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3	Inline Coupling of Simple and Complex Chemistry			
4	Modules within the Global Weather Forecast model FIM			
5	(FIM-Chem v1)			
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1 Abstract.

2 The global Flow-following finite-volume Icosahedral Model (FIM), which was developed in the Global 3 Systems Laboratory (GSL) of NOAA, has been coupled inline with aerosol and gas-phase chemistry schemes 4 of different complexity using the chemistry and aerosol packages from WRF-Chem v3.7, named as FIM-5 Chem v1. The three chemistry schemes include 1) the simple aerosol modules from the Goddard Chemistry 6 Aerosol Radiation and Transport model that includes only simplified sulfur chemistry, black carbon (BC), 7 organic carbon (OC), and sectional dust and sea salt modules (GOCART); 2) the photochemical gas-phase 8 mechanism RACM coupled to GOCART to determine the impact of more realistic gas-phase chemistry on 9 the GOCART aerosols simulations (RACM GOCART); and 3) a further sophistication within the aerosol 10 modules by replacing GOCART with a modal aerosol scheme that includes secondary organic aerosols (SOA) 11 based on the VBS approach (RACM SOA VBS). FIM-Chem is able to simulate aerosol, gas-phase chemical 12 species and SOA at various spatial resolutions with different levels of complexity and quantify the impact of 13 aerosol on numerical weather predictions (NWP). We compare the results of RACM GOCART and 14 GOCART schemes which uses the default climatological model fields for OH, H_2O_2 , and NO_3 . We find 15 significant reductions of sulfate that are on the order of 40% to 80% over the eastern US and are up to 40% 16 near the Beijing region over China when using the RACM GOCART scheme. We also evaluate the model 17 performance by comparing with the Atmospheric Tomography Mission (ATom-1) aircraft measurements in 18 2016 summer. FIM-Chem shows good performance in capturing the aerosol and gas-phase tracers. The model 19 predicted vertical profiles of biomass burning plumes and dust plumes off the western Africa are also 20 reproduced reasonably well.

21

1 1 Introduction

2 The impacts of aerosol on weather and climate are generally attributed to the direct, semidirect, indirect, and 3 surface albedo effects, with the direct effect predominating radiative forcing over a global scale [e.g. Bauer 4 and Menon, 2012]. However, there are significant differences in estimates of direct aerosol radiative forcing 5 between various global aerosol models, particularly with respect to the attribution of forcing to specific 6 aerosol species and sources [Myhre et al., 2013]. Discrepancies in direct radiative forcing are also found 7 between global aerosol model results and determinations based on satellite retrievals, with assumptions 8 related to aerosol composition and optical properties as the primary source of difference [e.g. Su et al., 2013]. 9 Several processes and steps are necessary to accurately include aerosol effects within a meteorological 10 forecast. Aerosol abundance, composition, and size distribution are the basic quantities needed within 11 calculations of the optical properties, which in turn are used within radiative transfer calculations to calculate 12 heating or cooling rates and are incorporated within the thermodynamic calculations of the numerical forecast. 13 The importance of aerosol impacts on the meteorological fields for climate modeling have been widely 14 recognized by many studies [e.g. Xie et al., 2013; Yang et al., 2014; Wang et al., 2014a, 2014b; Colarco et 15 al., 2014]. Since it is increasingly common for modeling systems to start using prognostic online aerosol 16 schemes and more accurate emissions, many studies exist that show the importance of including aerosols at 17 least for case studies or over limited time periods. On NWP timescales (5-10 days), Rodwell and Jung [2008] 18 showed an improvement in forecast skill and general circulation patterns in the tropics and extra-tropics by 19 using a monthly varying aerosol climatology rather than a fixed climatology in the European Centre for 20 Medium-Range Weather Forecasting (ECMWF) global forecasting system. The inclusion of the direct and 21 indirect effects of aerosol complexity into a version of the global NWP configuration of the Met Office 22 Unified Model (Met UM) shows that the prognostic aerosol schemes are better able to predict the temporal 23 and spatial variations of atmospheric aerosol optical depth, which is particularly important in cases of large 24 sporadic aerosol events such as large dust storms or forest fires [Mulcahy et al., 2014]. The aerosols from 25 biomass burning sources have been shown to have an effect on large-scale weather patterns within global 26 scale models [e.g. Sakaeda, 2011] and synoptic scale meteorology within the WRF-Chem regional model 27 [Grell et al., 2011]. Toll et al. [2015] showed considerable improvement in forecasts of near-surface 28 conditions during Russian wildfires in summer 2010 by including the direct radiative effect of realistic 29 aerosol distributions. Likewise, many global models [e.g. Haustein et al., 2012] and regional models [e.g. 30 WRF-Chem, Zhao et al., 2010] have established a clear connection between dust emissions and weather 31 patterns over synoptic to seasonal time scales. While positive impacts of predicted aerosols on weather 32 forecasts have been shown on an episodic basis, a systematic verification of current state-of-the-art 33 operational modeling systems does not yet demonstrate that the impact is statistically significant over longer 34 periods of time to warrant the required additional computational resources [Peuch et al., 2014]. Operational 35 forecast systems are usually highly tuned and still use aerosol climatologies. The inclusion of aerosols in the 36 presence of strong sources or sinks should lead to an improvement of predictive skills. A successful example 37 of a short-range weather forecasting coupled with the smoke tracer is the High-Resolution Rapid Refresh

coupled with Smoke (HRRR-Smoke) model [Ahmadov et al, 2017]. The model forecasts 3D smoke
 concentrations and its radiative impacts over the CONUS domain at 3km spatial gridding
 [https://rapidrefresh.noaa.gov/hrrr/HRRRsmoke/].

4 By applying the chemistry package from WRF-Chem v3.7 into the Flow-following finite-volume Icosahedra 5 Model (FIM, Bleck et al. 2015), named as FIM-Chem v1, we essentially make it possible to explore the 6 importance of different levels of complexity in gas and aerosol chemistry, as well as in physics 7 parameterizations on the interaction processes in global modeling systems. FIM is used in the sub-seasonal 8 experiment (SUBx) for sub-seasonal to seasonal (S2S) forecasting and is now considered a steppingstone 9 towards NOAA's Next Generation Global Prediction System, which will be based on the third generation 10 non-hydrostatic Finite Volume Cubed Sphere (FV3) dynamic core [Sun et al., 2018a, b]. The chemistry 11 component created here is designed to be moved flawlessly into FV3. WRF-Chem currently has 63 different 12 gas and aerosol chemistry options, as well as several microphysics and radiation parameterizations, which 13 are coupled to chemistry to simulate direct and indirect aerosol feedback processes. In this study we 14 demonstrate three examples of different complexities on the aerosol forecasts by FIM-Chem. The current 15 real-time forecast uses simple bulk aerosol modules from the GOCART model, with a simplified chemistry 16 for sulfate production. This chemistry scheme does not include NOx/Volatile Organic Compounds (VOC) 17 gas chemistry or SOA formation. Currently the real-time GOCART application uses climatological fields of 18 OH, H_2O_2 and NO_3 to drive the oxidation of SO_2 and oceanic dimethyl sulfide to sulfate.

Here we also investigate the sensitivity to the addition of complex gas-phase chemistry and a more reasonable inclusion of Secondary Organic Aerosol formation. Organic matter makes up the significant fraction of the sub-micron aerosol composition [*Zhang et al.*, 2007], and organic aerosol (OA) along with sulfate and black carbon are believed to be the main anthropogenic contributors to direct radiative forcing on a global scale [*Myhre et al.*, 2013]. A computationally efficient SOA parameterization based on the Volatility Basis Set approach [Donahue, 2011] was implemented in WRF-Chem by Ahmadov et al. (2012).

25 To evaluate the model performance, the observation data from the NASA Atmospheric Tomography aircraft 26 mission (ATom-1, 2016) is used, in which the DC-8 is instrumented to make high-frequency in situ 27 measurements of the most the chemical species over the Pacific and Atlantic Oceans, and across the Arctic 28 and US, to evaluate the model performance. Section 2 describes some aspects of the FIM and FIM-Chem 29 model, the coupling of aerosol configurations, gas-phase chemical schemes and an overview of the 30 observation data used to evaluate the model results. The chemical weather forecasts by using three different 31 gas and aerosol chemistry schemes with different level of complexities are shown in Section 3. Section 4 32 presents the evaluations of the chemical weather forecasts, and the model evaluations are investigated in

33 Section 5. We end with discussion and conclusions in Section 6.

34 2 Models and Observation

35 2.1 FIM

1 FIM is a hydrostatic global weather prediction model based on an icosahedral horizontal grid and a hybrid 2 terrain following/isentropic vertical coordinate [Bleck et al., 2015]. Icosahedral grids are generated by 3 projecting an icosahedron onto its enclosing sphere and iteratively subdividing the 20 resulting spherical 4 triangles until a desired spatial resolution is reached. The main attraction of geodesic grids lies in their fairly 5 uniform spatial resolution and in the absence of the two pole singularities found in spherical coordinates. The 6 primary purpose of using a near-isentropic vertical coordinate in a circulation model is to assure that 7 momentum and mass field constituents (potential temperature, moisture, chemical compounds, etc.) are 8 dispersed in the model in a manner emulating reality, namely, along neutrally buoyant surfaces. The FIM 9 model has been tested extensively on real-time medium-range forecasts to ready it for possible inclusion in 10 operational multi-model ensembles for medium-range to seasonal prediction, and the following simulations 11 are performed at G6 (~128 km) horizontal resolution. 12 In FIM-Chem, the column physics parameterizations have been taken directly from the 2011 version of the

GFS [Bleck et al., 2015]. The physical parameterizations include the Grell-Freitas convection parameterization [Grell and Freitas, 2014], the Lin et al. [1983] cloud microphysics scheme, coupled to the model aerosol parameterization and modified to include second moment effects, and the land surface

16 processes simulated by the NCEP's Noah land surface model [Koren et al. 1999 and Ek et al. 2003].

17 **2.2 FIM-Chem**

18 FIM-Chem, is a version of the FIM model coupled inline with chemical transport model including three

19 aerosol and gas-phase chemistry schemes of different complexities, where physics and chemistry components

20 of the model are simulated simultaneously. The chemical modules and coupling schemes are adopted from

- 21 the WRF-Chem model v3.6.1 [Grell et al. 2005; Fast et al. 2006; Powers et al., 2017]. The different three
- 22 chemical schemes have been listed in Table 1 for comparisons.

23 2.2.1 GOCART scheme

24 The first chemical option is the simplest aerosol modules that from the GOCART model, which includes

25 simplified sulfur chemistry for sulfate simulation from chemical reactions of SO₂, H₂O₂, OH, NO₃ and DMS,

26 bulk aerosols of black carbon (BC), organic carbon (OC), and sectional dust and sea salt. For OC and BC,

- 27 hydrophobic and hydrophilic components are considered and the chemical reactions using prescribed OH,
- H₂O₂, and NO₃ fields for gaseous sulfur oxidations [*Chin et al.*, 2000]. The dust scheme is using the Air
- 29 Force Weather Agency (AFWA) scheme with five dust size bins [LeGrand et al., 2019]. The bulk vertical
- 30 dust flux is based on the Marticorena and Bergametti scheme [Marticorena et al., 1995], whereas the particle
- 31 size distribution is built according to Kok, 2011, which is based on the brittle material fragmentation theory.
- 32 Four size bins are considered for the sea salt simulation. The sea salt emissions from the ocean are highly
- dependent on the surface wind speed [Chin et al., 2000]. There are totally 19 chemical tracers for transport
- 34 and 4 chemical reactions in the GOCART schemes. For 24 hours forecast, it takes about 4 minutes.

1 2.2.2 RACM_ GOCART scheme

2 The simple GOCART aerosol scheme does not include photolysis, full gas chemistry and secondary organic 3 aerosol production, and it normally uses climatological fields of OH, H₂O₂ and NO₃ to drive the oxidation of 4 SO2 and oceanic dimethyl sulfide (DMS) to produce sulfate. Based on the GOCART aerosol module, the 5 second chemical option includes the photochemical gas-phase mechanism of Regional Atmospheric 6 Chemistry Mechanism (RACM), which is able to determine the impact of the additional gas-phase 7 complexity on the aerosol simulations (RACM GOCART). The RACM chemistry mechanism is based upon 8 the earlier Regional Acid Deposition Model, version 2 (RADM2) mechanism [Stockwell t al., 1990] and the 9 more detailed Euro-RADM mechanism [Stockwell and Kley, 1994]. It includes a full range of photolysis, 10 biogenic VOCs, full NOx/VOC chemistry, inorganic and organic gaseous species to perform air pollution 11 studies that includes rate constants and product yields from the laboratory measurements [Stockwell et al., 12 1997]. The simplified sulfur chemistry for sulfate formation does not use climatological fields of OH, H_2O_2 13 and NO₃ from GOCART model to drive the oxidation of SO₂ as that in GOCART, and it is replaced by 14 explicitly simulating the gas-phase RACM chemistry. Meanwhile, the SO₂ is also impacted by the RACM 15 gas-phase chemistry, leading to differences with the GOCART simulations. There are 214 chemical reactions 16 and 68 chemical tracers for transport in the RACM GOCART scheme. It takes about 19 minutes for a 24 17 hours forecast.

18 2.2.3 RACM_SOA_VBS scheme

19 Other than the simple GOCART aerosol scheme in both GOCART and RACM GOCART, we implemented 20 a more complex gas-aerosol chemistry scheme of RACM SOA VBS in FIM-Chem. This scheme includes 21 the RACM based gas chemistry and the modal aerosol scheme MADE (Modal Aerosol Dynamics Model 22 for Europe) with SOA based on the VBS (Volatility Basis Set) approach [Ahmadov et al., 2012]. The 23 RACM SOA VBS scheme includes photolysis reactions for multiple species, full nitrogen and VOC 24 (anthropogenic and biogenic) chemistry, inorganic and organic aerosols. All the secondary gas species 25 required for the SO₂ oxidation are simulated explicitly by the gas chemistry scheme here. There are 233 26 chemical reactions and 103 transported chemical tracers in the RACM SOA VBS scheme. It takes about 22 27 minuets for 24 hours forecast. The new SOA mechanism contains four volatility bins for each SOA class, 28 and their organic vapors that condense onto aerosol. Equilibrium between gas and particle phase matter for 29 each bin is assumed in the model. The SOA species are added within the MADE aerosol module, which 30 considers composition within the Aitken and the accumulation modes separately. The VBS approach was 31 included for SOA production, updated SOA yields, and multigenerational VOC oxidation. The VOCs 32 forming SOA are divided into two groups, anthropogenic and biogenic. Isoprene, monoterpenes and 33 sesquiterpenes are emitted by biogenic sources, while other VOCs by anthropogenic sources. More detailed 34 descriptions about the VBS approach based on SOA scheme can be found in Ahmadov et al., 2012.

35 2.2.4 Emission, deposition, and aerosol optical properties

1 The preprocessor PREP-CHEM-SRC v1.5 [Freitas et al., 2011], a comprehensive tool aiming at preparing 2 emission fields of the chemical species for use in atmospheric-chemistry transport models, is used 3 to generate the emissions for FIM-Chem. It includes the Hemispheric Transport of Air Pollution 4 (HTAP) v2 global anthropogenic emission inventory [Janssens-Maenhout et al., 2015] and biogenic VOC 5 emissions simulated by the Model of Emissions of Gases and Aerosols from Nature (MEGAN) v2.0 6 parameterization [Guenther et al., 2006]. The diurnal variability based on a function of anthropogenic 7 activities is applied to the HTAP emissions and the diurnal cycle of solar radiation and air temperature is 8 applied to the biogenic emissions. The biomass burning emission estimated by the Brazilian Biomass Burning 9 Emissions Model [3BEM, Longo et al. 2010; Grell et al., 2011) is also included in the PREP-CHEM-SRC. 10 The 3BEM is based on near real-time remote sensing fire products to determine fire emissions and plume 11 rise characteristics [Freitas et al., 2007; Longo et al., 2010]. Although the same settings are used for these 3 12 schemes in PREP-Chem-SRC, the speciation profiles are modified for each specific mechanism. The fire 13 emissions are updated as they become available and are spatially and temporally distributed according to the 14 fire count locations obtained by remote sensing of Moderate Resolution Imaging Spectroradiometer 15 (MODIS) onboard Terra and Aqua satellites [Giglio et al., 2003]. The biomass burning emission factors are 16 from Andreae and Merlet [2001]. Over the CONUS domain the MODIS data are replaced by the Wildfire 17 Automated Biomass Algorithm (WF_ABBA) processing system. The WF_ABBA is able to detect and 18 characterize fires in near real-time, providing users with high temporal and spatial resolution fire detection 19 data (http://www.ssd.noaa.gov/PS/FIRE/Layers/ABBA/abba.html). In the current retrospective forecast of 20 2016, there is no day lag input for emission in the model. A one-dimension (1-D) time-dependent cloud 21 model implemented to calculate injection heights and emission rates online in all of the three chemical 22 schemes [Freitas et al., 2007].

23 Similar to WRF-Chem model, the flux of gases and aerosols from the atmosphere to the surface is calculated 24 by multiplying concentrations of the chemical species in the lowest model layer by the spatially and 25 temporally varying deposition velocities, the inverse of which is proportional to the sum of three 26 characteristic resistances (aerodynamic resistance, sublayer resistance, surface resistance [Grell et al. 2005]. 27 The GOCART aerosol dry deposition includes sedimentation (gravitational settling) as a function of particle 28 size and air viscosity and surface deposition as a function of surface type and meteorological conditions 29 [Wesely, 1989]. The dry deposition of sulfate is described differently. In the case of simulations without 30 calculating aerosols explicitly, sulfate is assumed to be presented in the form of aerosol particles, and the dry 31 deposition of aerosol and gas phase species is parameterized as described in Erisman et al. [1994]. For 32 RACM SOA VBS chemical option, the dry deposition velocity of the organic condensable vapors (OCVs) 33 is parameterized as proportional to the model calculated deposition velocity of a very soluble gas, nitric acid 34 (HNO₃). The parameter which determines the fraction (denoted as "depo fact") of HNO₃ is assumed in the 35 model since no observation constraints are available. The dry deposition velocity of HNO₃ is calculated by 36 the model during runtime [Ahmadov et al., 2012]. Wet deposition accounts for the scavenging of aerosols in

1 convective updrafts and rainout/washout in large-scale precipitation [Giorgi and Chameides, 1986; Balkanski

2 et al., 1993].

The aerosol optical properties such as extinction, single-scattering albedo, and the asymmetry factor for scattering are computed as a function of wavelength. Each chemical constituent of the aerosol is associated with a complex index of refraction. A detailed description of the computation of aerosol optical properties can be found in Fast et al. [2006] and Barnard et al. [2010].

7 2.3 Observations

8 The Atmospheric Tomography Mission (ATom) studies the impact of human-produced air pollution on 9 greenhouse gases and on chemically reactive gases in the atmosphere [Wofsy et al., 2018]. ATom deploys 10 instrumentation to sample the atmospheric composition, profiling the atmosphere in 0.2 to 12 km altitude 11 range. Flights took place in each of 4 seasons over a 22-month period. They originated from the Armstrong 12 Flight Research Center in Palmdale, California, flew north to the western Arctic, south to the South Pacific, 13 east to the Atlantic, north to Greenland, and returned to California across central North America over the 14 Pacific and Atlantic oceans from $\sim 80^{\circ}$ N to $\sim 65^{\circ}$ S. ATom establishes a single, contiguous global-scale data 15 set. This comprehensive data set is used to improve the representation of chemically reactive gases and short-16 lived climate forcers in global models of atmospheric chemistry and climate. Comparisons of model forecasts 17 with 5 flights from the first ATom mission (August 15-23, 2016) are shown here as examples of model 18 performance for specific events, such as wildfires and dust-storms, or specific conditions such as oceanic 19 versus continental. 20 The Particle Analysis by Laser Mass Spectrometry (PALMS) instrument samples the composition of single

21 particles in the atmosphere with diameters within ~150 nm - 5 µm range. It measures nearly all components

22 of aerosols from volatiles to refractory elements, including sulfates, nitrates, carbonaceous material, sea salt,

23 and mineral dust [Murphy et al., 2006]. The PALMS instrument was originally constructed for high-altitude

24 sampling [Thomson et al., 2000; Murphy et al., 2014] and has since been improved and converted for other

25 research aircraft. Uncertainty in mass concentration products is driven mainly by particle sampling statistics.

26 Relative 1-sigma statistical errors of 10-40% are typical for each 3-min sample at a mass loading of 0.1 ug/m3

27 [Froyd et al., 2019]. In August 2016, PALMS was sampling on the NASA DC-8 aircraft as part of the ATom

28 program (https://espo.nasa.gov/missions/atom/content/ATom). Aerosol composition determinations using

the PALMS instrument during ATom have been described and interpreted previously [Murphy et al., 2018,

30 2019; Schill et al., 2020; Bourgeois et al., 2020]. The PALMS mass concentrations for various species are

31 derived by normalizing the fractions of particles of each size and type to size distributions measured by

32 optical particle counters [Froyd et al., 2019].

33 Figure 1 shows the vertical profiles and transect time series of the ATom-1 flight tracks on August 15th and

34 17th, 2016 over Atlantic Ocean on August 23rd, 2006 over US. The August 15th flight originates from the

35 southwestern Atlantic and ends near the southern equatorial Atlantic; the August 17th flight is from the

36 southern equatorial Atlantic to the northern Atlantic; and the August 23rd flight is from Minnesota to Southern

1 California. For analysis and model validations, here we mark 16 vertical tracks and 3 horizontal tracks for

2 August 15th, 16 vertical tracks and 2 horizontal tracks for August 17th, and 8 vertical tracks and 4 horizontal

3 tracks for August 23^{rd} .

4 3 Chemical Composition Forecast

5 We perform a 5-days forecast started from 00:00 UTC July 29th 2016, and get the predicted results at 00:00 6 UTC August 3rd 2016 in Fig.2 and Fig.3. For the aerosol forecast, the GOCART and RACM GOCART 7 scheme are quite similar since they are using the same GOCART aerosol module. However, the major 8 difference is the impact of including gas-phase chemistry on aerosol. The simpler GOCART package uses 9 climatological fields for OH, H2O2, and NO3 from previous GEOS model simulations, while these species 10 are explicitly simulated in the RACM GOCART chemistry mechanism. The PM2.5 concentrations are the 11 sum of BC, OC, sulfate, the fine bins (diameter < 2.5 micrometers) of dust and sea salt. The forecast aerosol 12 results of surface PM2.5 and sulfate using GOGART and RACM GOCART and their differences 13 (RACM GOCART minus GOCART) are showed at Fig. 2. The general patterns of surface PM2.5 are quite 14 similar in these two schemes, with the maximum surface concentrations of more than 100 μ g/m³ over the 15 dust source region of western Africa, part of the southern African fire regions and part of the polluted areas 16 of south Asia and eastern China. However, the surface concentrations of PM2.5 in GOCART and 17 RACM GOCART (the latter minus former) show substantial differences, decreasing more than 15 μ g/m³ 18 over eastern US and 20 µg/m³ over eastern China, when using the RACM GOCART scheme. The main 19 factor that contributes to the significant differences of surface PM2.5 concentration is sulfate (see Fig.2 right 20 column). The maximum surface sulfate concentrations are over the eastern US, India and eastern China. We 21 find the reductions of sulfate are about 10 μ g/m³ on the order of 40-80% over the eastern US and are up to 22 40% over eastern China in RACM GOCART (Fig. 2b). The major differences for sulfate production between 23 GOCART and GOCART-RACM are the background fields of H2O2, OH and NO3. GOCART uses the model 24 climatological backgrounds fields of H2O2, OH and NO3 while GOCART-RACM uses the online calculated 25 fields of H₂O₂, OH and NO₃ from the RACM mechanism. 26 Fig. 3 shows the comparisons of surface H₂O₂, OH, and NO₃ between GOCART and RACM GOCART

27 schemes. Globally the prescribed surface H_2O_2 in GOCART is generally larger than that explicitly simulated 28 by RACM GOCART. The maximum of surface H₂O₂ regions over Africa, India and eastern Asia show 29 significant diversity. The explicitly real-simulated instantaneous surface H2O2 in RACM GOCART is much 30 lower, by 40-60% over India and eastern Asia and 20% over eastern US, while much higher (> 80%) over 31 middle Africa, northeastern regions of Canada, and northwestern areas of South America. Even though the 32 patterns of surface OH are quite comparable in the GOCART and RACM GOCART schemes at 00 UTC, 33 the real-simulated instantaneous surface OH is 80% lower over eastern China when using the 34 RACM GOCART scheme. The other big difference is over the western US with the simulated surface OH 35 in RACM GOCART being much higher over northwestern US and lower over the southwestern US at 00

1 UCT. The surface NO₃ differences are mainly over the Africa and north Indian Ocean, that the real-simulated

2 instantaneous surface NO₃ is much larger using the RACM_GOCART scheme at 00 UCT. Since surface

3 H₂O₂ and OH are the major species converting SO₂ to sulfate, their decreases cause sulfate reductions over

4 broad areas. The OH differences of GOCART and RACM_GOCART schemes at 12 UTC shows reduction

5 over Africa, India and Asia, corresponding to the decreasing sulfate over those aeras, accounting for the

The RACM GOCART model is able to predict gas phase species by using the RACM gas-phase mechanism.

6 major differences in sulfate production between the two mechanisms.

8 Ozone (O₃) and other gas pollutants are determined by the emissions of nitrogen oxides and reactive organic 9 species, gas- and aqueous-phase chemical reaction rates, depositions, and meteorological conditions. Fig. 4 10 represents the 5-days surface O₃ forecast globally at 12:00 UTC August 2nd and 00:00 UTC August 3rd, 2016, 11 which started from 00:00 UTC July 29th, 2016. Similar to other studies, a lot of chemical transport models 12 (CTMs) tend to significantly overestimate surface O₃ in the southeast US [Lin et al., 2008; Fiore et al., 2009; 13 Reidmiller et al., 2009; Brown-Steiner et al., 2015; Canty et al., 2015; Travis et al., 2016], which is an 14 important issue for the design of pollution control strategies [McDonald-Buller et al., 2011]. We see similar 15 problem in FIM-Chem that the predicted surface O3 concentration on 00:00 UTC August 3rd, 2016 is also

16 overestimated (see Fig. 4b). The relative low surface O3 is likely due to the O3 titration during the early 17 morning and nighttime periods. It well known that the O3 production involves complex chemistry driven by

18 emissions of anthropogenic nitrogen oxide radicals (NO_x=NO+NO₂) and isoprene from biogenic emissions.

19 The primary basis of O₃ may be due to the inventory of HTAP v2 anthropogenic emission over North America,

20 which is from U.S. EPA's 2005 National Emission Inventory (NEI2005). A few studies have pointed out that

21 the NO_x emissions in the NEI-2005 and NEI-2011 from the EPA is too high [Brioude, 2011; Travis et al.,

2016] over the US. It must be reduced by 30-60% from mobile and industrial sources in the NEI 2011
inventory [Katherine et al., 2016], while the NO_x emissions over United States should be reduced more for
2016 simulation since the NEI2005 NO_x emission is much larger than that of NEI2011
(https://cfpub.epa.gov/roe/). Also, the dry depositions of ozone, isoprene emissions and in the loss of NO_x
from formation of isoprene nitrates could also result into these overestimations [Lin et al., 2008; Fiore et al.,

27 2005].

7

28 The SOA parameterization based on the volatility basis and VBS approach applied within FIM-Chem has 29 the ability to simulate and predict SOA using the RACM SOA VBS scheme [Ahmadov et al., 2012], which 30 include the anthropogenic secondary organic aerosols (ASOA) and biogenic secondary organic aerosols 31 (BSAO) for both the nucleation and accumulation modes. Fig. 5 shows the predicted SOA at 12:00 UTC 32 August 2nd and 00:00 UTC August 3rd, 2016. The maximum surface SOA concentrations are over southern 33 Africa, which may be caused by the wildfire emissions. The Eastern US, western Europe and eastern Asia 34 are the other high SOA concentrations areas. There is not significant diurnal variability for the SOA spatial 35 distributions, and the diurnal cycle of fire emission has not been included.

36 4 Using ATom-1 observations to evaluate the FIM-Chem Model

1 The retrospective daily forecast uses cycling for the chemical fields since no data assimilation is included in

2 the chemical model. Meteorological fields are initialized by the GFS meteorological fields every 24 hours,

3 while the chemical fields from the last output (forecast at 24:00 UTC) are used as the initial conditions of the

4 current forecast (00:00 UTC). Stratospheric O₃ above tropopause is taken from satellite derived fields

5 available within GFS. For the ATom-1 forecast periods, considering there is no chemical initial conditions,

6 we performed a two-week spin-up period (from July 15th to July 28th) before the first observational

7 comparison day (July 29th, 2016) to help get a realistic chemical initial conditions for the ATom-1 forecast

8 period. It should be noted that stratospheric chemistry is incomplete (no halogen chemistry) in the model.

9 In this section, we compare 24 hours forecasts of FIM-Chem for the major aerosols and gas tracers for the

10 three different chemical schemes listed above. The FIM-Chem model results are sampled at the grid with

11 nearest latitude and longitude, and interpolated logarithmically in altitude according to the ATom-1

12 measurements. Temporally, 1-second measurements are matched to the nearest hour of the FIM-Chem hourly

- 13 model output, which translates into a spatial uncertainty of ~ 128 km, or ~1 model grid cell, for typical DC-
- 14 8 airspeeds.

4.1 Comparisons of the gas and aerosols species between FIM-Chem and the ATom-1 measurements over Atlantic

17 The comparison between RACM_GOCART and RACM_SOA_VBS schemes for the chemical species, e.g., 18 EC (elemental carbon, which is the same as BC), CO and O₃, that are mainly affected by the biomass burning 19 emissions from wildfires during August 15th and August 17th, are shown in Fig. 6. The model shows very 20 good performance in reproducing the profiles of EC and CO, especially capturing the biomass burning 21 plumes near the tropics. But it also shows some differences for EC in the results of GOCART (figures not 22 shown here since it is almost the same as that of RACM GOCART) and RACM GOCART schemes above 23 4~5 km, where model results are overestimated. Generally, the EC performance of RACM GOCART is 24 much better at low altitudes but has a high biased at high altitudes where the RACM SOA VBS 25 performs well. After investigating, we noticed that the GOCART and RACM GOCART aerosol modules 26 both assume there is no wet deposition for externally-mixed, hydrophobic BC, only for hydrophilic BC. This 27 assumption would result into the overestimation of EC at higher levels due to less wash out of hydrophobic 28 BC. Other models with simple wet removal schemes have shown similar overestimation of EC in the upper 29 troposphere (Schwarz et al., 2013; Yu et al., 2019). However, aerosols in the RACM SOA VBS scheme are 30 internally mixed, so there is a much larger wet deposition, and less EC in the upper levels. This an important 31 difference about the carbonaceous aerosol for both hydrophobic BC and OC in the wet removal. The 32 comparison with the observations provides a good resource for further improvements within the wet removal 33 parameterization. The second column in Fig. 6 compares CO for the observations, RACM GOCART and 34 RACM SOA VBS schemes. Overall, the forecast is able to capture the observed latitude-height profiles of 35 CO mixing ratio. However, they both show high biases at low altitude (about ~ 2 km) in the tropics. Other 36 than that, there are still some differences such as the underestimated CO mixing ratio above 6 km over the

1 tropics and overestimate near the surface. Also, the model does not reproduce the fire plume height correctly 2 for the biomass burning emissions over this area, which may be due to vertical transport or lower injection 3 heights near the fire source region. For O₃, the model is able to consistently capture O₃ mixing ratios with 4 both RACM_GOCART and RACM_SOA_VBS schemes, including the stratospheric intrusion near 40°S at 5 about 9 km height, though it is slightly higher near 40°N at about 12 km height. We find that over equatorial 6 areas at about 2-4 km height, the modeled O₃ mixing ratio is underestimated by about 30%. This may also 7 relate to the injection height of biomass burning that resulted in much lower CO at this altitude, since CO is 8 an important precursor for O₃ production. Near the surface the overpredicted CO in the RACM GOCART 9 and RACM SOA VBS schemes does not result in high O₃. It may be related to other O₃ precursors other 10 than CO, such as missing VOC and NOx sources. Large uncertainties in both the biogenic and anthropogenic 11 emission inventories are expected over Western Africa. Besides the aerosol and gas tracers associated with 12 the biomass burning emissions, we also compare the HCHO, OH and H₂O₂, which are the important 13 precursors or oxidants to many other species within the RACM GOCART and RACM SOA VBS schemes 14 (see Fig. 7). Generally, the pattern of the modeled HCHO mixing ratio is almost the same as that of the 15 ATom-1 measurements. The variations from south to north are captured by these two schemes except a little 16 underestimation near about 10 km height. For OH, the model reproduces the vertical and temporal variations, 17 including the large mixing ratios over the northern hemisphere. Some slight differences are apparent, e.g., 18 the overestimates over 44°S at 3-9 km height and the underestimates over 40°N above 10 km height. Similarly, 19 there is more spatial variability in the ATom-1 measurement of H_2O_2 . Above 6km the model overestimates 20 H₂O₂ south of 40°S and overestimates from 20°S to the northern hemisphere above 6 km. Overall, the model 21 and ATom-1 measurement are more consistent at lower altitudes for H₂O₂. 22 Figures 8 and 9 show more detailed comparisons for vertical tracks of meteorological fields and chemical

23 species in the biomass burning (Fig. 9a) and dust events (Fig. 9b). For the biomass burning plume the 16th 24 vertical profile on August 15th, 2016 near 20°S is shown while the 10th profile on August 17th, 2016 near 25 25°N for the Saharan dust plume is shown. The comparison of the meteorological fields of temperature, 26 virtual potential temperature, water vapor, relative humidity, wind speed and wind direction are shown in 27 Fig. 8 and do not change between the different chemical options. The model forecasted temperature and 28 virtual potential temperature almost overlap the ATom-1 measurements for both the August 15th and 17th 29 vertical tracks. For water vapor and relative humidity, the variations of the vertical profiles are also 30 reproduced by the model, except there are some smaller peaks in the observed profiles. There are still some 31 differences between model and ATom-1 observations for wind speed and wind direction, which may be due 32 to model vertical resolution. Overall, the model is able to capture the general vertical variations. For the 33 chemical species (see Fig. 9), the modeled EC using GOCART scheme is almost identical to that by the 34 RACM GOCART scheme (the green line is overlapped by the blue line). Both EC concentration plots show 35 a vertical variation of decreasing with altitude and the concentrations are overestimated above 2 km in 36 biomass burning plume (see Fig. 9a) and above 4 km in dust storm (see Fig. 9b). The results using the 37 RACM SOA VBS scheme shows much better performance to capture the vertical variations of EC. Other

1 than a slight overestimation at 2-4 km biomass plume (see Fig. 9a first column), the EC vertical profile is 2 very consistent to that of the observation when using RACM SOA VBS scheme. In the biomass burning 3 event (see Fig. 9b first column), the modeled vertical profile with the RACM SOA VBS scheme captures 4 the general changes of the vertical variations much better than those of the GOCART and RACM GOCART 5 schemes. As mentioned, previously, the assumption of no wet deposition for hydrophobic BC is the main 6 reason resulting in less EC at high altitude in the RACM SOA VBS scheme compared to the GOCART and 7 RACM GOCART schemes. Due to less available observed data for sea salt, it is difficult to perform specific 8 comparisons, but both the observation and model show strong decreases with altitude. During the dust event 9 (see Fig. 9b third column), even though the modeled dust concentrations are lower at about 2-6 km than the 10 observed concentrations, they are close to the observation at the surface and upper levels. For the gas-phase 11 species, the model results are from GOCART_RACM (blue line) and RACM_SOA_VBS (red line) schemes. 12 The observed O₃ in the biomass burning event (see Fig. 9a fourth column) shows a peak at about 2 km height, 13 then it decreases with altitude, but increases again at about 5-9 km height. The model results from these two 14 schemes are quite consistent. They both indicate a slight enhancement at 1.5 km height, though it is not able 15 to capture the magnitude of the observed peak, which is underestimated by \sim 50%. For CO, the model can 16 reproduce the peak at about 2 km height very well, though it overestimates the mixing ratio by 25% below 1 17 km in the biomass burning event (see Fig. 9a 5th column). The detailed variations of the O3 and CO vertical 18 profiles still show some slight differences between the model and observation, but the model generally 19 forecasts the vertical changes with altitude, and the CO using RACM GOCART is slightly lower than that 20 of the RACM_SOA_VBS scheme above 5 km height.

21 4.2 Comparisons of aerosols and gas tracers between FIM-Chem and ATom-1 over the United States

22 Figure 10 shows the comparisons of EC and sulfate between ATOM-1 measurements and FIM-Chem model 23 with three different chemical schemes over the United States. Other than the underestimates of wet removal 24 for EC in GOCART and RACM GOCART schemes that result in the overpredicted EC concentrations above 25 4 km height, the near surface (below 4 km) EC concentrations over southern California are also higher than 26 the observation. The overestimate over southern California is also shown in the RACM SOA VBS scheme. 27 Similarly, the predicted sulfate concentrations over southern California are much higher than the observation 28 too. Also, the surface sulfate concentrations throughout the U.S. are much higher than those of observations. 29 In the FIM-Chem model, the anthropogenic emissions are from the HTAP v2.1 inventory, which based on 30 the NEI2005 over United States. However, the BC emissions have declined by 50% in California from 1980 31 to 2008 following a parallel trend the reduction of fossil fuel BC emissions [Bahadur et al., 2011]. The older 32 emission inventory with relatively higher anthropogenic emissions of BC and SO2 may possibly induce the 33 overestimates of near- surface BC and sulfate concentrations for the 2016 simulation in the model results 34 over southern California and other areas. To test this hypothesis we performed the same GOCART 35 retrospective experiment using the Community Emissions Data System (CEDS) anthropogenic emission 36 [Hoesly et al., 2018] instead of the HTAP v2.1 inventory. The CEDS anthropogenic emission is much stronger than HTAP over California for SO₂ (see Fig.11). Thus, a significant enhancement in sulfate
 concentration near the surface of California is seen when using CEDS emissions, as shown in Figure 12. For
 the sulfate concentrations at upper levels, the GOCART scheme (see Fig. 10b the second column) using the

4 background fields of H₂O₂, OH and NO₃ shows much better performance in capturing the relatively lower

5 sulfate at upper levels compared to the other two schemes.

- 6 Figure 13 shows the comparisons of OH and H₂O₂ in GOCART, RACM GOCART and RACM SOA VBS 7 with ATom-1 observations. It can be seen that the prescribed OH is close to the ATom-1 observation, which 8 may be the major factor contributing to better sulfate agreement in GOCART. Considering the sulfur 9 chemical reaction mechanism and the aerosol scheme in RACM SOA_VBS is completely different to that 10 in GOCART and RACM GOCART, the comparison of oxidants may not be the only reason causing the 11 differences, which needs further analysis. For the gas species we compare CO, HCHO and O₃ (see Fig. 14) 12 using the RACM_GOCART and RACM_SOA_VBS schemes with the observation. Generally, the model 13 cases using either RACM_GOCART or RACM_SOA_VBS scheme show good performance in capturing 14 the CO and HCHO mixing ratios both at the surface and in the free troposphere. But they are both higher 15 than the observations near the surface over southern California, similar to EC and sulfate concentrations. This 16 may be also associated with the overestimation of anthropogenic emissions in the NEI-2005 over United 17 States for the year of 2016. Since CO and HCHO are precursors for O₃ production, the simulated O₃ also 18 shows slight enhancements compared to the observations that may be due to the higher CO and HCHO. Other 19 than that, the model is able to reproduce the O_3 profile over the US reasonably well, including the O_3 20 stratospheric intrusions at the upper levels. The simulated H₂O₂ in both RACM GOCART or 21 RACM SOA VBS schemes show better agreement with the observations at the upper levels than the 22 prescribed H_2O_2 fields in GOCART (Fig. 13). While the much lower H_2O_2 near the surface in the 23 RACM SOA VBS may be associated with better O₃ performance near the surface (Fig. 13).
- 24 Figure 15 focuses on the 4th vertical profile over Kansas on August 23rd, 2016. The model results with 25 different chemical schemes are very consistent in simulating the meteorological fields. The modeled 26 temperature and virtual potential temperature show nearly exact agreement with the observations. But there 27 are still some shortcomings in forecast water vapor and relative humidity, especially above 6 km, where the 28 model results are overpredicted by nearly a factor of 2 and with less vertical variability. The vertical trend of 29 modeled wind speed and wind direction are close to the observed changes that increase with altitude. Similar 30 to Figure 9, the EC vertical profile using the RACM SOA VBS scheme, without the hydrophobic 31 assumption in wet removal, is similar to that of the observations while the other 2 schemes significantly 32 overpredict. Both the observations and models show decreasing vertical trend for sea salt and dust. The 33 GOCART scheme is able to reproduce the sulfate, except for the underestimate at 1.5-3 km. Otherwise, it 34 almost overlaps the observed profile at the upper levels. The O_3 vertical profile is reproduced by the model 35 using both RACM GOCART and RACM SOA VBS schemes except a slight peak near 9 km where the 36 model is not able to capture the enhanced variability. The CO measurements have more fluctuations, but the 37 model roughly shows the major features of the vertical changes with altitude.

1 5 Correlations between FIM-Chem model and ATom-1 observations

2 For the aerosol size range of the GOCART scheme, the PALMS dataset allows for model evaluation of the 3 default sea salt emission algorithms by summing those bins less than 3 µm in the model results. The 4 comparison between the GOCART forecasts and ATom-1 data for all sea salt observations below 6 km are 5 shown in Figure 16. Different colors show different flight dates from August 15th (blue dots), 17th (green dots), 20th (orange), 22nd (red) and 23rd (purple). Generally, modeled sea salt appears too high, especially on 6 7 flights of August 15th (blue dots), 20th (orange dots) and 23rd (purple dots) above ~4km. Some high values 8 below ~4km are reproduced by the models on the flight of August 17th (green dots). Some of the disagreement 9 may be due to uncertainties in the size range of sea salt observations, particularly the upper cutoff of 3 um 10 that is approximate (Murphy et al., 2019). 11 We also investigate the relationships of some key species for the biomass burning plumes observed on 12 8/15/17 and 8/17/17 between 22°S to 22°N below 6km (Fig. 17) for the RACM SOA VBS scheme. The 13 color bar indicates the latitude from south to north. Relative to CO, the model biomass burning emission 14 ratios are reasonable for EC with the modeled ratio (black color dots) somewhat lower than the observations 15 (color dots). We note that in Fig.6, O₃ in the biomass burning region for the RACM SOA VBS scheme is 16 underpredicted. To analyze this O₃ bias in more detail, scatter plots of modeled and observed NO_y versus CO 17 and O₃ versus NO_y between 22°S and 12° N below 6km altitude are shown in Fig.17b and Fig. 17d, 18 respectively. The observations in Fig. 17d show a much different, and better defined slope of O₃ versus NO_y 19 compared to the model using RACM SOA VBS scheme. NOy, which is emitted entirely as NOx in fresh 20 plumes, is much higher in the model, suppressing OH (e.g., Fig. 7), HO₂, and subsequent ozone formation. 21 The NO_y to CO ratios in Fig. 17b show evidence in the model of NO_y removal through HNO₃ scavenging, 22 but it's clear the NO_y (or NO_x) to CO emission ratio is too high in the fire emissions. The CO emissions 23 themselves appear too high (as also shown in Fig. 6). Other factors, such as VOC emission ratios or photolysis 24 effects from convective clouds may come into play, but these emission overestimates appear to put the

25 biomass burning region in a different photochemical regime than shown in the ATom-1 observations.

26 6 Conclusions

A two way fully inline coupled global weather -chemistry prediction model FIM-Chem has been developed
 at NOAA Global Systems Laboratory (GSL) to forecast the chemical composition and quantify the impacts

29 on NWP. Three different gas/aerosol chemistry schemes - GOCART, RACM GOCART and

30 RACM SOA VBS from WRF-Chem have been implemented into FIM-Chem with some modifications as

- 31 different options of chemical schemes. The major conclusions are summarized as follows:
- 32 First, the RACM GOCART mechanism with explicitly simulated H₂O₂, OH and NO₃ is compared to the
- 33 base GOCART mechanism having a simple parameterization of sulfur/sulfate chemistry using prescribed
- 34 background fields of OH, H_2O_2 and NO₃. The explicit treatment results in about 10 μ g/m³ reductions of
- 35 sulfate and 15 μ g/m³ of PM_{2.5} over the eastern US, as well as more than 20 μ g reductions of PM_{2.5} over eastern

- 1 China. Meanwhile, the simulated instantaneous H₂O₂ is lower by 20% over eastern US and 40-60% over
- 2 India and eastern Asia, while the OH is 80% lower over eastern China in the RACM_GOCART scheme.
- 3 In this study, the evaluation and analysis of model performance are focused on the fire events over the Eastern

4 Atlantic from south to north on August 15th and 17th 2016, and the flight over the United States from

5 Minnesota to southern California using the NASA ATom-1 observations.

6 For the evaluation over Atlantic, the GOCART and RACM GOCART results are very consistent in 7 forecasting sulfate, sea salt and EC due to the same aerosol mechanism. For the fire events sampled near the 8 equatorial Atlantic (e.g. Fig. 6), the GOCART and RACM GOCART schemes show good performance in 9 reproducing the profiles of EC, and CO is captured reasonably well with the RACM GOCART and 10 RACM_SOA_VBS schemes. Generally, EC is simulated well by GOCART and RACM GOCART 11 mechanisms up to 4 km but above this the mechanisms are biased high, while EC in the 12 RACM SOA VBS scheme shows much better performance than that of the GOCART and 13 RACM GOCART schemes at the upper levels. This is because it's assumed there is no wet deposition for 14 hydrophobic BC in the GOCART and RACM GOCART schemes, which results into an underestimate of 15 EC wet removal and overestimate of EC concentrations at higher levels. The CO mixing ratio above ~2 km 16 is underestimated over the tropics and overestimated at altitudes below ~2km, which may be related to lower 17 simulated fire injection heights in the model. Otherwise, the general CO profiles are well reproduced. Both 18 RACM GOCART and RACM SOA VBS schemes are able to consistently reproduce O₃ mixing ratios, 19 including the stratospheric intrusion above ~ 9 km at 40°S. There is some slight underestimation of O₃ near 20 the tropics, which might be associated with the underprediction of CO outside the biomass burning signature 21 region. We also evaluated other gas-phase species: HCHO, OH and H₂O₂, which are important precursors to 22 many other chemical species within the RACM GOCART and RACM SOA VBS schemes (see Fig. 7). 23 Generally, the pattern of the modeled HCHO, OH and H₂O₂ mixing ratio are almost the same as that of the 24 ATom-1 observations except for some underestimates above 9 km for HCHO and OH at some latitudes, and 25 some overestimates of H₂O₂ above 6 km in the southern hemisphere.

For the evaluation from Minnesota to southern California, all of the chemical schemes are able to reproduce the general vertical gradients seen in the observations. The RACM SOA VBS scheme is able to reproduce

- the general vertical gradients seen in the observations. The RACM_SOA_VBS scheme is able to reproduce the vertical profile of EC much better than that of the GOCART and RACM_GOCART schemes, which overestimate the EC concentrations above 2-4 km due to the assumption of no wet deposition for hydrophobic BC. This comparison highlights the value of the ATom-1 data in examining basic assumptions within the wet removal parametrization of carbonaceous aerosol in the GOCART mechanism. The high SO₂ emissions
- 32 from either anthropogenic or fire sources play important role in enhancing the sulfate production. There are
- 33 high biases above ~ 3km for sulfate in the RACM GOCART and RACM SOA VBS schemes. Results from
- 34 the RACM_GOCART and RACM_SOA_VBS schemes show consistency with observed O₃ and CO vertical
- 35 profiles during the fire events. Both schemes show a slight enhancement of O_3 at 1.5 km even though it
- 36 underestimates the magnitude of the observed peak. For CO, the model results capture the peak at about 2
- 37 km very well but overestimates the mixing ratio by about 30% near the surface. For the gas-phase species,

1 the model either using the RACM GOCART or RACM SOA VBS scheme shows very good ability in 2 forecasting the CO, O₃ and HCHO mixing ratio both at the surface and free troposphere, including the O₃ 3 stratospheric intrusions at the upper levels (Fig. 14). For CO, a precursor for O₃ production, there appears to 4 be overestimated emissions over California causing much higher surface mixing ratios in the forecasts than 5 observed. For the comparisons of vertical profiles over California on August 23rd 2016, the modeled 6 meteorological fields of temperature and potential temperature show agreement with the observations. The 7 modeled water vapor and relative humidity are consistent with observations below 6 km though they are 8 overestimated above 6km. The RACM SOA VBS scheme shows the best agreement with EC. For sulfate, 9 the GOCART scheme is almost the same as the observation above 3km while it overestimates near the surface 10 due to the high anthropogenic emissions used within the inventory. The simulated O₃ and CO vertical profiles 11 almost overlap the ATom-1 measurements but with less vertical variability. Though data is somewhat sparse 12 in our analysis, the sea salt emission algorithm appears to be a model component that could be improved due 13 to apparent consistent overestimation. 14 The scatter plots of sea salt and gas tracers from biomass burning plumes shows that modeled sea salt appears 15 too high and some of the disagreement may be due to uncertainties in the size range of sea salt observations 16 (Fig. 16), and the NO_y (or NO_x) to CO emission ratio is too high in the fire emissions (Fig. 17). These emission 17 overestimates may put the biomass burning region in a different photochemical regime than shown in the 18 ATom-1 observations. 19 The comparison in this study successfully demonstrates that the FIM-Chem model with three difference 20 chemical schemes show good performance in forecasting the chemical composition for both aerosol and gas-21 phase tracers when compared with the high temporal resolution (1-second) observations of ATom-1. The wet 22 removal assumption for hydrophobic BC is not reasonable, which needs to be improved in the GOCART and 23 RACM GOCART schemes. It is not necessary to use the complexity of a gas-phase scheme if the focus is

only on aerosol forecasts, in order to save time and computer resources. Using anthropogenic emissions for the specific year of the simulation may help to improve the forecasts. Also, a new dynamic core of Finite-

- 26 volume cubed-sphere dynamical core (FV3) developed by GFDL will be used to replace of FIM and coupled
- with the chemical schemes in the next generation global prediction system (NGGPS), as FV3GFS-Chem, byusing that to demonstrates the chemical impacts on NWP.
- 29

30 Code and data availability

31 Basically, the chemical modules of GOCART, RACM_GOCART and RACM_SOA_VBS are based on the

32 WRF-Chem 3.7, which can be obtained from

33 http://www2.mmm.ucar.edu/wrf/users/download/get source.html. The FIM-Chem v1 code and model

34 configuration for chemical composition forecast here are available at http://doi.org/10.5281/zenodo.5044392.

35 ATom-1 data is publicly available at the Oak Ridge National Laboratory Distributed Active Archive Center:

36 <u>https://daac.ornl.gov/ATOM/guides/ATom_merge.html</u> (Wofsy et al., 2018).

1 Author contribution

- 2 Li Zhang and Georg A. Grell developed the model coupling code and implemented the chemical modules
- 3 from WRF-Chem into FIM model. Li Zhang designed the experiments and performed the simulations. Stuart
- 4 A. McKeen evaluated the model performance and provided the suggestions to improve model performance.
- 5 Ravan Ahmadov developed the RACM-SOA-VBS scheme in WRF-Chem. Karl D. Froyd and Daniel
- 6 Murphy performed the measurements and provided the measured data of ATom-1 experiments. Li Zhang
- 7 prepared the manuscript with contributions from all co-authors.

8 **Competing interests**

9 The authors declare that they have no conflict of interest.

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- 13

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1 Table 1. Chemical Scheme comparison.

	GOCART	RACM_GOCART	RACM_SOA_VBS
Number of transport Tracers	19	68	103
Number of Chemical Reactions	4	214	233
Aerosol scheme	GOCART	GOCART	SOA_VBS
GAS-phase chemistry scheme	/	RACM	RACM
Computational expense of 24 hours forecast	~4 minuets	~19 minuets	~22 minuets

1 Figure captions.

- 2 Figure 1. Vertical profiles and transect time series of the ATom-1 flight tracks on August 15th and 17th, 2016
- 3 over Atlantic Ocean and August 23rd 2006 over US.
- 4 Figure 2. 5-days forecast started from 00:00 UTC July 29th 2016 of surface PM_{2.5} and sulfate using (a)
- 5 GOCART and (b) RACM_GOCART schemes, and their (c) differences (RACM_GOCART minus
- 6 GOCART) at 00:00 UTC August 3^{rd} 2016. Unit: $\mu g / m^3$.
- 7 Figure 3. Comparisons of 5-days forecast started from 00:00 UTC July 29th 2016 of surface H₂O₂, OH, and
- 8 NO₃ between (a) GOCART and (b) RACM_GOCART schemes, and their differences (RACM_GOCART
- 9 minus GOCART) at (c) 00:00 UTC and (d) August 3rd 2016. Unit: ppb.
- 10 Figure 4. 5-days forecast started from 00:00 UTC July 29th 2016 of surface O₃ using RACM_GOCART
- 11 scheme at 12:00 UTC August 2nd and 00:00 UTC August 3rd 2016. Unit: ppb.
- 12 Figure 5. 5-days forecast started from 00:00 UTC July 29th 2016 of surface SOA using RACM_SOA_VBS
- 13 scheme at 12:00 UTC August 2nd and 00:00 UTC August 3^{rd} 2016. Unit: $\mu g/m^3$.
- 14 Figure 6. Height-latitude profiles of EC, CO and O₃ over Atlantic on August 15th and August 17th, 2016 for
- 15 (a) ATom-1; (b) RACM_GOCART; and (c) RACM_SOA_VBS.
- 16 Figure 7. Height-latitude profiles of HCHO, OH and H₂O₂ over Atlantic on August 15th and August 17th,
- 17 2016 for (a) ATom-1 observations; (b) RACM_GOCART; and (c) RACM_SOA_VBS.
- 18 Figure 8. ATom-1 observations and model results for temperature, virtual potential temperature, water vapor,
- 19 relative humidity, wind speed and wind direction in the (a) biomass burning and (b) dust events. The biomass
- 20 burning plume is from August 15, 2016, profile #16 near 20°S while the Saharan dust plume is from August
- 21 17, 2016, profile #10 near 25°N.
- 22 Figure 9. Comparisons between ATom-1 observations and model vertical profiles of EC, sea salt, dust, O₃
- and CO in (a) biomass burning event and (b) dust storm event. The biomass burning plume is from August
- 24 15, 2016, profile #16 near 20°S while the Saharan dust plume is from August 17, 2016, profile #10 near 25°N.
- 25 Green and blue lines are nearly identical for aerosol.
- Figure 10. Height-latitude profiles of EC and sulfate over United States on August 23rd, 2016 for (a) ATom-
- 27 1; (b) GOCART; (c) RACM_GOCART; and (d) RACM_SOA_VBS.
- Figure 11. Anthropogenic emissions of SO₂ of (a)HTAP and (b) CEDS inventories on August. Unit:
 mol/km²/hour.
- 30 Figure 12. Height-latitude profiles of sulfate over United States on August 23rd, 2016 for (a) ATom-1, (b)
- 31 GOCART with HTAP, (c) GOCART with CEDS anthropogenic emission.
- 32 Figure 13. Height-latitude profiles of OH and H₂O₂ over United States on August 23rd, 2016 for (a) ATom-
- 33 1; (b) GOCART; (c) RACM_GOCART; and (d) RACM_SOA_VBS.
- **Figure 14.** Height-latitude profiles of CO, O₃ and HCHO over United States on August 23rd, 2016 for (a)
- 35 ATom-1; (b) RACM_GOCART; and (c) RACM_SOA_VBS.
- **Figure 15.** Observations and model results for profile #4, 8/23/16 over southeastern Kansas.
- 37 Figure 16. GOCART model forecast versus ATom-1 observed sea salt below 6 km.

- 1 Figure 17. Model (black color dot) and observation (color dot) ratios of (a) EC relative to CO; (b) NO_y
- 2 relative to CO; (c) O₃ relative to CO and (d) O₃ relative to NO_y. Color scale is degree latitude.

3

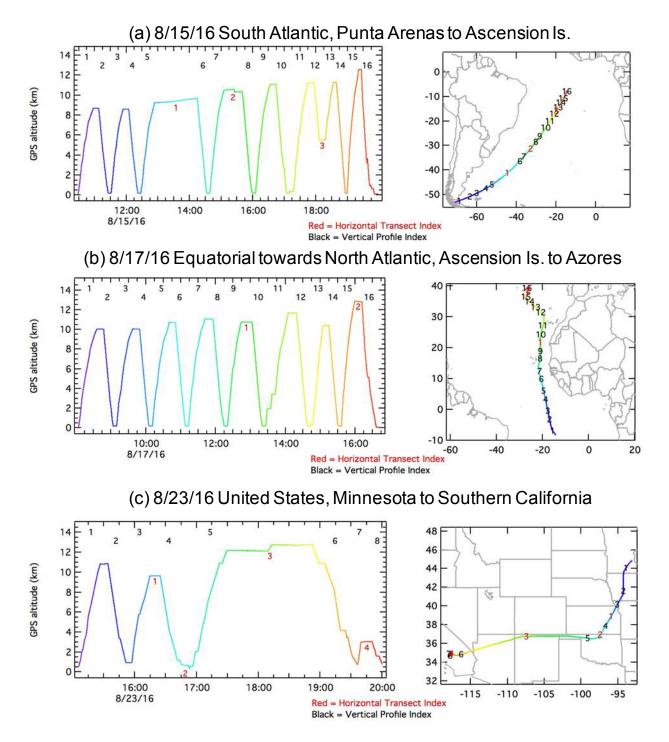


Figure 1: Vertical profiles and transect time series of the ATom-1 flight tracks on August 15th and 17th, 2016 over Atlantic Ocean and August 23rd 2006 over US.

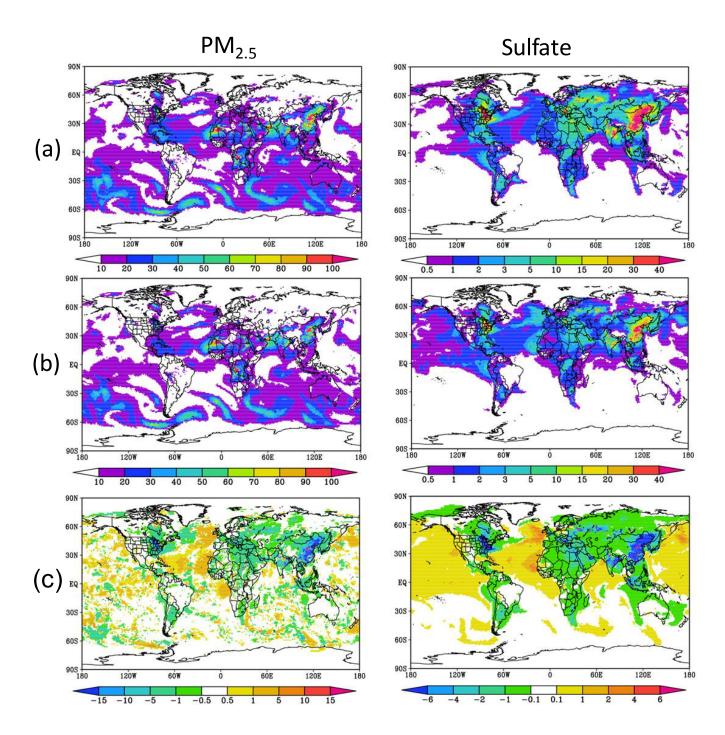


Figure 2: 5-days forecast started from 00:00 UTC July 29th 2016 of surface PM2.5 and sulfate using (a) GOCART and (b) RACM_GOCART schemes, and (c) their differences (RACM_GOCART minus GOCART) at 00:00 UTC August 3rd 2016. Unit: μ g /m3.

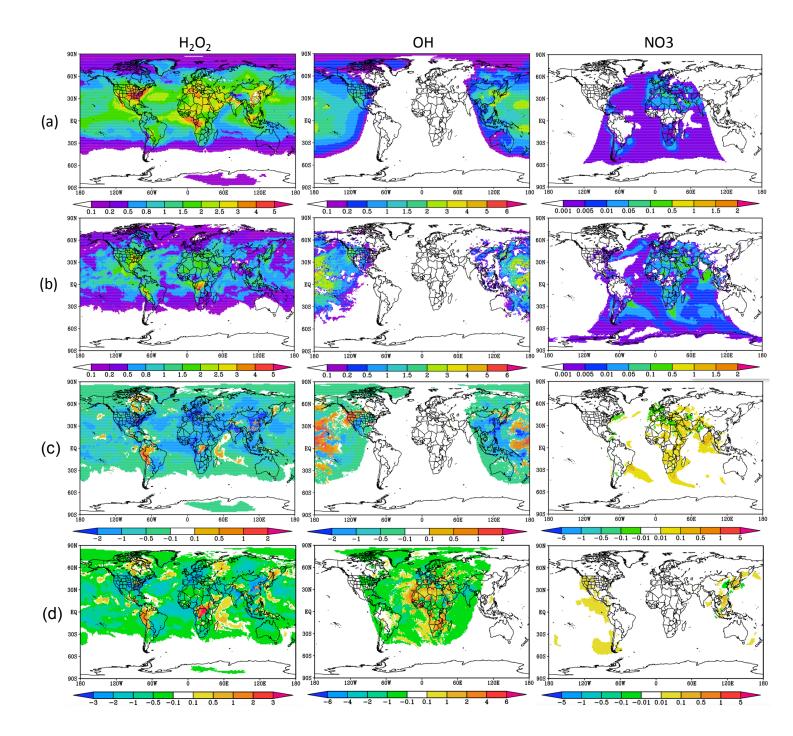


Figure 3: Comparisons of 5-days forecast started from 00:00 UTC July 29th 2016 of surface H2O2, OH, and NO3 between (a) GOCART and (b) RACM_GOCART schemes, and their differences (RACM_GOCART minus GOCART) at (c) 00:00 UTC and (d) 12:00 UTC August 3rd 2016. Unit: ppb.

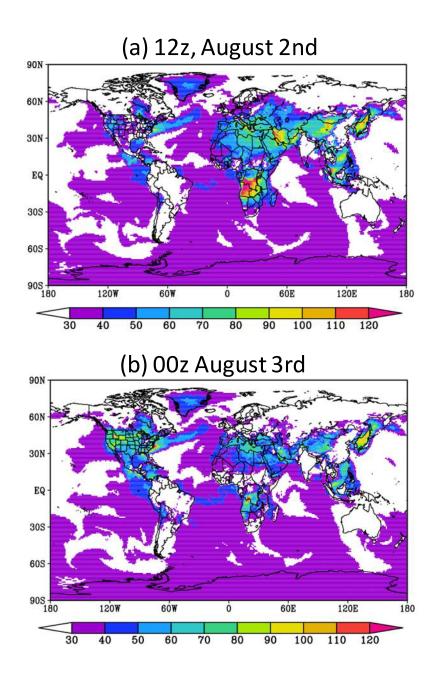


Figure 4: 5-days forecast started from 00:00 UTC July 29th 2016 of surface O3 using RACM_GOCART scheme at 12:00 UTC August 2nd and 00:00 UTC August 3rd 2016. Unit: ppb.

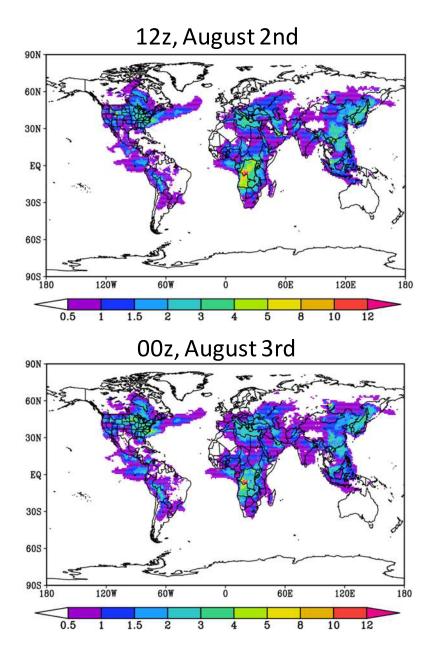


Figure 5: 5-days forecast started from 00:00 UTC July 29th 2016 of surface SOA using RACM_SOA_VBS scheme at 12:00 UTC August 2nd and 00:00 UTC August 3rd 2016. Unit: μg/m3.

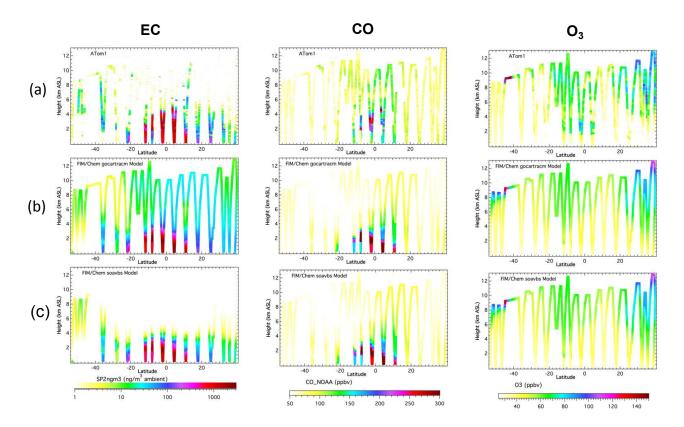


Figure 6: Height-latitude profiles of EC, CO and O3 over Atlantic on August 15th and August 17th, 2016 for (a) ATom-1; (b) RACM_GOCART; and (c) RACM_SOA_VBS.

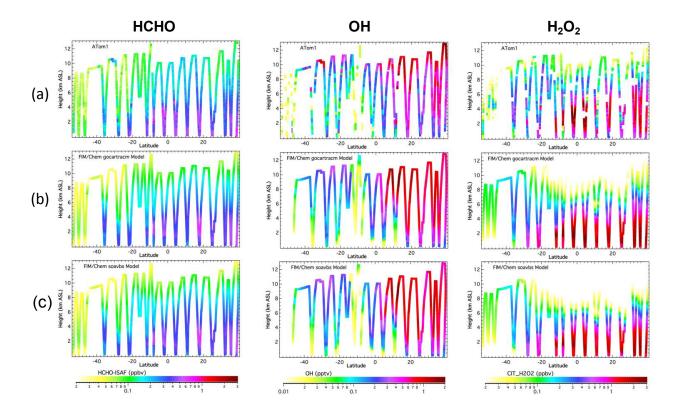


Figure 7: Height-latitude profiles of HCHO, OH and H2O2 over Atlantic on August 15th and August 17th, 2016 for (a) ATom-1 observations; (b) RACM_GOCART; and (c) RACM_SOA_VBS.

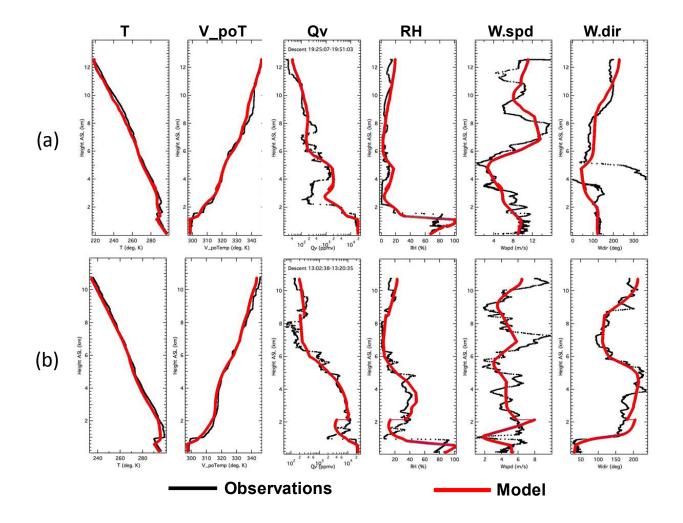


Figure 8: ATom-1 observations and model results for temperature, virtual potential temperature, water vapor, relative humidity, wind speed and wind direction in the (a) biomass burning and (b) dust events. The biomass burning plume is from August 15, 2016, profile #16 near 20°S while the Saharan dust plume is from August 17, 2016, profile #10 near 25°N.

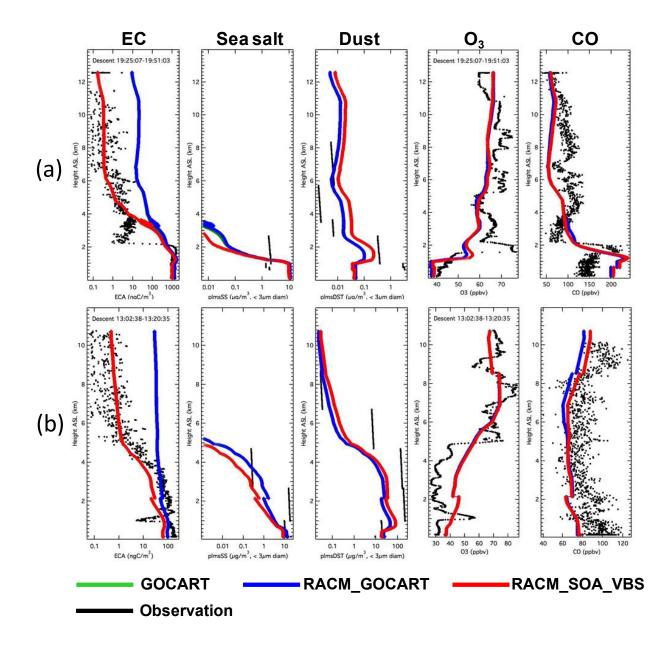


Figure 9: Comparisons between ATom-1 observations and model vertical profiles of EC, sea salt, dust, O3 and CO in (a) biomass burning event and (b) dust storm event. The biomass burning plume is from August 15, 2016, profile #16 near 20°S while the Saharan dust plume is from August 17, 2016, profile #10 near 25°N. Green and blue lines are nearly identical for aerosol.

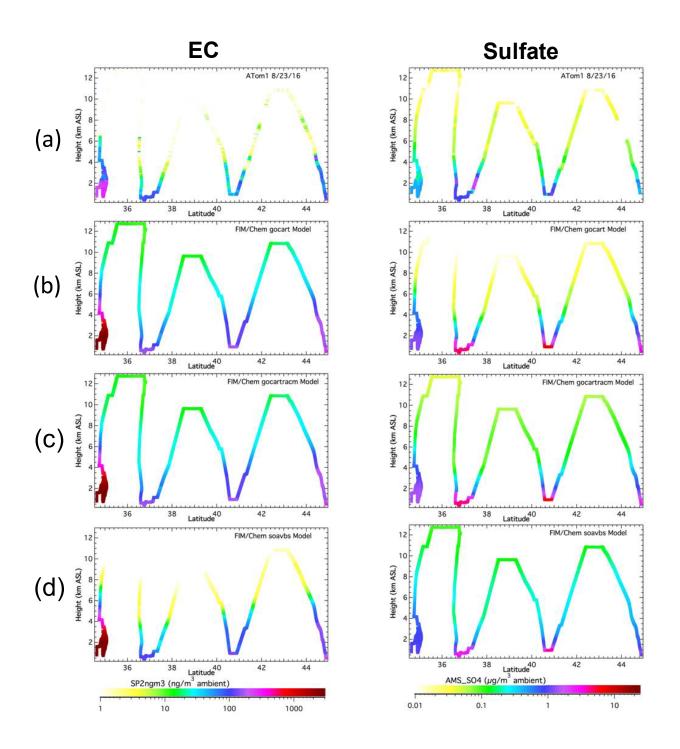


Figure 10: Height-latitude profiles of EC and sulfate over United States on August 23rd, 2016 for (a) ATom-1; (b) GOCART; (c) RACM_GOCART; and (d) RACM_SOA_VBS.

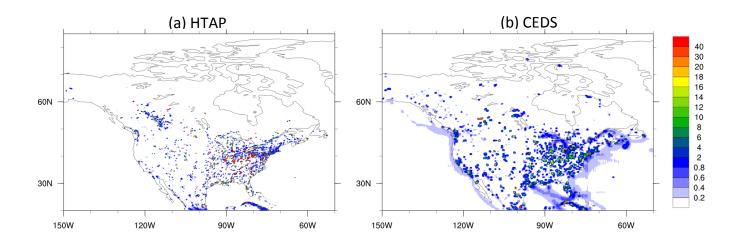


Figure 11: Anthropogenic emissions of SO2 of (a) HTAP and (b) CEDS inventories on August. Unit: mol/km2/hour.

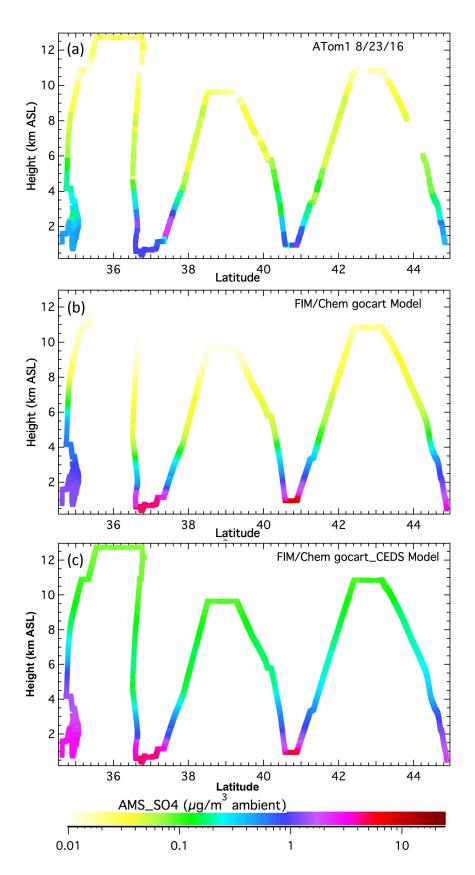


Figure 12: Anthropogenic emissions of SO2 of (a) HTAP and (b) CEDS inventories on August. Unit: mol/km2/hour.

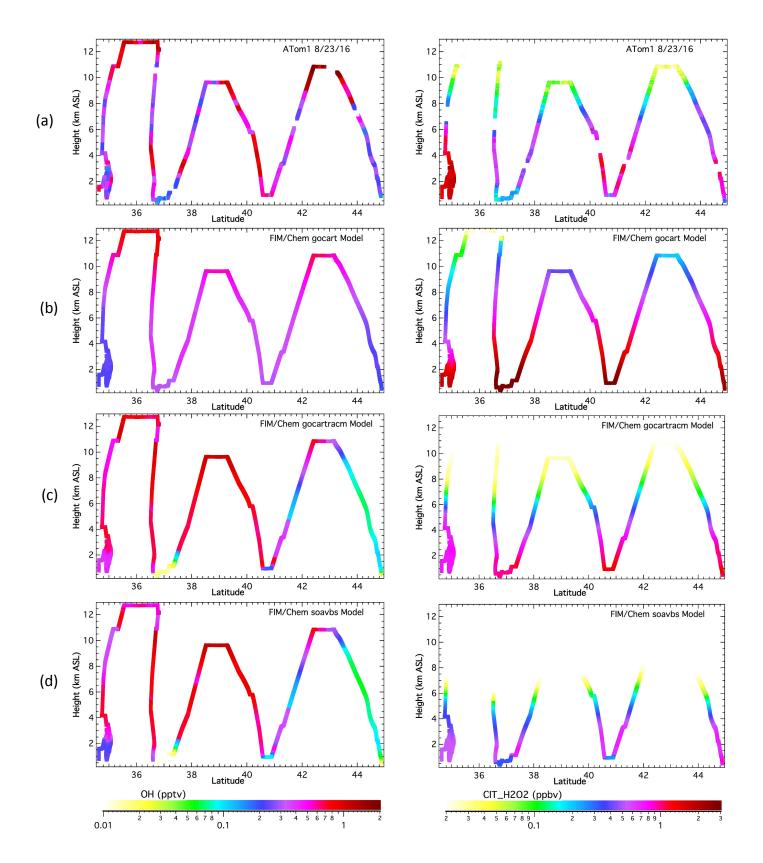


Figure 13: Height-latitude profiles of OH and H2O2 over United States on August 23rd, 2016 for (a) ATom-1; (b) GOCART; (c) RACM_GOCART; and (d) RACM_SOA_VBS.

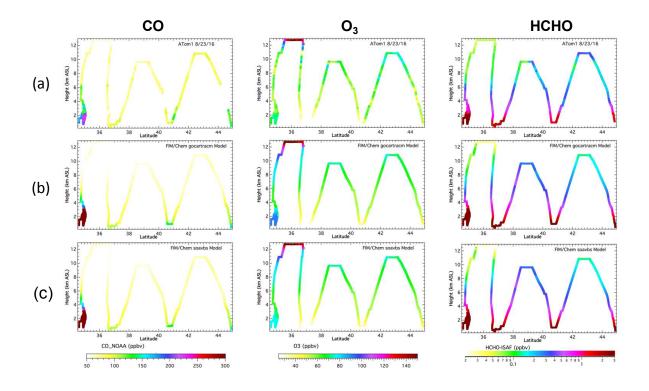


Figure 14: Height-latitude profiles of CO, O3 and HCHO over United States on August 23rd, 2016 for (a) ATom-1; (b) RACM_GOCART; and (c) RACM_SOA_VBS.

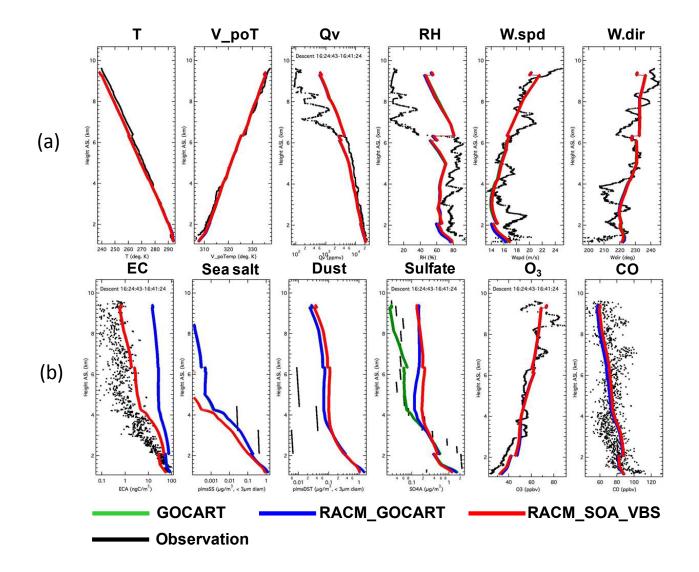


Figure 15: Observations and model results for profile #4, 8/23/16 over southeastern Kansas.

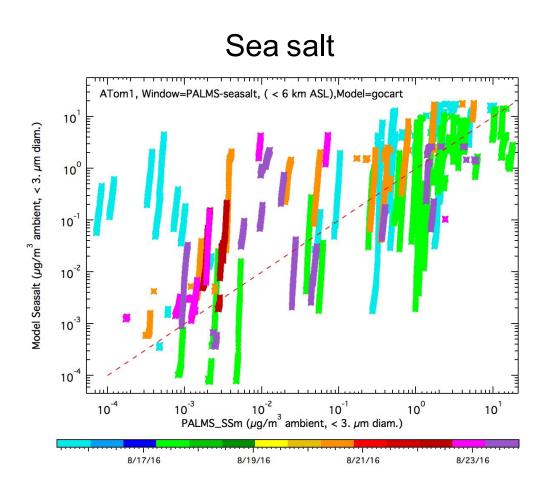


Figure 16: GOCART model forecast versus ATom-1 observed sea salt below 6 km.

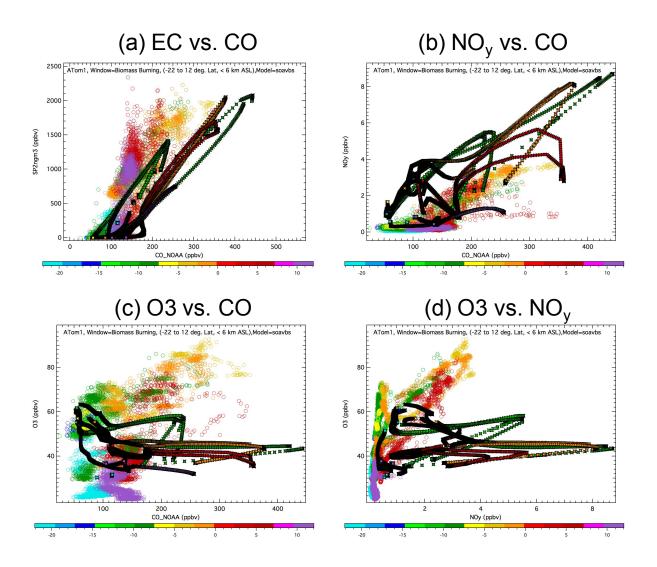


Figure 17: Model (black color dot) and observation (color dot) ratios of (a) EC relative to CO; (b) NOy relative to CO; (c) O3 relative to CO and (d) O3 relative to NOy. Color scale is degree latitude.