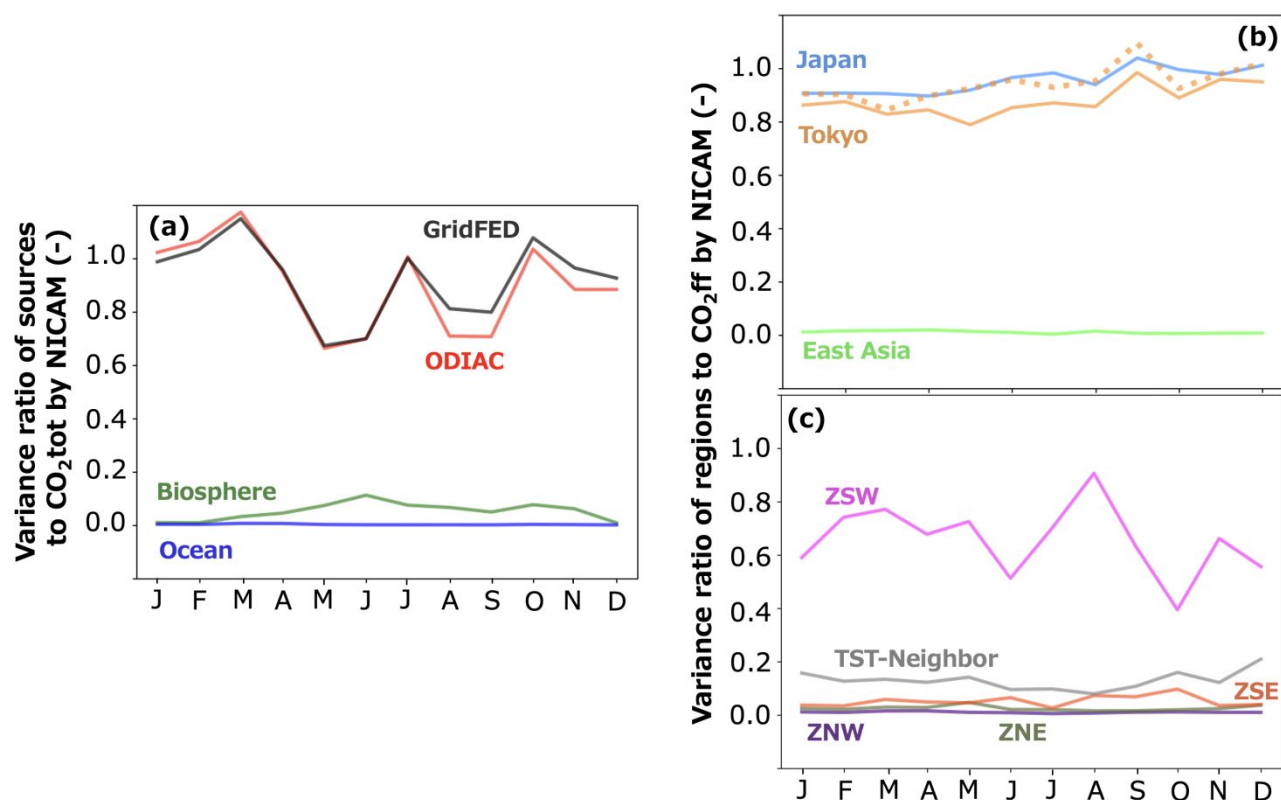
784 Fig. 3 Observed and NICAM-calculated CO₂tot at (a) Hateruma Island (HAT) and (b)

785 Minamitorishima Island (MNM) for 2019–2020. There were no observations for 5 to 24

786 March 2020 at HAT.

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790 Fig. 4 (a) Monthly means of the variance ratio (VR) of simulated CO₂ concentrations of791 different source categories to CO₂_{tot}. (b) Monthly means of VR of atmospheric CO₂

792 concentrations from regionally tagged fossil-fuel emissions of GridFED against those of

793 CO₂_{ff} from GridFED. The dotted orange line indicates CO₂_{tk}. (c) Monthly means of VR794 of CO₂_{ff} from the four Tokyo zones (shown in Fig. 1c) to CO₂_{ff} from Tokyo calculated by

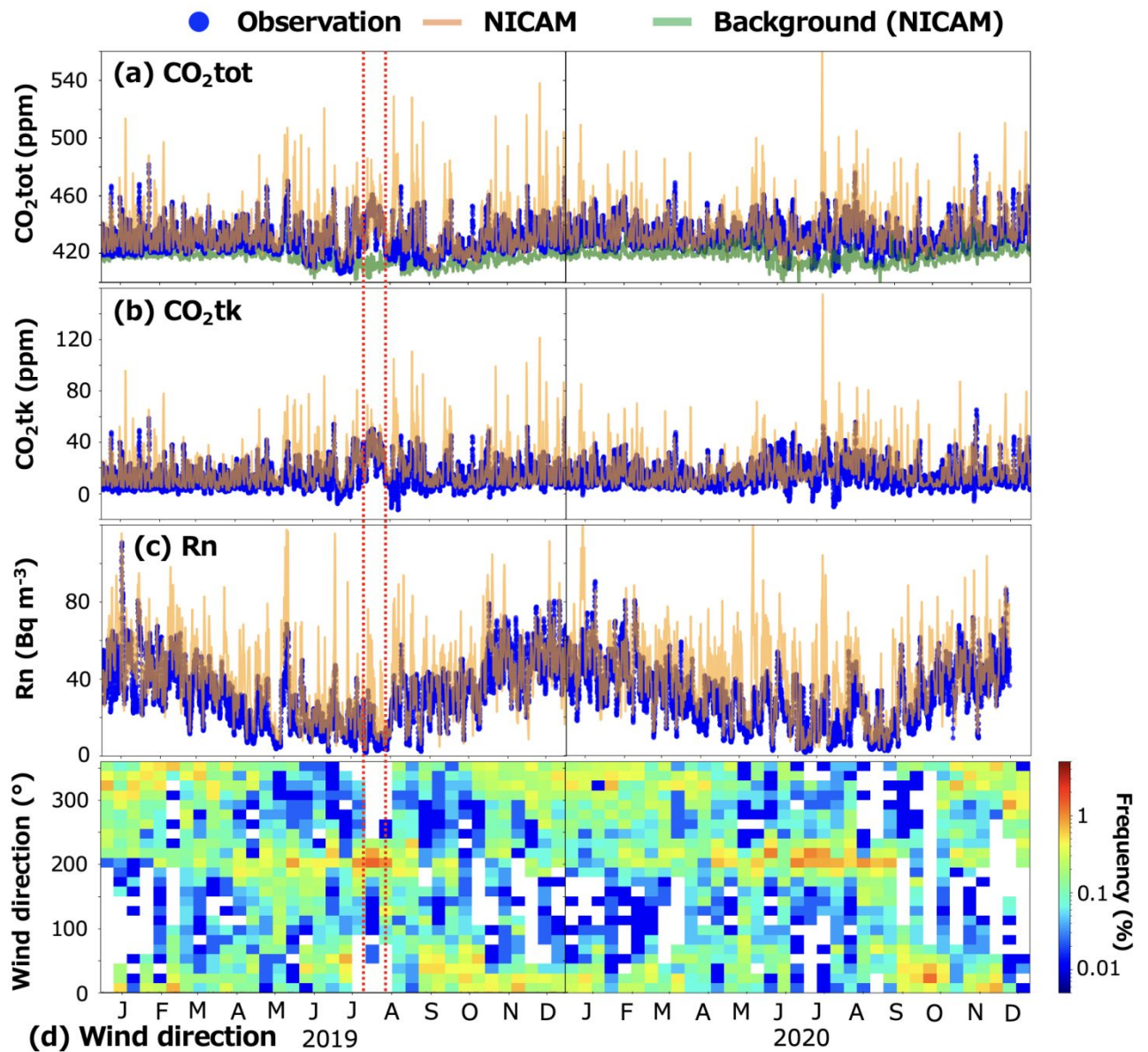
795 GridFED.

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801 Fig. 5 Observed and NICAM-calculated (a) CO₂tot, (b) CO₂tk, and (c) Rn at TST for 2019–

802 2020. (d) Frequencies of wind direction at TST for 2019–2020. Red dotted lines indicate

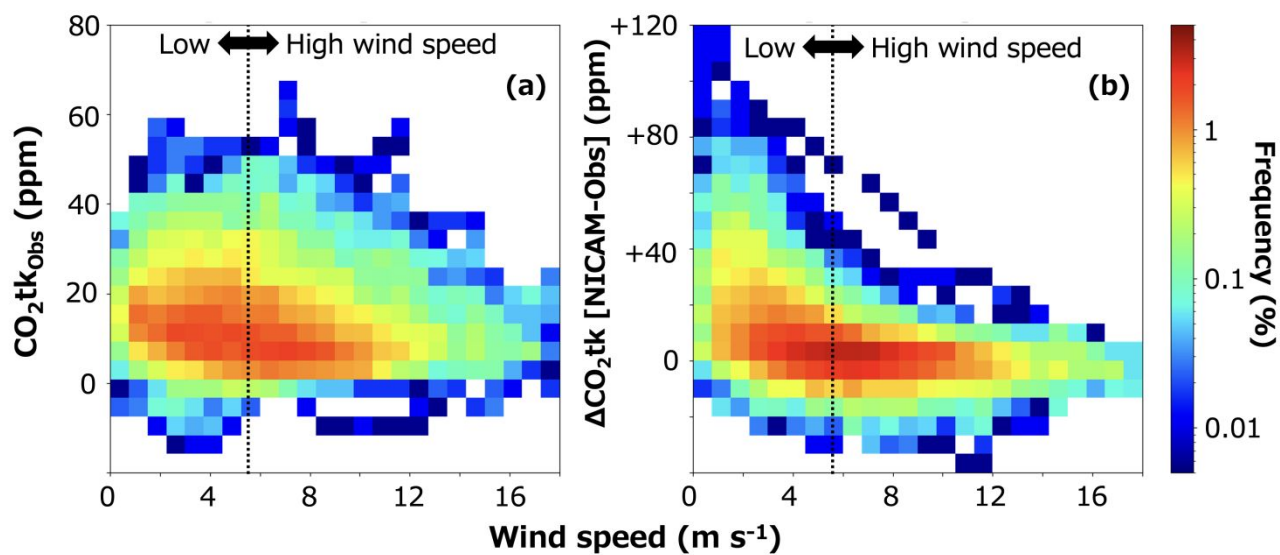
803 the high-emissions event caused by the continuous southern wind.

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809 Fig. 6 (a) CO₂tk^{Obs} and (b) the difference between calculated and observed CO₂tk with

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810 respect to wind speed.

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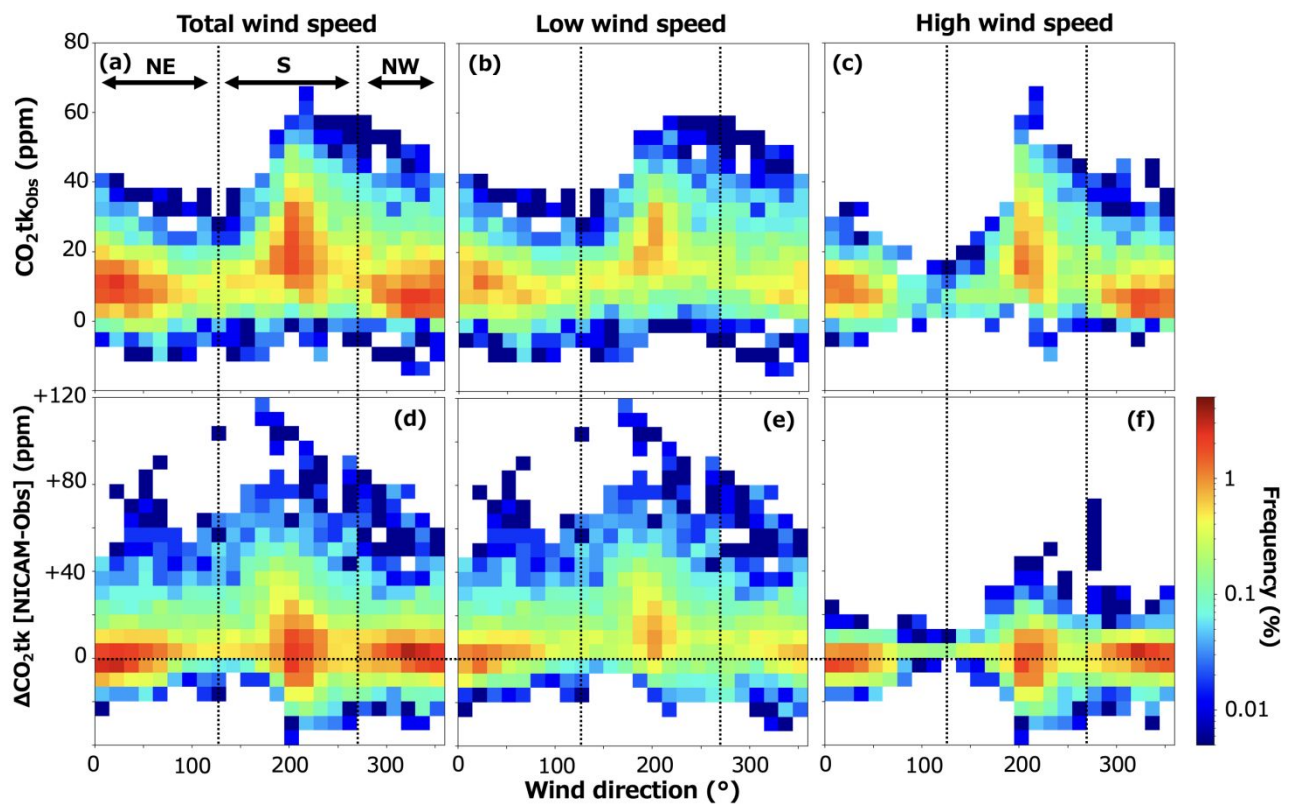
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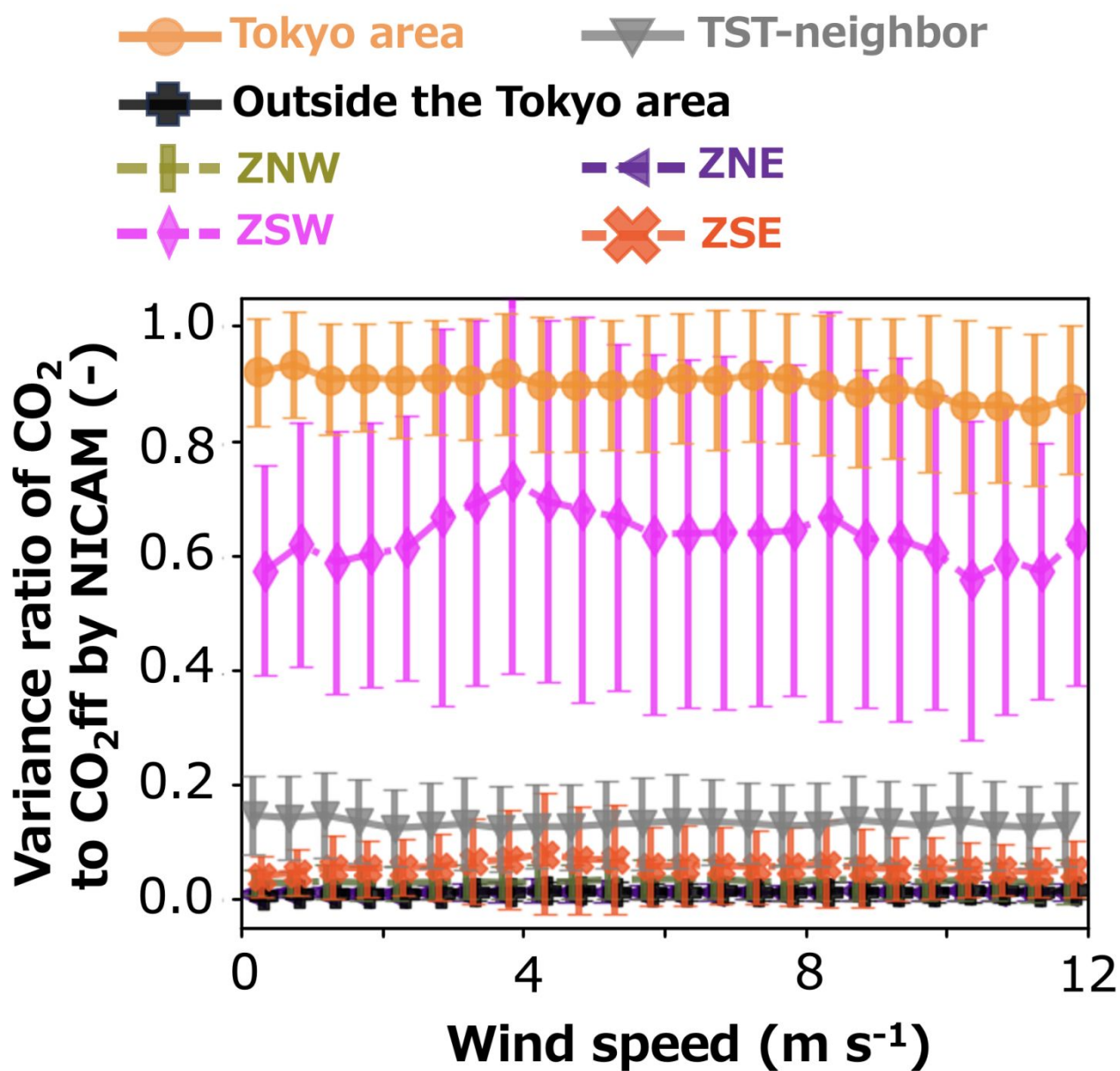
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819 Fig. 7 (a–c) $\text{CO}_2\text{tk}_{\text{Obs}}$ and (d–f) the difference between calculated and observed CO_2tk with820 respect to wind direction. (a, d) All wind speeds, (b, e) low wind speeds ($<5.5 \text{ m s}^{-1}$), (c,821 f) high wind speeds ($>5.5 \text{ m s}^{-1}$).

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Fig. 8 Variance ratio of CO₂ff from emission regions relative to total CO₂ff for wind-speed

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classes of 0.5 m s⁻¹. The VR values of ZNE, ZNW, and regions outside the Tokyo area

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are almost zero. The error bars are the standard deviations.

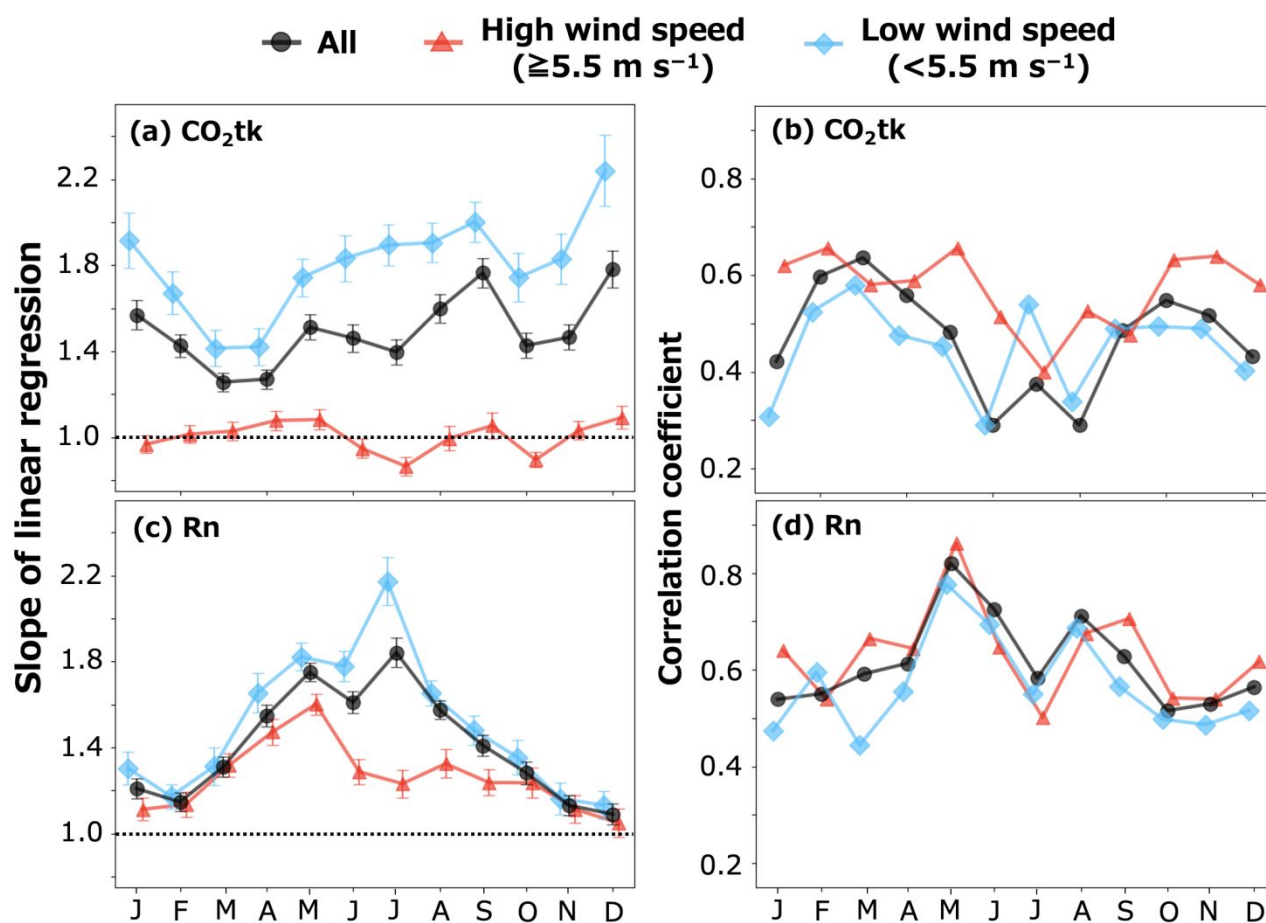
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835 Fig. 9 Mean values of (a) the slope of the linear regression line and (b) the correlation

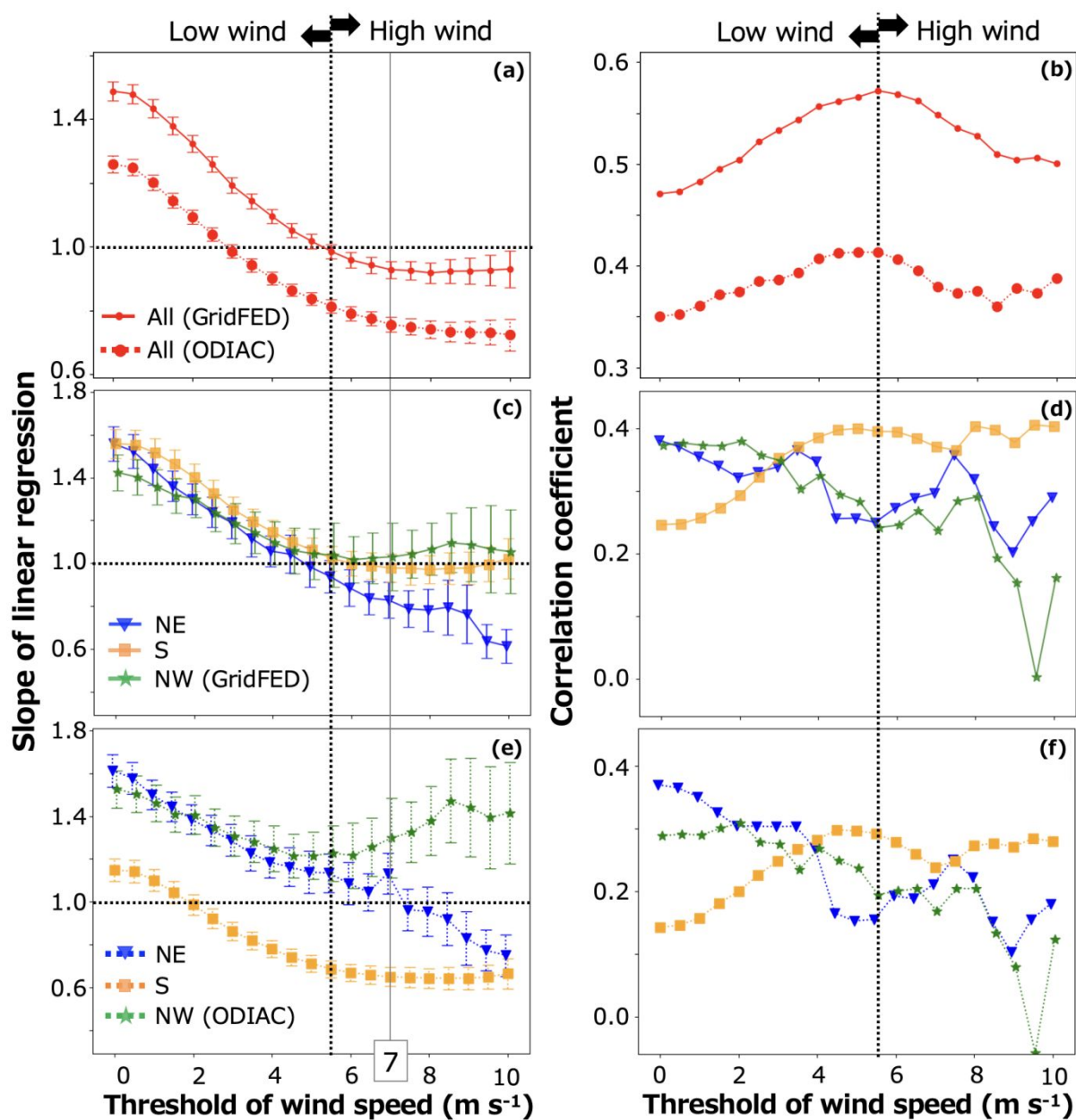
836 coefficient of CO₂tk between the observations and the NICAM model calculation.

837 Calculations of the regression line and correlation coefficient are for 30-day intervals.

838 The error bars are half of the standard error of the regression slope in (a). (c) and (d) are

839 same as (a) and (b), respectively, but for Rn.

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842 Fig. 10 The slope of the linear regression line with an intercept of zero (a, c, and e) and the

843 correlation coefficient (b, d, and f) between observed and calculated (NICAM model)

844 CO₂tk data for 2019–2020 at TST when wind speeds below the threshold are removed.

845 (a, b) All wind directions and (c, f) separate NE, S, and NW wind directions. c, d show

846 data from GridFED, and e, f show data from ODIAC. The error bars are half of the

847 standard error of the regression slope.

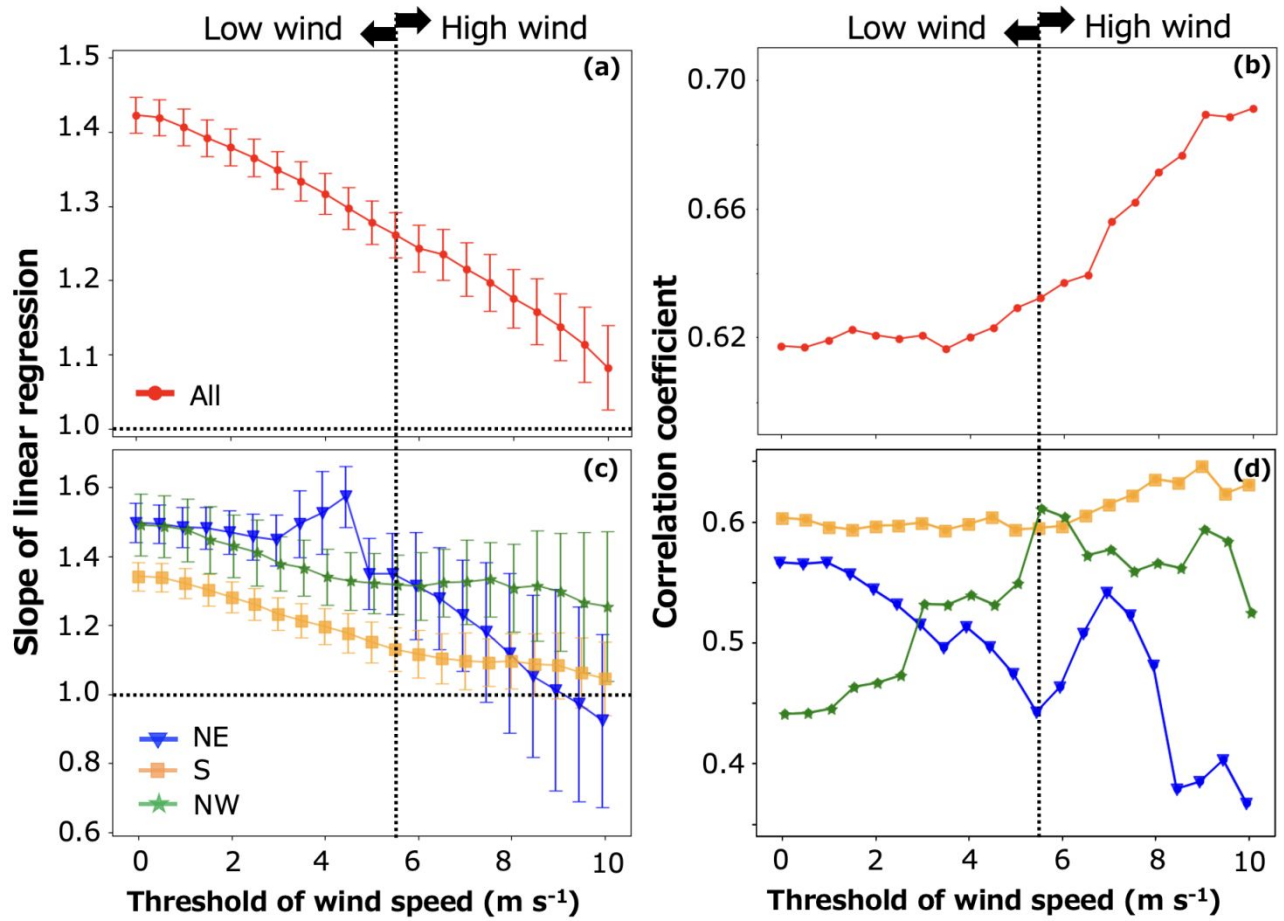
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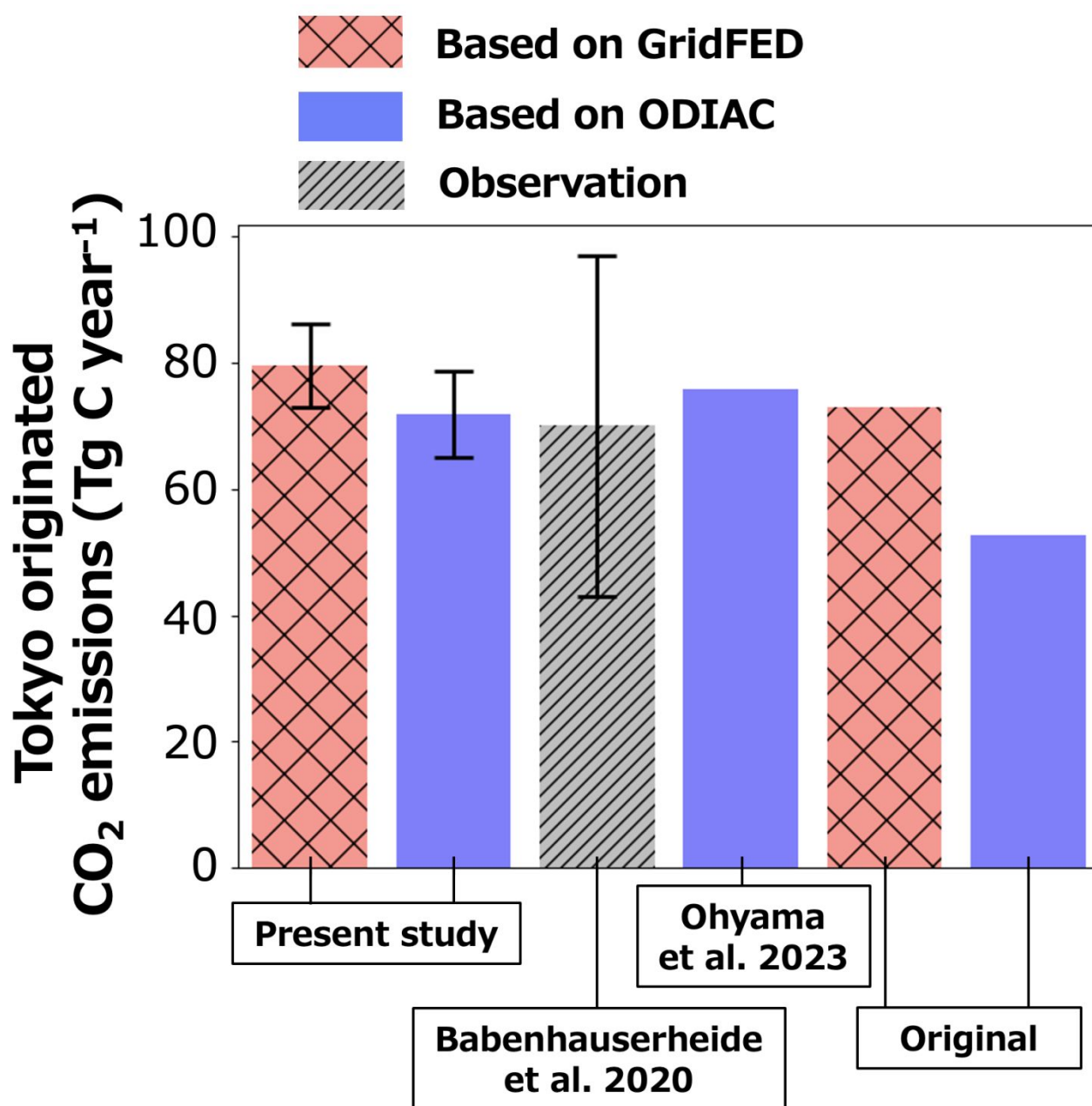


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854 Fig. 11 As Fig. 10, but for R_n.

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858 Fig. 12 Comparison of CO₂ emissions from the Tokyo area calculated in this study with the

859 results of Babenhauserheide et al. (2020) and Ohyama et al. (2023). The regions used

860 in the previous studies are different in a strict sense, but similar enough to that in our

861 study.

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List of Tables

Type	Value	Reference
Model setting		
Spatial resolution	Glevel-9 (~14km)	
Vertical numbers	40 (vertical resolution < 45 km)	
Turbulence scheme	Mellor-Yamada-Nakanishi-Niino Model	Nakanishi and Niino (2004) Noda et al. (2010)
Cumulus scheme	Chikira-Sugiyama Scheme	Chikira and Sugiyama (2010)
Nudging data	JRA-55 horizontal wind (time constant = 6 h)	Kobayashi et al. (2015)
CO₂ flux data		
Fossil fuel	GridFED ODIAC	Jones et al. (2021) Oda et al. (2018)
Biosphere	VISIT	Ito (2019)
Air-sea	JMA air-sea CO ₂ flux data	Iida et al., (2021)
Biomass burning	GFED	van der Werf et al. (2017)

JRA-55: The Japanese 55-year Reanalysis project

GridFED: The Global Carbon Budget Gridded Fossil Emissions Dataset

ODIAC: The Open-Data Inventory for Anthropogenic Carbon dioxide

VISIT: The Vegetation Integrative SIMulator for Trace gases

JMA: Japan Meteorological Agency

GFED: The Global Fire Emissions Database

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870 Table 1: Settings used for the NICAM model.