

Response to Comments from RC1

We appreciate the time and efforts by the editors and referees in reviewing this manuscript. We have addressed each of the concerns indicated in the review reports. Please see the one-to-one response (in blue) following the comments from the reviewer RC1. We believed that the revised version meets the journal publication requirements.

General Comments

The paper of Feng et al. entitled ‘LA Megacity: a high-resolution land-atmosphere modelling system for urban CO₂ emissions’ compares different model resolutions and emission maps to identify optimal configurations for simulating CO₂ fields over a megacity. Although this concept of comparing different models or model configurations is not new, urban air quality poses some additional challenges that the authors try to address in this paper. Additionally, they pay attention to monitoring requirements and their new network design methodology can certainly prove useful, also to estimate footprints. However, I believe the authors could stress more the importance and novelty of their study in the context of recent studies, as the summary of current literature lacks an overview of knowledge gaps/remaining challenges and how their study fits into this (except for the paragraph about studies that focused on LA). Other than that I thank the authors for their very nice work.

Specific comments

Why have the authors decided to use one-way nesting? What would be the advantage compared to two-way nesting and what are the consequences?

One-way nesting allows the parent and the nest to exchange information strictly downscale. In this way, the nest solution does not feed back to the parent solution. Two-way nesting allows the information exchange bi-directionally. The nesting feedback impacts the parent domain’s solution. This study evaluates the impact of the model physics and grid spacing on the model performance. In this case, one-way nesting is preferable to two-way nesting by which the 4-km model results will just be the smoothed 1.3-km model results.

The authors have chosen to simulate a two-month period per day, rather than doing the whole period in one simulation. This requires reinitialisation of the concentration fields for each day. How do the authors ensure conservation of mass between the simulations? Could you show that this reinitialisation has no impact on the simulated mass fractions?

Reinitialisation is commonly used in weather forecasts and regional modelling methods to prevent simulation drifting too much away from the truth. Running simulations for one-month long without reinitialisation is not proper. However, one should notice that the re-initialisation was only applied to modelled meteorology. The CO₂ fields were carried over from cycle to cycle without any re-initialization. The CO₂ mass therefore was conserved for the entire simulation.

Could the authors clearly specify whether the temporal variations for both emission product are equal? If not, how do they differ and what would be the consequence for the comparison of the products?

Both emission products were developed using “bottom-up” methods. Vulcan quantifies FFCO₂ emissions for the entire contiguous United States (CONUS) hourly at approximately 10-km spatial resolution for the year of 2002. The temporal variations are driven by a combination of modeled activity (building energy modeling) and monitoring (power plant emissions). Hestia-LA is a fossil fuel CO₂ emissions data product specific in space and time to individual buildings, road segments, and point sources covering the Los Angeles megacity domain for the years of 2011 and 2012. Hestia-LA uses much of the same information for the temporal variations except for the onroad emissions, for which local traffic data is employed as opposed to regional traffic data. Given the similarities, it is unlikely that the small difference in temporal variation could account for the spatial differences, through covariation with atmospheric transport, found here.

Given the limited in-situ GHG measurements that were available for CalNex, we mainly focused on the CO₂ concentration spatial differences over the LA basin caused by the different emission products used. One of the main conclusions of this study is that, driven by the high-resolution emission data product, i.e. Hestia, the model can reproduce the plumes from the point sources. On the other hand, the Vulcan run shows a more smeared-out CO₂ distribution over the LA basin (Figure 9b vs. Figure 9c).

The authors state that for the MYNN_UCM configuration the PBL height is better represented for d03 than for d02 and that this is also reflected by other configurations. However, it appears from figure 4 that for some configurations d02 is actually better during the afternoon. This requires some reflection in the text.

Thanks for the suggestions. The text has been modified for reflecting this concern (Page 13 Line 30).

Are the biases shown in Figure 6 for the whole period, including night time?

Figure 6 shows the statistics over daytime only. The clarification has been added in the figure caption in the revised paper. Thanks for the comments.

If so, how do the authors reach the conclusion that the dryness in the model causes a lower PBL height (Figure 4) in the afternoon, while the PBL height is actually higher a bit earlier during the day? I would like to see a clear explanation for this, as generally I would think that dryness would cause a higher PBL height.

Yes, dryness usually leads to the higher PBL height. Thanks for pointing out this error. The model overall dries the LA basin but with some exceptions, such as Pasadena area where the ceilometer was deployed, where the model actually moistens the air. The moistness is consistent with the lower PBL the model simulated in Pasadena.

Page 15, ln. 23-24: 'However, during daytime, with well-mixed conditions, the discrepancy between the WRF-Hestia and WRF-Vulcan runs becomes smaller.'; and similarly: Page 16, ln. 15-17: 'For the same reason, we show that FFCO₂ emissions do not play a dominant role around 1400 PST unless there are strong local signals...'. This is an interesting note. Usually, well-mixed daytime concentrations are sampled for inverse modelling, as these conditions are usually better represented by models. That leads to the question how well we could estimate posterior fluxes if a 40% increase in FFCO₂ emissions only leads to an increase of less than 1% in the total CO₂ concentration (which is a rough estimate from your Figure 8 at 1400 PST using both 1.3 km simulations). Could the authors digress a bit on the consequences of this note for inverse modelling?

True. Well-mixed daytime concentrations are sampled for inverse modelling, as these conditions are usually better represented by models. However, it should be borne in mind that removing the upwind background value is required in atmospheric inversion (Lauvaux et al., 2012); only ΔCO_2 is used in atmospheric inversion, not total CO_2 concentration ($\text{CO}_{2\text{tot}}$). How to derive ΔCO_2 , or, say, determine the background CO_2 ($\text{CO}_{2\text{bkg}}$), from the interested location remains challenges (e.g., Turnbull et al., 2015; Schuh et al., 2010). One of the common ways is subtracting the upwind CO_2 from the downwind location. Figure 8 shows the diurnal variation of $\text{CO}_{2\text{tot}}$. Roughly, if we consider CO_2 concentration at the PV site as $\text{CO}_{2\text{bkg}}$ (396 ppm for 1.3-km WRF-Hestia and 397 ppm for 1.3-km WRF-Vulcan), with 408 ppm and 405 ppm of $\text{CO}_{2\text{tot}}$ at Pasadena, ΔCO_2 for Pasadena is 12 ppm and 8 ppm for 1.3-km WRF-Hestia and 1.3-km WRF-Vulcan, respectively. In this case, the increase of FFCO_2 (mixing ratio) for 1.3-km WRF-Hestia vs. 1.3-km WRF-Vulcan is about 50%, which is close to your estimation.

Section 5 introduces a new network design method. Although mentioned before that this would be discussed, I would like to see a few sentences discussing the need for such new method and the limitations of other methods. Currently, this is only briefly mentioned in the discussion. Could the authors also make a recommendation on which method would be most suitable for future use?

Thank you for your suggestions. We have added more sentences discussing the need and limitation of the correlation method in section 6. See Page 25 Line 8-18.

The new method assesses the correlation of “observed CO_2 ” with the neighbouring CO_2 concentration based on the forward model simulation. First of all, this method is computationally economical relative to the footprint method. Secondly, the method doesn’t require adjoint models, which can avoid the complexity. Most importantly, it brings extreme flexibility without complexity for various platforms (i.e., in-situ, satellite, etc.) and especially outpaces the analysis for the dense sampling techniques, such as remote sensing dataset. Applying the footprint methods to satellite data at the regional scale modelling is extremely computationally time-consuming and complex.

However, as mentioned in the text, both transport and emissions play a role in the correlation method. The footprint method, in contrast, indicates the influence of the atmospheric transport to

the location of the observation only. Hence, the correlation method is subject to overestimation of the influence area versus the footprint method, due to the complicated nature of the atmospheric integrator.

Technical corrections

In Section 3.1 the authors list five criteria for profile selection. The difference between point 4 and 5 should be made more clear.

These two criteria have been merged. See Page 12 Line 18. Thanks!

In Section 3.4, the third paragraph, the authors mention the temperature difference between Granada Hills and downtown LA in F. I would suggest to use Kelvin to make comparison with the other temperature results in Kelvin easier.

Changed. See Page 16 Line 4.

In Section 5, please mention clearly whether you used any data selection or that all data was included for the correlation maps.

There are no data used in Section 5. See Page 21 Line 21 for clarification.

The discussion now starts with new results based on flask samples of radiocarbon. Please move this to the results section. Also I would suggest to introduce the use of radiocarbon earlier, as this not mentioned previously in the paper.

The comparison with the flask samples and the introduction of radiocarbon have been moved to section 3.6 following the comparison to in-situ measured total CO₂. Thanks!

Reference:

Lauvaux, T., Schuh, A. E., Uliasz, M., Richardson, S., Miles, N., Andrews, A. E., Sweeney, C., Diaz, L. I., Martins, D., Shepson, P. B., and Davis, K. J.: Constraining the CO₂ budget of the

corn belt: exploring uncertainties from the assumptions in a mesoscale inverse system, *Atmos. Chem. Phys.*, 12, 337-354, 10.5194/acp-12-337-2012, 2012.

Schuh, A. E., Denning, A. S., Corbin, K. D., Baker, I. T., Uliasz, M., Parazoo, N., Andrews, A. E., and Worthy, D. E. J.: A regional high-resolution carbon flux inversion of North America for 2004, *Biogeosciences*, 7, 1625-1644, 10.5194/bg-7-1625-2010, 2010.

Turnbull, J. C., Sweeney, C., Karion, A., Newberger, T., Lehman, S. J., Tans, P. P., Davis, K. J., Lauvaux, T., Miles, N. L., Richardson, S. J., Cambaliza, M. O., Shepson, P. B., Gurney, K., Patarasuk, R., and Razlivanov, I.: Toward quantification and source sector identification of fossil fuel CO₂ emissions from an urban area: Results from the INFLUX experiment, *Journal of Geophysical Research: Atmospheres*, 120, 2014JD022555, 10.1002/2014JD022555, 2015.

Response to Comments from RC2

We appreciate the time and efforts by the editors and referees in reviewing this manuscript. We have addressed each of the concerns indicated in the review reports. Please see the one-to-one response (in blue) following the comments from the reviewer RC2. We believe that the revised version meets the journal publication requirements.

Overview: The manuscript presents simulated carbon dioxide fields for 2 months centered over Los Angeles. The work demonstrates and tests the ability of a high-resolution meso-scale model to reproduce observed meteorological and carbon dioxide dynamics, with a focus on urban areas, LA in particular. The paper presents a valuable modelling approach in order to understand the temporal and spatial variability of weather variables and CO₂ mixing ratio in urban and background sites. This work is appropriately placed in ACP, and contributes to the burgeoning area of studying carbon emissions from urban areas. I have some general and specific concerns delineated below, that need to be addressed before its publication.

General Comments: Overall things look quite nice and interesting, but I have a couple of reservations that require more explanation and must be addressed. There needs to be better presentation of modelled vs observed fields in terms of table of scores and 1:1 plots. As currently presented, it is difficult to assess model performance. The second point is that discussions on the physical reasons why a parametrized scheme is better, or on the performance of the modelling, are missing. The last parts that study correlations of the simulated CO₂ fields with GHG measurements is interesting, and well oriented to further inverse modelling studies. I do not have specific remarks on this part.

- 1) **CO₂ initial and boundary condition.** This is only briefly touched upon in section 2.1, and it is unclear. From what I understand the model is initialized and coupled with CO₂ concentrations coming from observations. The simulations run for 36h. Do you use the predicted CO₂ field from the end of the previous day to start the following day ? Or do you only use CO₂ observations at the beginning of each run ? In the 2nd case, what is the spin-up time ? Is there a significant horizontal and vertical variability in the CO₂ observations ? What impact do varying boundary condition choices make on simulations? We know that in regional studies boundary

conditions play a tremendously important role (Lauvaux et al. TELLUS 2012). The authors must better described what they've done for boundary conditions, and make quantitative assessments of impacts of boundary condition choices on simulations.

We initialized CO₂ fields from the NOAA curtain dataset at the beginning of the first cycle. The simulation runs for 36 hour for each cycle with 12-hour setback for spin-up. For each cycle, only the meteorology is re-initialized; CO₂ fields are carried over from the last cycle. For instance, the first simulation cycle is 00 UTC 15 May to 12 UTC 16 May 2010, and the second cycle is 00 UTC 16 May to 12 UTC 17 May 2010. The initial conditions for 00 UTC 15 May include NARR, NCEP SST and NOAA curtain (CO₂). The initial conditions for 00 UTC 16 May include NARR, NCEP SST and WRF-modelled CO₂ on 00 UTC 16 May from the previous cycle. Briefly, we did not re-initialize CO₂ for each cycle to assure mass conservation over the model domain. The clarification for CO₂ IC and BC has been added in the revised paper (see Page 11 Line 27-29).

We agree that the boundary conditions (BCs) are critical for the CO₂ simulations. In this study, we found there is no significant horizontal and vertical variability in the NOAA curtain dataset; semi-constant BC was used. We have also applied CO₂ modelled by GEOS-Chem BC for our region of interest, which introduced ~+10 ppm model-data mismatch in the WRF model results. This is similar to the findings by (Lauvaux et al., 2012), who found the model-data mismatch was more than 20 ppm in summer over the corn belt area. It also reflects the challenges in determining CO₂ background values for regional scale simulations. We therefore end up with using semi-constant values (“NOAA Curtain”) as the model BC in the paper. The NOAA Curtain dataset mainly represents oceanic clean air. In May – June, west to southwest clean marine flow prevails over the Los Angeles Megacity. Using a semi-constant dataset is fairly close to the reality, introducing lower errors to the regional, modelled CO₂ relative to global models, such as GEOS-Chem. However, during October to March, Santa Ana wind events occur frequently, during which easterly to north-easterly winds predominate over the LA basin, and the oceanic air is polluted. In this case, using constant values is no longer feasible.

- 2) As a large part of the simulated domains is on the sea, and as LA is largely influenced by maritime air masses, is it not a problem to ignore ocean fluxes ? Classically, **oceanic CO₂ fluxes** are parameterised following Takahashi et al. (1997). A sensitivity test with ocean

parametrized fluxes would be appreciated.

The LA megacity is one of the top three fossil fuel emitters in the U.S. Roughly estimated from Hestia at the Pasadena site, the order of fossil fuel emission is about 10-20 $\text{umol/m}^2/\text{s}$. The typical oceanic CO_2 flux $-0.15 \text{ umol/m}^2/\text{s}$ (Torres et al., 2011), $0.2 \text{ umol/m}^2/\text{s}$ (Mu et al., 2014), represents only 1-2% of FFCO_2 fluxes and even less compared to $\text{CO}_{2\text{tot}}$. Because of that, we have ignored the oceanic CO_2 signal for simplicity in this study. Yet we do agree that a sensitivity test with oceanic flux would be interesting and should be included in future work. This explanation has been added to the revised paper. See Page 11 Line 18-23.

- 3) One objective of the paper is to assess the **PBL schemes**, but they are not physically described and the differences between the schemes are not presented. Therefore the conclusions are only limited to WRF technical configuration and physical aspects are not addressed. The 3 PBL schemes have to be described properly (closure, mixing lengths ...) to highlight the differences. Then strengths and weaknesses of each scheme need to be highlighted relating to their characteristics.

In this study, we have selected three most commonly used TKE-driven PBL schemes for comparison, including MYJ, MYNN, and BouLac. MYJ (Janjić, 1994) determines the PBL from the TKE where the PBL top is defined as the height where the TKE profile decreases to the threshold of $0.2 \text{ m}^2\text{s}^{-2}$. MYNN2 (Nakanishi and Niino, 2006) is tuned to a database of large eddy simulations (LES) in order to overcome the typical biases associated with other MY-type schemes, such as insufficient growth of convective boundary layer and under-estimated TKE. Additionally, MYNN also considers sub-grid TKE terms, and it determines the PBL top as the height at which the TKE falls below $1.0 \times 10^{-6} \text{ m}^2 \text{ s}^{-2}$. BouLac (Bougeault and Lacarrere, 1989) has an option designed for use with BEP multi-layer and UCM. It determines PBL top at which TKE reaches $0.005 \text{ m}^2 \text{ s}^{-2}$. They all are 1.5 order local closure schemes that only consider immediately adjacent vertical levels in the model, which may not fully account for deeper vertical mixing associated with larger eddies and associated countergradient flux correction terms and, thus, tends to prevent the PBL from mixing as deeply to produce cooler and moister conditions. On the contrary, the non-local closure schemes considering a deeper layer account for countergradient fluxes and, thus, generally represent deep PBL circulation better than local schemes. The PBL schemes were reviewed by Cohen et al. (2015).

The main reason that we focus on the TKE-driven PBL schemes only is that the explicitly estimated turbulence fluxes can be used to drive Lagrangian particle dispersion models to computer influence footprints for subsequent atmospheric inversions. Through the model evaluation, we aimed to determine an optimal model configuration for modelling urban CO₂ over the LA megacity, and eventually to use the same system for synthesis analysis in future. In this study, we concluded that MYNN in combination with UCM is optimal for the LA modelling framework, which is consistent with the findings of Coniglio et al. (2013) who showed MYNN supports deep convection springtime.

The strengths and weaknesses of each scheme with their characteristics have been added to the revised paper. See Page 9 Line 3-15. Thanks!

- 4) In the same way, 2 **urban surface schemes** are tested without having presented their physical differences. The scientific interest is therefore limited. We need to know the scientific reasons why UCM seems better.

UCM is a single-layer urban canopy model, representing urban geometry and 3-D urban surfaces such as walls, roofs and roads. Furthermore, the sensible heat fluxes from the surface are calculated with Monin-Obukhov similarity theory and Jurges formula. The important factor of anthropogenic heat (AH) and its diurnal profiles are included and added to the sensible heat flux from the street canyon (Chen et al., 2011). BEP allows a direct interaction between the buildings and the PBL. BEP considers the 3-D urban surface and the vertical distribute source of buildings and momentum sinks throughout the whole canopy layer. The effects of vertical and horizontal surfaces on momentum, TKE and potential temperature are included. However, BEP requires very high vertical resolution within the PBL and is only compatible with MYJ and BouLac PBL schemes. Given that BEP is computationally expensive, we only test it with BouLac in this study. The scientific reasons to explain the urban schemes' characteristics have been added to the revised paper. See Page 14 Line 9-12. Thanks!

- 5) In the **comparison to aircraft PBL height**, the method to determine PBL height is based on the vertical virtual potential temperature gradient. Among the existing methods to determine this parameter (Ri number, parcel method ...), none is perfect. What is the impact of the choice of the

method on the results ?

We have used the vertical virtual potential temperature gradient and Ri number methods to determine PBL top (see Figures R1 and R2 below). Compared to the vertical virtual potential temperature gradient method, the Ri method shows larger bias in the modelled PBL top, deeper for daytime, shallower for nighttime, but the overall conclusion remains the same in terms of model inter-comparison, namely MYNN_UCM shows better agreement with ceilometer measured PBL height. We therefore show only the vertical virtual potential temperature gradient determined PBL in the text.



Figure R1. Absolute difference between the aircraft-determined and modelled PBL height for each profile (flt_yyyymmdd, blue bars) using virtual potential temperature gradient (top) and Richardson number (bottom). The pink bars in the last column represent the averaged bias over all of the profiles for each configuration. Note that the shorter the bar is, the better agreement the model has with the observations.

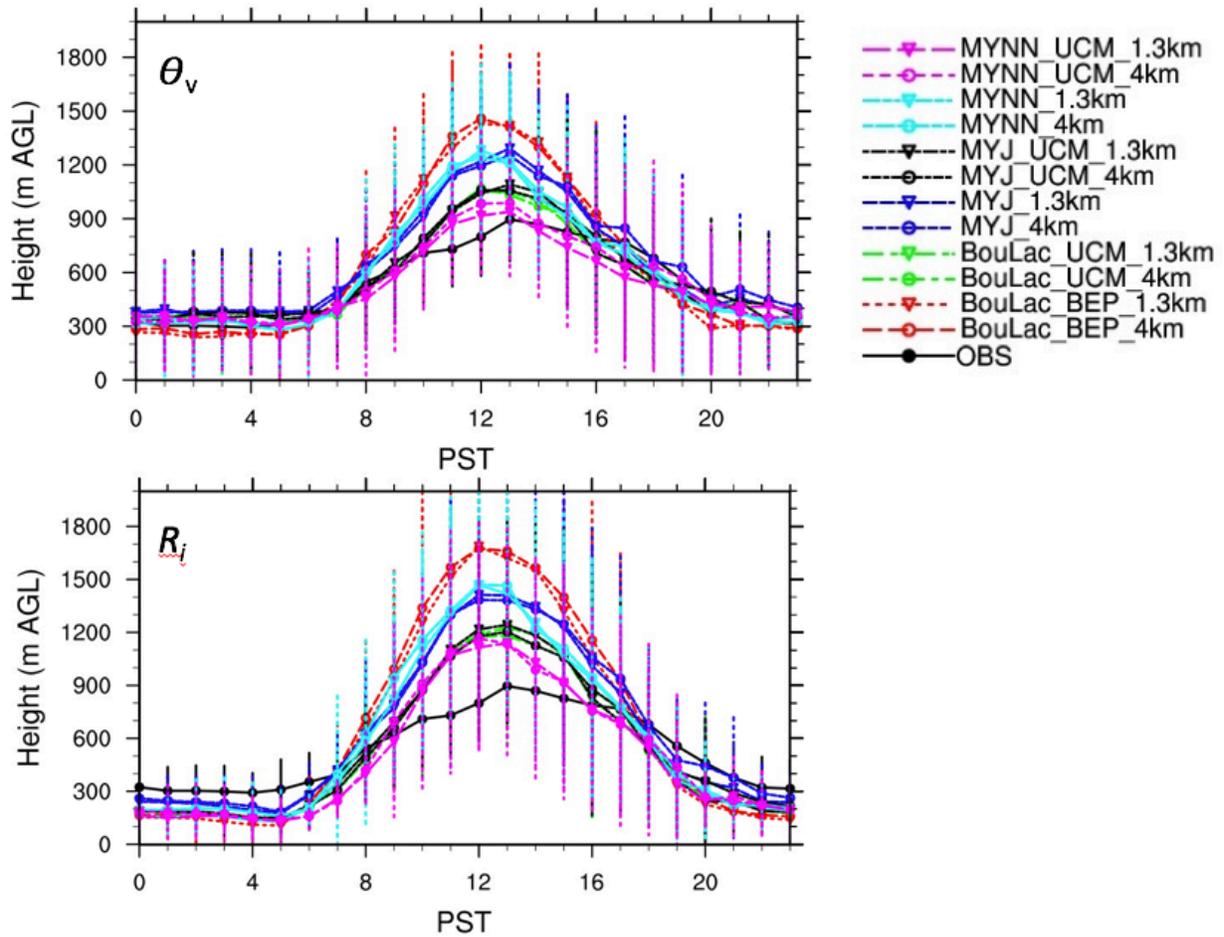


Figure R2. Average diurnal variation of the ceilometer-measured (obs) and modelled PBL heights at California Institute of Technology (Caltech) in Pasadena, CA during 15 May through 15 June 2010. Error bars indicate one standard deviations. Upper: the vertical virtual potential temperature (θ_v) gradient determined PBL. Lower: the R_i number determined PBL. Note that the ceilometer-measured PBL top (black solid line) is the same in these two panels.

For the 3 PBL schemes, biases on PBL heights are significant : errors of 160m in PBL height are not small by any measure. You can see for instance Riette and Lac (2016) for evaluation of PBL height over 1 year with an operation NWP model, with more satisfying values. Qualitative statements should be toned down. What is the error standard deviation? Figure 3 is not appropriate as only biases are represented without standard deviation, and without length scale. How do you also explain that biases are smaller at 4km than at 1.3km, and that the results are different than the comparison to ceilometer?

Please note that Figure 3 (in the manuscript) and Figure R1 (in the response) show the absolute difference between the observation and model for each aircraft profile we selected, so the error of 160 m in PBL height is the mean over seven aircraft profiles only (small sample). We did not intend to make any specific conclusion based on seven profiles. The take-home message of Figure 3 is that the differences between the modelled and aircraft-determined PBL height differ case by case, and none of the model physics options is systematically better than the others. To further define the optimal physics for the PBL height simulation, we presented the all-hours statistics with the ceilometer data in section 3.2 and Figure 4.

Given the relative large number of the ceilometer measurements, similar model evaluation (Table R1) to that of Riette and Lac (2016) has been done and been added to the revised paper (Table 3). Compared to the values evaluated by Riette and Lac (2016), -9.17 m for bias and 115 m for RMSE (PMMC09), the scores of MYNN_UCM fall in a comparable range.

Table R1. Comparison Statistics of model performance relative to the ceilometer data over 1100 – 1700 PST (unit: m AGL)

	Mean	Bias	Standard deviation	RMSE
OBS	835.7	-	223.8	-
MYNN_UCM_d03	828.8	-6.9	82.7	89.7
MYNN_UCM_d02	820.4	-15.3	66.1	94.5
MYNN_d03	1055.6	219.9	205.8	278.2
MYNN_d02	1029.4	193.7	200.0	254.3
MYJ_UCM_d03	961.4	125.8	154.9	168.8
MYJ_UCM_d02	971.4	135.7	109.3	157.7
MYJ_d03	1115.3	279.7	174.4	308.7
MYJ_d02	1105.1	269.5	150.9	291.6
BouLac_UCM_d03	936.1	100.5	147.3	149.9
BouLac_UCM_d02	958.7	123.1	104.8	148.7
BouLac_BEP_d03	1233.9	398.3	239.0	442.2
BouLac_BEP_d02	1244.3	408.6	219.5	446.0

6) **Dynamics** : why do you use one-way nested domains and not 2-way ?

One-way nesting allows the parent and the nest to exchange information strictly downscale. In this way, the nest solution does not feed back to the parent solution. Two-way nesting allows the information exchange bi-directionally. The nesting feedback impacts the parent domain's solution. This study evaluates the impact of the model physics and grid spacing on the model performance. In our experiment, one-way nesting is preferable to two-way nesting for which the 4-km model results will just be smoothed 1.3-km model results.

Advection and temporal schemes should be specified in Table 1, with the time steps for the different resolutions. Page 7 line 16 : what is the height of the 1st level ?

5th and 3rd order differencing for horizontal and vertical advection respectively are used. 3rd order Runge-Kutta is used for time integration with 45, 24, and 5 s for outermost, middle, innermost domains, respectively. These specifications have been added to Table 1 in the revised paper. The first level of the model setup is about 8 m above ground level (see Page 8 Line 21).

7) **Comparison to radar wind profiler** : what is the period of evaluation ? Is it 2 months ? Tables of scores for wind speed and duration would be useful and easier to read than scores included in the text.

The evaluation was done over daytime for the entire one-month simulation. Our intent in this paper is to present the model errors varying with height. For this purpose a figure is preferable.

Also, in Fig.5, if it is related to a 2 months period, it would be better to normalize the vertical coordinate by the PBL height.

We appreciate your suggestion and will take it into account in future work.

8) **Comparison to NWS surface stations** : all the stations are not represented on Fig.S1 and the domain is not the same. As a complement to Fig.6, a table with scores for MYNN_UCM is necessary, not only with biases but also with rmse. As a complement to Fig.6, it would be useful to provide two figures with the orography and the urban fraction for 1.3km resolution, and to discuss if the scores are related to orography, urban area... At 1.3km, what is the resolution of the orography database ?

Figure S1 is a map showing the location of all of the GHG measurement over the LA basin, which matches the triangles in Figure 1b, 6, 9a, 9b, and 12. Figure 1b shows the orography for the 1.3 km domain. Figure S1 shows the orography as well, although the domain is not exactly the same as other figures. Usually to the locations of NWS station relative to the location of the GHG measurements (triangles), we estimated the relevant orography. We choose to keep the figures as in the original manuscript to avoid redundancy.

We tried to explain the model bias with orography at the beginning, but could find no clear correlation. The RMSE maps below have been added to the revised paper (Figure 7).

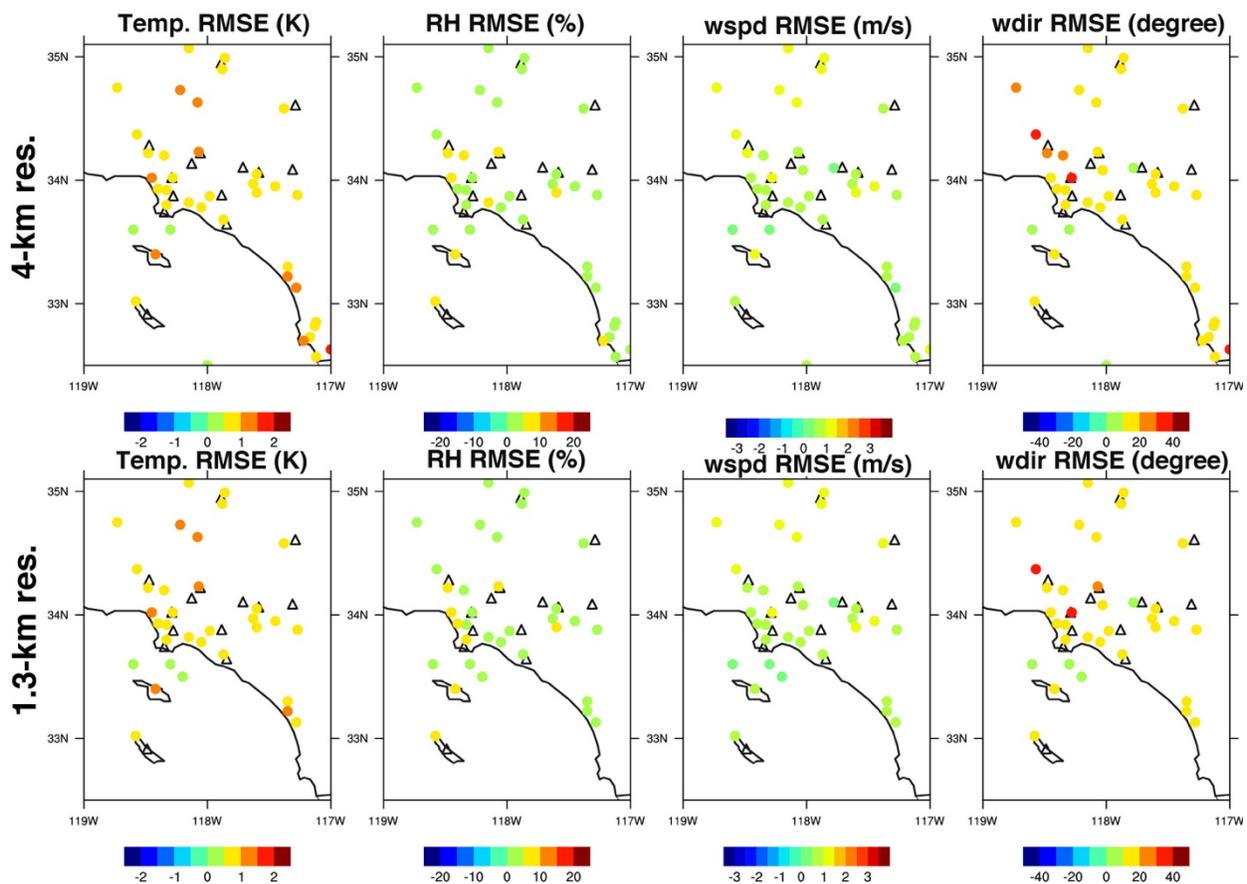


Figure R3. RMSE maps of the MYNN_UCM runs versus National Weather Stations (NWS) over the LA megacity (Model – NWS): (a1-a4) 4-km run; (b1 – b4) 1.3-km run. Black triangles indicate the locations of the GHG measurement sites.

9) **Comparison to in-situ CO₂** : once again, a table of scores (bias and rmse) with the 4 simulations, as a complement to Fig.7, is missing.

Thanks for the suggestion. We have added the two tables (Table 4 and 5) below as complements to Figure 7 in the revised paper.

Table R2. Statistics of modelled CO₂ (unit: ppm) with different configurations relative to in-situ CO₂ between 1300 – 1700 PST

	Pasadena		Palos Verdes	
	bias	RMSE	bias	RMSE
1.3 km WRF-Hestia	8.91	18.43	2.57	17.00
4 km WRF-Hestia	7.03	14.50	8.09	19.64
1.3 km WRF-				
Vulcan	1.20	11.10	5.03	10.62
4 km WRF-Vulcan	-1.38	9.13	4.20	9.40

Table R3. Statistics of daily afternoon averaged modelled CO₂ (unit: ppm) with different configurations relative to in-situ CO₂*

	Pasadena		Palos Verdes	
	bias	RMSE	bias	RMSE
1.3 km WRF-Hestia	-1.39	6.21	-0.75	4.71
4 km WRF-Hestia	0.58	4.38	-1.77	4.59
1.3 km WRF-				
Vulcan	-3.43	5.51	1.37	5.21
4 km WRF-Vulcan	-4.41	6.12	0.58	4.38

*Averaged over 1300 – 1700 PST

10) This study focuses only on **two months** of modelling and observations (May-June 2010).

Conclusions thus must be quite limited, as one cannot extrapolate to generalized model performance from such a limited duration comparison, which could be particularly favourable or

unfavourable. The limited duration of model/observations must be presented, and its impact on conclusions should be discussed.

The Los Angeles basin is surrounded to the north and east by mountain ranges with summits of 2-3 km, with the ocean to the west and the desert to the north. From April to September, LA is in a warm, dry, and stable air mass. Alongshore steady wind flow predominates this area. In contrast, from October to March, moist onshore flows bring precipitation to LA.

Details about LA climate can be found in the study of Conil and Hall (2006).

The focus of this study is from the middle of May to the middle of June, which is representative of the dry season. We agree that the study based on a one-month simulation has its limitations. The model has to be evaluated and verified as the time period and spatial region of interest change.

The limitation of this study has been added to the revised paper (see Page 26 Line 16-25).

One element of this is discussing time/computation to simulate one-month, and whether the current model construct could be expected to run for years to compare w/ the observational record being recorded in LA & USA.

This one-month high-resolution simulation with 288x288x50 grids and 5-s time steps has taken 11520 CPU hours (45 hours x 256 processors) on NAS High performance supercomputer Pleiades. See Page 26 Line 22-25. Using the same number of processors on Pleiades, a one-year simulation will take about 23 days to complete, which is still reasonable. It is, however, not practical for the large scale, i.e., the contiguous United States.

Specific comments :

P8 line 5 : It can be added that the coupling between mesoscale meteorological model and lagrangian particle model can be used in an operational framework to deal with accidental release (Lac et al., 2008).

Added. See Page 9 Line 18-20.

Table 1 : There could be probably a mistake for shortwave radiation scheme : does RRTMG deal with SW radiation ?

The RRTMG shortwave scheme has been included in version 3.1 and above.

Abstract : The acronym FFCO₂ is used before being presented.

Thanks for catching this. The full name has been added in the revised paper.

References :

- Riette and Lac : A New Framework to Compare Mass-Flux Schemes Within the AROME Numerical Weather Prediction Model, *Boundary-Layer Meteorology*, 2016, 1—29.
- Lac, C., F. Bonnardot, O. Connan, C. Camail, D. Maro, D. Hebert, M. Rozet, and J. Pergaud, Evaluation of a mesoscale dispersion modelling tool during the CAPITOUL experiment, *Meteorol. Atmos. Phys.*, 102, 263-287, 2008.
- Bougeault, P., and Lacarrere, P.: Parameterization of Orography-Induced Turbulence in a Mesobeta--Scale Model, *Monthly Weather Review*, 117, 1872-1890, 10.1175/1520-0493(1989)117<1872:POOITI>2.0.CO;2, 1989.
- Chen, F., Kusaka, H., Bornstein, R., Ching, J., Grimmond, C. S. B., Grossman-Clarke, S., Loridan, T., Manning, K. W., Martilli, A., Miao, S., Sailor, D., Salamanca, F. P., Taha, H., Tewari, M., Wang, X., Wyszogrodzki, A. A., and Zhang, C.: The integrated WRF/urban modelling system: development, evaluation, and applications to urban environmental problems, *International Journal of Climatology*, 31, 273-288, 10.1002/joc.2158, 2011.
- Cohen, A. E., Cavallo, S. M., Coniglio, M. C., and Brooks, H. E.: A Review of Planetary Boundary Layer Parameterization Schemes and Their Sensitivity in Simulating Southeastern U.S. Cold Season Severe Weather Environments, *Weather and Forecasting*, 30, 591-612, doi:10.1175/WAF-D-14-00105.1, 2015.
- Coniglio, M. C., Jr., J. C., Marsh, P. T., and Kong, F.: Verification of Convection-Allowing WRF Model Forecasts of the Planetary Boundary Layer Using Sounding Observations, *Weather and Forecasting*, 28, 842-862, doi:10.1175/WAF-D-12-00103.1, 2013.
- Conil, S., and Hall, A.: Local Regimes of Atmospheric Variability: A Case Study of Southern California, *Journal of Climate*, 19, 4308-4325, 10.1175/JCLI3837.1, 2006.
- Janjić, Z. I.: The Step-Mountain Eta Coordinate Model: Further Developments of the Convection, Viscous Sublayer, and Turbulence Closure Schemes, *Monthly Weather Review*, 122, 927-945, 10.1175/1520-0493(1994)122<0927:TSMECM>2.0.CO;2, 1994.
- Lauvaux, T., Schuh, A. E., Uliasz, M., Richardson, S., Miles, N., Andrews, A. E., Sweeney, C., Diaz, L. I., Martins, D., Shepson, P. B., and Davis, K. J.: Constraining the CO₂ budget of the

- corn belt: exploring uncertainties from the assumptions in a mesoscale inverse system, *Atmos. Chem. Phys.*, 12, 337-354, 10.5194/acp-12-337-2012, 2012.
- Mu, L., Mu, L., Stammerjohn, S. E., Lowry, K. E., and Yager, P. L.: Spatial variability of surface pCO₂ and air-sea CO₂ flux in the Amundsen Sea Polynya, Antarctica, *Elementa* (Washington, D.C.), 2, 000036, 10.12952/journal.elementa.000036, 2014.
- Nakanishi, M., and Niino, H.: An Improved Mellor–Yamada Level-3 Model: Its Numerical Stability and Application to a Regional Prediction of Advection Fog, *Boundary-Layer Meteorol.*, 119, 397-407, 10.1007/s10546-005-9030-8, 2006.
- Torres, R., Pantoja, S., Harada, N., González, H. E., Daneri, G., Frangopulos, M., Rutllant, J. A., Duarte, C. M., Rúaiz-Halpern, S., Mayol, E., and Fukasawa, M.: Air-sea CO₂ fluxes along the coast of Chile: From CO₂ outgassing in central northern upwelling waters to CO₂ uptake in southern Patagonian fjords, *Journal of Geophysical Research: Oceans*, 116, 10.1029/2010JC006344, 2011.

1 **LA Megacity: a High-Resolution Land-Atmosphere**
2 **Modelling System for Urban CO₂ Emissions**

3
4 **Sha Feng^{1,2*}, Thomas Lauvaux^{3,2}, Sally Newman⁴, Preeti Rao², Ravan**
5 **Ahmadov^{5,6}, Aijun Deng³, Liza I. Díaz-Isaac³, Riley M. Duren², Marc L.**
6 **Fischer⁷, Christoph Gerbig⁸, Kevin R. Gurney⁹, Jianhua Huang⁹, Seongeun**
7 **Jeong⁷, Zhijin Li², Charles E. Miller², Darragh O’Keeffe⁹, Risa Patarasuk⁹,**
8 **Stanley P. Sander², Yang Song⁹, Kam W. Wong^{4,2}, Yuk L. Yung⁴**

9
10 [1] JIFRESSE, University of California, Los Angeles, Los Angeles, CA

11 [2] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA

12 [3] Department of Meteorology and Atmospheric Science, Pennsylvania State University,
13 State College, PA

14 [4] Division of Geological and Planetary Sciences, California Institute of Technology,
15 Pasadena, CA

16 [5] Cooperative Institute for Research in Environmental Sciences, University of Colorado
17 at Boulder, Boulder, CO

18 [6] Earth System Research Laboratory, National Oceanic and Atmospheric
19 Administration, Boulder, CO, USA

20 [7] Lawrence Berkeley National Laboratory, Berkeley, CA

21 [8] Max Planck Institute for Biogeochemistry, Hans-Knöll-Str.10, 07745 Jena, Germany

22 [9] School of Life Science, Arizona State University, Tempe, AZ

23
24 [*] now at Department of Meteorology, Pennsylvania State University, University Park,
25 PA 16802, USA

1 Correspondence to: Sha Feng (sfeng@psu.edu)

2

1 **Abstract**

2 Megacities are major sources of anthropogenic fossil fuel CO₂ (FFCO₂) emissions. The
3 spatial extents of these large urban systems cover areas of 10,000 km² or more with
4 complex topography and changing landscapes. We present a high-resolution land-
5 atmosphere modelling system for urban CO₂ emissions over the Los Angeles (LA)
6 megacity area. The Weather Research and Forecasting (WRF)-Chem model was coupled
7 to a very high-resolution FFCO₂ emission product, Hestia-LA, to simulate atmospheric
8 CO₂ concentrations across the LA megacity at spatial resolutions as fine as ~1 km. We
9 evaluated multiple WRF configurations, selecting one that minimized errors in wind
10 speed, wind direction, and boundary layer height as evaluated by its performance against
11 meteorological data collected during the CalNex-LA campaign (May-June 2010). Our
12 results show no significant difference between moderate- (4-km) and high- (1.3-km)
13 resolution simulations when evaluated against surface meteorological data, but the high-
14 resolution configurations better resolved PBL heights and vertical gradients in the
15 horizontal mean winds. We coupled our WRF configuration with the Vulcan 2.2 (10 km
16 resolution) and Hestia-LA (1.3-km resolution) fossil fuel CO₂ emission products to
17 evaluate the impact of the spatial resolution of the CO₂ emission products and the
18 meteorological transport model on the representation of spatiotemporal variability in
19 simulated atmospheric CO₂ concentrations. We find that high spatial resolution in the
20 fossil fuel CO₂ emissions is more important than in the atmospheric model to capture CO₂
21 concentration variability across the LA megacity. Finally, we present a novel approach
22 that employs simultaneous correlations of the simulated atmospheric CO₂ fields to
23 qualitatively evaluate the greenhouse gas measurement network over the LA megacity.
24 Spatial correlations in the atmospheric CO₂ fields reflect the coverage of individual
25 measurement sites when a statistically significant number of sites observe emissions from
26 a specific source or location. We conclude that elevated atmospheric CO₂ concentrations
27 over the LA megacity are composed of multiple fine-scale plumes rather than a single
28 homogenous urban dome. Furthermore, we conclude that FFCO₂ emissions monitoring in
29 the LA megacity requires FFCO₂ emissions modelling with ~1 km resolution because
30 coarser resolution emissions modelling tends to overestimate the observational
31 constraints on the emissions estimates.

1 **1 Introduction**

2 Carbon dioxide (CO₂) is a major anthropogenic contributor to climate change. It has
3 increased from its preindustrial (1750) level of 278 ± 2 ppm (Etheridge et al., 1996) to
4 over 400 ppm in recent years, as reported by the National Oceanic and Atmospheric
5 Administration (NOAA) and Scripps Institution of Oceanography [<http://co2now.org/>].
6 Clear evidence has shown that the continued increase of the atmospheric CO₂
7 concentration is dominated by global fossil fuel consumption during the same period
8 (IPCC, 2013) and land use change (Houghton, 1999).

9 Urban areas are significant sources of fossil fuel CO₂ (FFCO₂), representing more than
10 50% of the world's population and more than 70% of FFCO₂ (UN, 2006). In particular,
11 megacities (cities with urban populations greater than 10 million people) are major
12 sources of anthropogenic emissions, with the world's 35 megacities emitting more than
13 20% of the global anthropogenic FFCO₂, even though they only represent about 3% of
14 the Earth's land surface (IPCC, 2013). The proportion of emissions from megacities
15 increases monotonically with the world population and urbanization (UN, 2006, 2010).
16 Developed and developing megacities around the world are working together to pursue
17 strategies to limit CO₂ and other greenhouse gas (GHG) emissions (C40, 2012).

18 Carbon fluxes can be estimated using “bottom-up” and “top-down” methods. Typically,
19 FFCO₂ emissions are determined using “bottom-up” methods, by which fossil fuel usage
20 from each source sector is convolved with the estimated carbon content of each fuel type
21 to obtain FFCO₂ emission estimates. Space-time resolved FFCO₂ data sets using “bottom-
22 up” methods clearly reveal the fingerprint of human activity with the most intense
23 emissions being clustered around urban centres and associated power plants (e.g., Gurney
24 et al., 2009; Gurney et al., 2012). At the global and annual scale, FFCO₂ emission
25 estimates remain uncertain at $\pm 5\%$, varying widely by country and reporting method (Le
26 Quéré et al., 2014). At the urban scale, the uncertainties of FFCO₂ emission estimates are
27 often 50-200 % (Turnbull et al., 2011; Asefi-Najafabady et al., 2014). On the other hand,
28 “top-down” methods could potentially estimate biases in bottom-up emissions, and could
29 also detect trends that cities can use for decision-making, due to changing economic
30 activity or implementation of new emission regulations.

1 “Top-down” methods involve atmospheric measurements and usually include an
2 atmospheric inversion of CO₂ concentrations, using atmospheric transport models to
3 estimate carbon fluxes (i.e., posterior fluxes) by adjusting the fluxes (i.e., prior fluxes) to
4 be consistent with observed CO₂ concentrations (e.g., Lauvaux et al., 2012; Lauvaux et
5 al., 2015; Tarantola, 2005; Enting et al., 1994; Gurney et al., 2002; Baker et al., 2006;
6 Law et al., 2003). In general, a prior flux is required for estimating the fluxes using an
7 atmospheric inversion. The uncertainties in “top-down” methods can be attributed to
8 errors in the observations (e.g., Tarantola, 2005), emission aggregation errors from the
9 prior fluxes (e.g., Gurney et al., 2012; Engelen et al., 2002), and physical representation
10 errors in the atmospheric transport model (e.g., Díaz Isaac et al., 2014; Gerbig et al.,
11 2008; Kretschmer et al., 2012; Lauvaux et al., 2009; Sarrat et al., 2007). Previous studies
12 showed that regional high-resolution models can capture the measured CO₂ signal much
13 better than the lower resolution global models and simulate the diurnal variability of the
14 atmospheric CO₂ field caused by recirculation of nighttime respired CO₂ well (Ahmadov
15 et al., 2009). Previous studies (Ahmadov et al., 2009; Pillai et al., 2011; Pillai et al., 2010;
16 Rödenbeck et al., 2009) have discussed the advantages of high resolution CO₂ modelling
17 on different domains and applications. Recent efforts to study FFCO₂ emissions on urban
18 scales have benefited from strategies that apply in-situ observations concentrated within
19 cities and mesoscale transport models (e.g., Wu et al., 2011; Lauvaux et al., 2015; Strong
20 et al., 2011; Lac et al., 2013; Bréon et al., 2015).

21 The Los Angeles (LA) megacity is one of the top three FFCO₂ emitters in the U.S. The
22 atmospheric CO₂ concentrations show complex spatial and temporal variability resulting
23 from a combination of large FFCO₂ emissions, complex topography, and challenging
24 meteorological variability (e.g., Brioude et al., 2013; Wong et al., 2015; Angevine et al.,
25 2012; Conil and Hall, 2006; Ulrickson and Mass, 1990; Lu and Turco, 1995; Baker et al.,
26 2013; Chen et al., 2013; Newman et al., 2013). Past studies exploring CO₂ concentrations
27 over the LA megacity used measurement methods ranging from ground-based to
28 airborne, from in-situ to column. Those studies consistently reported robust
29 enhancements (e.g., 30-100 ppm in-situ and 2-8 ppm column) and significant variability
30 of the CO₂ concentrations for the LA megacity (Newman et al., 2013; Wunch et al., 2009;
31 Wong et al., 2015; Kort et al., 2012; Wennberg et al., 2012; Newman et al., 2016). There

1 have been limited radiocarbon (^{14}C) isotopic tracer studies (Newman et al., 2013;;
2 Djuricin et al., 2010; Riley et al., 2008; Newman et al, 2016). Newman et al. (2013)
3 showed that FFCO₂ constituted 10 - 25 ppm of the CO₂ excess observed in the LA basin
4 by averaging the flask samples at 1400 PST during 15 May – 15 June, 2010. Djuricin et
5 al. (2010) demonstrated that fossil fuel combustion contributed approximately 50~70 %
6 of CO₂ sources in LA. Recently, using CO₂ mole fractions and $\Delta^{14}\text{C}$ and $\delta^{13}\text{C}$ values of
7 CO₂ in the LA megacity observed in inland Pasadena (2006–2013) and coastal Palos
8 Verdes peninsula (autumn 2009–2013), Newman et al. (2016) demonstrated that fossil
9 fuel combustion is the dominant source of CO₂ for inland Pasadena. Airborne campaigns
10 over LA (typically days to weeks in duration) included ARCTAS-CA (Jacob et al., 2010)
11 and CalNex-LA (Brioude et al., 2013). All of these earlier studies were limited in their
12 ability to investigate the spatial and temporal characteristics of LA carbon fluxes given
13 relatively sparse observations. To better understand and quantify the total emissions,
14 trends, and detailed spatial, temporal, and source sector patterns of emissions over the LA
15 megacity requires both a denser measurement network and a land-atmosphere modelling
16 system appropriate for such a complex urban environment. In this paper, we couple the
17 Weather Research and Forecasting (WRF) – Chem model to a high-resolution FFCO₂
18 emission product, Hestia-LA, to study the spatiotemporal variability of urban CO₂
19 concentrations over the LA megacity.

20 The mesoscale circulation over the LA megacity is challenging for atmospheric transport
21 models due to a variety of phenomena, such as “Catalina” eddies off the coast of southern
22 California and the coupling between the land-sea breeze and winds induced by the
23 topography (Angevine et al., 2012; Conil and Hall, 2006; Ulrickson and Mass, 1990;
24 Kusaka and Kimura, 2004b; Kusaka et al., 2001). In this paper we present a set of
25 simulations exploring WRF model physics configurations for the LA megacity,
26 evaluating the model performance against meteorological data from the CalNex-LA
27 campaign period, 15 May – 15 June 2010. Angevine et al. (2012) investigated how WRF
28 model performance varied with spatial resolution and PBL scheme, etc., for the CalNex-
29 LA campaign period; however, they focused the model meteorological evaluation on the
30 spatial resolutions of 12- and 4-km. In the present study we focus on three critical aspects
31 of the WRF model configuration – the planetary boundary layer (PBL) scheme, the urban

1 surface scheme, and the model spatial resolution – as well as the effects of the FFCO₂
2 emissions product spatial resolution. Through these four aspects, the impacts of physical
3 representation errors and emission aggregation errors on the modelled CO₂ concentrations
4 across the LA megacity are investigated.

5 Moreover, a novel approach is proposed to evaluate the design of the greenhouse gas
6 (GHG) measurement network for the LA megacity. The LA measurement network
7 consists of 14 observation sites designed to provide continuous atmospheric CO₂
8 concentrations to assess the anthropogenic carbon emissions distribution and trends. The
9 goal of the network design exploration is to optimize the atmospheric observational
10 constraints on the surface fluxes. Kort et al. (2013) found that a minimum of eight
11 optimally located, in-city surface CO₂ observation sites were required for accurate
12 assessment of CO₂ emissions in LA using the “footprint” method (backward mode) and
13 based on a national FFCO₂ emission product Vulcan (Gurney et al, 2009; Gurney et al,
14 2012). Here we assess the influence of each observation site using spatial correlations in
15 terms of the simulated CO₂ (forward mode) at high-resolution. This method brings
16 flexibility to allow us to evaluate the existing measurement network or to design a
17 measurement network for various observation platforms, i.e., in-situ, aircraft, satellite,
18 etc. In this paper, we will investigate the application to in-situ measurement network
19 design.

20 The remainder of the paper is organized as follows. Section 2 describes the modelling
21 framework, including initial conditions and boundary conditions for WRF-Chem. In
22 section 3, we assess the quality of the model results, focusing on accurate representation
23 of the PBL height, wind speed and wind direction, and CO₂ concentration. Section 4
24 presents the spatial and temporal patterns of simulated CO₂ concentration fields over the
25 LA megacity using various FFCO₂ emissions products. Section 5 describes the forward
26 mode approach for evaluating the spatial sensitivity of the 2015-era surface GHG
27 measurement sites within the LA megacity. Discussion of model errors, model sampling
28 strategy, and the density of the LA GHG measurement network from the forward model
29 perspective is given in section 6. A summary is given in section 7. Section 8 lists the
30 author contributions.

1

2 **2 Modelling Framework**

3 Sensitivity experiments were conducted using WRF-Chem version 3.6.1 with various
4 PBL schemes, urban surface schemes, and model resolutions to define an optimized
5 configuration for simulating atmospheric CO₂ concentration fields over the LA megacity.
6 The impact of the resolution of FFCO₂ emission products is investigated in section 4.

7 **2.1 WRF model setup**

8 All of the model runs used one-way triple-nested domains with resolutions of 12-, 4-, and
9 1.3-km. The coarse domain (d01) covers most of the western US; the intermediate
10 domain (d02) covers California and part of Mexico (Figure 1a); the innermost domain
11 (d03) covers the majority of the South Coast Air Basin, a portion of the southern San
12 Joaquin Valley and extends into the Pacific Ocean to include Santa Catalina and San
13 Clemente Islands (Figure 1b). The Los Angeles basin, a subset of South Coast Air Basin,
14 is surrounded to the north and east by mountain ranges with summits of 2-3 km, with the
15 ocean to the west and the desert to the north. The basin consists of the West Coast Basin,
16 Central Basin, and Orange County Coastal Plain. The boundaries of these three regions
17 are the Newport Inglewood Fault and the boundary between Los Angeles County and
18 Orange County. In this study, our analysis is limited to the innermost domain (d03),
19 referred to hereafter as the LA megacity. All three of the model domains use 51 terrain
20 following vertical levels from surface to 100 hPa, of which 29 layers are below 2 km
21 above ground level (AGL) and the first level is about 8 m AGL.

22 The meteorological fields and surface parameters, such as soil moisture, were initialized
23 by the three-hourly North American Regional Reanalysis (NARR) data set with a
24 horizontal resolution of 32 km (Mesinger et al., 2006) and the six-hourly NCEP sea
25 surface temperature data set with a horizontal resolution of 12 km
26 (<ftp://polar.ncep.noaa.gov/pub/history/sst/ophi>). A summary of WRF configurations
27 common to all sensitivity runs is shown in Table 1. The impact of varying the PBL
28 parameterization, urban surface, and model resolution was investigated by conducting
29 sensitivity runs summarized in Table 2.

1 PBL schemes are used to parameterize the unresolved turbulent vertical fluxes of heat,
2 momentum, and constituents within the PBL. There are tens of mesoscale PBL schemes
3 available in the WRF package. The details of PBL schemes can be found in the review
4 paper by Cohen et al. (2015). Briefly, the PBL schemes represent turbulent mixing on the
5 local or non-local basis. The local schemes only consider immediately adjacent vertical
6 levels in the model. This tends to prevent vertical mixing and to produce relatively
7 shallow PBL. Non-local schemes allow for a deeper mixing layer. We selected the three
8 commonly used turbulent kinetic energy (TKE)-driven local PBL schemes (1.5 order) for
9 the sensitivity runs: the Mellor-Yamada-Janjie technique (MYJ), Mellor-Yamada
10 Nakanishi and Niino Level 2.5 (MYNN), and Bougeault-Lacarrère (BouLac). MYJ
11 (Janjić, 1994) defines the PBL top where the TKE profiles decrease to a threshold of 0.2
12 m^2s^{-2} ; MYNN (Nakanishi and Niino, 2006) is tuned to a database of large eddy
13 simulations (LES) and sets the PBL top where the TKE falls below $1.0 \times 10^{-6} \text{m}^2 \text{s}^{-2}$;
14 BouLac (Bougeault and Lacarrere, 1989) defines the PBL top where TKE reaches 0.005
15 $\text{m}^2 \text{s}^{-2}$.

16 The TKE-driven PBL schemes explicitly estimate the turbulent fluxes from mean
17 atmospheric states and/or their gradients and can be used to drive a Lagrangian particle
18 dispersion model in subsequent atmospheric inversions (e.g., Lauvaux et al., 2008). The
19 coupling between the mesoscale meteorological and Lagrangian particle models can be
20 used in an operational framework to deal with accidental release (Lac et al., 2008).

21 For an accurate representation of the LA CO_2 distribution, the necessity of incorporating
22 a urban surface scheme was tested by alternatively including a single-layer urban canopy
23 model (UCM, Kusaka and Kimura, 2004a), a multiple-layer building environment
24 parameterization (BEP, Martilli et al., 2009), and no urban surface scheme. Note that
25 BEP requires very high vertical resolution within the PBL and is only compatible with
26 MYJ and BouLac PBL schemes. Given that BEP is computationally expensive, we only
27 test it with BouLac in this study. A detailed description of urban parameterization
28 schemes available in WRF is provided by Chen et al. (2011).

29 We chose to test and evaluate our WRF-Chem configuration during the middle of May –
30 middle of June 2010 time period of the CalNex-LA campaign (Ryerson et al., 2013) to

1 take advantage of the extra meteorological measurements recorded during the campaign.
2 Hourly simulations were conducted for 36-h periods starting with a 12-h meteorological
3 spin-up at 12:00 UTC of the previous day. Hence, when concatenating the model output,
4 each new run is introduced at 0000 UTC. All of the analyses in the following sections are
5 limited to the region of the LA megacity.

6 **2.2 Configuration for the CO₂ simulation**

7 This paper analyses the impact of both physical representation errors and emission
8 aggregation errors on the modelled CO₂ concentrations across the LA megacity. WRF-
9 Chem version 3.6.1 allows for online CO₂ tracer transport coupled with the Vegetation
10 Photosynthesis and Respiration Model (VPRM) (Ahmadov et al., 2007; Xiao et al.,
11 2004). VPRM calculates hourly net ecosystem exchange based on MOIDS satellite
12 estimates of the land surface water index and enhanced vegetation index (EVI), short
13 wave radiance and surface temperature. A detailed description of VPRM can be found in
14 Mahadevan et al. (2008). In this study, the defaults of the VPRM parameters were used
15 given limited number of observation available for optimization.

16 Anthropogenic FFCO₂ fluxes were alternatively prescribed from the Vulcan 2.2 and
17 Hestia-LA 1.0 FFCO₂ emission products developed at Arizona State University (Gurney
18 et al., 2009; Gurney et al., 2012; Gurney et al., 2015; Rao et al., 2015). Both emission
19 products were developed using “bottom-up” methods. Vulcan quantifies FFCO₂
20 emissions for the entire contiguous United States (CONUS) hourly at approximately 10-
21 km spatial resolution for the year of 2002, The temporal variations are driven by a
22 combination of modelled activity (building energy modelling) and monitoring (power
23 plant emissions) (Gurney et al., 2009). Hestia-LA, by contrast, is a fossil fuel CO₂
24 emissions data product specific in space and time to the individual building, road
25 segments, and point sources covering the the Los Angeles megacity domain for the years
26 of 2011 and 2012 (Rao et al., 2015; Gurney et al., 2015; Gurney et al., 2012; Zhou and
27 Gurney, 2010). It quantifies hourly FFCO₂ emissions for the counties of Los Angeles,
28 Orange, San Bernardino, Ventura, and Riverside, at approximately 1.3 km x 1.3 km.
29 Hestia-LA uses much of the same information for the temporal variations of Vulcan
30 except for the onroad emissions, for which local traffic data is employed as opposed to

1 regional traffic data. Given the similarities, it is unlikely that the small difference in
2 temporal variation between Hestia-LA and Vulcan could account for the spatial
3 differences, through covariation with atmospheric transport, found in this study. For more
4 details about Hestia-LA, see Rao et al. (2015).

5 Atmospheric CO₂ concentrations in WRF-Chem were alternatively driven by the Vulcan
6 and Hestia-LA emissions at the resolutions of 4 km and 1.3 km. Hence, four different
7 emission datasets were generated – Vulcan 10 km emissions transported at 4-km or 1.3-
8 km resolution, and Hestia-LA 1.3 km emissions transported at 4-km or 1.3-km resolution.
9 The Hestia-LA emissions were aggregated from the native building-level resolution to
10 the 1.3 and 4 km resolutions via direct summation in the specified model grids. Hestia-
11 LA 2011 is temporally shifted for creating the weekday-weekend cycle for the year of
12 2010. The Vulcan FFCO₂ emissions were interpolated by using a bilinear operator and by
13 preserving the value of the integral of data between the source (10-km) and destination
14 (4- and 1.3-km) grid. Additionally, the ratio of the total carbon emissions over the state
15 between the years of 2002 and 2015 from California Air Resource Board
16 (<http://www.arb.ca.gov/>) was uniformly applied to the Vulcan emissions to temporally
17 scale Vulcan from the 2002 base year to 2010.

18 No CO₂ ocean fluxes were prescribed in this study. The order of magnitude of oceanic
19 CO₂ fluxes is minus one in the unit of $\mu\text{mol}/\text{m}^2/\text{s}$: $-0.15 \mu\text{mol}/\text{m}^2/\text{s}$ along the coast of
20 Chile calculated by Torres et al. (2011), $+0.2 \mu\text{mol}/\text{m}^2/\text{s}$ for Southern Ocean by Mu et al.
21 (2014), while fossil fuel emissions are about $20 \mu\text{mol}/\text{m}^2/\text{s}$ (roughly estimated from
22 Hestia-LA at the Pasadena site). At regional scales, anthropogenic and biogenic fluxes
23 are much larger than ocean fluxes, so we assume the ocean fluxes are negligible.

24 Lateral boundary conditions and initial conditions for CO₂ concentration fields were
25 taken from the three-dimensional CO₂ background (often called the “NOAA curtain” for
26 background) estimated from measurements in the Pacific (Jeong et al., 2013). Unlike
27 meteorology, CO₂ fields were initialized only at the start time of the entire simulation and
28 were carried over simulation cycle to cycle (without any re-initialization) until the end of
29 the entire simulation to conserve CO₂ air mass over the model domains.

30

1 **3 Model – data comparison**

2 Meteorological observations obtained during the CalNex-LA campaign
3 (<http://www.esrl.noaa.gov/csd/projects/calnex/>) include PBL height sampled by NOAA
4 P-3 flights and aerosol backscatter ceilometer (Haman et al., 2012; Scarino et al., 2013), a
5 radar wind profiler operated by the South Coast Air Quality Management District near
6 Los Angeles International Airport (LAX), and CO₂ in situ measurements (Newman et al.,
7 2013). Additionally, the NWS (National Weather Service, www.weather.gov) surface
8 observations are used.

9 **3.1 Comparison to aircraft PBL height**

10 During CalNex-LA, 17 P-3 research flights sampled the daytime and nighttime PBL,
11 marine surface layer, and the overlying free troposphere throughout California (Ryerson
12 et al., 2013). We imposed four criteria for selecting aircraft profiles of potential
13 temperature for PBL height comparisons:

- 14 1) Aircraft profiles sample within the innermost model domain (d03, Figure 1b);
- 15 2) Profiles sample during daytime (1100 PST – 1700 PST) when the CO₂ concentrations
16 in PBL is well mixed;
- 17 3) Profiles acquired within ±30 min of the model output;
- 18 4) Ability to determine the PBL height from the vertical gradient of potential
19 temperature.

20 Based on these four criteria, we selected seven aircraft profiles collected between 16 May
21 and 19 May 2010. Figure 2 shows a profile acquired on 19 May 2010 when the aircraft
22 was sampling over Pasadena, California.

23 The model diagnostic PBL height calculated by each PBL scheme can differ due to the
24 Richardson bulk number (R_i) used (e.g., Kretschmer et al., 2014; Hong et al., 2006; Yver
25 et al., 2013). To avoid this difference, we determined modelled PBL height based on the
26 vertical virtual potential temperature gradient. The case in Figure 2 shows that the
27 modelled PBL height agrees within 50 meters of the aircraft-determined and ceilometer-
28 measured PBL height

1 Figure 3 shows the absolute difference between the modelled and aircraft-determined
2 PBL height for each selected aircraft profile. The differences between the modelled and
3 aircraft-determined PBL height differ case by case, and none of the model physics is
4 systematically better than others. However, BouLac_BEP and MYNN have larger biases
5 than others. The averaged bias of BouLac_BEP is 289 m for d02, 295 m for d03; MYNN
6 bias is 179 m for d02 and 216 m for d03. For other configurations, the averaged biases
7 are smaller than 160 m. The modelled PBL bias appears somewhat smaller in the 4-km
8 runs than the 1.3-km runs. This, however, is based on seven selected aircraft profiles
9 only. To further define the optimal physics for the PBL height simulation, we will present
10 the all-hours statistics with the ceilometer data in section 3.2.

11 **3.2 Comparison to ceilometer PBL height**

12 Accurate simulation of the time evolution of the PBL depth is crucial to properly simulate
13 the vertical mixing and ventilation of CO₂ emitted at the surface. The ceilometer
14 measurements during CalNex-LA (Haman et al., 2012) allow us to evaluate the time
15 evolution of the modelled PBL depth. Compared with the ceilometer-measured PBL
16 height, the maximum discrepancies between model and observations occur from around
17 1100 PST – 1200 PST when the nocturnal PBL is fully collapsed and 1700 PST when it
18 starts to form again (Figure 4). Among all of the model physics, MYNN_UCM shows the
19 best agreement with the observations, while BouLac_BEP differs from ceilometer the
20 most. The absolute bias of the MYNN_UCM modelled PBL height ranges from 5 to 198
21 m and 0 to 184 m with mean biases of -15.3 m (d02) and -6.9 m (d03) and root-mean-
22 square error (*RMSE*) of 89.7 m and 94.5 m for 4- and 1.3-km resolution, respectively,
23 which is similar to the range in the study of Riette and Lac (2016). They evaluated the
24 model performance with different model sizes for an operational weather forecast system
25 (AROME, application of Research to Operations at Mesosclae) against the observed PBL
26 height at five observation sites, showing mean bias of -9.17 m and *RMSE* of 115 m for
27 200 × 200 grids, 6.17 m and 95.5 m for 108 × 108 grids. In our experiences, the statistics
28 of MYNN_UCM_1.3km and MYNN_UCM_4km suggest the 1.3-km model resolution
29 improves the model performance of the PBL simulation as compared with the ceilometer.
30 The improvement in the high-resolution model runs can be seen in the statistics for

1 MYJ_UCM, BouLac_UCM, and BouLac_BEP, but not MYNN or MYJ (Table 3). Note
2 that the ceilometer measurements were all at Caltech and thus reflect basin interior
3 conditions. These are expected to be very different from coastal conditions in terms of the
4 temporal evolution and eventual height of the mid-day PBL as well as the timing of the
5 nocturnal PBL collapse. The domain is much larger and more varied than captured by a
6 single location.

7 We also notice that UCM-coupled simulations agree with the ceilometer better than other
8 combinations (Table 3, MYNN_UCM vs. MYNN, MYJ_UCM vs. MYJ, BouLac_UCM
9 vs. BouLac_BEP). The inclusion of UCM yields model simulations with comparably
10 higher relative humidity over the LA megacity (not shown). This corresponds to lower
11 PBL height, which largely reduces the discrepancy of the modelled PBL from the
12 observations (see UCM runs with their counterparts in Figure 4).

13 **3.3 Comparison to radar wind profiler**

14 Atmospheric dynamics has a direct influence on the CO₂ transport. Realistically
15 reproducing the vertical gradient of wind fields is crucial. In Figure 5, we show the
16 average difference in the wind profiles between the models and the radar wind profiler at
17 LAX (Angevine et al., 2012). Most of the simulations show relatively larger wind speed
18 bias near the surface: BouLac_BEP, MYJ, and MYNN with bias of 2.4 ± 2.2 m/s,
19 BouLac_UCM and MYJ_UCM with bias of 2.0 ± 2.3 m/s. In contrast, it is encouraging
20 to see that MYNN_UCM agrees with the radar measurement with mean bias of 1.4 ± 2.0
21 m/s, a lower mean bias than for the other configurations. As we found in the PBL
22 evaluation, UCM-coupled simulations tend to reduce the wind speed bias at this location.

23 For wind direction, likewise, MYNN_UCM agrees with the observations slightly better
24 below 800 m (~ 1.1 m/s for the averaged error), although the model bias is much less
25 pronounced across the configurations. However, we notice that MYNN_UCM shows
26 larger wind direction bias between 800 – 1400 m than others due to relatively lower PBL
27 height simulated (not shown).

1 Improvement provided by the 1.3-km model resolution is visible near the PBL height
2 (800 – 1400 m). A finer model resolution tends to resolve the vertical gradients of the
3 atmospheric state better.

4 Angevine et al. (2012) evaluated a set of model configurations with the highest model
5 resolution at 4 km for CalNex-LA using the same radar wind profiler data. The optimal
6 configuration (the total energy–mass flux boundary layer scheme and ECMWF
7 reanalysis) they found showed 1.1 ± 2.7 m/s bias in wind speed and $-2.6 \pm 67^\circ$ in wind
8 direction near the surface. Here MYNN_UCM displays similar performance to their
9 optimal configuration. At the 4-km model resolution, the biases of MYNN_UCM are 1.4
10 ± 2.0 m/s in wind speed and $-1.3 \pm 20.0^\circ$ in wind direction.

11 In summary, the MYNN_UCM configuration showed the best agreement with
12 meteorological observations among the configurations we evaluated at given locations. In
13 section 3.4, we examine the performance of MYNN_UCM across the LA megacity.

14 **3.4 Comparison to NWS surface stations**

15 We introduce the observations from the NWS surface network to demonstrate the model
16 performance across the LA megacity. The objective analysis program OBSGRID is used
17 to remove erroneous data and observations that are not useful (Deng et al., 2009; Rogers
18 et al., 2013).

19 Figure 6 shows the model bias of temperature, relative humidity, wind speed, and wind
20 direction compared to the NWS surface data across the LA megacity. The locations of the
21 GHG measurement sites are marked (see details in Table 6 and Figure S1). Overall, there
22 is little difference in the simulated surface atmospheric state variables between the 4-km
23 and 1.3-km runs; i.e., the 1.3-km run does not show any significant improvement
24 compared to the 4-km run at the surface (even though it resolves the vertical gradient of
25 atmospheric states and PBL better, Figure 4 and 5).

26 For temperature (Figure 6a1 and 6b1), the model is colder than the observations by 0.5 -
27 1.0 K. Larger temperature biases occur in the desert. For relative humidity (Figure 6a2
28 and 6b2), the model is dryer (teal blue) than the observations but with two exceptions:
29 Santa Monica coastal area and Pasadena to Mt. Wilson area (light green). See Figure S1

1 for the location. The model dryness is consistent with the findings of Nehrkorn et al.
2 (2012). The model is 5% dryer over the basin with a somewhat larger bias of 5% - 10%
3 near Granada Hills and Ontario. These two locations have the highest temperature in the
4 summer – typically 7 K or more warmer than downtown LA in May-June (77 °F for
5 downtown LA and 84 °F for Ontario. See
6 <http://www.intellicast.com/Local/History.aspx>). For the Pasadena area, the model is
7 moister than the observations. The moistness tends to cause lower PBL heights, which
8 can be seen in the comparison to the ceilometer-determined PBL height at Caltech in
9 Pasadena, California (Figure 4): MYNN_UCM has a shallower PBL in comparison to the
10 ceilometer during the 1400 PST – 1800 PST time period.

11 The model overestimates wind speed by ~1.0 m/s (Figure 6a3 and 6b3). The tendency of
12 the model to overestimate wind speed is fully documented in previous studies (e.g.,
13 Angevine et al., 2012; Brioude et al., 2013; Nehrkorn et al., 2012; Yver et al., 2013). For
14 surface wind direction, model bias is within $\pm 10^\circ$ for most of the LA megacity. The
15 larger biases appear near the foothills of Santa Monica Mountains, San Gabriel
16 Mountains, and University of Southern California (USC) due to the topography.

17 Compared with other model physics (not shown), we notice that USC, located just south
18 of downtown LA, is a challenging location for mesoscale modelling, in particular for
19 wind simulations. All of the model physics consistently show a relatively large wind bias
20 at USC except BouLac_BEP that is not seen in the remainder of the domain. We also
21 noticed that adding UCM to MYNN decreases the modelled temperature, while all of the
22 other models' physics have a warm bias compared to observations.

23 All of the analyses above focused on the meteorology over the LA megacity. The results
24 indicate little difference horizontally between 4- and 1.3-km runs across the basin.
25 Similarly, there are only small differences in the *RMSE* maps as well (Figure 7). This
26 consistent with the assumption in Angevine et al. (2012) that a finer grid may not give
27 better results. However, the 1.3-km run tends to resolve the vertical gradients of
28 atmospheric state variables and PBL better, which likely improves the vertical mixing
29 and ventilation of modelled atmospheric CO₂ concentrations. In the following sections,

1 we will use the MYNN_UCM configuration with the resolution of 4 km and 1.3 km for
2 the simulations of atmospheric CO₂ concentration fields over the LA megacity.

3 **3.5 Comparisons to in-situ CO₂**

4 We coupled Hestia and Vulcan FFCO₂ emission products individually with the
5 MYNN_UCM to generate four sets of simulated CO₂ concentrations: WRF-Hestia 1.3-
6 km, WRF-Hestia 4-km, WRF-Vulcan 1.3-km, and WRF-Vulcan 4-km. The runs with the
7 same model resolution have the same meteorology but differ in emissions, and vice versa.

8 During CalNex-LA, in-situ observation sites at Pasadena and Palos Verdes continuously
9 measured surface CO₂ concentrations. Measurements were recorded using a Picarro
10 (Santa Clara, CA) Isotopic CO₂ Analyser (cavity ring-down spectrometer), model G1101-
11 i, for Pasadena and an infrared gas analyser from PP Systems (Haverford, MA), model
12 CIRAS-SC for Palos Verdes. In addition, periodic flask samples were collected for
13 analysis of ¹⁴CO₂ for extracting fossil fuel and biogenic signals. See Newman et al.
14 (2016) for details about the sites and sampling information. Figure 8 shows the
15 comparison of the time series of hourly (Figure 8a,b) and daily afternoon (Figure 8c,d)
16 averaged CO₂ concentrations (1300 PST – 1700 PST) between model and observations.
17 Tables 4 and 5 is the comparison statistics of the four CO₂ runs against the in-situ
18 measurements as a complement to Figure 8a,b and Figure 8c,d, respectively. Overall, the
19 model captures the temporal variability of CO₂ but overestimates CO₂ during nighttime.
20 During afternoons, the model agrees with the observations fairly well (Figure 8c and 8d)
21 except for a few events: all simulations underestimate CO₂ concentrations by about 10
22 ppm around 28 May and 4-6 June for Pasadena and 21 May for Palos Verdes. These
23 events lasting two – three days are likely related to synoptic scale processes. Using the
24 averaged Pacific Ocean CO₂ signal as background may explain the failure to capture
25 these events. Further investigation of the background air would provide insights related to
26 synoptic variability but is beyond the scope of this work.

27 Inter-comparison of the diurnal patterns among these four runs (Figure 9a) shows WRF-
28 Hestia runs tend to overestimate the CO₂ concentration around noon and underestimate
29 CO₂ in the late afternoon at the Pasadena site, while WRF-Vulcan runs tend to

1 underestimate the CO₂ concentration for the entire period. Hence, WRF-Hestia runs show
2 larger model bias based on the statistics for the daytime afternoon hour but smaller errors
3 based on the daytime afternoon average (Table 4 and 5). Next we focus on this diurnal
4 variability.

5 Clear diurnal variations of the surface CO₂ concentrations were observed for both sites
6 (Figure 9). The observed CO₂ concentrations increase at night and remain high until
7 sunrise, and they quickly drops as the boundary layer grows after sunrise (Figure 9a and
8 9b). The amplitude of this diurnal cycle is greater in Pasadena than in Palos Verdes.

9 For the Pasadena site, during nighttime, when the PBL is shallow, CO₂ is trapped locally:
10 the more fossil fuel is emitted, the higher CO₂ concentration is simulated. Consequently,
11 the WRF-Vulcan runs show considerably lower CO₂ concentration than the WRF-Hestia
12 runs due to the lower emissions in Vulcan at the Pasadena site (Figure 9c). However,
13 during daytime, with well-mixed conditions, the discrepancy between the WRF-Hestia
14 and WRF-Vulcan runs becomes smaller at this site. Among these runs, the 1.3-km WRF-
15 Hestia run successfully captures the diurnal variation of the surface CO₂ concentration,
16 although a noontime peak is in the model not present in the observations. By contrast, the
17 4-km WRF-Hestia run underestimates the CO₂ concentration during 0200 PST – 0700
18 PST even though emissions were comparable between Hestia 4-km and Hestia 1.3-km
19 (Figure 9c). The underestimation of the simulated CO₂ concentration likely results from
20 the representation errors in the atmospheric transport due to the coarser model resolution.

21 For Palos Verdes, however, none of the model results match the observations. All of the
22 runs show a peak in the simulated CO₂ concentration around 0800 PST, which very likely
23 corresponds to the failure to simulate the eastward marine flow as a part of the Catalina
24 eddy (e.g., Bosart, 1983; Davis et al., 2000). This CO₂ concentration peak is incorrectly
25 reproduced by the model advecting the FFCO₂ emitted from the strong point sources in
26 Long Beach, California (Figure 1d) and in turn contaminating the air of Palos Verdes.

27 **3.6 Comparisons to flask-sampled CO₂**

28 The isotopic tracer radiocarbon (¹⁴C) can be used for distinguishing between fossil fuel
29 and biogenic sources of CO₂ (Djuricin et al., 2010; Newman et al., 2013; Newman et al.,

1 2016; Pataki et al., 2006; Pataki et al., 2007; Levin et al., 2003; Miller et al., 2012;
2 Turnbull et al., 2006; Turnbull et al., 2009). During CalNex-LA, flask samples collected
3 on alternate afternoons at 1400 PST were combined to produce two CO₂ samples samples
4 per month in Pasadena (weekly samples were combined to produce one radiocarbon
5 sample per month in Palos Verdes) for extracting anthropogenic and biogenic signals
6 from the total CO₂ concentration. Note that the two samples for Palos Verdes were
7 sampled from 1 May to 31 May and from 1 June to 30 June, not exactly overlapping the
8 CalNex-LA period; the two for Pasadena were sampled from 15 May to 31 May and from
9 1 June to 15 June, overlapping the CalNex-LA period. See Newman et al. (2016) for
10 details about the sites and sampling information. Figure 10 presents the comparisons of
11 the modelled and flask-sampled anthropogenic fossil fuel and biogenic CO₂. From both
12 the flask samples and model simulations, the CO₂ signal from the biosphere is much
13 weaker than FFCO₂ in the LA megacity. The two-week flask sampled biogenic CO₂ is
14 about 2 ppm on average. We note that the 1.3-km WRF-Vulcan run overestimates the
15 FFCO₂ concentrations by 20 ppm over the second half of the month (Figure 10d),
16 implying that low-resolution CO₂ emissions can be very critical for a coastal site
17 (complex terrain) with strong point sources nearby.

18 Strong temporal variability of the simulated biogenic and FFCO₂ can be seen for both
19 sites (Figure 10a,10c,10e,10g). For the Pasadena site, the 1.3-km run shows nearly flat
20 biogenic CO₂ concentrations during 15 May to 30 May when the 4-km run has more
21 variability (Figure 10e). A large botanical garden covering 207 acres (The Huntington
22 Library, Art Collections, and Botanical Gardens) is about 1.6 km away from the Pasadena
23 site, which may suggest that higher model resolution (1.3 km vs. 4 km) could resolve the
24 land cover better. However, there is still up to about 3-ppm discrepancy in the modelled
25 biogenic CO₂ from the flask samples (Figure 10f). Similar discrepancy can be seen for
26 Palos Verdes as well (Figure 10h). Reasonably determining CO₂ from biogenic sources
27 remains challenging. Additional measurements are needed to constrain biogenic fluxes.

28

1 **4 Spatial pattern of the surface CO₂**

2 The spatial pattern of surface CO₂ concentration exhibits diurnal variability over the LA
3 megacity due to the complexity of the topography and the variability of circulation
4 patterns, PBL heights, and FFCO₂ emissions. Each plays an important role in sequence or
5 at the same time. Here, we only focus on the pattern at 1400 PST when the atmospheric
6 CO₂ concentration is well mixed in the PBL. At 1400 PST, there is a close relationship
7 between CO₂ concentration and atmospheric transport; the error due to the PBL height
8 determination is at a minimum. For the same reason, we assume that FFCO₂ emissions do
9 not play a dominant role around 1400 PST unless there are strong local signals from point
10 sources, such as power plants, refineries, airports etc.

11 In this section, we define the 1.3-km WRF-Hestia run as the reference simulation. For
12 simplicity, all of the relevant CO₂ spatial patterns we present are selected from the second
13 model layer (about 24 m AGL). Figure 11a and 11b display the topography and the
14 average CO₂ concentration at 1400 PST overlaid with the first empirical orthogonal
15 function (EOF1) of the surface wind pattern, respectively. The locations of the 13 GHG
16 measurement sites in the LA megacity domain are marked in the figures (see Table 6 and
17 Figure S1 for details about the observation sites). Note that the 2015-era surface GHG
18 measurement network includes 14 sites in total, while 13 sites are embedded in the
19 innermost model domain. According to the geography mentioned in section 2.1, the
20 Granada Hills (GH), Compton, and USC sites are located in the West Coast Basin, the
21 Pasadena and Mt. Wilson (MWO) sites are in the Central Basin, and California State
22 University Fullerton (CSUF), Ontario, and San Bernardino (SB) sites are in the Orange
23 County Coastal Plan. Additionally, the Dryden and Victorville (VV) sites are located in
24 deserts; the Palos Verdes (PV), University of California Irvine (UCI), and San Clemente
25 Island (SCI) are on the coast. Although the Dryden site is actually a TCCON (Total
26 Carbon Column Observing Network, Wunch et al., 2011) site, in the analysis, we assume
27 it provides near-surface point measurements like the other sites, for simplicity.

28 Blocked by the mountains, the emitted CO₂ is trapped in the basin; the desert is usually as
29 clean as the upwind ocean. Specifically, Dryden (not shown on the figure), VV, SCI (not
30 shown on the figure), Palos Verdes and UCI are much cleaner than other sites (Figure

1 11b). At 1400 PST, sea breeze prevails over the LA megacity. Affected by the geometry
2 of Palos Verdes Peninsula, the sea breeze is divided into west and southwest onshore
3 flows that then converge in the Central Basin. Strong CO₂ signals emitted from electricity
4 production and industry (with annual emission of 86.9 million kgC, Figure 1d) are
5 trapped in a limited area. We notice that the south-western flow, which appears stronger
6 than the western flow, prevents the high CO₂ concentration in the West Coast Basin from
7 propagating further east and dilutes into the Central Basin. Controlled by the orography,
8 strong southerly flows occur between the Santa Monica and San Gabriel Mountains,
9 keeping the contaminated air from propagating to the west. Driven by the same
10 meteorology, the 1.3-km WRF-Vulcan run shows a more smeared out CO₂ distribution
11 over the LA basin (Figure 11c) due to the coarser resolution of the original Vulcan
12 emissions. High CO₂ plumes seen in the 1.3-km WRF-Hestia run from point sources are
13 replaced by broad areas of elevated CO₂ concentration in the 1.3-km WRF-Vulcan. The
14 large differences in the simulated surface CO₂ fields between the 1.3-km WRF-Hestia and
15 WRF-Vulcan runs are found around LAX and north of the Palos Verdes Peninsula where
16 strong point sources are located (dipole-like pattern in Figure 11d).

17

18 **5 Sampling density of the 2015-era GHG measurement network**

19 In this section, we present a forward network design framework, using the modelled CO₂
20 concentrations and their relationship with neighbouring grid cells. **Note no actual**
21 **observation data but only pseudo data are used in this section.** Compared to previous
22 studies using tower footprints (i.e. linearized adjoint models) as in Kort et al. (2013), we
23 propose here a forward model assessment of the network using the high-resolution model
24 results. We assume that each observation site can be associated with a specific CO₂ air
25 mass at any given time. To define this CO₂ air mass, we estimate the spatial coherence in
26 the modelled CO₂ concentration fields. We constrain the coverage of each LA GHG
27 measurement site by calculating the simultaneous correlation of the site to the rest of the
28 domain using the simulated CO₂ concentration time series. Figure 12 shows the
29 correlation map (R) of each site for the 1.3-km WRF-Hestia run. Only areas meeting a
30 significance level of 0.01 in the t-test ($|R| \geq 0.46$) are coloured. Based on the spatial

1 patterns of the correlation maps, all of the observation sites can be grouped into (i)
2 coastal/island sites, i.e., UCI, SCI, and Palos Verdes (right three panels in bottom row of
3 Figure 12), (ii) western basin sites, i.e., GH, Pasadena, MWO, USC, and Compton (top
4 row in Figure 12), (iii) eastern basin sites, (i.e., CSUF, Ontario, SB; middle row in Figure
5 12), and (iv) desert sites, i.e., Dryden and VV (left two panels in bottom row of Figure
6 12).

7 Not surprisingly, the coastal/island sites are mainly correlated with CO₂ concentration in
8 upwind areas offshore where there is limited FFCO₂ contamination. The white channel
9 from Catalina Island to the Huntington Beach area demonstrates the influence of terrain-
10 induced flows and mountain blocking. The western basin sites are mainly correlated with
11 CO₂ concentration throughout the western portion of the basin, and the eastern basin sites
12 are mainly correlated with CO₂ concentrations throughout the eastern portion of the
13 basin. The desert sites are anti-correlated with the basin. CSUF also shows anti-
14 correlation with the desert. Two reasons can explain this anti-correlation. Firstly, CO₂ is
15 trapped and accumulates in the basin due to the mountain barrier; the basin is
16 contaminated, the desert is clean. Secondly, after CO₂ accumulates in the basin over a
17 certain amount of time, episodic strong sea breezes may push this basin CO₂ over the
18 mountains to the desert. As a result, the basin will be relatively clean while the desert is
19 contaminated.

20 Based on the correlation maps, we can also see how the coverage of each site varies with
21 the FFCO₂ emissions data products and with the model resolutions. Figure 13 shows the
22 correlation maps across the runs for the Compton, Palos Verdes, and CSUF stations. All
23 runs use the optimal physics we determined for the LA megacity, i.e., MYNN_UCM. The
24 correlation maps for each site differ with the FFCO₂ emissions data product used, model
25 resolution, or their combination (Figure 13). Given that the 1.3-km WRF-Hestia is the
26 reference run, the difference of this to the 1.3-km WRF-Vulcan run reflects the errors
27 induced by emissions resolution. The discrepancy between the 1.3-km WRF-Hestia run
28 and the 4-km WRF-Hestia run reflects the model representation errors. The 4-km WRF-
29 Vulcan run is subject to model representation errors and emission aggregation errors at
30 the same time. For simplicity, we will not emphasize but only show the comparison of
31 the 4-km WRF-Vulcan to the others.

1 Compton is isolated from the rest of the basin in the 1.3-km WRF-Hestia run but
2 correlated with most of the basin in the 1.3-km WRF-Vulcan run. A similar discrepancy
3 is seen for Palos Verdes. Additionally, Palos Verdes appears to be a clean site in the 1.3-
4 km WRF-Hestia run but dramatically contaminated in the 1.3-km WRF-Vulcan run (even
5 correlated with the LA downtown area). For CSUF, the anti-correlation between basin
6 and desert noted above is not visible in the 1.3-km WRF-Vulcan run. Compared to the
7 1.3-km WRF-Hestia run, the 4-km WRF-Hestia run overall shows a somewhat larger
8 region with significant correlation for each site.

9 To highlight the discrepancy in the spatial patterns caused by the model representation
10 errors and emission aggregation errors in the view of the existing GHG measurement
11 network, a composite map for each run is shown in Figure 14. These maps are
12 constructed by determining the number of sites for which the absolute value of R is
13 greater than 0.46 for each grid cell (i.e., colour-filled area in Figure 12 and 11). $R=0.46$ is
14 the critical value for the t -test at the significance level of 0.01. In the 1.3-km WRF-Hestia
15 run (reference), the West Coastal Basin and Orange County Coastal Plain are correlated
16 with up to 6 measurement sites. A gap appears over the Central Basin correlated with up
17 to 3 sites due to the wind pattern (Figure 11a and 11b). The San Gabriel Mountains and
18 Peninsular Ranges are rarely correlated to any of the sites due to the elevated terrain. The
19 4-km WRF-Hestia run shows a similar pattern but with more sites covered over the
20 Peninsular Ranges and the coast because of the failure to resolve topography by the 4-km
21 model resolution.

22 In the 1.3-km WRF-Vulcan run, by contrast, a large area of the basin is correlated with
23 most of the sites (nine out of 13). The Compton area is even correlated with 11 sites,
24 which is only correlated with about two sites in the 1.3-km WRF-Hestia run. A similar
25 contrast can be seen for the GH, USC, and Palos Verdes areas where the multiple strong
26 point sources nearby in Hestia-LA have been aggregated into one 10 km by 10 km grid
27 cell in Vulcan (Figure 1d vs. 1c). Relatively coarser FFCO₂ emissions artificially increase
28 the coverage of each site, which highlights the importance of using a high-resolution
29 emission product, i.e., Hestia, for the CO₂ simulation for urban environment to represent
30 the spatial variability in CO₂ and design the optimal network of surface GHG
31 measurement.

1

2 **6 Discussion**

3 The results presented in this paper have shown that the choice of model resolution and
4 emission products can strongly influence the interpretation of atmospheric CO₂ signals.
5 Hestia quantifies FFCO₂ emissions down to individual buildings and roadways, such that
6 strong point sources create large plumes that are extremely sensitive to atmospheric
7 transport. Reproducing dynamics realistically by the atmospheric transport model is
8 crucial around strong point sources, such as power plants, refineries, airports, etc. For
9 instance, a considerable number of point sources are located in Long Beach harbour
10 (Figure 1d), about 7 km away from the Palos Verdes site. In late spring and summer,
11 Palos Verdes is a clean site, with little evidence of FFCO₂ emissions from the LA
12 megacity most of the time. However, we can clearly see that Palos Verdes is often
13 simulated to be contaminated by FFCO₂ in all of the runs, especially during early
14 morning (Figure 9b) due to incorrectly simulated east marine flows advecting the strong
15 FFCO₂ emissions, which cannot be seen in the observations. Biases in wind speed and
16 direction become critical for such a location. Palos Verdes may be challenging for the
17 atmospheric inversion if used as a background site.

18 Simulating CO₂ at locations with strong CO₂ fluxes gradients remains challenging. For a
19 location like Compton with strong point sources nearby emitting CO₂ at 86.9 million kgC
20 per year (recorded in Hestia-LA version 1.0), a fine resolution emission product becomes
21 very important due to the strong FFCO₂ gradient. A relatively coarse emission product
22 likely produces a spurious signal due to aggregating a strong point source into a large
23 grid cell (Figure 11b and 9c). For instance, dipole-like CO₂ gradients were created in the
24 difference between the 1.3-km WRF-Vulcan and WRF-Hestia runs (Figure 11d).

25 In this paper, we focus on the spatial distribution of the CO₂ concentration over the LA
26 megacity. The choice of model resolution also significantly impacts the vertical gradients
27 of the CO₂ concentration as a result of the terrain resolved. In the 1.3-km model grids,
28 the elevation of MWO is 1129 m, while in the 4 km grids it is 753 m; the actual elevation
29 is 1670 m. The representation errors in the 4-km model resolution are relatively large.
30 When there is finer topographic resolution, more CO₂ is accumulated in the basin due to

1 blocking by the mountains. Around noon, the model results show CO₂ enhancement of
2 10 ppm over MWO in both the 1.3-km WRF-Vulcan and WRF-Hestia runs but only up to
3 3 ppm in the 4-km model runs. Sampling strategies should be investigated for mountain
4 sites like MWO (e.g., Law et al., 2008) as well as coastal sites where the topography
5 resolved varies by model resolution. Meteorological evaluation at surface sites is not
6 sufficient to show differences in vertical mixing.

7 Figure 12 presents the simultaneous correlation maps for each site in terms of the
8 simulated CO₂ concentration time series. The coverage of the correlation maps is
9 determined by two factors at the same time: atmospheric transport and surface fluxes.
10 This method differs from the footprint method (Kort et al., 2013). The footprint method
11 maps the influence of atmospheric transport only at the location of the observation; no
12 emission pattern is considered. Here both transport and emissions play a role in the area
13 covered by the observation site. Therefore, the correlation maps are subject to
14 overestimation of the influence area versus the footprint method, due to the complicated
15 nature of the atmospheric integrator. As an example, in Figure 12, the coloured grids of
16 the correlation map are not necessarily *physically* related to the observation site. Those
17 far from the site may lose the track of the initial sources. Conversely, there is definitely
18 no *physical* influence from the uncorrelated areas to the observation site.

19 However, this new network design method has a unique strengths compared to the
20 footprint method. First of all, this method is computationally economical relative to the
21 footprint method. Secondly, the method does not require adjoint models, avoiding
22 another complexity. Most importantly, it brings extreme flexibility without any
23 complexity for evaluating the existing measurement network or designing the
24 measurement network with various observation platforms (i.e., in-situ, satellite, etc.) and,
25 especially, outpaces the analysis for dense sampling techniques, such as use of remote
26 sensing datasets. Applying the footprint method to satellite data for regional scale
27 modelling is extremely computationally time-consuming and complex.

28 Figure 15 shows the fraction of the total FFCO₂ emissions detected over the LA megacity
29 as function of the number of the observation sites for all of the runs. Because the
30 correlation maps have the possibility of overestimating the influence area, we focus on

1 the uncorrelated areas only. Assuming that the coverage of the GHG measurement
2 network is not sufficient if an area is correlated to no more than two sites, then ~28.9 %
3 of FFCO₂ is potentially under-constrained by the current GHG measurement sites (Figure
4 15a: WRF-Hestia 1.3-km). These areas include most of the mountains, Santa Monica Bay
5 and the upwind coast, and the south part of the Central Basin (Figure 13), about 21.1 %
6 of total area. However, this analysis is a qualitative assessment of the observational
7 constraint. Consideration of errors in the CO₂ emissions needs to be taken into account
8 for a complete assessment of the network.

9 Figure 15 also reflects the impact of the FFCO₂ emissions used to simulate the CO₂ fields.
10 In the 1.3-km WRF-Hestia run, there are no areas covered by more than six sites, while
11 the 1.3-km WRF-Vulcan run shows 39.8 % of FFCO₂ emissions over the LA megacity to
12 be covered by more than six sites. Additionally, the distribution appears nearly normal
13 for the 1.3-km WRF-Vulcan run. A similar discrepancy is seen between the 4-km WRF-
14 Hestia and WRF-Vulcan runs. These differences further highlight the importance of
15 using the high-resolution FFCO₂ emissions product for the urban CO₂ simulation.

16 The LA climate has two typical local regimes. From April to September, LA is warm,
17 dry, and stable. Steady alongshore wind flow predominates. In contrast, from October to
18 March, moist onshore flows bring precipitation to LA (Conil and Hall, 2006). The period
19 of interest for this study is from the middle of May to the middle of June 2010. The
20 results of this study represent the model performance for the dry seasons. Studying another
21 time of a year may yield different results. A longer-term model evaluation is also desired,
22 which, however, is computationally and observationally time-consuming. This one-
23 month long high-resolution simulation took 11520 CPU hours (45 hours × 256 processors)
24 on the petascale supercomputer Pleiades at the NASA Advanced Supercomputing (NAS)
25 Division.

26

27 **7 Conclusion**

28 A set of WRF configurations varying by PBL scheme, urban surface scheme, and model
29 resolution has been evaluated by comparing the PBL height determined by aircraft
30 profiles and ceilometer, wind speed and wind direction measured by radar wind profiler,

1 and surface atmospheric states measured by NWS stations. The results suggest that there
2 is no significant difference between the 4-km and 1.3-km resolution simulations in terms
3 of atmospheric model performances at the surface, but the 1.3-km model runs resolve the
4 vertical gradients of wind fields and PBL height somewhat better. The model inter-
5 comparisons show the model using the WRF configured MYNN_UCM PBL and urban
6 surface schemes has overall better performance than others. Coupled to FFCO₂ emissions
7 products (Hestia-LA and Vulcan 2.2), a land-atmosphere modelling system was built
8 with MYNN_UCM for studying the heterogeneity of urban CO₂ emissions over the LA
9 megacity.

10 The Vulcan and Hestia-LA FFCO₂ emission products were used to investigate the impact
11 of the model representation errors and emission aggregation errors in the modelled CO₂
12 concentration. Compared to in-situ measurements during CalNex-LA, the 1.3-km
13 modelled CO₂ concentrations clearly outperform the results at 4-km resolution for
14 capturing both the spatial distribution and the temporal variability of the urban CO₂
15 signals due to strong FFCO₂ emission gradients across the LA megacity, even though no
16 clear improvement in the meteorological evaluation was observed across the basin. The
17 inter-comparison of the WRF-Hestia and WRF-Vulcan runs reinforces the importance of
18 using high-resolution emission products to represent correct, large spatial gradients in
19 atmospheric CO₂ concentrations for urban environments.

20 Based on the 1.3-km WRF-Hestia run, the coverage of the current GHG measurement
21 site over the LA megacity was evaluated using the modelled spatial correlations. Kort et
22 al. (2013) concluded a network of eight surface observation sites provided the minimum
23 sampling required for accurate monitoring of FFCO₂ emissions in LA using Vulcan at 4-
24 km model resolution. In this study, however, using Vulcan FFCO₂ emissions tend to
25 overestimate the observational constraint spatially, suggesting that the information lies in
26 multiple fine-scale plumes rather than a single urban dome over the Los Angeles basin.
27 Thanks to the much finer-resolution model and FFCO₂ emission product Hestia-LA, the
28 coverage of each observation site seems constrained to a more limited area. Using a high-
29 resolution emission data product and a high-resolution model configuration is necessary
30 for accurately assessing the urban measurement network.

1

2 **8 Author contributions**

3 S. Feng and T. Lauvaux designed the model experiments, evaluated the model
4 performance, and developed the assessment of the measuring network; S. Newman
5 provided the calibrated CO₂ measurements and support for the model evaluations. P. Rao,
6 R. Patarasuk, D. O’Keeffe, J. Huang, Y. Song, and K.R. Gurney developed and prepared
7 the Vulcan and Hestia emission products; R. Ahmadov contributed to the development of
8 the WRF-VPRM model and relevant guidelines; A. Deng provided quality control for the
9 observations from the National Weather Stations; L.I. Díaz-Isaac tested PBL algorithms;
10 S. Jeong and M.L. Fischer provided the background CO₂ concentration for the LA
11 megacity (region); R.M. Duren, C. Gerbig, Z. Li, C. E. Miller, S. Sander, K.W. Wong,
12 and Y. L. Yung provided comments and discussion on the results of the study.

13

14 **Acknowledgements**

15 A portion of this work was performed at the Jet Propulsion Laboratory, California
16 Institute of Technology, under contract with NASA. The Megacities Carbon Project is
17 sponsored in part by the National Institute of Standards and Technology (NIST). S.
18 Newman acknowledges funding from the Caltech/JPL President & Director’s Research
19 and Development Fund. K. R. Gurney thanks NIST grant 70NANB14H321.R.
20 Ahmadov was supported by the US Weather Research Program within the NOAA/OAR
21 Office of Weather and Air Quality. S. Jeong and M.L. Fischer acknowledge the support
22 by the Laboratory Directed Research and Development Program, Office of Science, of
23 the US Department of Energy under Contract No. DE-AC02-05CH11231. Thanks to W.
24 Angevine at NOAA for radar wind profiler data, K. Aikin at NOAA for Aircraft WP-3D
25 data, and B. Lefer at University of Houston for ceilometer data.

1 **References**

- 2 Ahmadov, R., Gerbig, C., Kretschmer, R., Koerner, S., Neininger, B., Dolman, A. J., and
3 Sarrat, C.: Mesoscale covariance of transport and CO₂ fluxes: Evidence from
4 observations and simulations using the WRF-VPRM coupled atmosphere-biosphere
5 model, *Journal of Geophysical Research: Atmospheres*, 112, D22107,
6 10.1029/2007JD008552, 2007.
- 7 Ahmadov, R., Gerbig, C., Kretschmer, R., Körner, S., Rödenbeck, C., Bousquet, P., and
8 Ramonet, M.: Comparing high resolution WRF-VPRM simulations and two global
9 CO₂ transport models with coastal tower measurements of CO₂, *Biogeosciences*, 6,
10 807-817, 10.5194/bg-6-807-2009, 2009.
- 11 Angevine, W. M., Eddington, L., Durkee, K., Fairall, C., Bianco, L., and Brioude, J.:
12 Meteorological Model Evaluation for CalNex 2010, *Monthly Weather Review*, 140,
13 3885-3906, 10.1175/MWR-D-12-00042.1, 2012.
- 14 Asefi-Najafabady, S., Rayner, P. J., Gurney, K. R., McRobert, A., Song, Y., Coltin, K.,
15 Huang, J., Elvidge, C., and Baugh, K.: A multiyear, global gridded fossil fuel CO₂
16 emission data product: Evaluation and analysis of results, *Journal of Geophysical*
17 *Research: Atmospheres*, 119, 10,213-210,231, 10.1002/2013JD021296, 2014.
- 18 Baker, D. F., Law, R. M., Gurney, K. R., Rayner, P., Peylin, P., Denning, A. S.,
19 Bousquet, P., Bruhwiler, L., Chen, Y. H., Ciais, P., Fung, I. Y., Heimann, M., John,
20 J., Maki, T., Maksyutov, S., Masarie, K., Prather, M., Pak, B., Taguchi, S., and Zhu,
21 Z.: TransCom 3 inversion intercomparison: Impact of transport model errors on the
22 interannual variability of regional CO₂ fluxes, 1988–2003, *Global Biogeochemical*
23 *Cycles*, 20, n/a-n/a, 10.1029/2004GB002439, 2006.
- 24 Baker, K. R., Misenis, C., Obland, M. D., Ferrare, R. A., Scarino, A. J., and Kelly, J. T.:
25 Evaluation of surface and upper air fine scale WRF meteorological modeling of the
26 May and June 2010 CalNex period in California, *Atmospheric Environment*, 80,
27 299-309, <http://dx.doi.org/10.1016/j.atmosenv.2013.08.006>, 2013.
- 28 Bosart, L. F.: Analysis of a California Catalina Eddy Event, *Monthly Weather Review*,
29 111, 1619-1633, 10.1175/1520-0493(1983)111<1619:AOACCE>2.0.CO;2, 1983.

1 Bougeault, P., and Lacarrere, P.: Parameterization of Orography-Induced Turbulence in a
2 Mesobeta--Scale Model, *Monthly Weather Review*, 117, 1872-1890, 10.1175/1520-
3 0493(1989)117<1872:POOITI>2.0.CO;2, 1989.

4 Bréon, F. M., Broquet, G., Puygrenier, V., Chevallier, F., Xueref-Remy, I., Ramonet, M.,
5 Dieudonné, E., Lopez, M., Schmidt, M., Perrussel, O., and Ciais, P.: An attempt at
6 estimating Paris area CO₂ emissions from atmospheric concentration
7 measurements, *Atmos. Chem. Phys.*, 15, 1707-1724, 10.5194/acp-15-1707-2015,
8 2015.

9 Brioude, J., Angevine, W. M., Ahmadov, R., Kim, S. W., Evan, S., McKeen, S. A., Hsie,
10 E. Y., Frost, G. J., Neuman, J. A., Pollack, I. B., Peischl, J., Ryerson, T. B.,
11 Holloway, J., Brown, S. S., Nowak, J. B., Roberts, J. M., Wofsy, S. C., Santoni, G.
12 W., Oda, T., and Trainer, M.: Top-down estimate of surface flux in the Los Angeles
13 Basin using a mesoscale inverse modeling technique: assessing anthropogenic
14 emissions of CO, NO_x and CO₂ and their impacts, *Atmos. Chem. Phys.*, 13, 3661-
15 3677, 10.5194/acp-13-3661-2013, 2013.

16 C40: Climate 40 Group, <http://live.c40cities.org/>, 2012.

17 Chen, D., Li, Q., Stutz, J., Mao, Y., Zhang, L., Pikelnaya, O., Tsai, J. Y., Haman, C.,
18 Lefer, B., Rappenglück, B., Alvarez, S. L., Neuman, J. A., Flynn, J., Roberts, J. M.,
19 Nowak, J. B., de Gouw, J., Holloway, J., Wagner, N. L., Veres, P., Brown, S. S.,
20 Ryerson, T. B., Warneke, C., and Pollack, I. B.: WRF-Chem simulation of NO_x and
21 O₃ in the L.A. basin during CalNex-2010, *Atmospheric Environment*, 81, 421-432,
22 <http://dx.doi.org/10.1016/j.atmosenv.2013.08.064>, 2013.

23 Chen, F., and Dudhia, J.: Coupling an Advanced Land Surface–Hydrology Model with
24 the Penn State–NCAR MM5 Modeling System. Part I: Model Implementation and
25 Sensitivity, *Monthly Weather Review*, 129, 569-585, 10.1175/1520-
26 0493(2001)129<0569:CAALSH>2.0.CO;2, 2001.

27 Chen, F., Kusaka, H., Bornstein, R., Ching, J., Grimmond, C. S. B., Grossman-Clarke, S.,
28 Loridan, T., Manning, K. W., Martilli, A., Miao, S., Sailor, D., Salamanca, F. P.,
29 Taha, H., Tewari, M., Wang, X., Wyszogrodzki, A. A., and Zhang, C.: The

1 integrated WRF/urban modelling system: development, evaluation, and applications
2 to urban environmental problems, *International Journal of Climatology*, 31, 273-
3 288, 10.1002/joc.2158, 2011.

4 Cohen, A. E., Cavallo, S. M., Coniglio, M. C., and Brooks, H. E.: A Review of Planetary
5 Boundary Layer Parameterization Schemes and Their Sensitivity in Simulating
6 Southeastern U.S. Cold Season Severe Weather Environments, *Weather and
7 Forecasting*, 30, 591-612, doi:10.1175/WAF-D-14-00105.1, 2015.

8 Conil, S., and Hall, A.: Local Regimes of Atmospheric Variability: A Case Study of
9 Southern California, *Journal of Climate*, 19, 4308-4325, 10.1175/JCLI3837.1, 2006.

10 Davis, C., Low-Nam, S., and Mass, C.: Dynamics of a Catalina Eddy Revealed by
11 Numerical Simulation, *Monthly Weather Review*, 128, 2885-2904, 10.1175/1520-
12 0493(2000)128<2885:DOACER>2.0.CO;2, 2000.

13 Deng, A., Stauffer, D. R., Gaudet, B. J., Dudhia, J., Hacker, J., Bruyere, C., Wu, W.,
14 Vandenberghe, F., Liu, Y., and Bourgeois, A.: Update on WRF-ARW End-to-End
15 Multi-scale FDDA System, 10th Annual WRF Users' Workshop, Boulder, CO,
16 June 23, 2009.

17 Díaz Isaac, L. I., Lauvaux, T., Davis, K. J., Miles, N. L., Richardson, S. J., Jacobson, A.
18 R., and Andrews, A. E.: Model-data comparison of MCI field campaign
19 atmospheric CO₂ mole fractions, *Journal of Geophysical Research: Atmospheres*,
20 119, 2014JD021593, 10.1002/2014JD021593, 2014.

21 Djuricin, S., Pataki, D. E., and Xu, X.: A comparison of tracer methods for quantifying
22 CO₂ sources in an urban region, *Journal of Geophysical Research: Atmospheres*,
23 115, n/a-n/a, 10.1029/2009JD012236, 2010.

24 Engelen, R. J., Denning, A. S., and Gurney, K. R.: On error estimation in atmospheric
25 CO₂ inversions, *Journal of Geophysical Research: Atmospheres*, 107, 4635,
26 10.1029/2002JD002195, 2002.

27 Enting, I. G., Heimann, M., Wigley, T. M. L., Commonwealth, S., and Industrial
28 Research, O.: Future emissions and concentrations of carbon dioxide: key

1 ocean/atmosphere/land analyses, Division of Atmospheric Research technical paper
2 ;no. 31, 120 p., CSIRO, Australia, 120 p. pp., 1994.

3 Etheridge, D. M., Steele, L. P., Langenfelds, R. L., Francey, R. J., Barnola, J. M., and
4 Morgan, V. I.: Natural and anthropogenic changes in atmospheric CO₂ over the last
5 1000 years from air in Antarctic ice and firn, *Journal of Geophysical Research:*
6 *Atmospheres*, 101, 4115-4128, 10.1029/95JD03410, 1996.

7 Gerbig, C., Körner, S., and Lin, J. C.: Vertical mixing in atmospheric tracer transport
8 models: error characterization and propagation, *Atmos. Chem. Phys.*, 8, 591-602,
9 10.5194/acp-8-591-2008, 2008.

10 Grell, G. A., and Dévényi, D.: A generalized approach to parameterizing convection
11 combining ensemble and data assimilation techniques, *Geophysical Research*
12 *Letters*, 29, 38-31-38-34, 10.1029/2002GL015311, 2002.

13 Gurney, K. R., Law, R. M., Denning, A. S., Rayner, P. J., Baker, D., Bousquet, P.,
14 Bruhwiler, L., Chen, Y.-H., Ciais, P., Fan, S., Fung, I. Y., Gloor, M., Heimann, M.,
15 Higuchi, K., John, J., Maki, T., Maksyutov, S., Masarie, K., Peylin, P., Prather, M.,
16 Pak, B. C., Randerson, J., Sarmiento, J., Taguchi, S., Takahashi, T., and Yuen, C.-
17 W.: Towards robust regional estimates of CO₂ sources and sinks using atmospheric
18 transport models, *Nature*, 415, 626-630,
19 http://www.nature.com/nature/journal/v415/n6872/supinfo/415626a_S1.html,
20 2002.

21 Gurney, K. R., Mendoza, D. L., Zhou, Y., Fischer, M. L., Miller, C. C., Geethakumar, S.,
22 and de la Rue du Can, S.: High Resolution Fossil Fuel Combustion CO₂ Emission
23 Fluxes for the United States, *Environmental Science & Technology*, 43, 5535-5541,
24 10.1021/es900806c, 2009.

25 Gurney, K. R., Razlivanov, I., Song, Y., Zhou, Y., Benes, B., and Abdul-Massih, M.:
26 Quantification of Fossil Fuel CO₂ Emissions on the Building/Street Scale for a
27 Large U.S. City, *Environmental Science & Technology*, 46, 12194-12202,
28 10.1021/es3011282, 2012.

- 1 Gurney, K. R., Romero-Lankao, P., Seto, K. C., Hutyra, L. R., Duren, R., Kennedy, C.,
2 Grimm, N. B., Ehleringer, J. R., Marcutuillio, P., Hughes, S., Pincetl, S., Chester,
3 M. V., Runfola, D. M., Feddema, J. J., and Sperling, J.: Climate change: Track
4 urban emissions on a human scale citation, *Nature*, 525, 179–181,
5 10.1038/525179a, 2015.
- 6 Haman, C. L., Lefer, B., and Morris, G. A.: Seasonal Variability in the Diurnal Evolution
7 of the Boundary Layer in a Near-Coastal Urban Environment, *Journal of*
8 *Atmospheric and Oceanic Technology*, 29, 697-710, 10.1175/JTECH-D-11-
9 00114.1, 2012.
- 10 Hong, S.-Y., Dudhia, J., and Chen, S.-H.: A Revised Approach to Ice Microphysical
11 Processes for the Bulk Parameterization of Clouds and Precipitation, *Monthly*
12 *Weather Review*, 132, 103-120, 10.1175/1520-
13 0493(2004)132<0103:ARATIM>2.0.CO;2, 2004.
- 14 Hong, S.-Y., Noh, Y., and Dudhia, J.: A New Vertical Diffusion Package with an Explicit
15 Treatment of Entrainment Processes, *Monthly Weather Review*, 134, 2318-2341,
16 10.1175/MWR3199.1, 2006.
- 17 Houghton, R. A.: The annual net flux of carbon to the atmosphere from changes in land
18 use 1850–1990*, *Tellus B*, 51, 298-313, 10.1034/j.1600-0889.1999.00013.x, 1999.
- 19 Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., and
20 Collins, W. D.: Radiative forcing by long-lived greenhouse gases: Calculations with
21 the AER radiative transfer models, *Journal of Geophysical Research: Atmospheres*,
22 113, n/a-n/a, 10.1029/2008JD009944, 2008.
- 23 IPCC: Climate Change 2013. The Physical Science Basis. Contribution of Working
24 Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate
25 Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung,
26 A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)], Cambridge University Press,
27 Cambridge, United Kingdom and New York, NY, USA, 1535pp., 2013.
- 28 Jacob, D. J., Crawford, J. H., Maring, H., Clarke, A. D., Dibb, J. E., Emmons, L. K.,
29 Ferrare, R. A., Hostetler, C. A., Russell, P. B., Singh, H. B., Thompson, A. M.,

1 Shaw, G. E., McCauley, E., Pederson, J. R., and Fisher, J. A.: The Arctic Research
2 of the Composition of the Troposphere from Aircraft and Satellites (ARCTAS)
3 mission: design, execution, and first results, *Atmos. Chem. Phys.*, 10, 5191-5212,
4 10.5194/acp-10-5191-2010, 2010.

5 Janjić, Z. I.: The Step-Mountain Eta Coordinate Model: Further Developments of the
6 Convection, Viscous Sublayer, and Turbulence Closure Schemes, *Monthly Weather*
7 *Review*, 122, 927-945, 10.1175/1520-0493(1994)122<0927:TSMECM>2.0.CO;2,
8 1994.

9 Jeong, S., Hsu, Y.-K., Andrews, A. E., Bianco, L., Vaca, P., Wilczak, J. M., and Fischer,
10 M. L.: A multitower measurement network estimate of California's methane
11 emissions, *Journal of Geophysical Research: Atmospheres*, 118, 11,339-311,351,
12 10.1002/jgrd.50854, 2013.

13 Kort, E. A., Frankenberg, C., Miller, C. E., and Oda, T.: Space-based observations of
14 megacity carbon dioxide, *Geophysical Research Letters*, 39, L17806,
15 10.1029/2012GL052738, 2012.

16 Kort, E. A., Angevine, W. M., Duren, R., and Miller, C. E.: Surface observations for
17 monitoring urban fossil fuel CO₂ emissions: Minimum site location requirements
18 for the Los Angeles megacity, *Journal of Geophysical Research: Atmospheres*, 118,
19 1577-1584, 10.1002/jgrd.50135, 2013.

20 Kretschmer, R., Gerbig, C., Karstens, U., and Koch, F. T.: Error characterization of CO₂
21 vertical mixing in the atmospheric transport model WRF-VPRM, *Atmos. Chem.*
22 *Phys.*, 12, 2441-2458, 10.5194/acp-12-2441-2012, 2012.

23 Kretschmer, R., Gerbig, C., Karstens, U., Biavati, G., Vermeulen, A., Vogel, F.,
24 Hammer, S., and Totsche, K. U.: Impact of optimized mixing heights on simulated
25 regional atmospheric transport of CO₂, *Atmos. Chem. Phys.*, 14, 7149-7172,
26 10.5194/acp-14-7149-2014, 2014.

27 Kusaka, H., Kondo, H., Kikegawa, Y., and Kimura, F.: A Simple Single-Layer Urban
28 Canopy Model For Atmospheric Models: Comparison With Multi-Layer And Slab

1 Models, *Boundary-Layer Meteorol*, 101, 329-358, 10.1023/A:1019207923078,
2 2001.

3 Kusaka, H., and Kimura, F.: Thermal Effects of Urban Canyon Structure on the
4 Nocturnal Heat Island: Numerical Experiment Using a Mesoscale Model Coupled
5 with an Urban Canopy Model, *Journal of Applied Meteorology*, 43, 1899-1910,
6 10.1175/JAM2169.1, 2004a.

7 Kusaka, H., and Kimura, F.: Coupling a Single-Layer Urban Canopy Model with a
8 Simple Atmospheric Model: Impact on Urban Heat Island Simulation for an
9 Idealized Case, *Journal of the Meteorological Society of Japan. Ser. II*, 82, 67-80,
10 10.2151/jmsj.82.67, 2004b.

11 Lac, C., Bonnardot, F., Connan, O., Camail, C., Maro, D., Hebert, D., Rozet, M., and
12 Pergaud, J.: Evaluation of a mesoscale dispersion modelling tool during the
13 CAPITOUL experiment, *Meteorology and Atmospheric Physics*, 102, 263-287,
14 10.1007/s00703-008-0343-2, 2008.

15 Lac, C., Donnelly, R. P., Masson, V., Pal, S., Riette, S., Donier, S., Queguiner, S.,
16 Tanguy, G., Ammoura, L., and Xueref-Remy, I.: CO2 dispersion modelling over
17 Paris region within the CO2-MEGAPARIS project, *Atmos. Chem. Phys.*, 13, 4941-
18 4961, 10.5194/acp-13-4941-2013, 2013.

19 Lauvaux, T., Uliasz, M., Sarrat, C., Chevallier, F., Bousquet, P., Lac, C., Davis, K. J.,
20 Ciais, P., Denning, A. S., and Rayner, P. J.: Mesoscale inversion: first results from
21 the CERES campaign with synthetic data, *Atmos. Chem. Phys.*, 8, 3459-3471,
22 10.5194/acp-8-3459-2008, 2008.

23 Lauvaux, T., Pannekoucke, O., Sarrat, C., Chevallier, F., Ciais, P., Noilhan, J., and
24 Rayner, P. J.: Structure of the transport uncertainty in mesoscale inversions of CO2
25 sources and sinks using ensemble model simulations, *Biogeosciences*, 6, 1089-
26 1102, 10.5194/bg-6-1089-2009, 2009.

27 Lauvaux, T., Schuh, A. E., Bocquet, M., Wu, L., Richardson, S., Miles, N., and Davis, K.
28 J.: Network design for mesoscale inversions of CO2 sources and sinks, 2012, 64,
29 10.3402/tellusb.v64i0.17980, 2012.

- 1 Lauvaux, T., Miles, N. L., Deng, A., Richardson, S. J., Cambaliza, M. O., Davis, K. J.,
2 Gaudet, B., Gurney, K. R., Huang, J., Karion, A., Oda, T., Patarasuk, R.,
3 Razlivanov, I., Sarmiento, D., Shepson, P. B., Sweeney, C., Turnbull, J. C., and
4 Wu, K.: High resolution atmospheric inversion of urban CO₂ emissions during the
5 dormant season of the Indianapolis Flux Experiment (INFLUX), 2015.
- 6 Law, R. M., Rayner, P. J., Steele, L. P., and Enting, I. G.: Data and modelling
7 requirements for CO₂ inversions using high-frequency data, *Tellus B*, 55, 512-521,
8 10.1034/j.1600-0889.2003.00029.x, 2003.
- 9 Law, R. M., Peters, W., Rödenbeck, C., Aulagnier, C., Baker, I., Bergmann, D. J.,
10 Bousquet, P., Brandt, J., Bruhwiler, L., Cameron-Smith, P. J., Christensen, J. H.,
11 Delage, F., Denning, A. S., Fan, S., Geels, C., Houweling, S., Imasu, R., Karstens,
12 U., Kawa, S. R., Kleist, J., Krol, M. C., Lin, S. J., Lokupitiya, R., Maki, T.,
13 Maksyutov, S., Niwa, Y., Onishi, R., Parazoo, N., Patra, P. K., Pieterse, G., Rivier,
14 L., Satoh, M., Serrar, S., Taguchi, S., Takigawa, M., Vautard, R., Vermeulen, A. T.,
15 and Zhu, Z.: TransCom model simulations of hourly atmospheric CO₂:
16 Experimental overview and diurnal cycle results for 2002, *Global Biogeochemical*
17 *Cycles*, 22, n/a-n/a, 10.1029/2007GB003050, 2008.
- 18 Le Quéré, C., Peters, G. P., Andres, R. J., Andrew, R. M., Boden, T. A., Ciais, P.,
19 Friedlingstein, P., Houghton, R. A., Marland, G., Moriarty, R., Sitch, S., Tans, P.,
20 Arneeth, A., Arvanitis, A., Bakker, D. C. E., Bopp, L., Canadell, J. G., Chini, L. P.,
21 Doney, S. C., Harper, A., Harris, I., House, J. I., Jain, A. K., Jones, S. D., Kato, E.,
22 Keeling, R. F., Klein Goldewijk, K., Körtzinger, A., Koven, C., Lefèvre, N.,
23 Maignan, F., Omar, A., Ono, T., Park, G. H., Pfeil, B., Poulter, B., Raupach, M. R.,
24 Regnier, P., Rödenbeck, C., Saito, S., Schwinger, J., Segschneider, J., Stocker, B.
25 D., Takahashi, T., Tilbrook, B., van Heuven, S., Viovy, N., Wanninkhof, R.,
26 Wiltshire, A., and Zaehle, S.: Global carbon budget 2013, *Earth Syst. Sci. Data*, 6,
27 235-263, 10.5194/essd-6-235-2014, 2014.
- 28 Levin, I., Kromer, B., Schmidt, M., and Sartorius, H.: A novel approach for independent
29 budgeting of fossil fuel CO₂ over Europe by 14CO₂ observations, *Geophysical*
30 *Research Letters*, 30, n/a-n/a, 10.1029/2003GL018477, 2003.

1 Lu, R., and Turco, R. P.: Air pollutant transport in a coastal environment—II. Three-
2 dimensional simulations over Los Angeles basin, *Atmospheric Environment*, 29,
3 1499-1518, [http://dx.doi.org/10.1016/1352-2310\(95\)00015-Q](http://dx.doi.org/10.1016/1352-2310(95)00015-Q), 1995.

4 Mahadevan, P., Wofsy, S. C., Matross, D. M., Xiao, X., Dunn, A. L., Lin, J. C., Gerbig,
5 C., Munger, J. W., Chow, V. Y., and Gottlieb, E. W.: A satellite-based biosphere
6 parameterization for net ecosystem CO₂ exchange: Vegetation Photosynthesis and
7 Respiration Model (VPRM), *Global Biogeochemical Cycles*, 22, GB2005,
8 10.1029/2006GB002735, 2008.

9 Description of the modifications made in WRF.3.1 and short user's manual of BEP,
10 2009.

11 Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., Jović,
12 D., Woollen, J., Rogers, E., Berbery, E. H., Ek, M. B., Fan, Y., Grumbine, R.,
13 Higgins, W., Li, H., Lin, Y., Manikin, G., Parrish, D., and Shi, W.: North American
14 Regional Reanalysis, *Bulletin of the American Meteorological Society*, 87, 343-
15 360, 10.1175/BAMS-87-3-343, 2006.

16 Miller, J. B., Lehman, S. J., Montzka, S. A., Sweeney, C., Miller, B. R., Karion, A.,
17 Wolak, C., Dlugokencky, E. J., Southon, J., Turnbull, J. C., and Tans, P. P.: Linking
18 emissions of fossil fuel CO₂ and other anthropogenic trace gases using atmospheric
19 14CO₂, *Journal of Geophysical Research: Atmospheres*, 117, n/a-n/a,
20 10.1029/2011JD017048, 2012.

21 Mu, L., Mu, L., Stammerjohn, S. E., Lowry, K. E., and Yager, P. L.: Spatial variability of
22 surface pCO₂ and air-sea CO₂ flux in the Amundsen Sea Polynya, Antarctica,
23 *Elementa* (Washington, D.C.), 2, 000036, 10.12952/journal.elementa.000036, 2014.

24 Nakanishi, M., and Niino, H.: An Improved Mellor–Yamada Level-3 Model: Its
25 Numerical Stability and Application to a Regional Prediction of Advection Fog,
26 *Boundary-Layer Meteorol*, 119, 397-407, 10.1007/s10546-005-9030-8, 2006.

27 Nehr Korn, T., Henderson, J., Leidner, M., Mountain, M., Eluszkiewicz, J., McKain, K.,
28 and Wofsy, S.: WRF Simulations of the Urban Circulation in the Salt Lake City

- 1 Area for CO₂ Modeling, *Journal of Applied Meteorology and Climatology*, 52,
2 323-340, 10.1175/JAMC-D-12-061.1, 2012.
- 3 Newman, S., Xu, X., Affek, H. P., Stolper, E., and Epstein, S.: Changes in mixing ratio
4 and isotopic composition of CO₂ in urban air from the Los Angeles basin,
5 California, between 1972 and 2003, *Journal of Geophysical Research:*
6 *Atmospheres*, 113, n/a-n/a, 10.1029/2008JD009999, 2008.
- 7 Newman, S., Jeong, S., Fischer, M. L., Xu, X., Haman, C. L., Lefer, B., Alvarez, S.,
8 Rappenglueck, B., Kort, E. A., Andrews, A. E., Peischl, J., Gurney, K. R., Miller,
9 C. E., and Yung, Y. L.: Diurnal tracking of anthropogenic CO₂ emissions in the
10 Los Angeles basin megacity during spring 2010, *Atmos. Chem. Phys.*, 13, 4359-
11 4372, 10.5194/acp-13-4359-2013, 2013.
- 12 Newman, S., Xu, X., Gurney, K. R., Hsu, Y. K., Li, K. F., Jiang, X., Keeling, R. F., Feng,
13 S., O'Keefe, D., Patarasuk, R., Wong, K. W., Rao, P., Fisher, M. L., and Yung, Y.
14 L.: Toward consistency between bottom-up CO₂ emissions trends and top-down
15 atmospheric measurements in the Los Angeles megacity, *Atmos Chem Phys*, 16(6),
16 3843–3863, doi:10.5194/acp-16-3843-2016, 2016.
- 17 Pataki, D. E., Alig, R. J., Fung, A. S., Golubiewski, N. E., Kennedy, C. A., McPherson,
18 E. G., Nowak, D. J., Pouyat, R. V., and Romero Lankao, P.: Urban ecosystems and
19 the North American carbon cycle, *Global Change Biology*, 12, 2092-2102,
20 10.1111/j.1365-2486.2006.01242.x, 2006.
- 21 Pataki, D. E., Xu, T., Luo, Y. Q., and Ehleringer, J. R.: Inferring biogenic and
22 anthropogenic carbon dioxide sources across an urban to rural gradient, *Oecologia*,
23 152, 307-322, 10.1007/s00442-006-0656-0, 2007.
- 24 Pillai, D., Gerbig, C., Marshall, J., Ahmadov, R., Kretschmer, R., Koch, T., and Karstens,
25 U.: High resolution modeling of CO₂ over Europe: implications for representation
26 errors of satellite retrievals, *Atmos. Chem. Phys.*, 10, 83-94, 10.5194/acp-10-83-
27 2010, 2010.
- 28 Pillai, D., Gerbig, C., Ahmadov, R., Rödenbeck, C., Kretschmer, R., Koch, T.,
29 Thompson, R., Neininger, B., and Lavrié, J. V.: High-resolution simulations of

1 atmospheric CO₂ over complex terrain – representing the Ochsenkopf mountain tall
2 tower, *Atmos. Chem. Phys.*, 11, 7445-7464, 10.5194/acp-11-7445-2011, 2011.

3 Rao, P., Gurney, K. R., Patarasuk, R., Song, Y., Miller, C. E., Duren, R. M., and
4 Eldering, A.: Spatio-temporal Variations in Onroad Vehicle Fossil Fuel CO₂
5 Emissions in the Los Angeles Megacity, *Atmospheric Environment*, under review,
6 2015.

7 Riette, S., and Lac, C.: A New Framework to Compare Mass-Flux Schemes Within the
8 AROME Numerical Weather Prediction Model, *Boundary-Layer Meteorol.*, 1-29,
9 10.1007/s10546-016-0146-9, 2016.

10 Riley, W. J., Hsueh, D. Y., Randerson, J. T., Fischer, M. L., Hatch, J. G., Pataki, D. E.,
11 Wang, W., and Goulden, M. L.: Where do fossil fuel carbon dioxide emissions from
12 California go? An analysis based on radiocarbon observations and an atmospheric
13 transport model, *Journal of Geophysical Research: Biogeosciences*, 113, n/a-n/a,
14 10.1029/2007JG000625, 2008.

15 Rödenbeck, C., Gerbig, C., Trusilova, K., and Heimann, M.: A two-step scheme for high-
16 resolution regional atmospheric trace gas inversions based on independent models,
17 *Atmos. Chem. Phys.*, 9, 5331-5342, 10.5194/acp-9-5331-2009, 2009.

18 Rogers, R. E., Deng, A., Stauffer, D. R., Gaudet, B. J., Jia, Y., Soong, S.-T., and
19 Tanrikulu, S.: Application of the Weather Research and Forecasting Model for Air
20 Quality Modeling in the San Francisco Bay Area, *Journal of Applied Meteorology
21 and Climatology*, 52, 1953-1973, 10.1175/JAMC-D-12-0280.1, 2013.

22 Ryerson, T. B., Andrews, A. E., Angevine, W. M., Bates, T. S., Brock, C. A., Cairns, B.,
23 Cohen, R. C., Cooper, O. R., de Gouw, J. A., Fehsenfeld, F. C., Ferrare, R. A.,
24 Fischer, M. L., Flagan, R. C., Goldstein, A. H., Hair, J. W., Hardesty, R. M.,
25 Hostetler, C. A., Jimenez, J. L., Langford, A. O., McCauley, E., McKeen, S. A.,
26 Molina, L. T., Nenes, A., Oltmans, S. J., Parrish, D. D., Pederson, J. R., Pierce, R.
27 B., Prather, K., Quinn, P. K., Seinfeld, J. H., Senff, C. J., Sorooshian, A., Stutz, J.,
28 Surratt, J. D., Trainer, M., Volkamer, R., Williams, E. J., and Wofsy, S. C.: The
29 2010 California Research at the Nexus of Air Quality and Climate Change

1 (CalNex) field study, *Journal of Geophysical Research: Atmospheres*, 118, 5830-
2 5866, 10.1002/jgrd.50331, 2013.

3 Sarrat, C., Noilhan, J., Dolman, A. J., Gerbig, C., Ahmadov, R., Tolk, L. F., Meesters, A.,
4 G. C. A., Hutjes, R. W. A., Ter Maat, H. W., Pérez-Landa, G., and Donier, S.:
5 Atmospheric CO₂ modeling at the regional scale: an intercomparison of 5 meso-
6 scale atmospheric models, *Biogeosciences*, 4, 1115-1126, 10.5194/bg-4-1115-2007,
7 2007.

8 Scarino, A. J., Obland, M. D., Fast, J. D., Burton, S. P., Ferrare, R. A., Hostetler, C. A.,
9 Berg, L. K., Lefer, B., Haman, C., Hair, J. W., Rogers, R. R., Butler, C., Cook, A.
10 L., and Harper, D. B.: Comparison of mixed layer heights from airborne high
11 spectral resolution lidar, ground-based measurements, and the WRF-Chem model
12 during CalNex and CARES, *Atmos. Chem. Phys. Discuss.*, 13, 13721-13772,
13 10.5194/acpd-13-13721-2013, 2013.

14 Strong, C., Stwertka, C., Bowling, D. R., Stephens, B. B., and Ehleringer, J. R.: Urban
15 carbon dioxide cycles within the Salt Lake Valley: A multiple-box model validated
16 by observations, *Journal of Geophysical Research: Atmospheres*, 116, n/a-n/a,
17 10.1029/2011JD015693, 2011.

18 Tarantola, A.: Inverse problem theory and methods for model parameter estimation,
19 Book, Whole, Society for Industrial and Applied Mathematics, Philadelphia, PA,
20 2005.

21 Torres, R., Pantoja, S., Harada, N., González, H. E., Daneri, G., Frangopulos, M.,
22 Rutllant, J. A., Duarte, C. M., Rúa-Halpern, S., Mayol, E., and Fukasawa, M.: Air-
23 sea CO₂ fluxes along the coast of Chile: From CO₂ outgassing in central northern
24 upwelling waters to CO₂ uptake in southern Patagonian fjords, *Journal of*
25 *Geophysical Research: Oceans*, 116, n/a-n/a, 10.1029/2010JC006344, 2011.

26 Turnbull, J., Rayner, P., Miller, J., Naegler, T., Ciais, P., and Cozic, A.: On the use of
27 ¹⁴CO₂ as a tracer for fossil fuel CO₂: Quantifying uncertainties using an
28 atmospheric transport model, *Journal of Geophysical Research: Atmospheres*, 114,
29 n/a-n/a, 10.1029/2009JD012308, 2009.

1 Turnbull, J. C., Miller, J. B., Lehman, S. J., Tans, P. P., Sparks, R. J., and Southon, J.:
2 Comparison of $^{14}\text{CO}_2$, CO, and SF₆ as tracers for recently added fossil fuel CO₂ in
3 the atmosphere and implications for biological CO₂ exchange, *Geophysical*
4 *Research Letters*, 33, n/a-n/a, 10.1029/2005GL024213, 2006.

5 Turnbull, J. C., Karion, A., Fischer, M. L., Faloon, I., Guilderson, T., Lehman, S. J.,
6 Miller, B. R., Miller, J. B., Montzka, S., Sherwood, T., Saripalli, S., Sweeney, C.,
7 and Tans, P. P.: Assessment of fossil fuel carbon dioxide and other anthropogenic
8 trace gas emissions from airborne measurements over Sacramento, California in
9 spring 2009, *Atmos. Chem. Phys.*, 11, 705-721, 10.5194/acp-11-705-2011, 2011.

10 Ulrickson, B. L., and Mass, C. F.: Numerical Investigation of Mesoscale Circulations
11 over the Los Angeles Basin. Part II: Synoptic Influences and Pollutant Transport,
12 *Monthly Weather Review*, 118, 2162-2184, 10.1175/1520-
13 0493(1990)118<2162:NIOMCO>2.0.CO;2, 1990.

14 UN: World Urbanization Prospects e Revision 2005, Factsheet 7: Mega-cities, 2006.
15 United Nations, Department of Economic and Social Affairs, Population Division.
16 World Urbanization Prospects: The 2005 Revision. Working Paper No.
17 ESA/P/WP/200, 2006.

18 UN: World Urbanization Prospects: The 2009 Revision, 2010.

19 Wennberg, P. O., Mui, W., Wunch, D., Kort, E. A., Blake, D. R., Atlas, E. L., Santoni, G.
20 W., Wofsy, S. C., Diskin, G. S., Jeong, S., and Fischer, M. L.: On the Sources of
21 Methane to the Los Angeles Atmosphere, *Environmental Science & Technology*,
22 46, 9282-9289, 10.1021/es301138y, 2012.

23 Wong, K. W., Fu, D., Pongetti, T. J., Newman, S., Kort, E. A., Duren, R., Hsu, Y. K.,
24 Miller, C. E., Yung, Y. L., and Sander, S. P.: Mapping CH₄ : CO₂ ratios in Los
25 Angeles with CLARS-FTS from Mount Wilson, California, *Atmos. Chem. Phys.*,
26 15, 241-252, 10.5194/acp-15-241-2015, 2015.

27 Wu, L., Bocquet, M., Lauvaux, T., Chevallier, F., Rayner, P., and Davis, K.: Optimal
28 representation of source-sink fluxes for mesoscale carbon dioxide inversion with

1 synthetic data, *Journal of Geophysical Research: Atmospheres*, 116, n/a-n/a,
2 10.1029/2011JD016198, 2011.

3 Wunch, D., Wennberg, P. O., Toon, G. C., Keppel-Aleks, G., and Yavin, Y. G.:
4 Emissions of greenhouse gases from a North American megacity, *Geophysical*
5 *Research Letters*, 36, L15810, 10.1029/2009GL039825, 2009.

6 Xiao, X., Hollinger, D., Aber, J., Goltz, M., Davidson, E. A., Zhang, Q., and Moore Iii,
7 B.: Satellite-based modeling of gross primary production in an evergreen needleleaf
8 forest, *Remote Sensing of Environment*, 89, 519-534,
9 <http://dx.doi.org/10.1016/j.rse.2003.11.008>, 2004.

10 Yver, C. E., Graven, H. D., Lucas, D. D., Cameron-Smith, P. J., Keeling, R. F., and
11 Weiss, R. F.: Evaluating transport in the WRF model along the California coast,
12 *Atmos. Chem. Phys.*, 13, 1837-1852, 10.5194/acp-13-1837-2013, 2013.

13 Zhou, Y., and Gurney, K.: A new methodology for quantifying on-site residential and
14 commercial fossil fuel CO₂ emissions at the building spatial scale and hourly time
15 scale, *Carbon Management*, 1, 45-56, 10.4155/cmt.10.7, 2010.

16
17

Table 1. Common elements of the WRF-Chem configuration used in all runs.

Option	Description
Microphysics	WSM5 (Hong et al., 2004)
Longwave radiation	RRTMG (Iacono et al., 2008)
Shortwave radiation	RRTMG (Iacono et al., 2008)
Land surface	Noah land surface model (Chen and Dudhia, 2001)
Cumulus scheme	Grell-3 (Grell and Dévényi, 2002) applied to 12-km domain (d01) only
Advection	5 th and 3 rd order differencing for horizontal and vertical advection respectively
Time step	3 rd order Runge-Kutta; 45, 24, and 5 s for outermost, middle, innermost domains, respectively

1

2

Table 2. WRF configurations used for the sensitivity runs.

Configuration	PBL scheme	Urban surface scheme	Grid spacing (km)
BouLac_BEP_d02	BouLac	BEP	4
BouLac_BEP_d03	BouLac	BEP	1.3
BouLac_UCM_d02	BouLac	UCM	4
BouLac_UCM_d03	BouLac	UCM	1.3
MYJ_d02	MYJ	None	4
MYN_d03	MYJ	None	1.3
MYJ_UCM_d02	MYJ	UCM	4
MYJ_UCM_d03	MYJ	UCM	1.3
MYNN_d02	MYNN	None	4
MYNN_d03	MYNN	None	1.3
MYNN_UCM_d02	MYNN	UCM	4
MYNN_UCM_d03	MYNN	UCM	1.3

1

2

Table 3. Comparison Statistics of model performance on PBL height (unit: m AGL) relative to the ceilometer data over 1100 – 1700 PST at Caltech

	Mean	Bias	<i>Stdv*</i>	<i>RMSE</i>
OBS	835.7	-	223.8	-
MYNN_UCM_d03	828.8	-6.9	82.7	89.7
MYNN_UCM_d02	820.4	-15.3	66.1	94.5
MYNN_d03	1055.6	219.9	205.8	278.2
MYNN_d02	1029.4	193.7	200.0	254.3
MYJ_UCM_d03	961.4	125.8	154.9	168.8
MYJ_UCM_d02	971.4	135.7	109.3	157.7
MYJ_d03	1115.3	279.7	174.4	308.7
MYJ_d02	1105.1	269.5	150.9	291.6
BouLac_UCM_d03	936.1	100.5	147.3	149.9
BouLac_UCM_d02	958.7	123.1	104.8	148.7
BouLac_BEP_d03	1233.9	398.3	239.0	442.2
BouLac_BEP_d02	1244.3	408.6	219.5	446.0

*Stdv = standard deviation

Table 4. Statistics of hourly modelled CO₂ (unit: ppm) with different configurations relative to in-situ CO₂ between 1300 – 1700 PST

	Pasadena		Palos Verdes	
	bias	<i>RMSE</i>	bias	<i>RMSE</i>
WRF-Hestia 1.3-km	8.91	18.43	2.57	17.00
WRF-Hestia 4 km	7.03	14.50	8.09	19.64
WRF-Vulcan 1.3 km	1.20	11.10	5.03	10.62
WRF-Vulcan 4 km	-1.38	9.13	4.20	9.40

1

2

Table 5. Statistics of daily afternoon averaged modelled CO₂ (unit: ppm) with different configurations relative to in-situ CO₂*

	Pasadena		Palos Verdes	
	bias	<i>RMSE</i>	bias	<i>RMSE</i>
WRF-Hestia 1.3 km	-1.39	6.21	-0.75	4.71
WRF-Hestia 4 km	0.58	4.38	-1.77	4.59
WRF-Vulcan 1.3 km	-3.43	5.51	1.37	5.21
WRF-Vulcan 4 km	-4.41	6.12	0.58	4.38

* Averaged over 1300 – 1700 PST

1

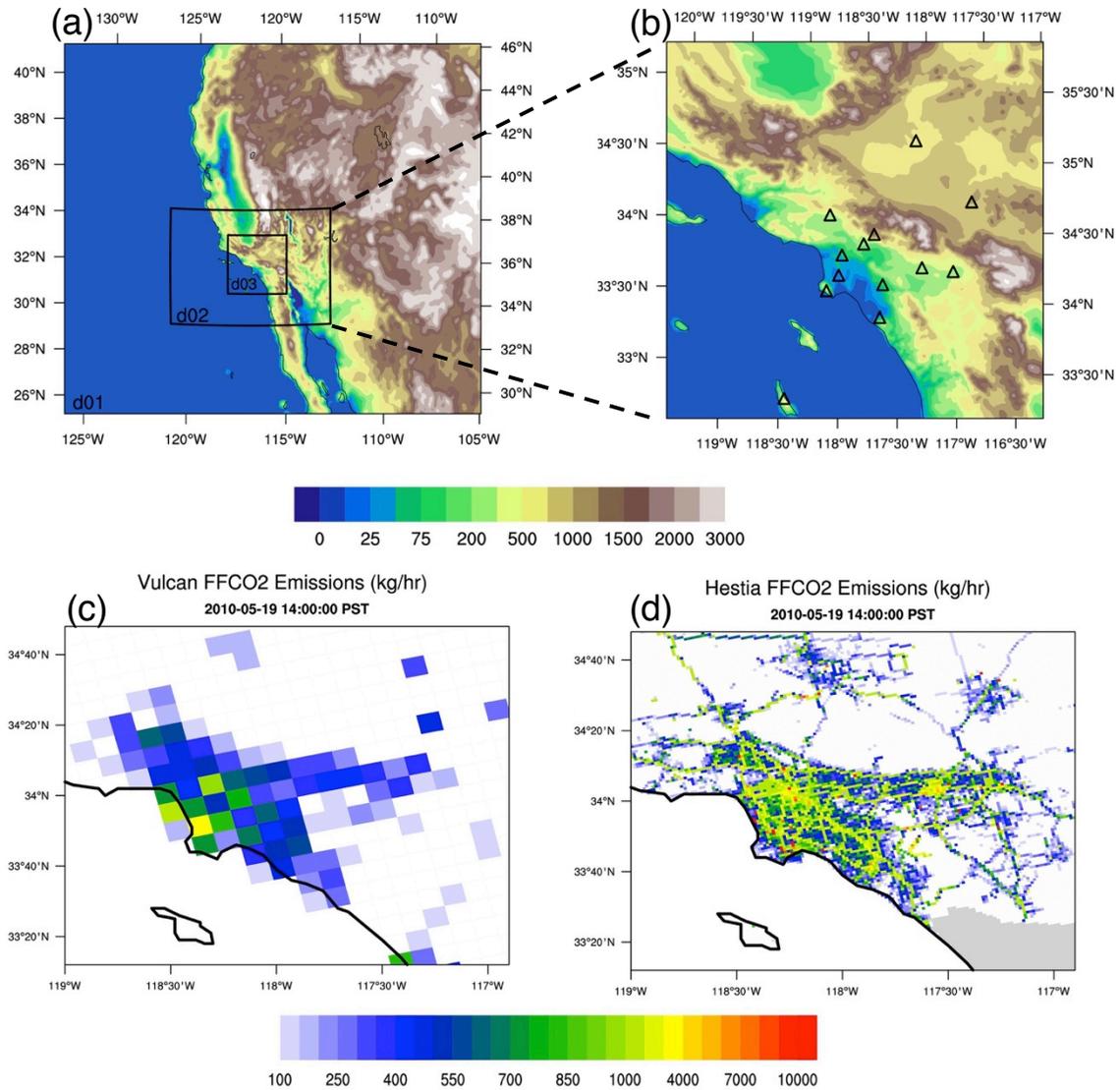
Table 6. Locations of the 2015-era GHG measurement sites in the model domain[■]

Code*	Name	Type	Lat. (° N)	Lon. (° E)
GH	Granada Hills	Tower	34.28	-118.47
Pasadena	Pasadena	Building top	34.14	-118.13
MWO	Mt. Wilson	Mountain top	34.22	-118.06
USC	University of South California	Building top	34.02	-118.29
Compton	Compton	Tower	33.87	-118.28
CSUF	California State University, Fullerton	Building top	33.88	-117.88
Ontario	Ontario	Tower	34.06	-117.58
SB	San Bernardino	Tower	34.09	-118.35
Dryden [‡]	Dryden	TCCON	34.95	-117.89
VV	Victorville	Tower	34.61	-117.29
UCI	University of California, Irvine	Building top	33.64	-117.84
SCI	San Clemente Island	Tower	32.92	-118.49
PV	Palos Verdes	In-situ non-standard	33.74	-118.35

◊La Jolla site is operating but not included in this paper

*Codes used in this paper

[‡] In the analysis, we assume Dryden site is a near-surface point measurement like other sites rather than a column observation for simplicity. TCCON is the Total Carbon Column Observing Network (Wunch et al., 2011).



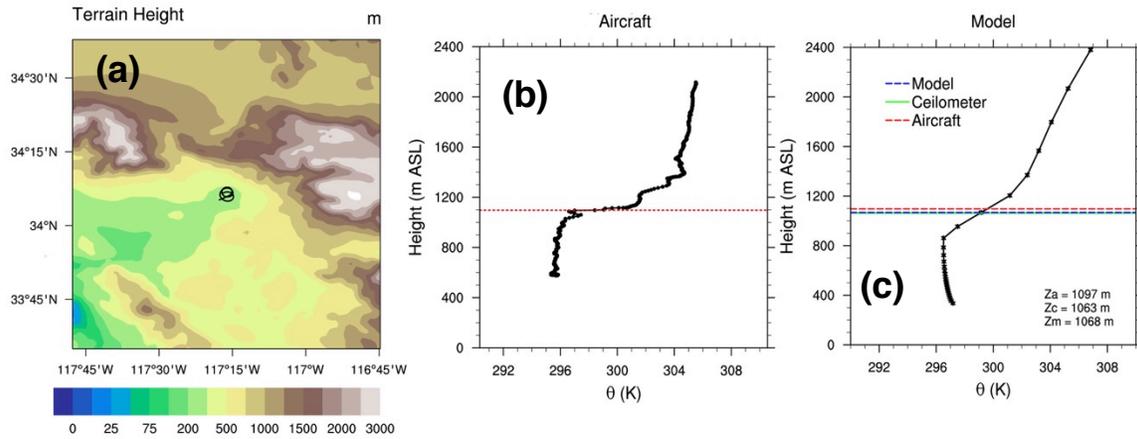
1

2

3 Figure 1. (a) Model domains. Contours are terrain height (unit: m). (b) The 1.3-km
 4 model domain (d03) and terrain height (unit: m). Triangles represent the locations of the
 5 GHG measurement sites. (c and d) Snapshots of the Vulcan and Hestia FFCO₂ emissions
 6 (unit: kg/hr) over the LA megacity at 14:00 PST on 15 May 2010.

7

1



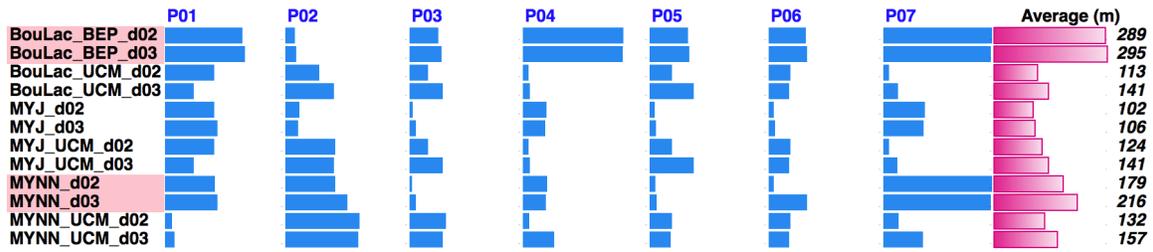
2

3

4 Figure 2. A case selected on 19 May 2010 at 12:25 (PST) (a) Location of the vertical
5 profile flown by the CalNex aircraft and the neighbouring terrain heights (units: m). (b)
6 In-situ potential temperature profile measured by the aircraft. The red dashed line at
7 ~1100 m is the PBL height calculated based on the vertical gradient of potential
8 temperature Θ (K). (c) Modelled potential temperature profile from the
9 MYNN_UCM_d02 configuration. The red dashed line is the aircraft-determined PBL
10 height (Z_a in masl). The solid green line is the PBL height measured by the Caltech
11 ceilometer (Z_c in masl). The blue dashed line is the modelled PBL height (Z_m in m),
12 almost identical to the green line.

13

1



2

3

4 Figure 3. Absolute difference between the aircraft-determined and modelled PBL height

5 for each profile: P01, P02, ..., and P07 (blue bars). The pink bars in the last column

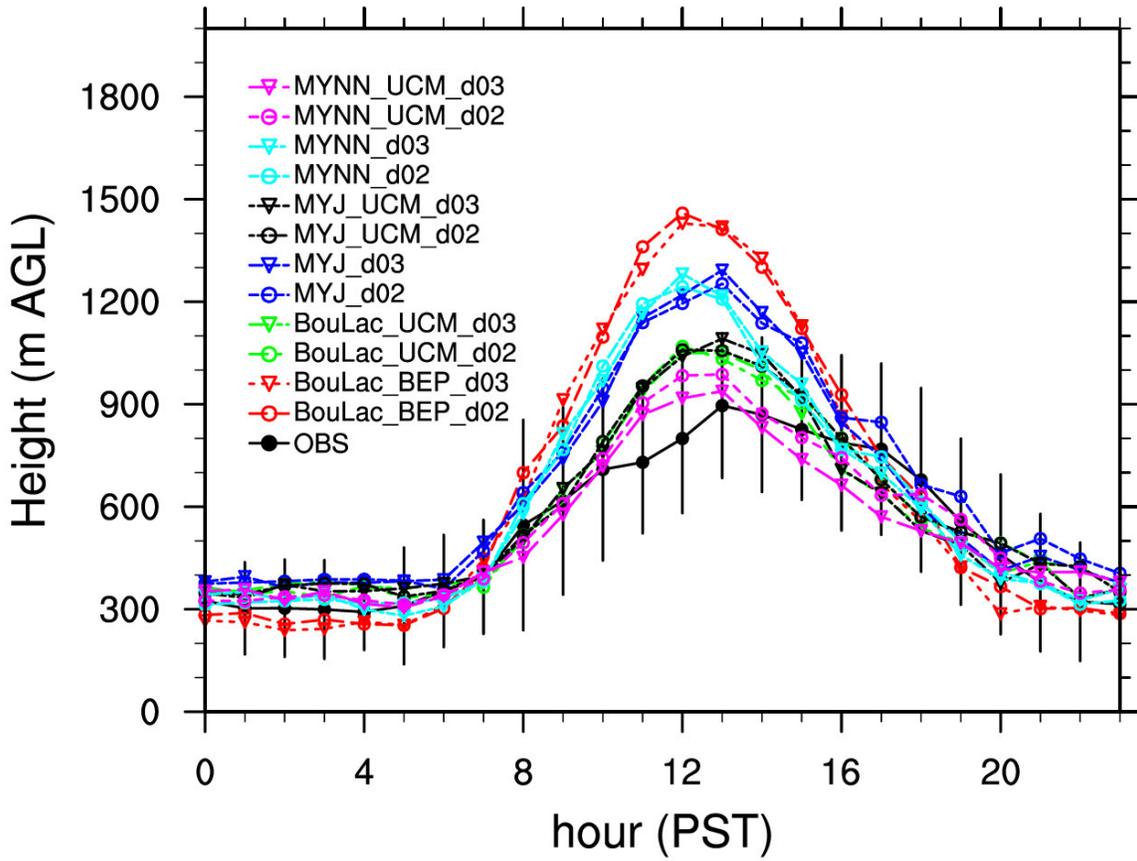
6 represent the averaged bias over all of the profiles for each configuration. Note that the

7 shorter the bar, the better agreement of the model with the observations.

8

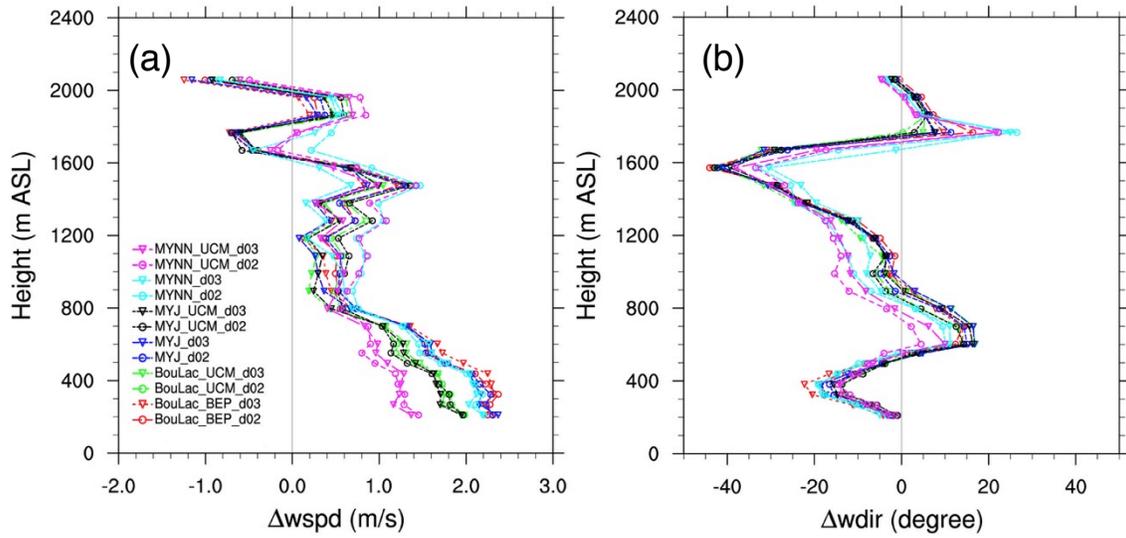
9

10



1
2
3
4
5
6
7

Figure 4. Average diurnal variation of the ceilometer-measured and modelled PBL heights at California Institute of Technology (Caltech) in Pasadena, CA during 15 May through 15 June 2010. Error bars indicate standard deviations of the means of the ceilometer measurement.



1

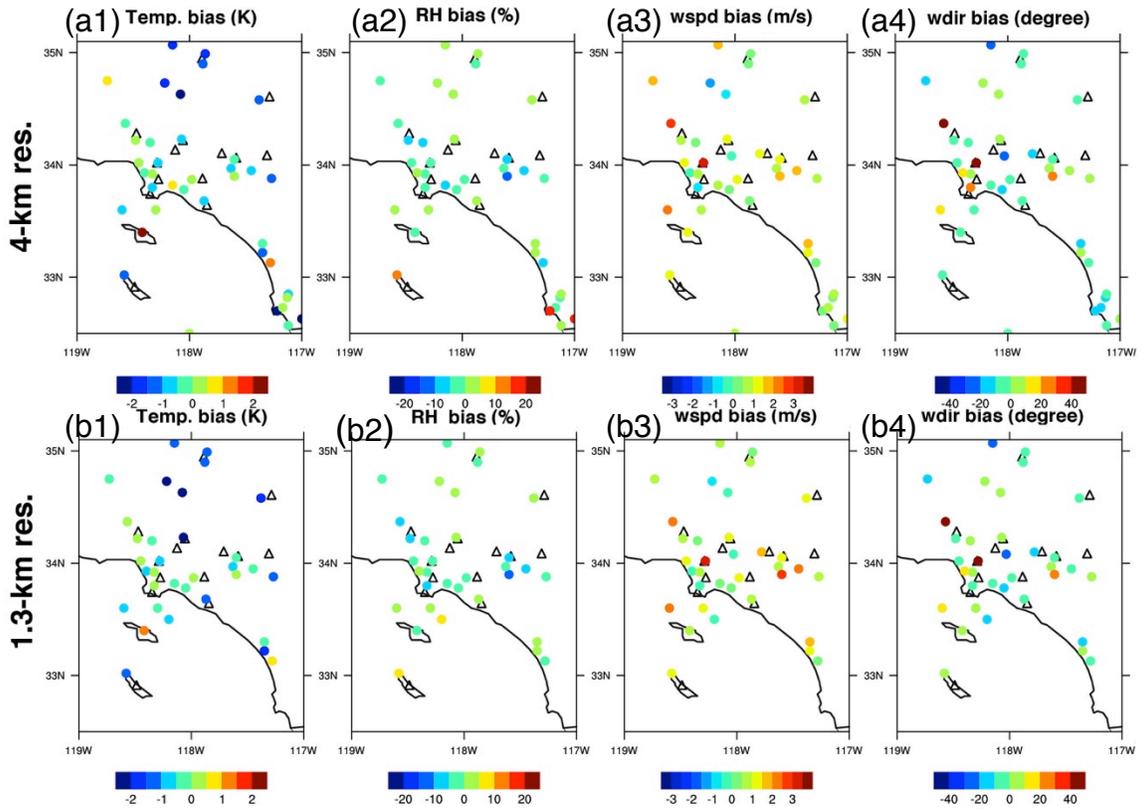
2

3 Figure 5. Average differences of wind profiles between the simulations and observations
 4 (model – wind radar profiler) at the Los Angeles International Airport (LAX). (a) The
 5 difference for wind speed (unit: m/s); (b) for wind direction (unit: degree). Note that
 6 these results are for daytime 1100 – 1700 PST only.

7

8

1
2



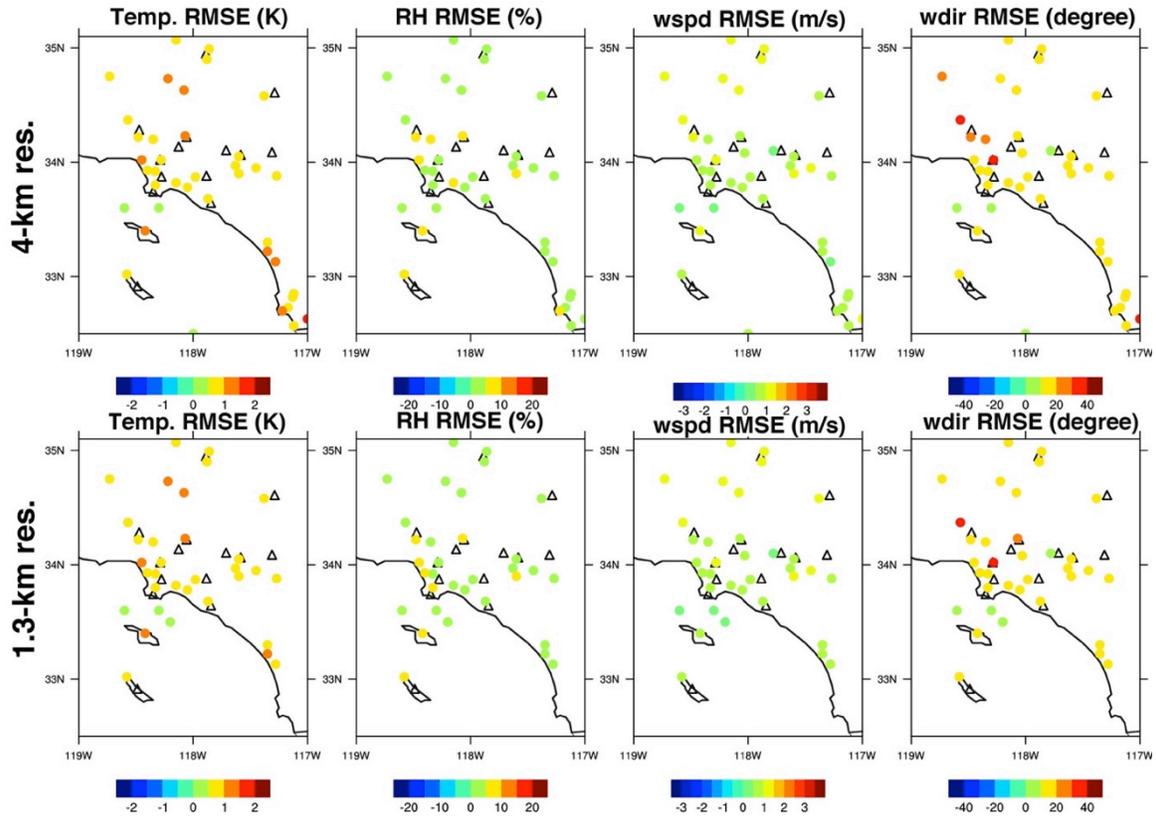
3

4 Figure 6. Bias maps of atmospheric state variables from the MYNN_UCM runs versus
5 National Weather Stations (NWS) over the LA megacity (Model – NWS): (a1-a4) 4-km
6 run; (b1 – b4) 1.3-km run. Black triangles indicate the locations of the GHG
7 measurement sites. Note daytime 1100 – 1700 PST only.

8

9

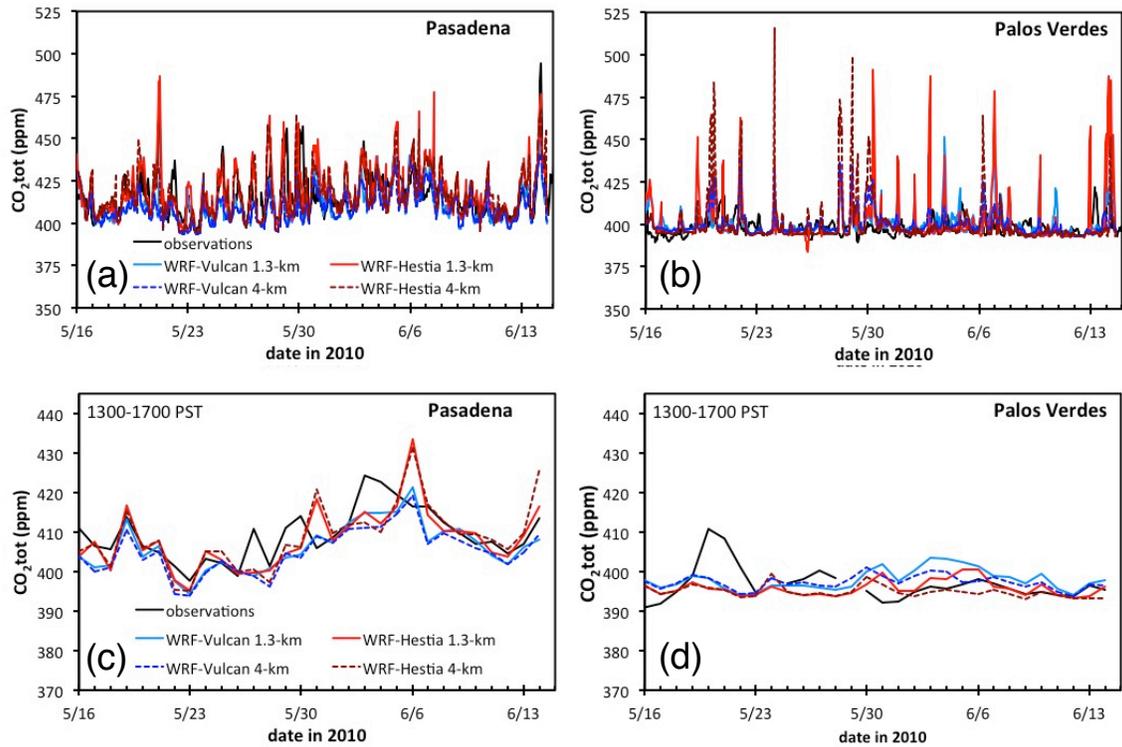
10



1
2
3
4
5
6
7
8

Figure 7. *RMSE* maps of atmospheric state variables from the MYNN_UCM runs versus National Weather Stations (NWS) over the LA megacity: (a1-a4) 4-km run; (b1 – b4) 1.3-km run. Black triangles indicate the locations of the GHG measurement sites. Note daytime 1100 – 1700 PST only.

1

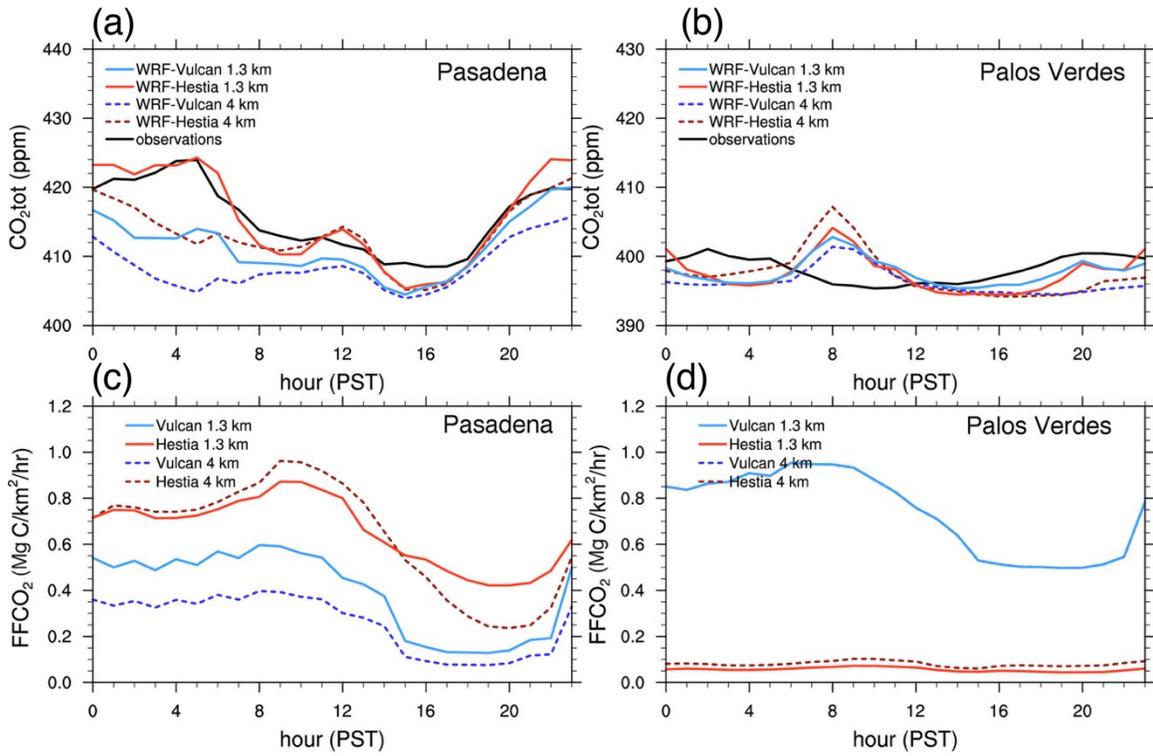


2

3 Figure 8. Comparison of the observed and modelled CO₂ concentrations at the (a and c)
4 Pasadena and (b and d) Palos Verdes sites: (a and b) hourly time series, (c and d) daily
5 afternoon averages for 1300 – 1700 PST.

6

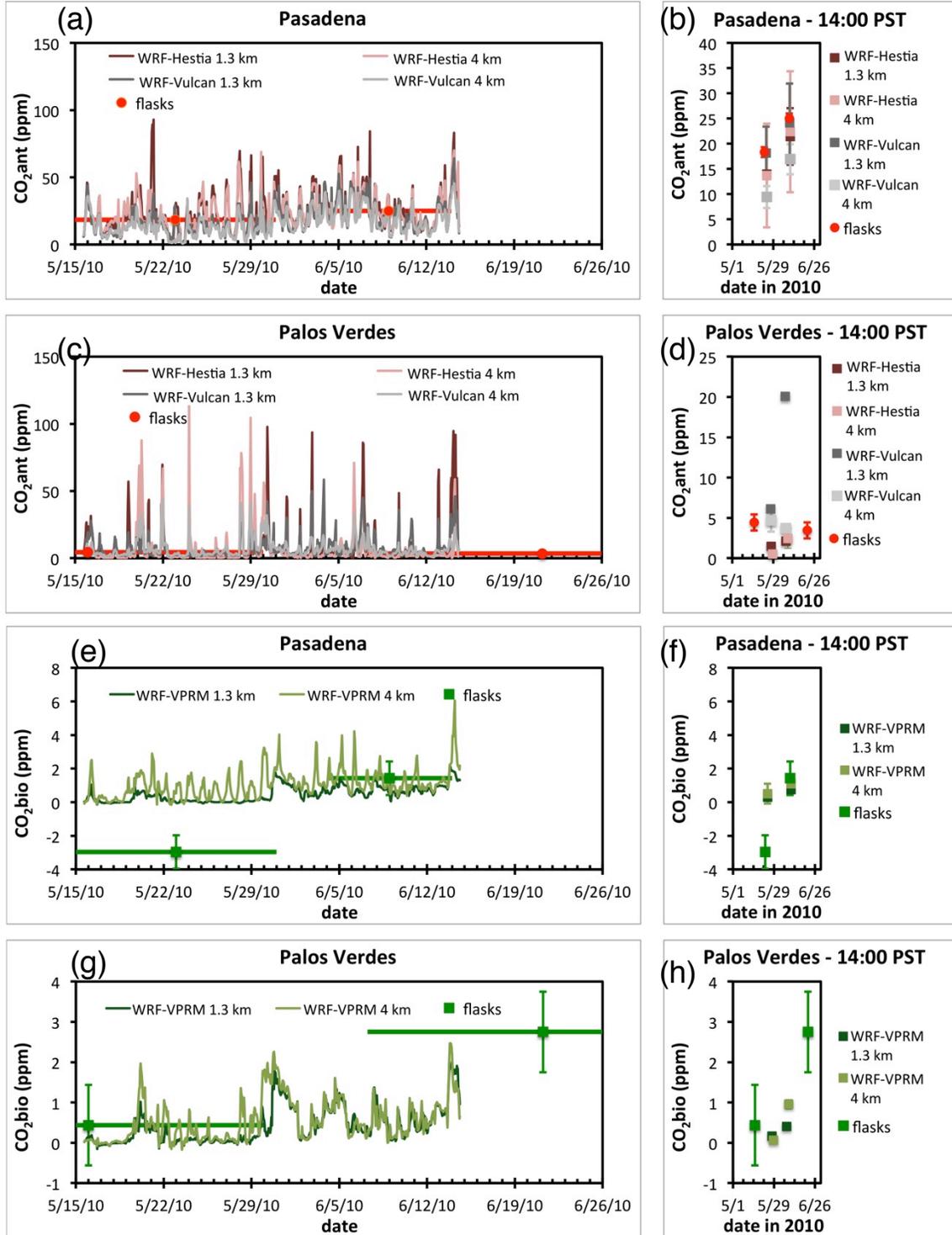
1



2

3 Figure 9. Averaged diurnal variation of observed and modelled CO₂ concentration and
4 FFCO₂ emissions for the (a and c) Pasadena and (b and d) Palos Verdes sites during
5 CalNex-LA. Note that Vulcan 4-km overlaps with Vulcan 1.3-km in Figure 9d.

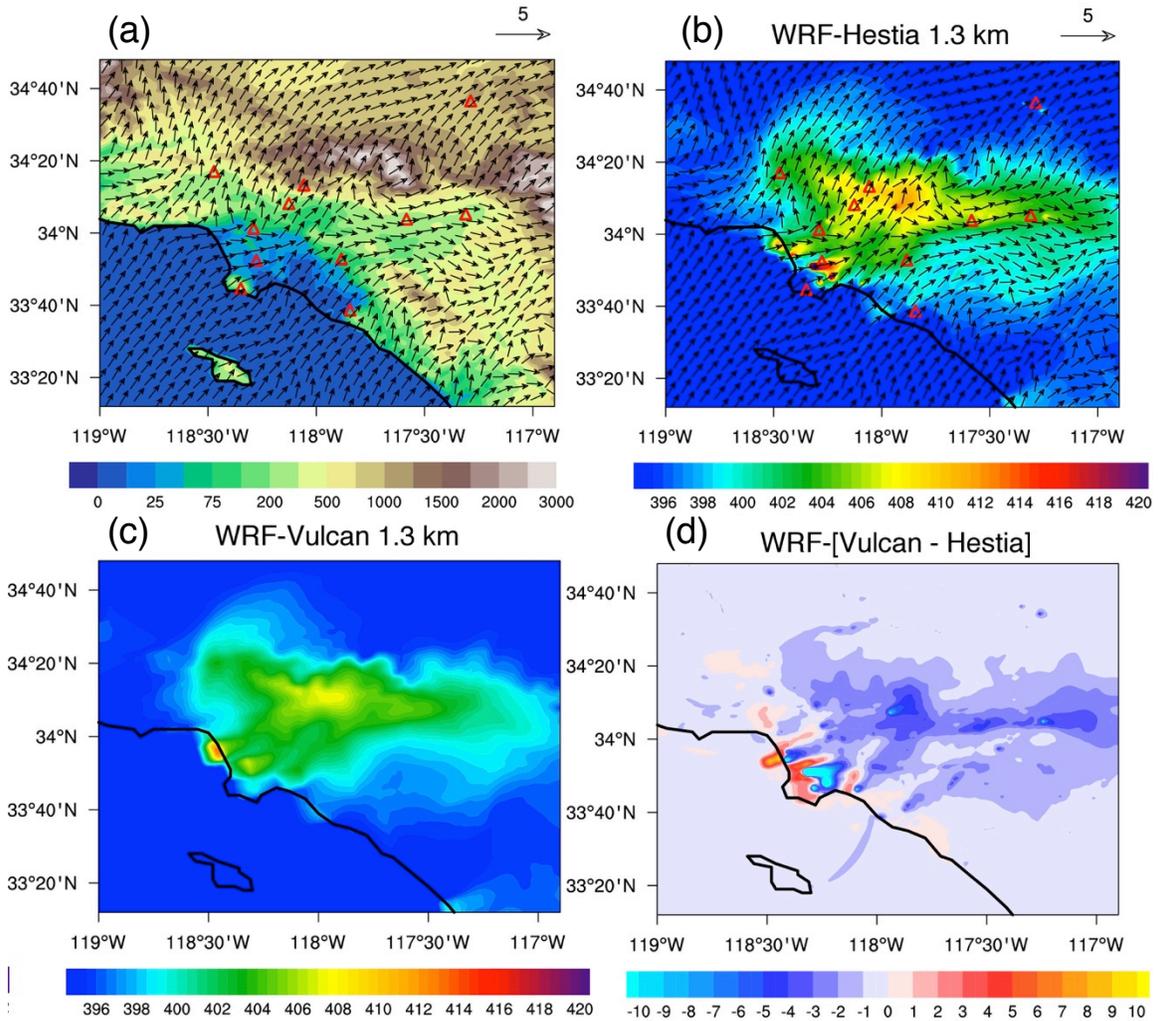
6



1
 2 Figure 10. Comparisons of flask-sampled and modelled (a-d) anthropogenic fossil fuel
 3 and (e-h) biogenic CO₂ concentration. Left column: hourly time series. The horizontal
 4 error bars on the flask-sampled data points indicate the range of dates combined in each
 5 sample. Note that much of the time period for the $\Delta^{14}\text{C}$ samples at the Palos Verdes site

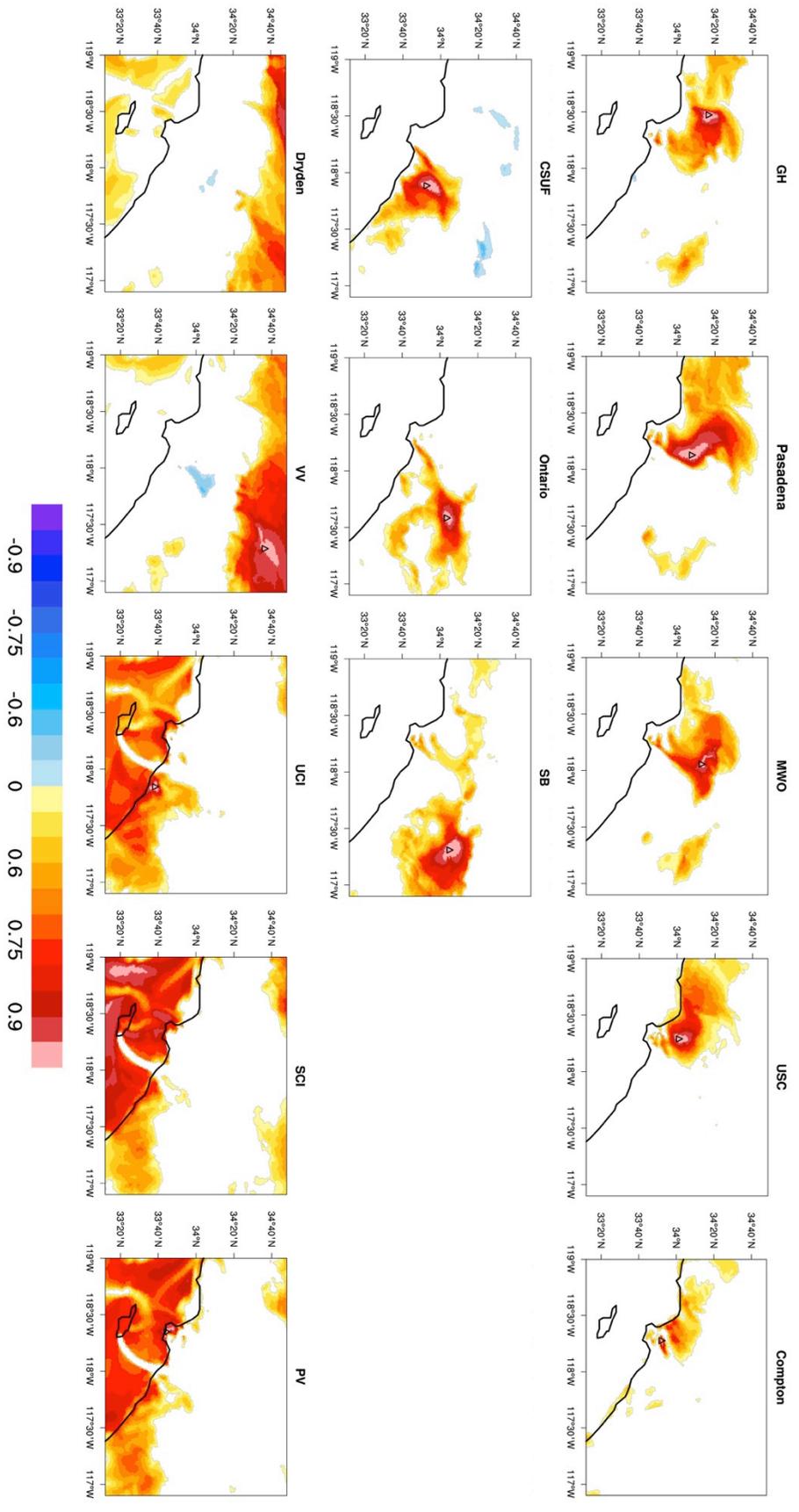
1 is before or after our modelling period. Right column: Averages at 1400 PST during
2 CalNex-LA. See Newman et al. (2016) for details about the sites and sampling
3 information.

1



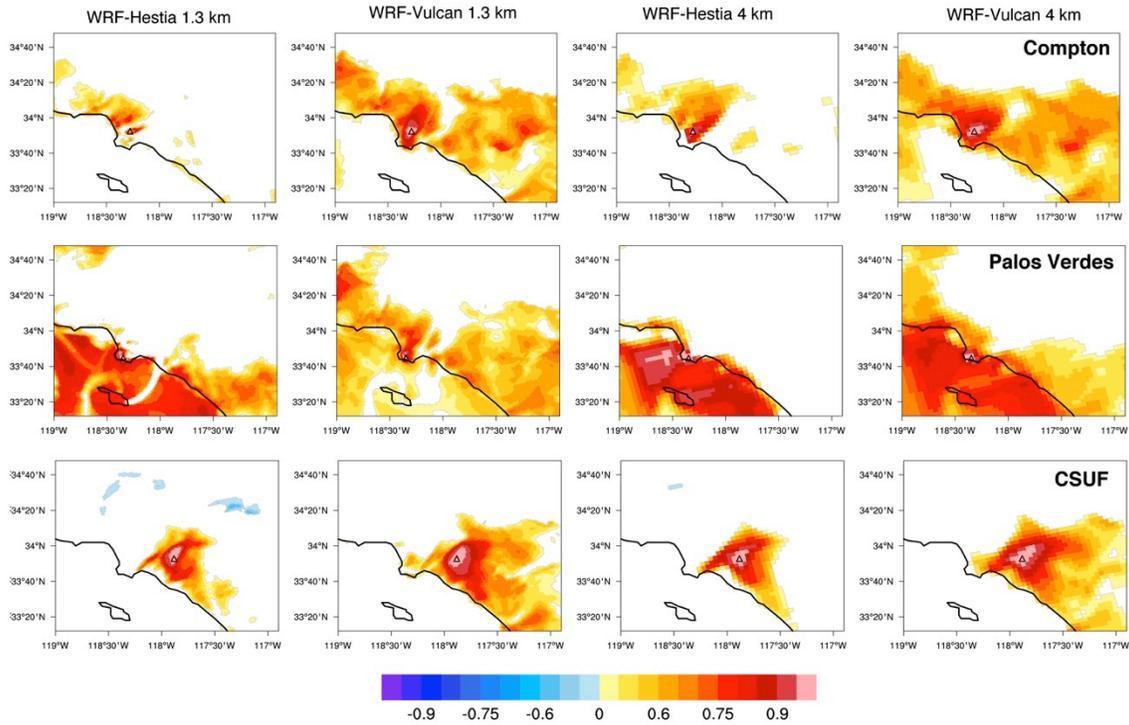
2

3 Figure 11. (a and b) The first empirical orthogonal function (EOF 1) for the surface wind
4 pattern (black arrows) simulated by MYNN_UCM_d03 at 1400 PST during CalNex-LA.
5 EOF 1 accounts for 48.1 % of the variance in the average winds. Contours: (a) terrain
6 height (unit: m); (b) the modelled surface CO₂ concentration (unit: ppm) from the 1.3-km
7 WRF-Hestia run. The red triangles indicate the locations of the GHG measurement sites.
8 (c) The modelled CO₂ concentrations from the 1.3-km WRF-Vulcan run (unit: ppm). (d)
9 The difference in the modelled CO₂ concentrations between the 1.3-km WRF-Vulcan and
10 WRF-Hestia runs (unit: ppm).



1 Figure 12. The spatial correlation map (R) of the 1.3-km WRF-Hestia simulated CO₂
2 concentration between each site and the remainder of the domain at 1400 PST during the
3 CalNex-LA campaign. The correlation map was constructed by calculating the
4 simultaneous correlation of the site CO₂ to the CO₂ over rest of the LA megacity. Note
5 that only those pixels that pass the *t*-test at the significance level of 0.01 ($|R| \geq 0.46$) are
6 coloured.

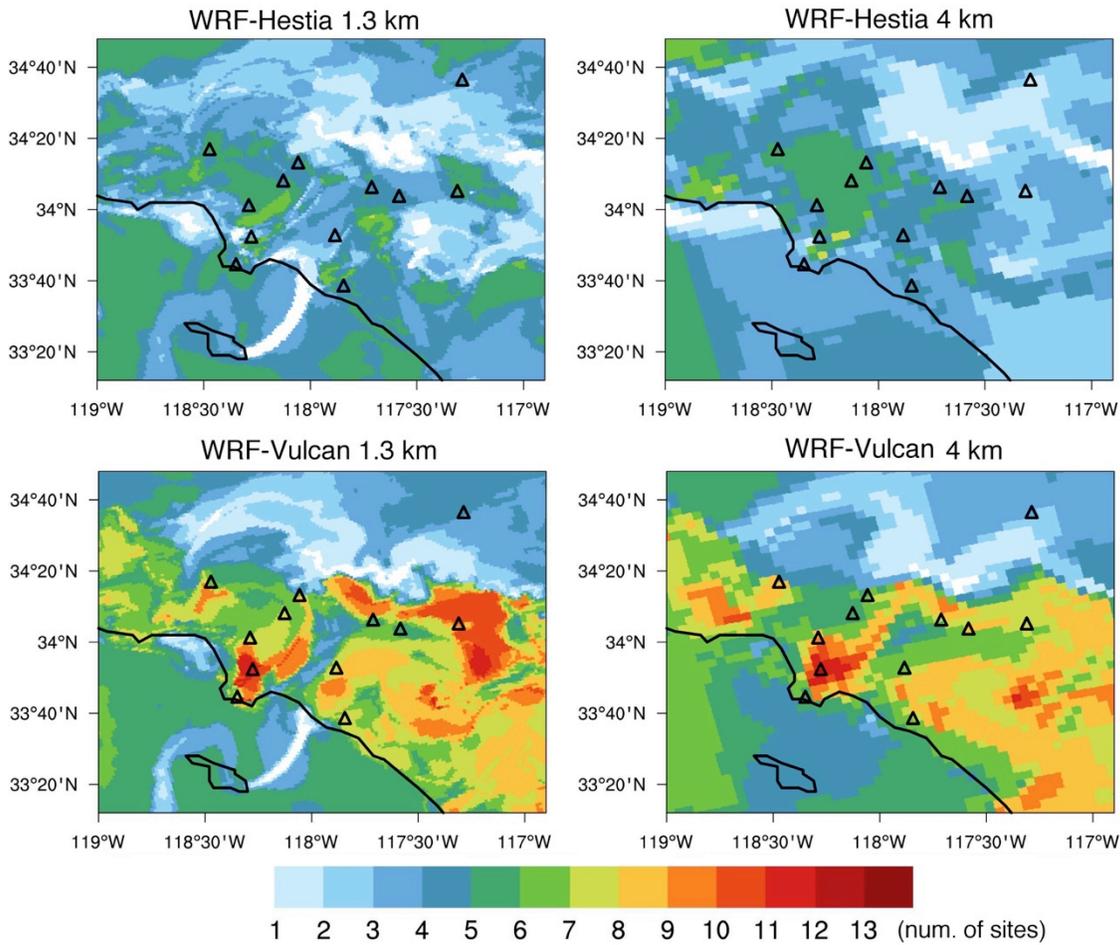
1



2

3 Figure 13. Same as Figure 12 but for the Compton (top row), Palos Verdes (middle row),
4 and CSUF (bottom row) sites only. Shown are the correlation maps of these three
5 measurement sites for the 1.3-km WRF-Hestia (first column), 1.3-km WRF-Vulcan
6 (second column), 4-km WRF-Hestia (third column), and 4-km WRF-Vulcan runs (fourth
7 column). Note that only those pixels that pass the t -test at the significance level of 0.01
8 ($|R| \geq 0.46$) are coloured.

1



2

3 Figure 14. Composite maps of spatial correlation (R in Figure 12 and 13) for the 1.3-km
4 WRF-Hestia, 1.3-km WRF-Vulcan, 4-km WRF-Hestia, and 4-km WRF-Vulcan runs.
5 Each composite map was constructed by determining the number of the observation sites
6 for which $|R|$ is greater than 0.46 at each grid cell. $|R| = 0.46$ is the critical value at the
7 significance level of 0.01 of t -test. Specifically, white cells indicate that no sites are
8 correlated well at the location; dark red cells indicate that over 13 sites have good
9 correlation at the location. The SCI and Dryden sites are not shown on these maps.

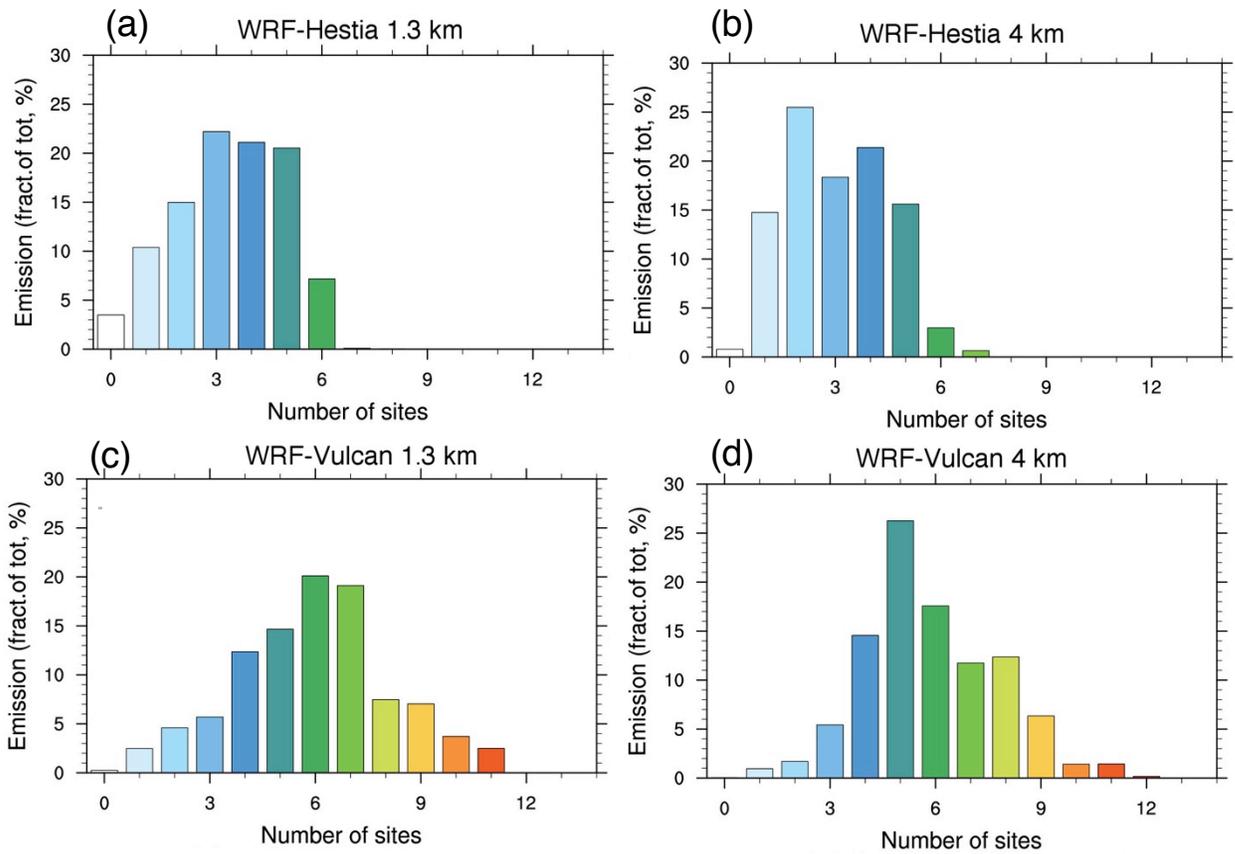
10

11

12

13

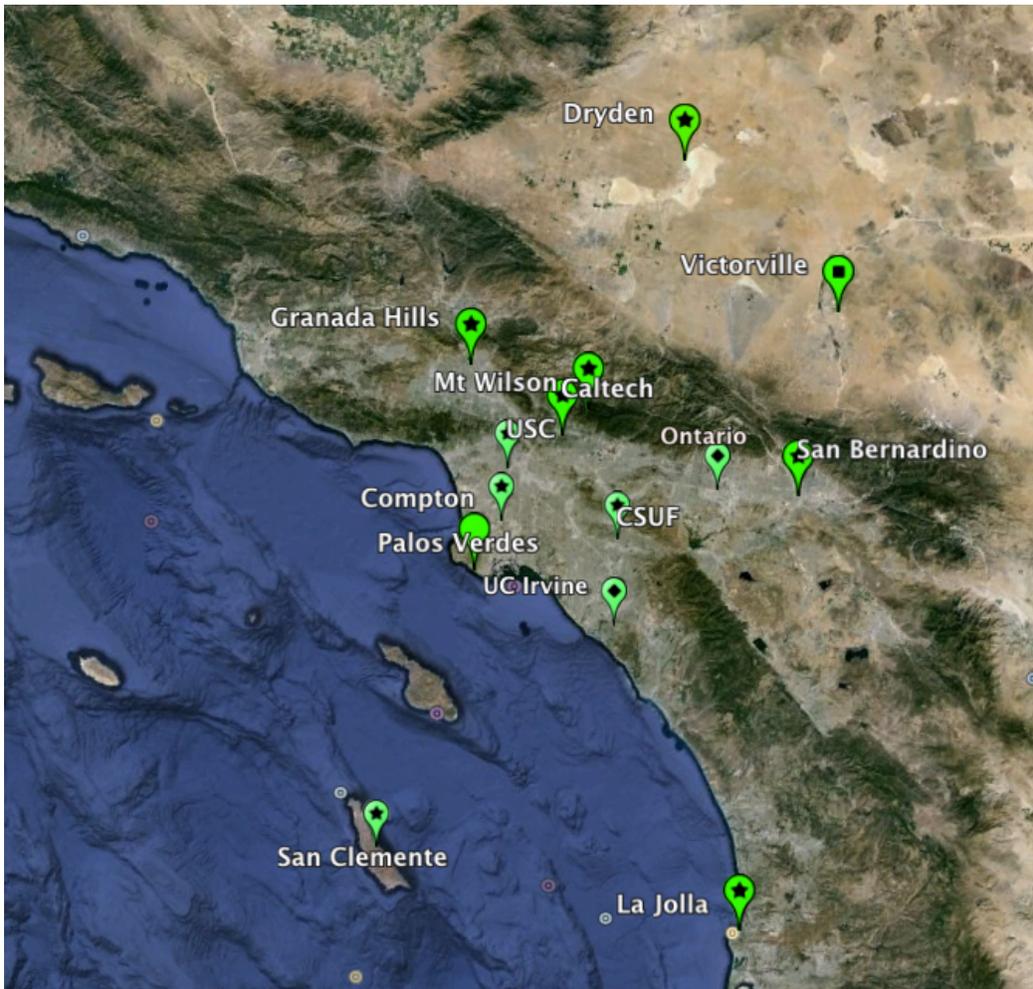
1
2



3
4
5
6
7
8

Figure 15. The fraction of the FFCO₂ emission over the LA megacity as function of the number of the GHG measurement sites that covers the area (see Figure 14) for (a) 1.3-km WRF-Hestia, (b) 4-km WRF-Hestia, (c) 1.3-km WRF-Vulcan, and (d) 4-km WRF-Vulcan runs during CalNex-LA. Colour scale is the same as in Figure 14.

1



2

3 Figure S1. Google Earth map showing the location of the 14 GHG measurement sites, only 13 of
4 which are within the innermost model domain, the exception being the La Jolla site.

5