Air Quality Analysis for the Light- and Medium-Duty Vehicle Multipollutant Rule

Memo to the Docket

United States
Environmental Protection
Agency

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1 Introduction/Overview

The Environmental Protection Agency (EPA) has finalized a rule to build on and improve the previous emission control program for on-highway light- and medium-duty engines and vehicles by further reducing air pollution from light- and medium-duty engines across the United States. This rulemaking is formally titled "Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles," and is more generally referred to as the "Light Medium Duty Vehicle" (LMDV) rule. The rule impacts emissions of criteria and air toxic pollutants as well as greenhouse gases (GHGs). This document includes information related to the air quality modeling analysis done in support of the final rule and focuses on impacts to ambient concentrations of criteria and air toxic pollutants.

EPA conducted an air quality modeling analysis of a regulatory scenario involving light- and medium-duty "onroad" vehicle emission reductions and corresponding changes in "upstream" emission sources like EGU (electric generating unit) emissions and refinery emissions. For this analysis, emission inventories were produced, and air quality modeling was performed for three scenarios: a 2016 base case, a 2055 reference scenario, and a 2055 LMDV regulatory or policy case.[1] Decisions about the emission scenarios and other elements used in the air quality modeling were made early in the analytical process for the final rulemaking, and the decision was made to model the proposed standards as the policy case. Accordingly, the air quality analysis does not fully represent the final regulatory scenario; however, we consider the modeling results to be a fair reflection of the impact the standards will have on air quality in 2055. The policy case assumes battery electric vehicle (BEV) penetration will reach 71 percent for passenger cars and 66 percent for light-duty trucks in model year 2050. The policy case also assumes a phase-in of gasoline particulate filters for gasoline vehicles beginning in model year 2027.

An air quality modeling platform consists of all the emissions inventories and ancillary data files used for emissions modeling, as well as the meteorological, initial condition, and boundary condition files needed to run the air quality model. An emissions modeling platform consists of the emissions modeling data and techniques including the emission inventories, the ancillary data files, and the approaches used to transform inventories for use in air quality modeling.

This analysis utilizes the 2016v3 emissions modeling platform,[2] which includes a base year (2016) and projection year (2023 and 2026) inventories, along with ancillary emissions data, and scripts and software for preparing the emissions for air quality modeling. The Technical Support Document (TSD) Preparation of Emissions Inventories for the 2016v3 North American Emissions Modeling Platform describes how the emission inventories for each year of data available in the platform were developed.[3]

Section 2 of this document gives a summary of the emissions inventory inputs to the air quality modeling. Section 3 of this document describes the methodology for developing onroad

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[1] The reference case represents a scenario without the light- and medium-duty standards being analyzed. Additional information about the use of the base case is available in Section 7.5.

[2] 2016v3 Emissions Modeling Platform. https://www.epa.gov/air-emissions-modeling/2016v3-platform SMOKE inputs available from https://gaftp.epa.gov/Air/emismod/2016/v3/

[3] U.S. EPA (2023) Technical Support Document: Preparation of Emissions Inventories for the 2016v3 North American Emissions Modeling Platform. https://www.epa.gov/air-emissions-modeling/2016-version-3-technical-support-document.

mobile emission inventories, Section 4 focuses on the methodology for developing electrical generating unit (EGU) emission inventories, and Section 5 focuses on the methodology for developing petroleum sector emission inventories. Section 6 provides emissions summary tables. Sections 7 and 8 provide an overview of the air quality modeling methodology and supplemental air quality modeling results.

2 Emissions Inventory Methodology

This section provides an overview of the emission inventories used in the air quality analysis for the final rule. These inventories include point sources, nonpoint sources, onroad and nonroad mobile sources, commercial marine vessels (CMV), locomotive and aircraft emissions, biogenic emissions, and fires for the U.S., Canada, and Mexico. The emissions used for the 2055 policy scenario were the same as those in the 2055 reference scenario for all emissions sectors except for onroad mobile source emissions, EGU emissions, and petroleum sector emissions (specifically refineries, crude oil production well sites and pipelines, and natural gas production well sites and pipelines).

For this study, the 2016 emission inventories used were based on those for the 2016v3 platform except for the U.S. onroad and nonroad[4] mobile sources. For the 2055 cases, the U.S. onroad and nonroad mobile sources were projected to year 2055 levels, while other anthropogenic emissions sources were retained at the 2016v3 platform projected emissions levels for the year 2026. A high-level summary of the emission inventories used is provided in this section, while the development of the U.S. onroad mobile source emissions is described in detail in Section 3, the development of the EGU emissions is described in Section 4, and the development of petroleum sector emissions is described in Section 5.

2.1 Emissions Inventory Sector Summary

For the purposes of preparing the air quality model-ready emissions, emission inventories are split into “sectors”. The significance of a sector is that each sector includes a specific group of emission sources, and those data are run through the emissions modeling system independently from the other sectors up to the point of the final merging process. The final merging process combines the sector-specific low-level (of the vertical levels in the air quality model) gridded, speciated, hourly emissions together to create CMAQ-ready emission inputs. While pertinent atmospheric emissions related to the problem being studied are included in each modeling platform, the splitting of inventories into specific sectors for emissions modeling varies by platform. The sectors for the 2016v3 emissions modeling platform used in this study are shown in Table 2-1. Descriptions for each sector are provided. For more detail on the data used to

[4] The 2016 U.S. nonroad mobile source emissions inventory in the 2016v3 platform includes emissions for Texas and California which were developed using their own tools. For this study, those state-supplied emissions were replaced with 2016 nonroad emissions computed with an updated version of the Motor Vehicle Emission Simulator, MOVES4.RC2.

develop the 2016v3 inventories and on the processing of those inventories into air quality model-ready inputs, see the 2016v3 emissions modeling platform TSD.[5]

Table 2-1 Inventory sectors included in the emissions modeling platform

Inventory Sector	Sector Description
Mobile – Nonroad	Mobile sources that do not drive on roads, excluding locomotives, aircraft, and commercial marine vessels (see Section 2.3)
Mobile – Onroad	Onroad mobile source gasoline and diesel vehicles from moving and non-moving vehicles that drive on roads (see Section 3)
Mobile – Category 3 Commercial Marine Vessels	Commercial marine vessels with Category 3 engines within and outside of U.S. waters
Mobile – Category 1 and 2 Commercial Marine Vessels	Commercial marine vessels with Category 1 and 2 engines within and outside of U.S. waters
Mobile – Rail	U.S. Class I line haul, Class II/III line haul, passenger, and commuter locomotives (does not include railyards and switchers)
Nonpoint – Fertilizer	NH_3 emissions from U.S. fertilizer sources
Nonpoint – Livestock	Primarily NH_3 and VOC emissions from U.S. livestock sources
Nonpoint – Area Fugitive Dust	PM emissions from paved roads, unpaved roads and airstrips, construction, agriculture production, and mining and quarrying in the U.S.
Nonpoint – Residential Wood Combustion	U.S. residential wood burning emissions from devices such as fireplaces, woodstoves, pellet stoves, indoor furnaces, outdoor burning in fire pits and chimneys
Nonpoint – Oil and Gas	Oil and gas exploration and production, both onshore and offshore
Nonpoint – Solvents	Nonpoint VOC emissions from solvents such as cleaners, personal care products, and adhesives.
Nonpoint – Other	All nonpoint emissions in the U.S. not included in other sectors, including industrial processes, waste disposal, storage and transport of chemicals and petroleum, waste disposal, commercial cooking, and miscellaneous area sources
Point – Airports	Aircraft engines and ground support equipment at U.S. airports
Point – Electrical Generating Units	Electric generating units that provide power to the U.S. electric grid
Point – Oil and Gas	Point sources related to the extraction and distribution of oil and gas in the U.S.
Point – Other	All point sources in the U.S. not included in other sectors. Includes rail yards and refineries.
Point – Fires – Agricultural	Fires due to agricultural burning in the U.S.
Point – Fires – Wild and Prescribed	Wildfires and prescribed burns in the U.S.
Point – Non-U.S. Fires	Fires within the domain but outside of the U.S.
Biogenic (beis)	Emissions from trees, shrubs, grasses, and soils within and outside of the U.S.
Canada – Mobile – Onroad	Onroad mobile sources in Canada (see Section 2.5)
Mexico – Mobile – Onroad	Onroad mobile sources in Mexico (see Section 2.5)

[5] U.S. EPA (2023) Technical Support Document: Preparation of Emissions Inventories for the 2016v3 North American Emissions Modeling Platform. https://www.epa.gov/air-emissions-modeling/2016-version-3-technical-support-document.

Inventory Sector	Sector Description
Canada/Mexico – Point	Canadian and Mexican point sources
Canada/Mexico – Nonpoint and Nonroad	Canadian and Mexican nonroad sources and nonpoint sources not included in other sectors
Canada – Agricultural Point	Canadian agricultural ammonia sources
Canada – oil and gas 2D	Canadian low-level point oil and gas sources
Canada – Nonpoint – Area Fugitive Dust	Area source fugitive dust sources in Canada
Canada – Point – Point Fugitive Dust	Point source fugitive dust sources in Canada

2.2 The Emissions Modeling Process

The CMAQ air quality model requires hourly emissions of specific gas and particle species for the horizontal and vertical grid cells contained within the modeled region (i.e., modeling domain). To provide emissions in the form and format required by the model, it is necessary to "pre-process" the emissions inventories for the sectors described above. The process of emissions modeling transforms the emissions inventories from their original temporal, pollutant, and spatial resolution into the hourly, speciated, gridded resolution required by the air quality model. Emissions modeling includes the chemical speciation, temporal allocation, and spatial allocation of emissions along with final formatting of the data that will be input to the air quality model.

Chemical speciation creates the "model species" needed by CMAQ, for a specific chemical mechanism, from the "inventory pollutants" of the input emission inventories. These model species are either individual chemical compounds (i.e., "explicit species") or groups of species (i.e., "lumped species"). The chemical mechanism used for this platform is the CB6 mechanism.[6] This platform generates the PM2.5 model species associated with the CMAQ Aerosol Module version 7 (AE7). See Section 3.2 of the 2016v3 platform TSD for more information about chemical speciation in the 2016v3 platform.

Temporal allocation is the process of distributing aggregated emissions to a finer temporal resolution, for example converting annual emissions to hourly emissions as is required by CMAQ. While the total annual, monthly, or daily emissions are important, the hourly timing of the occurrence of emissions is also essential for accurately simulating ozone, PM, and other pollutant concentrations in the atmosphere. Many emissions inventories are annual or monthly in nature. Temporal allocation takes these aggregated emissions and distributes the emissions to the hours of each day. This process is typically done by applying temporal profiles to the inventories in this order: monthly, day of the week, and diurnal, with monthly and day-of-week profiles applied only if the inventory is not already at that level of detail. See Section 3.3 of the 2016v3 platform TSD for more information about temporal allocation of emissions in the 2016v3 platform.

Spatial allocation is the process of distributing aggregated emissions to a finer spatial resolution, as is required by CMAQ. Over 60 spatial surrogates are used to spatially allocate U.S. county-level emissions to the12-km grid cells used by the air quality model. See Section 3.4 of the 2016v3 platform TSD for a description of the spatial surrogates used for allocating county-level emissions in the 2016v3 platform.

[6] Yarwood, G., et al. (2010) Updates to the Carbon Bond Chemical Mechanism for Version 6 (CB6). Presented at the 9th Annual CMAS Conference, Chapel Hill, NC. Available at https://www.cmascenter.org/conference/2010/abstracts/emery_updates_carbon_2010.pdf.

The primary tool used to perform the emissions modeling to create the air quality model-ready emissions was the SMOKE modeling system, version 4.9 (SMOKE 4.9).[7] When preparing emissions for CMAQ, emissions for each sector are processed separately through SMOKE. The elevated point source emissions are passed to CMAQ directly so the model can perform plume rise based on hourly meteorological conditions, while the low-level emissions are combined to create model-ready 2-D gridded emissions. Gridded emissions files were created for a 36-km national grid named 36US3 and for a 12-km national grid named 12US2, both of which include the contiguous states and parts of Canada and Mexico as shown in Figure 2-1. This figure also shows the region covered by other grids that are relevant to the development of emissions for this and related studies.

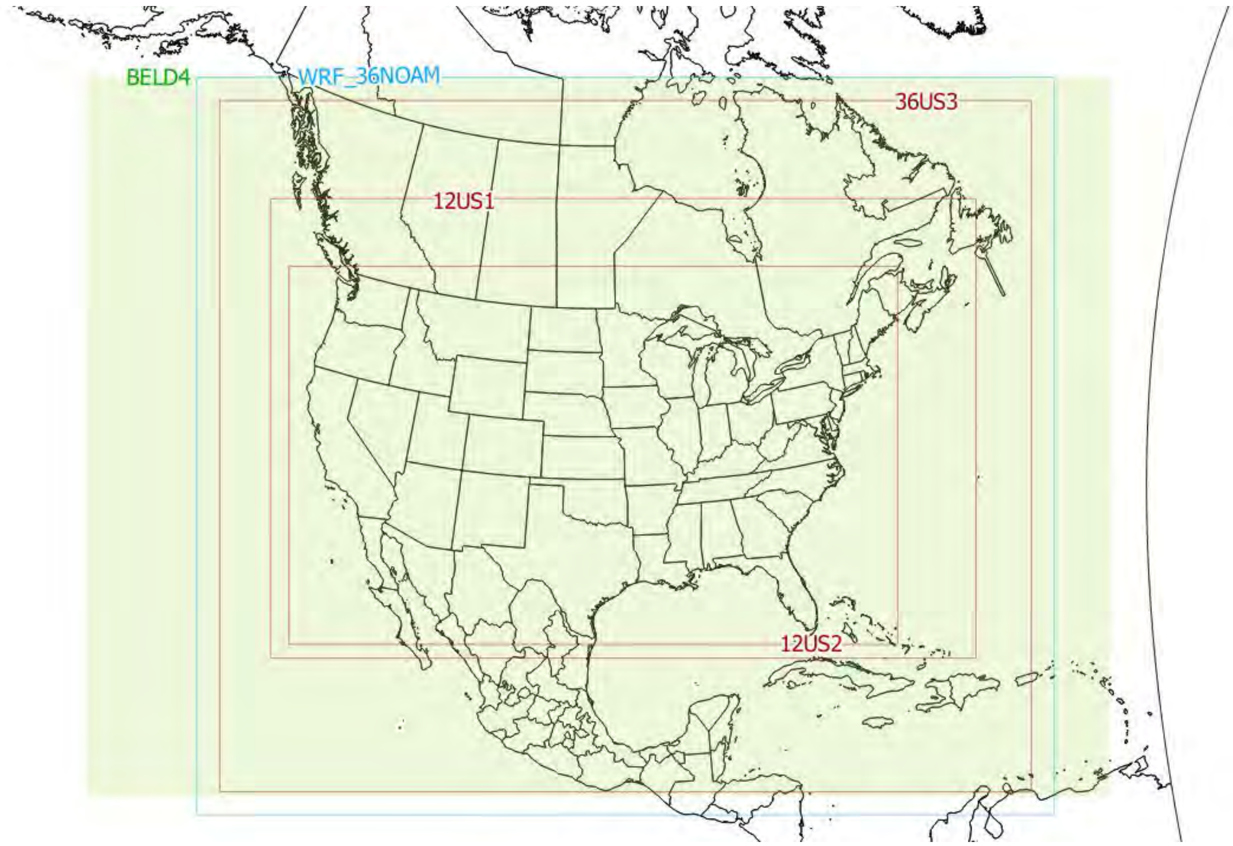

Figure 2-1 Air quality modeling domains

2.3 Emissions Inventory Methodology for 2016v3-Compatible Sectors

Except for the onroad mobile source emissions, the emissions used for the 2016 air quality case are consistent with those developed through the 2016v3 Platform. For the 2055 cases, the following were made to be consistent with the 2026 emissions developed by the Inventory Collaborative (described in the 2016v3 Emissions Modeling Platform TSD): emissions for sectors other than onroad and nonroad mobile sources in the U.S. and emissions for the onroad mobile source sector in Canada and Mexico. Development of the 2055 nonroad emissions is described in Section 2.4. The development of the U.S. onroad mobile source emissions for each

[7] http://www.smoke-model.org/

case is described below in Section 3. Additionally, the 2016v3 inventories, which have improved state and county apportionment as compared to 2016v2, were used for CMV. For the point (non-EGU) sector, 2016v3 was used. Another update that was made for this modeling was to use the Biogenic Emissions Inventory System (BEIS) version 4 coupled with the Biogenic Emissions Landuse Dataset version 6 within CMAQ, which was run using inline biogenics.

2.4 2055 Emissions Inventory Methodology for the Nonroad Sector

To prepare the nonroad mobile source emissions, an updated version of the Motor Vehicle Emission Simulator (MOVES), MOVES4.RC2, was run using inputs compatible with the 2016v3 platform for all states. The nonroad component of MOVES was configured to create a national nonroad inventory for 2055. The 2055 MOVES nonroad inventory was used in all states.

2.5 2055 Emissions Inventory Methodology for Fugitive Dust

The inventory for road dust is generated using vehicle miles traveled (VMT)[8], and the total projected VMT in 2055 did not change between the reference and LMDV regulatory scenario (only the fraction of EVs changed). Road dust inventories for 2055 were projected using 2055 VMT (see Section 3.2.2) and are presented in Table 6-4.

3 Onroad Emissions Inventory Methodology

This section focuses on the approach and data sources used to develop gridded, hourly emissions for the onroad mobile sector that are suitable for input to an air quality model in terms of the format, grid resolution, and chemical species. While the emission factors used to develop emissions for the reference and policy scenarios differed, the approach and all other data sources used to calculate emissions for both scenarios were identical.

Onroad mobile source emissions result from motorized vehicles operating on public roadways. These include passenger cars, motorcycles, minivans, sport-utility vehicles, light-duty trucks, heavy-duty trucks, and buses. The sources are further divided by the fuel they use, including diesel, gasoline, E-85, electricity, and compressed natural gas (CNG). The sector accounts for emissions from parked vehicle processes (e.g., starts, hot soak, and extended idle) and on-network processes (i.e., from vehicles as they move along the roads). The onroad emissions are generated using Sparse Matrix Operator Kernel Emissions (SMOKE) programs that leverage MOVES-generated emission factors with county, fuel type, source type, and road type-specific activity data, along with hourly meteorological data.

The MOVES-generated onroad emission factors were combined with activity data (e.g., VMT, vehicle populations) to produce emissions within the SMOKE modeling system. The collection of programs that compute the onroad mobile source emissions are known as SMOKE-MOVES. SMOKE-MOVES uses a combination of vehicle activity data, emission factors from MOVES, meteorology data, and temporal allocation information needed to estimate hourly onroad emissions. Additional types of ancillary data are used for the emissions processing, such as spatial surrogates which spatially allocate emissions to the grid used for air quality modeling.

[8] See Section 4.2.3.1 of the 2016v2 TSD for more detail on how fugitive dust is projected.

More details on the generation of the emission factors, activity data, and on the modeling of the emissions are in the following subsections. National onroad emission summaries for key pollutants are provided in Section 4.

3.1 Emissions Factor Table Development

Onroad mobile source emission factors were generated for the modeled cases by running versions of MOVES4[9] (MOVES4.RC2, MOVES4.R1 and MOVES4.R2). The MOVES4 versions used for air quality modeling incorporated updated information not available for the MOVES4 release. MOVES4.R2 also included policy case-specific inputs, including higher EV fractions, reduced energy consumption, and reductions in HC, NOx and PM emission rates to reflect rule requirements. Detailed information on the model updates is available in a memo to the docket.[10]

The LMDV reference and regulatory cases include assumptions about light-, medium-, and heavy-duty EV sales. The reference case EV fractions are based on modeling of light-duty electric vehicle costs and consumer preferences while the heavy-duty fractions account for our understanding of state adoption of California's Advanced Clean Trucks rule. For the policy case, the heavy-duty EV fractions remained the same, but the light- and medium-duty EV fractions were updated for consistency with EV sales fractions generated by the OMEGA model for the NPRM action case. For air quality modeling, the case-specific BEV fractions were incorporated into each county's fuel mix described in Section 3.2.2.5 below.

The emission factor tables input to SMOKE-MOVES are generated by running MOVES. These tables differentiate emissions by process (i.e., running, start, vapor venting, etc.), fuel type, vehicle type, road type, temperature, speed bin for rate per distance processes, hour of day, and day of week. To generate the MOVES emission factors across the U.S., MOVES was run to produce emission factors for a series of temperatures and speeds for a set of "representative counties," to which every other county in the country is mapped. The representative counties for which emission factors are generated are selected according to their state, elevation, fuels used in the region, vehicle age distribution, and inspection and maintenance programs. Every county in the country is mapped to a representative county based on its similarity to the representative county with respect to those attributes. The representative counties selected for the 2016v3 platform were retained for this analysis. More details on the methodology behind choosing representative counties is available in the 2016v3 TSD.

Emission factors were generated by running MOVES for each representative county for two "fuel months" – January to represent winter months and July to represent summer months – because in some parts of the country different types of fuels are used in each season. MOVES was run for the range of temperatures that occur in each representative county for each season. The calculations of the temperature ranges needed for each fuel month were based on meteorology for every county and grid cell in the continental U.S. for each hour of the year. The SMOKE interface accounts for the sensitivity of the on-road emissions to temperature and

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[9] USEPA (2023) Motor Vehicle Emission Simulator: MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. https://www.epa.gov/moves.

[10] Mo (2024). *Revisions to MOVES for Air Quality Modeling to support the FRM for the Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles*. Memorandum to Docket EPA-HQ-OAR-2022-0829. February, 2024

humidity by using the gridded hourly temperature information available from the meteorological model outputs used for air quality modeling.

Appropriate versions of MOVES were run using the above approach to create emission factors for each of the three modeling cases: 2016 base year, 2055 reference, and a 2055 regulatory case. A new set of emission factor tables were developed for this study using the same representative counties as were used the 2016v3 platform. The county databases (CDBs) input to MOVES for 2016 were equivalent to those used for the 2016v3 platform. To prepare the 2055 CDBs used to generate year 2055 emissions factors, the vehicle age distributions were projected to reflect the year 2055 as were the tables representing the inspection and maintenance programs. The fuels used were also representative of year 2055. The CDBs for each of the 2055 modeling cases incorporated the case-specific fuel mix as detailed in Section 3.2.2.5 below.

3.2 Activity and Other Data Development

To compute onroad mobile source emissions, SMOKE selects the appropriate MOVES emission rates for each county, hourly temperature, speed bin, and source classification code (SCC) (which includes the fuel type, source type and road type), then multiplies the emission rate by the appropriate activity data such as VMT (vehicle miles travelled), VPOP (vehicle population), SPEED/SPDIST (speed distributions and averages), HOTELING (hours of extended idle), ONI (hours of off-network idling), or STARTS (engine starts), to produce emissions. For each of these activity datasets, first a national dataset was developed; this national dataset is called the "EPA default" dataset. Data submitted by state agencies were incorporated into the activity datasets used for the study where they were available and passed quality assurance checks.

The activity data for the 2016 base year were consistent with the activity data used in the 2016v3 platform. Additional details on the development of activity data are available in the 2016v3 platform TSD.

In addition to activity data, this section also describes inputs for fuel parameters and county-specific vehicle inspection and maintenance programs.

3.2.1 2016 Base Year Activity data

3.2.1.1 Vehicle Miles Traveled (VMT)

EPA calculated default 2016 VMT by backcasting the 2017 NEI VMT to 2016. The 2017 NEI Technical Support Document[11] contains details on the development of the 2017 VMT. The data backcast to 2016 were used for states that did not submit 2016 VMT data. The factors to adjust VMT from 2017 to 2016 were based on VMT data from the Federal Highway Administration (FHWA) county-level VM-2 reports. For most states, EPA calculated county-road type factors based on FHWA VM-2 County data for 2017 and 2016. Separate factors were calculated by vehicle type for each MOVES road type. Some states have a very different distribution of urban activity versus rural activity between 2017 NEI and the FHWA data, due to inconsistencies in the definition of urban versus rural. For those states, a single county-wide projection factor based on total FHWA VMT across all road types was applied to all VMT, independent of road type.

[11] U.S. EPA (2021) 2017 National Emissions Inventory: January 2021 Updated Release, Technical Support Document. https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-technical-support-document-tsd

County-total-based (instead of county+road type) factors were used for all counties in IN, MS, MO, NM, TN, TX, and UT because many counties had large increases in one particular road type and decreases in another road type.

For the 2016v3 platform, VMT data submitted by state and local agencies were incorporated and used in place of EPA defaults. Note that VMT data need to be provided to SMOKE for each county and SCC. The onroad SCCs characterize vehicles by MOVES fuel type, vehicle (aka source) type, emissions process, and road type. Any VMT provided at a different resolution than this were converted to a full county-SCC resolution to prepare the data for processing by SMOKE.

A final step was performed on all state-submitted VMT. The distinction between a “passenger car” (MOVES source type 21) versus a “passenger truck” (MOVES source type 31) versus a “light commercial truck” (MOVES source type 32) is not always consistent between different datasets. This distinction can have a noticeable effect on the resulting emissions, since MOVES emission factors for passenger cars are quite different than those for passenger trucks and light commercial trucks. To ensure consistency in the 21/31/32 splits across the country, all state-submitted VMT for MOVES vehicle types 21, 31, and 32 (all of which are part of HPMS vehicle type 25) was summed, and then re-split using the 21/31/32 splits from the EPA 2016v2 default VMT. VMT for each source type as a percentage of total 21/31/32 VMT was calculated by county from the EPA default VMT. Then, state-submitted VMT for 21/31/32 was summed and re-split according to those percentages.

For 2016v3, total 2016 VMT is unchanged from 2016v2. However, road type distributions were updated to be consistent with those in 2020 NEI[12] in Florida, Illinois, Minnesota, Missouri, South Carolina, and West Virginia to correct anomalies found in the 2016v1 and 2016v2 data.

3.2.1.2 Vehicle Population (VPOP)

The EPA default VPOP dataset was based on the EPA default VMT dataset described above. In the areas where EPA backcasted 2017 NEI VMT:

2016v3 VPOP = 2016v3 VMT * (VPOP/VMT ratio by county-SCC6).

Where the ratio by county-SCC is based on 2017 NEI with MOVES3 fuel splits and SCC6 means the first six digits of the SCC code that include fuel type and source type but exclude the road type and process. In the areas where we used 2016v1 VMT resplit to MOVES3 fuels, 2016v3 VPOP = 2016v2 VPOP = 2016v1 VPOP with two resplits: first, source types 21/31/32 were resplit according to 2017 NEI EPA default 21/31/32 splits so that the whole country has consistent 21/31/32 splits. Next, fuels were resplit to MOVES3 fuels. There are some areas where 2016 VMT was submitted but 2016 VPOP was not; those areas are using 2016v1 VPOP (with resplits). The same method was applied to the 2016 EPA default VMT to produce an EPA default VPOP dataset.

3.2.1.3 Speed Activity (SPEED/SPDIST)

SMOKE-MOVES uses speed distributions similarly to how they are used when running MOVES in inventory mode. The speed distribution file, called SPDIST, specifies the amount of

[12] U.S. EPA (2023) 2020 National Emissions Inventory, Technical Support Document. https://www.epa.gov/air-emissions-inventories/2020-national-emissions-inventory-nei-technical-support-document-tsd

time spent in each MOVES speed bin for each county, vehicle (aka source) type, road type, weekday/weekend, and hour of day. This file contains the same information at the same resolution as the Speed Distribution table used by MOVES but is reformatted for SMOKE. Using the SPDIST file results in a SMOKE emissions calculation that is more consistent with MOVES than the previous hourly speed profile (SPDPRO) approach, because emission factors from all speed bins can be used, rather than interpolating between the two bins surrounding the single average speed value for each hour as is done with the SPDPRO approach.

The SPEED inventory that includes a single overall average speed for each county, SCC, and month, was also read in by SMOKE. SMOKE requires the SPEED dataset to exist even when speed distribution data are available, even though only the speed distribution data affects the selection of emission factors. The SPEED and SPDIST datasets are from the 2017 NEI and are based on a combination of the Coordinating Research Council (CRC) A-100 data and 2017 NEI MOVES CDBs.

3.2.1.4 Hoteling Hours (HOTELING)

Hoteling hours activity is used to calculate emissions from extended idling and auxiliary power units (APUs) for heavy duty diesel vehicles. For the 2016v3 platform, hoteling hours were computed using a factor calculated by EPA's Office of Transportation and Air Quality based on recent studies.

The method used in 2016v3 is the following:

1. Start with 2016 VMT for combination long haul trucks (i.e., MOVES source type 62) on restricted roads, by county. Only VMT on urban and rural restricted highways for MOVES source type 62 is included in the hoteling calculation.
2. Multiply the VMT by 0.007248 hours/mile.[13]
3. Apply parking space reductions to keep hoteling within the estimated maximum hours by county, except for states that requested EPA do not do that (CO, ME, NJ, NY).

Hoteling hours were adjusted down in counties for which there were more hoteling hours assigned to the county than could be supported by the known parking spaces. To compute the adjustment, the hoteling hours for the county were computed using the above method, and reductions were applied directly to the 2016 hoteling hours based on known parking space availability so that there were not more hours assigned to the county than the available parking spaces could support if they were full every hour of every day.

A dataset of truck stop parking space availability with the total number of parking spaces per county was used in the computation of the adjustment factors. [14] This same dataset is used to develop the spatial surrogate for hoteling emissions. Since there are 8,784 hours in the year 2016; the maximum number of possible hoteling hours in a particular county is equal to 8,784 *

[13] USEPA (2023). *Population and Activity of Onroad Vehicles in MOVES4*. EPA-420-R-23-005. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. https://www.epa.gov/moves/moves-technical-reports.

[14] From *2016 version 1 hoteling workbook.xlsx* developed based on the input dataset for the hoteling spatial surrogate in the 2016v1 platform.

the number of parking spaces in that county. Hoteling hours for each county were capped at that theoretical maximum value for 2016 in that county unless the number of parking spaces listed was less than 12, in which case the hours were not reduced.

For 2016v3, hoteling was calculated as:

2016v3 HOTELING = 2017NEI HOTELING * 2016v3 VMT/2017NEI VMT

This is effectively consistent with applying the 0.007248 factor directly to the 2016v3 VMT. Then, for counties that provided 2017 hoteling but did not have vehicle type 62 restricted VMT in 2016 – that is, counties that should have hoteling, but do not have any VMT from which to calculate it – EPA backcast 2017 hoteling to 2016 using the FHWA-based county total 2017 to 2016 trend. Finally, the annual parking-space-based caps for hoteling hours were applied. The same caps were used as for 2017 NEI, except recalculated for a leap year (multiplied by 366/365).

For 2016v3, road type distributions and/or hoteling were adjusted in states where there was hoteling in every county in the state: FL, IL, MN, MO, SC, and WV. 2016v2 VMT in those six states was redistributed by road type based on 2020 NEI road type distributions (by county/vehicle, with county/HPMS filling in where a county/vehicle isn't available in 2020 NEI), and then hoteling was recalculated based on the new VMT in those six states using the standard VMT/HOTELING factor and parking space adjustments. Notably, this resulted in an overall increase in hoteling in Missouri, although hoteling is now in fewer counties).

3.2.1.5 Off-Network Idling Hours (ONI)

After creating VMT inputs for SMOKE-MOVES, off-network idle (ONI) activity data were also needed. ONI is defined in MOVES as time during which a vehicle engine is running idle and the vehicle is somewhere other than on the road, such as in a parking lot, a driveway, or at the side of the road. This engine activity contributes to total mobile source emissions but does not take place on the road network.

Examples of ONI activity include:

- light duty passenger vehicles idling while waiting to pick up children at school or to pick up passengers at the airport or train station,
- single unit and combination trucks idling while loading or unloading cargo or making deliveries, and
- vehicles idling at drive-through restaurants.

Note that ONI does not include idling that occurs on the road, such as idling at traffic signals, stop signs, and in traffic—these emissions are included as part of the running and crankcase running exhaust processes on the other road types. ONI also does not include long-duration idling by long-haul combination trucks (hoteling/extended idle), as that type of long duration idling is accounted for in other MOVES processes.

ONI activity hours were calculated based on VMT. For each representative county, the ratio of ONI hours to onroad VMT (on all road types) was calculated using the MOVES ONI Tool by source type, fuel type, and month. These ratios were then multiplied by each county's total VMT (aggregated by source type, fuel type, and month) to get hours of ONI activity.

3.2.1.6 Engine Starts (STARTS)

Onroad "start" emissions are the instantaneous exhaust emissions that occur at the engine start (e.g., due to the fuel rich conditions in the cylinder to initiate combustion) as well as the additional running exhaust emissions that occur because the engine and emission control systems have not yet stabilized at the running operating temperature. Operationally, start emissions are defined as the difference in emissions between an exhaust emissions test with an ambient temperature start and the same test with the engine and emission control systems already at operating temperature. As such, the units for start emission rates are instantaneous grams/start.

MOVES uses vehicle population information to sort the vehicle population into source bins defined by vehicle source type, fuel type (gas, diesel, etc.), regulatory class, model year and age. The model uses default data from instrumented vehicles (or user-provided values) to estimate the number of starts for each source bin and to allocate them among eight operating mode bins defined by the amount of time parked ("soak time") prior to the start. Thus, MOVES accounts for different amounts of cooling of the engine and emission control systems. Each source bin and operating mode has an associated g/start emission rate. Start emissions are also adjusted to account for fuel characteristics, LD inspection and maintenance programs, and ambient temperatures.

2016v3 STARTS = 2016v3 VMT * (2017 STARTS/ 2017 VMT by county&SCC6)

For 2016v3, Georgia Environmental Protection Division provided new weekday activity for starts per day for 20 counties. These new starts were used for the weekdays for those 20 counties, while MOVES default starts/day were used for weekend days. Since annual activity data are required by the FF10 activity file format, the number of starts/day was multiplied by the number of weekdays and weekends in the year to calculate the annual total starts for the 20 counties by county and source type. The starts for light duty vehicle source types 21, 31, and 32 were summed and then re-split between the 21, 31, and 32 source types based on splits from EPA default activity data, so that 21/31/32 splits are from a consistent data source nationwide. Since George only provided their activity data by county and vehicle type, the 2016v2 splits were used as the basis for distribution of the starts to fuel type and month.

3.2.1.7 Fuels

The 2016 scenario used MOVES4.RC2 default fuels. These fuels are the same as the fuels in MOVES4.0.0.[15]

3.2.2 2055 Projected Activity Data

The projected 2055 activity data are primarily based on the 2016v3 platform's projected 2026 data, updated to be consistent with the default data and algorithms in MOVES4.R1, as well as to estimate geographic differences in fuel and age distributions. To accomplish this analysis, the following steps were taken:

[15] U.S. EPA (2023) Fuel Supply Defaults: Regional Fuels and the Fuel Wizard in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-025

1. Calendar year 2055 CDBs were developed for each representative county, as described in more detail later in this section. Each scenario (the reference case and the policy case) had its own set of CDBs.

2. MOVES was run with each CDB to calculate detailed activity data for each representative county. MOVES4.R1 was used for the 2055 reference case scenario and MOVES4.R2 was used for the 2055 policy case scenario.

3. The MOVES activity results for each representative county were allocated to the individual counties represented by each representative county using the 2016v3 platform allocations.

The following sections describe how the 2055 CDBs were developed to calculate the 2055 projected activity data.

3.2.2.1 Data Used As-is from the 2016v3 Platform

The starting point for developing the 2055 CDBs was the 2016v3 platform for calendar year 2026. The following data were used as-is from the 2016v3 platform data in the 2055 CDBs:

- Geography tables: State, County, Zone, and ZoneMonthHour

- VMT distribution tables: MonthFraction, DayFraction, and HourFraction

- Speed distribution table: AvgSpeedDistribution

- Road distribution tables: RoadTypeDistribution and ZoneRoadType

- Retrofit table: OnroadRetrofit

3.2.2.2 Default Data Used As-is from MOVES

National default data and algorithms in MOVES4.R1 and MOVES4.R2 were used for the following tables:

- Some (but not all) fuels tables: FuelFormulation, FuelSupply, and FuelUsageFraction

- Starts tables: StartsPerDayPerVehicle, StartsMonthAdjust, StartsHourFraction, StartsAgeAdjustment, and StartsOpModeDistribution

- Hotelling tables: HotellingHoursPerDay, HotellingMonthAdjust, HotellingHourFraction, HotellingAgeFraction, and HotellingActivityDistribution

- Off-Network Idle tables: TotalIdleFraction, IdleModelYearGrouping, IdleMonthAdjust, and IdleDayAdjust

- I/M table: IMCoverage

Note that in MOVES4.R1 and MOVES4.R2, starts, hotelling, and off-network idle tables are optional tables, and therefore can be empty in a CDB if the intention is to use default data. Therefore, these tables are empty in the 2055 CDBs. However, the fuels tables and I/M table are required inputs. Since the default database contains county (or region) specific data, the 2055 CDBs contain the relevant subset of the default database's data. See the MOVES4 technical reports[16,17,18,19,20,21] for more information about how these default data were derived.

3.2.2.3 Default Data from MOVES4.R1 Allocated Using 2016v3 Platform

National default data in MOVES4.R1 were allocated to representative counties for the following tables:

- VMT table: HPMSVTypeYear
- VPOP table: SourceTypeYear

VMT fractions by HPMSVTypeID and county were calculated from the 2026 VMT projections in the 2016v3 platform and used to allocate the national default VMT projections for 2055 to the county level. Similarly, VMT fractions by sourceTypeID and county were calculated from the 2016v3 platform to allocate the national default VPOP projections for 2055. See the MOVES4 technical report for more information about how the national default data were derived.[20]

3.2.2.4 2055 Age Distributions

Each CDB has a sourceTypeAgeDistribution table. The 2055 age distributions by representing county were primarily derived using July 1, 2020 vehicle registration data purchased from IHS Markit-Polk, vehicle stock and sales projections from the Annual Energy Outlook (AEO) 2023[22], and vehicle scrappage rates presented in the Transportation Energy Data Book (TEDB).[23] The age distributions were calculated using a modified version of the age

[16] U.S. EPA (2023) Exhaust Emission Rates for Light Duty Onroad Vehicles in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-028

[17] U.S. EPA (2023) Exhaust Emission Rates for Heavy Duty Onroad Vehicles in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-027

[18] U.S. EPA (2023) Emission Adjustments for Onroad Vehicles in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-021

[19] U.S. EPA (2023) Evaporative Emissions from Onroad Vehicles in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-023

[20] U.S. EPA (2023) Population and Activity of Onroad Vehicles in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-005

[21] U.S. EPA (2023) Greenhouse Gas and Energy Consumption Rates for Onroad Vehicles in MOVES4. Office of Transportation and Air Quality. US Environmental Protection Agency. Ann Arbor, MI. August 2023. EPA-420-R-23-026

[22] US Energy Information Administration (EIA), Annual Energy Outlook 2023, Supplemental Tables 38, 39, 44, 45 and 49, Washington, DC: March 2023.

[23] Davis, S. and R Boundy (2022), Transportation Energy Data Book, Ed. 40, Oak Ridge National Laboratory, ORNL/TM-2022/2376, https://tedb.ornl.gov/wp-content/uploads/2022/03/TEDB_Ed_40.pdf

distribution projection algorithm described in Appendix C of the Population and Activity of Onroad Vehicles in MOVES4 technical report.[20] The algorithm was modified to maintain differences between counties, such that counties that had newer-than-average fleets in 2020 continue to have newer-than-average fleets in 2055 and, similarly, counties with older fleets now have older fleets in the future. The fundamental approach to solving this problem was to define how age distributions in a local area are different from the national average, and then apply that difference to future years.

The following algorithm was implemented for calculating a representative county's base age distribution:

1. Subset the 2020 registration data to get vehicle counts by source type and model year for all counties represented by the representative county.

2. Group all model years 1990 and older together, because MOVES groups all vehicles ages 30 and older together.

3. Calculate age fractions by source type.

4. Replace age 0 (model year 2020) fractions with the ratio of vehicle sales to stock from AEO. This is because the July 1 registration data pull represents an incomplete year.

5. Renormalize the age distributions, retaining the age 0 fractions.

The following equations were used to project a representative county's base age distribution one year into the future:

- Population distribution for the next calendar year = Population distribution for the current calendar year, minus vehicles scrapped in the current calendar year, plus locally adjusted new vehicle sales in the next year

- Vehicles scrapped in the current calendar year = Scrappage factor times the base scrappage rate times the population distribution for the current calendar year

- Scrappage factor = (Total number of vehicles in the current year, minus total number of vehicles in the next year, plus locally adjusted new vehicle sales in the next year) divided by the sum of the base scrappage rate times the current year's population distribution. The purpose of the scrappage factor is to scale the base scrappage rate to balance the equation accounting for the total number of vehicles in each calendar year. For example, if the total number of vehicles remains constant from one year to the next and vehicle sales are high, then the scrappage factor would be high as well, as more vehicles would be scrapped to balance out the higher sales while maintaining constant number of total vehicles.

The population distribution of the current calendar year is known; thus, the algorithm starts with the base age distribution and then the algorithm iterates, so the output of the algorithm is the input for the next year. The total number of vehicles in the next year and the vehicle sales in the next year are also known, based on AEO. The base scrappage curve is also known, based on data presented in TEDB.

The differences between local areas were accounted for by applying a local sales scaling factor to the number of new vehicles sold in the next year in the equations above. This scaling factor was defined as the difference between the local and the national population fractions summed over an age range [1, j], divided by the national population fraction over the same age range. Essentially, this is using the fraction of newer vehicles in a local fleet compared to the national average as a surrogate for what future sales in a local area might be.

The precise age range [1, j] used was determined for each source type, chosen so that the difference between the local average age and the projected national average age in 2055 was as close as possible to the difference between the local and national average ages in 2020. That is, the chosen age ranges tried to maintain the same delta in average age between the local and the national case in the future. The chosen age ranges by source type were:

- Motorcycles: [1, 7]
- Passenger cars: [1, 10]
- Passenger trucks: [1, 4]
- Light commercial trucks: [1, 4]
- Other buses: [1, 10]
- Transit buses: [1, 10]
- School buses: [1, 8]
- Refuse trucks: [1, 9]
- Single unit trucks: [1, 7]
- Motor homes: [1, 9]
- Combination short-haul trucks: [1, 9]

Note that for some counties, some source types were not present in the IHS Markit-Polk data. In these rare cases, the national default age distributions were assumed. Additionally, combination long-haul trucks were assumed to have the same age distribution nationally.

The algorithm and data described above were used to calculate SourceTypeAgeDistribution tables for each representing county in 2055. The same age distributions were used for all scenarios. The following figures show the resulting projected average age in 2055 by county for the light-duty source types.

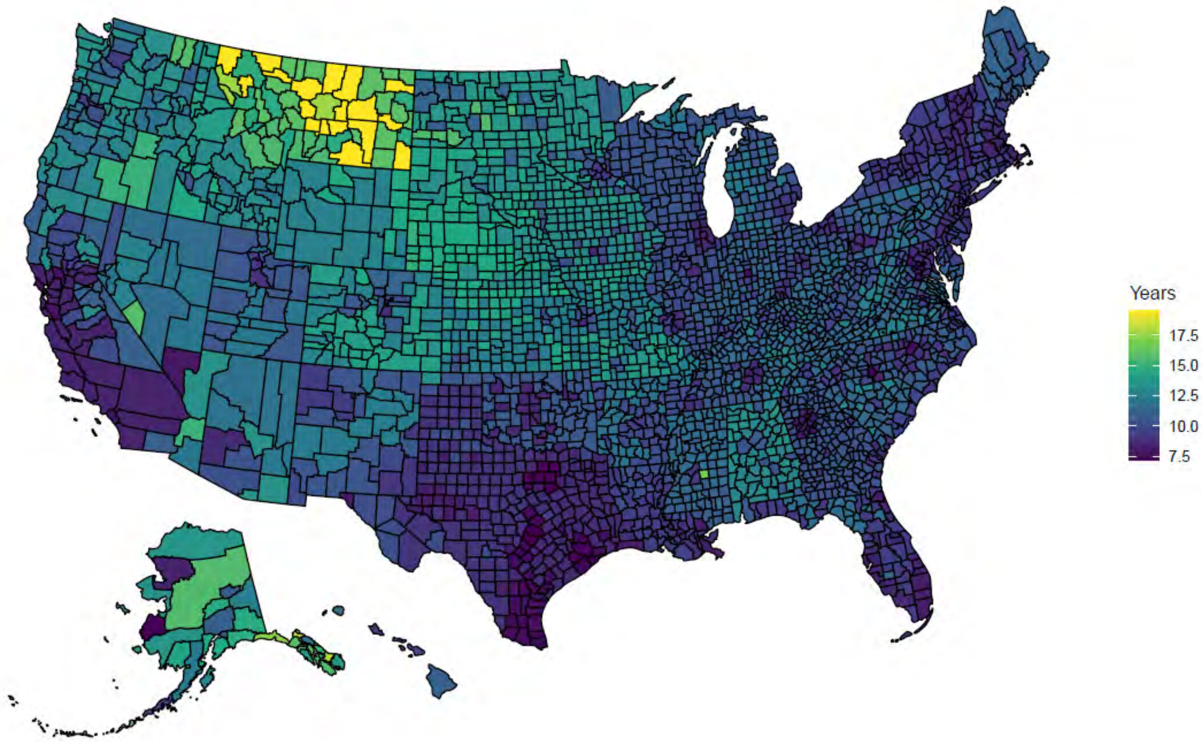

Figure 3-1 Projected average age of passenger cars in 2055

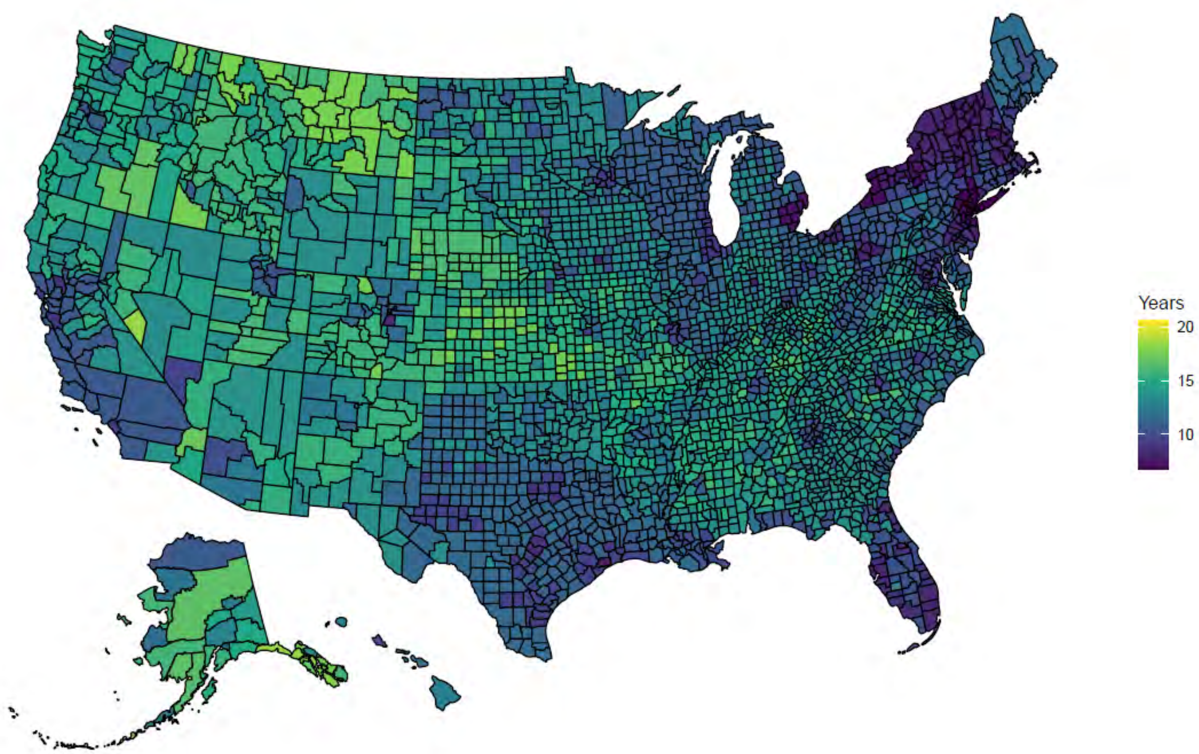

Figure 3-2 Projected average age of passenger trucks in 2055

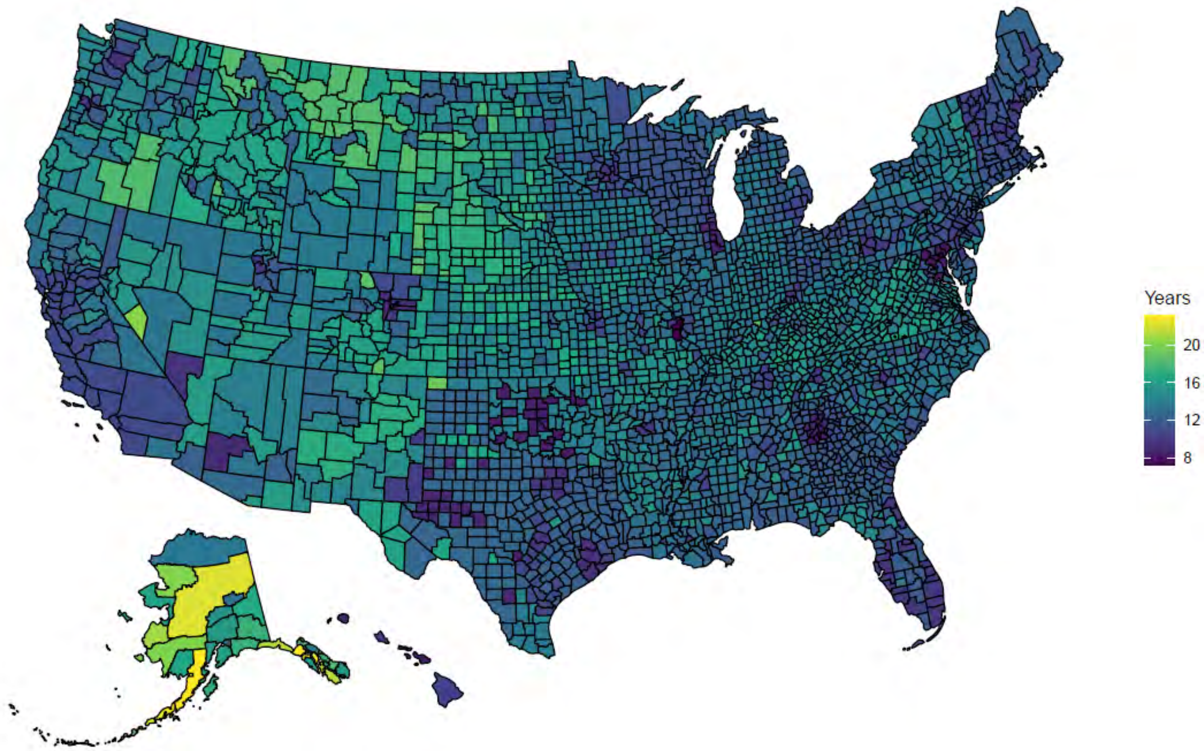

Figure 3-3 Projected average age of light commercial trucks in 2055

3.2.2.5 2055 Fuel Mix

The mix of the fuel types used in vehicles (or "fuel distributions") for 2055 rely on national projections, which vary by scenario. The national projected fuel distributions for ICE vehicles in the reference case rely on July 1, 2020, vehicle registration data purchased from IHS Markit-Polk, vehicle sales projections from AEO 2023,[22] EPA's Revised 2023 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions Standards,[24] and CARB's Advanced Clean Trucks regulation. More information about the national projected fuel distributions for the reference case can be found in the MOVES4 technical report. Electric vehicle fractions in the 2055 reference case were based on EVI-X reference case estimates as explained in the RIA.[20]

Fuel distributions for the regulatory case assume a shift to more electric vehicles. We assume BEV penetration will reach 71 percent for passenger cars and 66 percent for light-duty trucks in model year 2050. Additional details are available in the RIA.

To maintain consistency with the scenario being modelled, we used a different approach from that used in the NPRM to project representative county fuel type distributions. For the FRM, the starting data for representative county fuel type distributions were the results of a geospatial allocation analysis from EVI-X: EV stock by calendar year, vehicle type, and county, which were in turn based on national EV stock from OMEGA. For more information on the EVI-X analysis, see Chapter 5.1 of the RIA.

[24] U.S. EPA (2021). Revised 2023 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions Standards (86 FR 74434, December 30, 2021)

Since MOVES' fuel type distributions inputs are by model year (not calendar year), we calculated the annual fraction of EV sales to EV stock from OMEGA's national projections, and then applied this fraction to EVI-X's EV stock by county to get annual EV sales by vehicle type and county. This assumes the fraction of new EVs compared to existing EVs is relatively constant throughout the country.

Then, because the air quality modeling is performed at the representative county level and not for all individual counties, the EV sales by vehicle type and county were aggregated to the representative county level.

To assure these values were reasonable, we set the national average to be the limit on the fraction of EVs that we modeled per representative county in non-Metropolitan Statistical Areas (MSAs). That is, in this analysis, counties that represent only non-MSA counties were limited to the national EV sales fraction. All other counties had a maximum limit of 100% EVs. While not every county approached these limits, some surpassed them. When we compared the EV sales to all sales by vehicle type and representative county (calculated by applying the representative county's age distribution to the vehicle population and taking age 0 vehicles as the sales estimate), we counted the number of "excess" EVs according to these limits and recategorized and reallocated where they appear using the following algorithm:

1. Where there were excess car EVs, we recategorized as many as possible as truck EVs in the same representative county (or vice-versa).
2. Where there were excess pickup EVs, we recategorized as many as possible as van EVs in the same representative county (or vice-versa).
3. In representative counties where there were still excess EVs, we proportionally reallocated them to all representative counties in the same IPM region that did not have excess EVs.
4. In the remaining representative counties where there were still excess EVs after the above steps, we proportionally reallocated them to all counties in the country that did not have excess EVs.

After the step described above, we mapped the OMEGA vehicle categories to MOVES vehicles as follows:

- "Car" corresponds one-to-one to passenger cars in MOVES (sourceTypeID 21 and regClassID 20).
- "Truck" corresponds to regClassID 30 in MOVES. These vehicles are split into passenger trucks (sourceTypeID 31) and light commercial trucks (sourceTypeID 32) using the FF10 31/32 splits by representative county.
- "MDV" or medium-duty vans are assumed to be all 2bs, and therefore correspond to source types 31 and 32 with regClassID 41. They are split into 31s and 32s using the same splits as "trucks".
- "MDP" or medium-duty pickups are assumed to be all 3s, and therefore correspond to sourceTypeID 52 with regClass 41.

The number of ICE sales per representative county were calculated by subtracting the EV sales from the total sales by vehicle type. These were then distributed between the ICE fuel types using the national default ICE distributions for each model year.

Once all excess EVs were reallocated, the light-duty fuel distributions were formatted for use in the MOVES SampleVehiclePopulation table and were stored in the CDBs.

Note that the heavy-duty fuel distributions were not assumed to vary geographically. The national average fuel distributions for all heavy-duty source types were used uniformly across all representative counties. The following figures compare the projected EV penetration rates by county in 2055 between the reference case and the regulatory case for each light- and medium-duty source type.

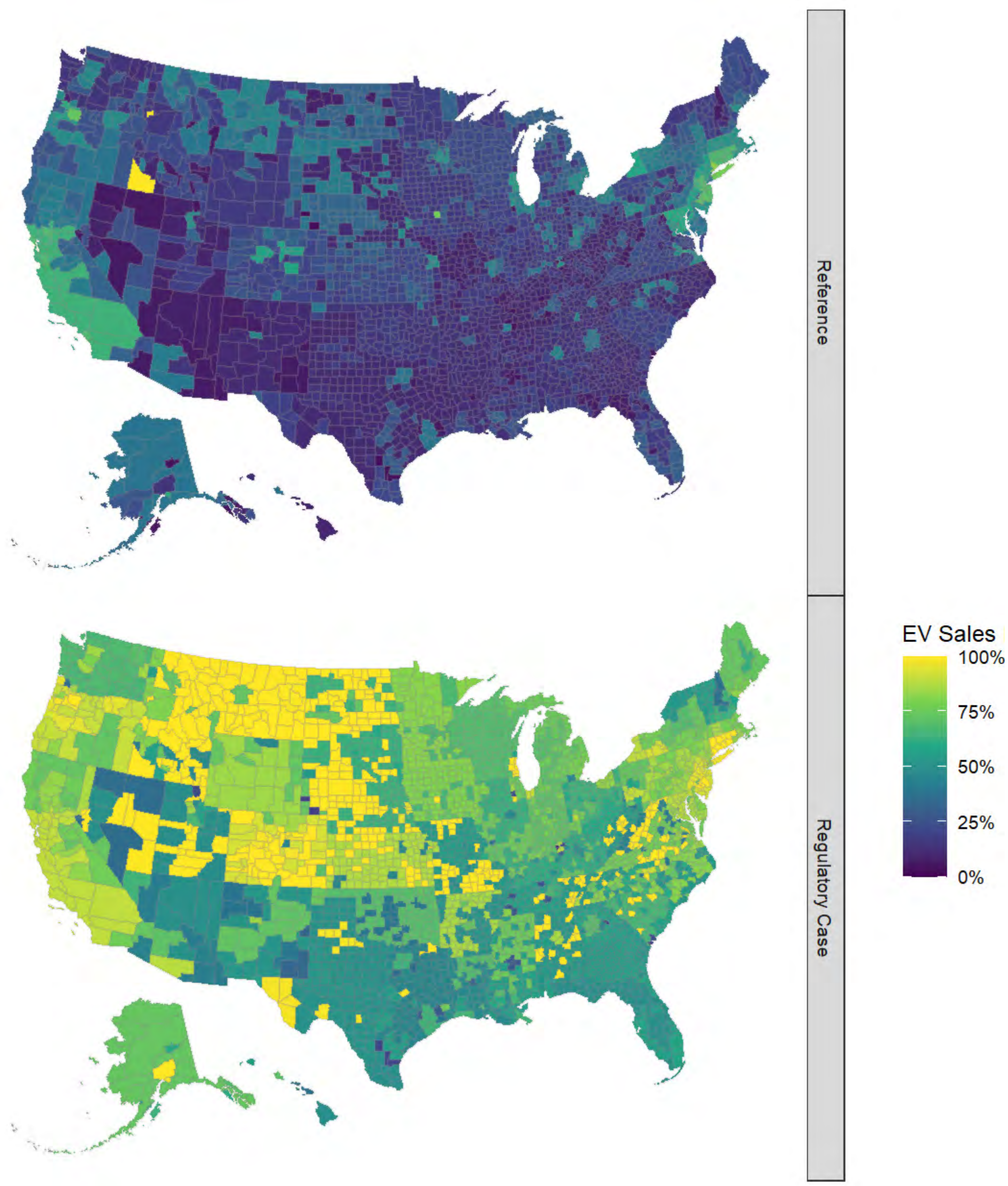

Figure 3-4 Comparing passenger car EV penetrations in 2055

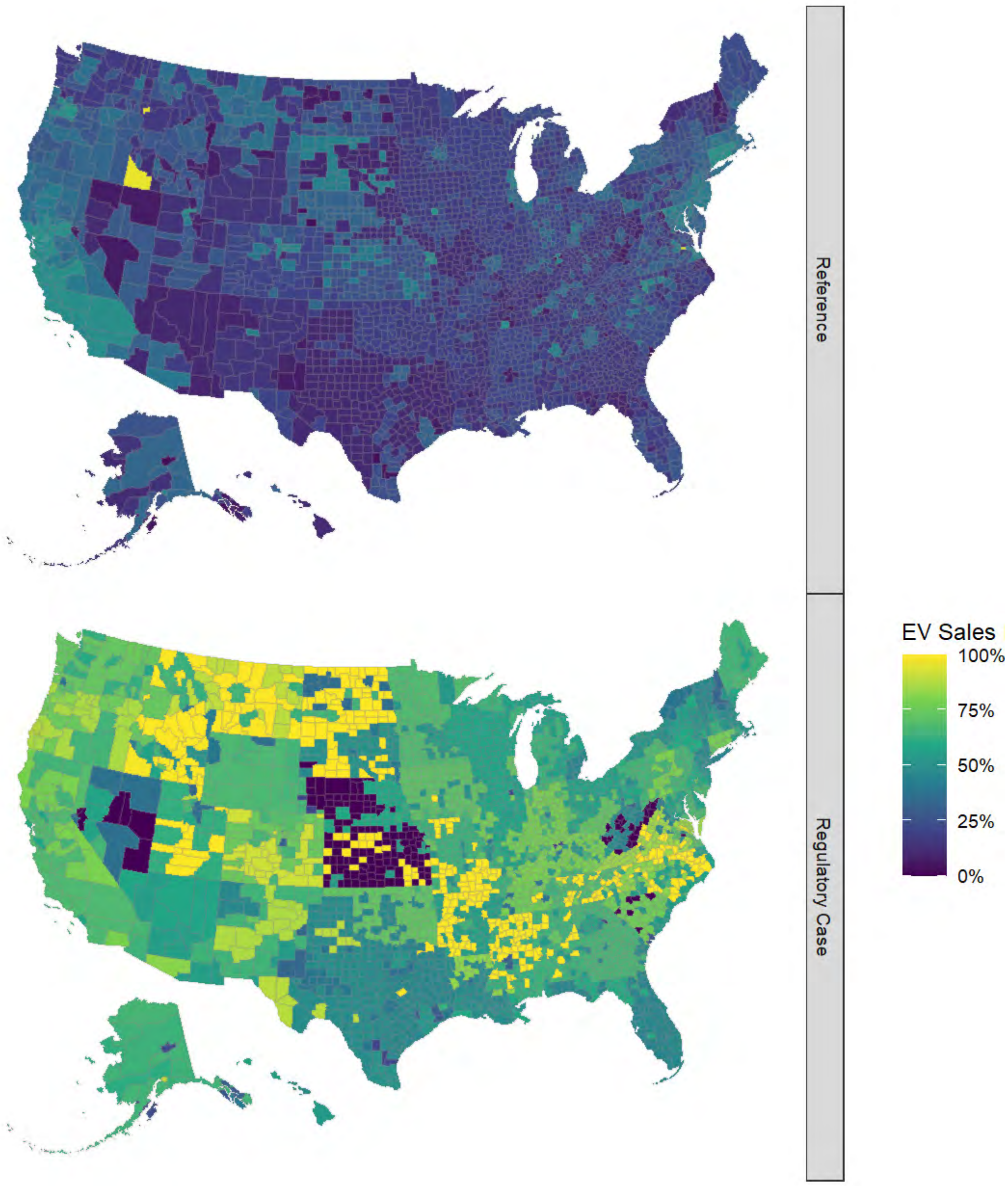

Figure 3-5 Comparing passenger truck EV penetrations in 2055

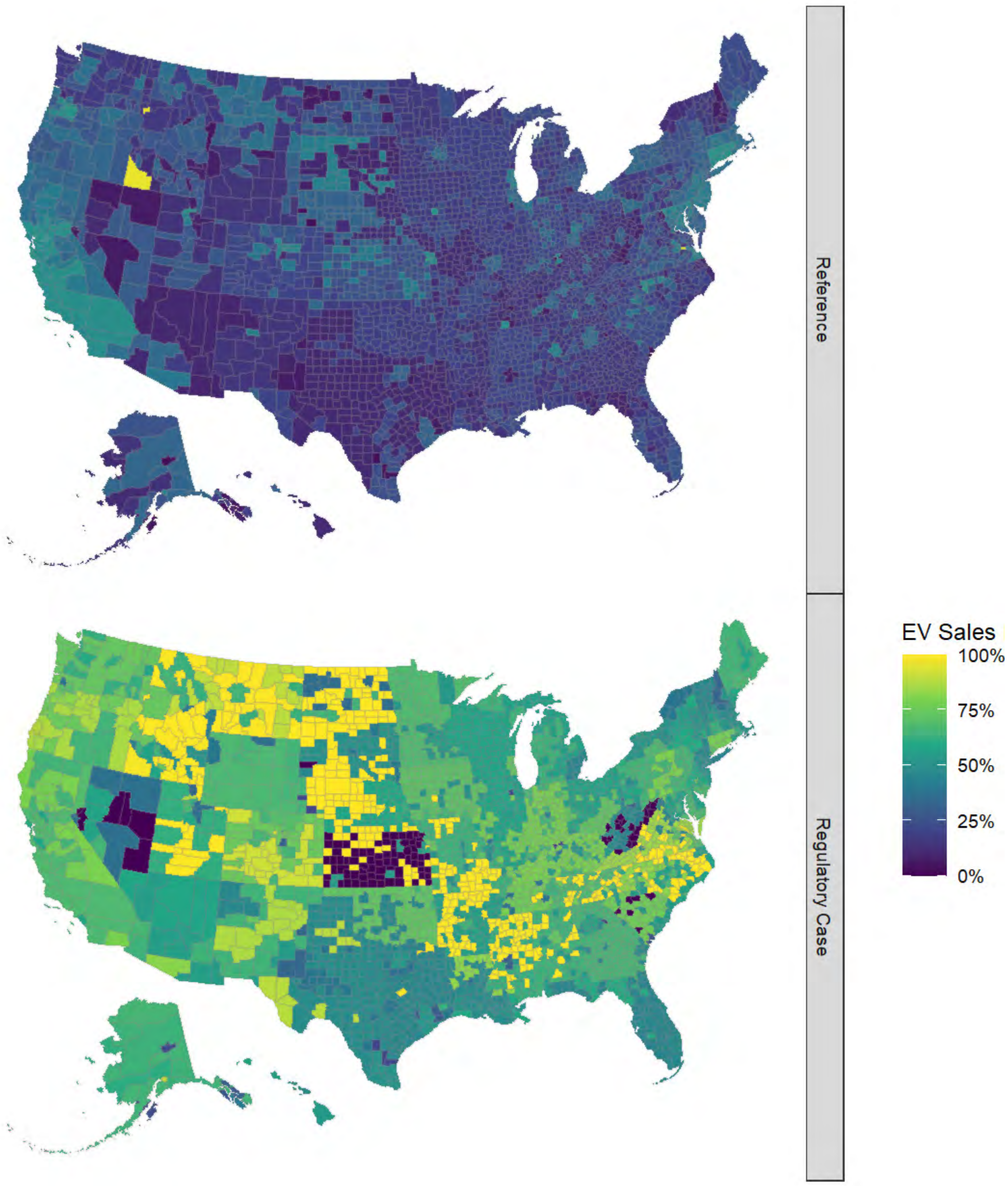

Figure 3-6 Comparing light commercial truck EV penetrations in 2055

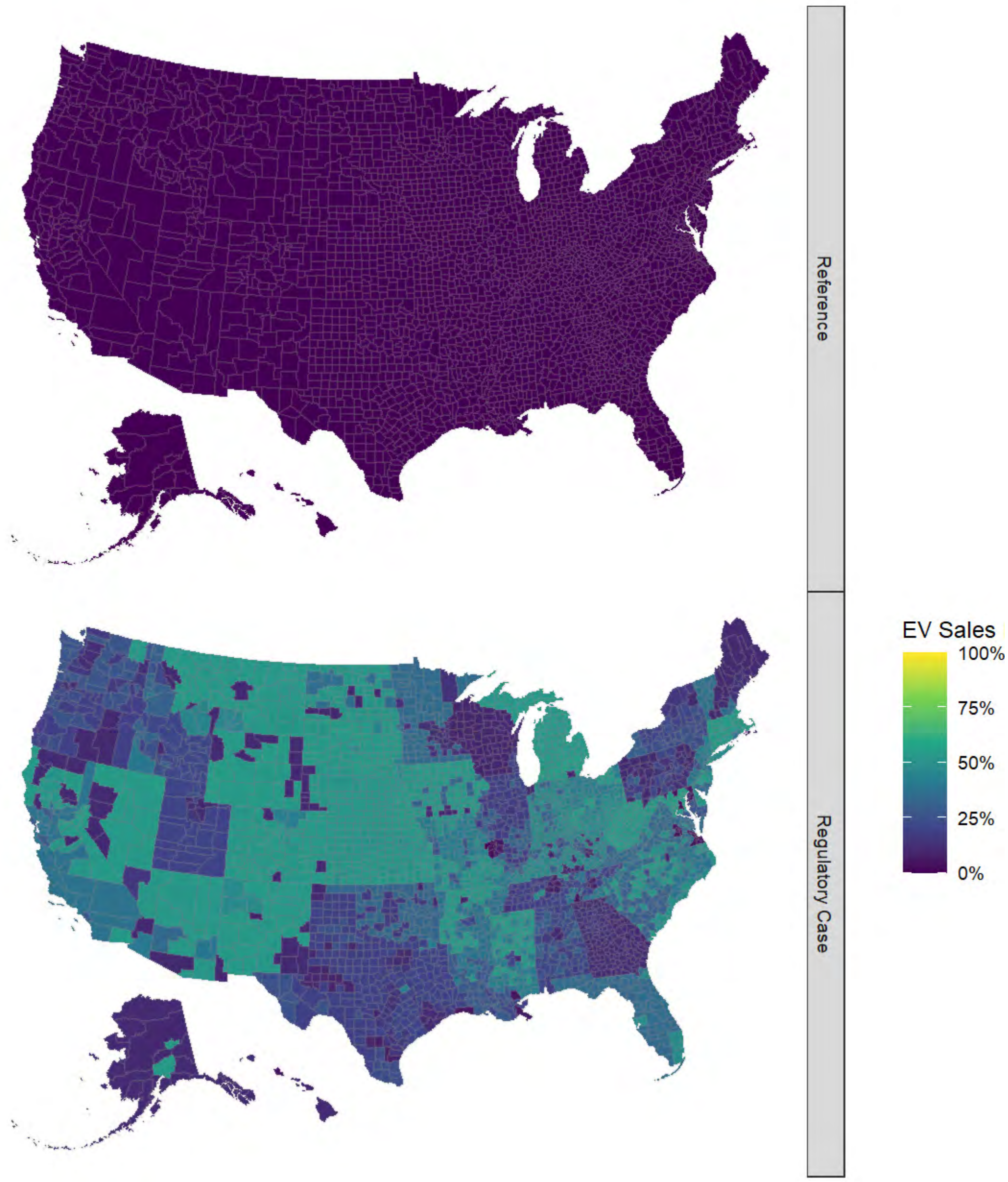

Figure 3-7 Comparing class 3 single unit truck EV penetrations in 2055

3.3 Onroad Emissions Modeling

The SMOKE-MOVES process for creating the air quality model-ready onroad mobile emissions consists of the following steps:

1) Select the representative counties to use in the MOVES runs.

2) Determine which months will be used to represent other months' fuel characteristics.

3) Create inputs needed only by MOVES. MOVES requires county-specific information on vehicle populations, age distributions, speed distribution, road type distributions,

temporal profiles, inspection-maintenance programs, and presence of Low Emission Vehicle (LEV) program for each of the representative counties.

4) Create inputs needed both by MOVES and by SMOKE, including temperatures and activity data.

5) Run MOVES to create emission factor tables for the temperatures and speeds that exist in each county during the modeled period.

6) Run SMOKE to apply the emission factors to activity data (VMT, VPOP, HOTELING, STARTS, ONI) to calculate emissions based on the gridded hourly temperatures in the meteorological data.

7) Aggregate the results to the county-SCC level for summaries and quality assurance.

The onroad emissions are processed as five components that are merged into the final onroad sector emissions:

- rate-per-distance (RPD) uses VMT as the activity data plus speed and speed profile information to compute on-network emissions from exhaust, evaporative, permeation, refueling, and brake and tire wear processes;
- rate-per-vehicle (RPV) uses VPOP activity data to compute off-network emissions from exhaust, evaporative, and permeation processes;
- rate-per-profile (RPP) uses VPOP activity data to compute off-network emissions from evaporative fuel vapor venting, including hot soak (immediately after a trip) and diurnal (vehicle parked for a long period) emissions;
- rate-per-start (RPS) uses START activity data to compute off-network emissions from vehicle starts;
- rate-per-hour (RPH) uses hoteling hours activity data to compute off-network emissions for idling of long-haul trucks from extended idling and auxiliary power unit process; and
- rate-per-hour-ONI (RPHO) uses off-network idling hours activity data to compute emissions for vehicles while idling off-network, (e.g., idling in a parking lot or unloading freight). This is a new emission calculation which was added to the Cleaner Trucks Initiative (CTI) version of MOVES.

As described above, versions of MOVES4[9] (MOVES4.RC2, MOVES4.R1 and MOVES4.R2). were run for three scenarios: 2016, a 2055 reference case, and a 2055 regulatory case. Scenario specific EV fractions were developed for each representative county. MOVES was used to compute onroad emissions in California.

SCC descriptions for onroad emissions

SCCs in the onroad sector follow the pattern 220**FVV**0**RPP**, where:

- F = MOVES fuel type (1 for gasoline, 2 for diesel, 3 for CNG, 5 for E-85, and 9 for electric)
- VV = MOVES vehicle (aka source) type, see Table 3-1
- R = MOVES road type (1 for off-network, 2 for rural restricted, 3 for rural unrestricted, 4 for urban restricted, 5 for urban unrestricted)
- PP = SMOKE aggregate process. In the activity data, the last two digits of the SCC are always 00, because activity data is process independent. MOVES separately tracks over a dozen processes, but for computational reasons it is not practical to model all of these processes separately within SMOKE-MOVES. Instead, "aggregate" processes are used in SMOKE. To support this, the MOVES processes are mapped to SMOKE aggregate processes according to Table 3-2. The MOVES3.R1 model includes a process, 92, that corresponds to emissions from off-network idling (ONI).

Table 3-1 MOVES vehicle types

MOVES Vehicle Type	Description
11	Motorcycle
21	Passenger Car
31	Passenger Truck
32	Light Commercial Truck
41	Intercity Bus
42	Transit Bus
43	School Bus
51	Refuse Truck
52	Single Unit Short-haul Truck
53	Single Unit Long-haul Truck
54	Motor Home
61	Combination Short-haul Truck
62	Combination Long-haul Truck

Table 3-2 SMOKE-MOVES aggregate processes

MOVES Process ID	Process description	SMOKE aggregate process
01	Running Exhaust	72
02	Start Exhaust	72
09	Brakewear	40
10	Tirewear	40
11	Evap Permeation	72
12	Evap Fuel Vapor Venting	72
13	Evap Fuel Leaks	72
15	Crankcase Running Exhaust	72
16	Crankcase Start Exhaust	72
17	Crankcase Extended Idle Exhaust	53
18	Refueling Displacement Vapor Loss	62
19	Refueling Spillage Loss	62
90	Extended Idle Exhaust	53
91	Auxiliary Power Exhaust	91
92	Off-network Idle Exhaust	92

3.3.1 Spatial Surrogates

Onroad county activity data were allocated to a national 12 km grid for air quality modeling using spatial surrogates. For all processes other than the ONI process present in the MOVES3 model, the spatial surrogates used to allocate onroad activity to the national 12km grid are the same as in the 2016v3 platform and are described in the 2016v3 platform TSD. ONI and other off-network activity data including VPOP and STARTS were spatially allocated using the surrogates listed in Table 3-3.

Table 3-3 Spatial surrogates for on-network idling (ONI)

Source Type	Description	Spatial Surrogate	Description
11	Motorcycle	307	NLCD All Development
21	Passenger Car	307	NLCD All Development
31	Passenger Truck	307	NLCD All Development
32	Light Commercial Truck	308	NLCD Low + Med + High
41	Other Bus (non-transit, non-school)	258	Other Bus Terminals
42	Transit Bus	259	Transit Bus Terminals
43	School Bus	506	Education
51	Refuse Truck	306	NLCD Med + High
52	Single Unit Short-haul Truck	306	NLCD Med + High
53	Single Unit Long-haul Truck	306	NLCD Med + High
54	Motor Home	304	NLCD Open + Low
61	Combination Short-haul Truck	306	NLCD Med + High
62	Combination Long-haul Truck	306	NLCD Med + High

3.3.2 Temporal Profiles

For on-network and hoteling emissions, VMT and hoteling activity were temporally allocated from annual or monthly values to hourly and SMOKE was run for every day of the year. The temporal profiles for VMT and hoteling activity are the same as in the 2016v3 platform and are described in more detail in the 2016v3 platform TSD. ONI monthly activity data were temporally allocated to hourly values using a subset of the temporal profiles that are used to temporally allocate VMT. VMT data were temporally allocated using temporal profiles which vary by region (e.g., county, MSA), source type, and road type. ONI activity was developed for each county and source type, but not road type. This means ONI cannot be temporalized in exactly the same way as VMT. Instead, a subset of the VMT temporal profiles was selected to be applied to ONI. Only temporal profiles for unrestricted road types were chosen to be used for ONI, since off-network idling activity is assumed to better match the temporal pattern of unrestricted road type driving, rather than on freeways. There are also different VMT temporal profiles for urban road types and rural road types. ONI activity has no urban or rural designation, and so within each county, we can only apply either a rural temporal profile or an urban temporal profile. Therefore, we used the MOVES county classification as either an urban county or a rural county for the purposes of choosing appropriate temporal profiles for ONI in each county.[13] In urban counties, ONI activity was temporally allocated using VMT profiles for urban unrestricted roads. For rural unrestricted roads, ONI activity was temporally allocate using VMT profiles.

3.3.3 Chemical Speciation

For onroad and nonroad mobile sources, historically the speciation of total organic gas and particulate matter emissions has been done by MOVES. However, this is now largely done outside of MOVES as a post-processing step. This has the advantages of making MOVES simpler and faster to run and making it easier to change or update chemical mechanisms and speciation profiles used in the emissions modeling process. Some speciation is still done inside MOVES for “integrated species” – species of gases and particulate matter which are calculated directly by MOVES. In many cases, these integrated species are affected by parameters like temperature or fuel formulation, which are better accounted for within MOVES. For total organic gases, MOVES calculates 15 integrated species, such as methane and benzene, and the remainder is called NonHAPTOG and speciated outside MOVES. PM emissions can be speciated outside of MOVES using similar methodology, but for this platform, $PM_{2.5}$ onroad emissions were speciated within MOVES. For nonroad, PM speciation profiles were assigned in MOVES post-processing and then applied in SMOKE.

In MOVES, speciation profiles for both gaseous and PM emissions are assigned by emission process, fuel subtype, regulatory class, and model year. Each of these dimensions are available in MOVES output except for fuel subtype, which is aggregated as part of each fuel type. To apply speciation outside of MOVES and make it compatible with the needs of SMOKE, we need to determine the speciation profile mapping by SMOKE process (aggregation of MOVES emission processes) and SMOKE Source Classification Code (SCC), which are defined by fuel type, source type, and road type.

For this platform, MOVES runs were performed in inventory mode for each representative county and season (i.e., winter and summer) to compute NonHAPTOG output by emission process, fuel type, regulatory class, and model year. Emissions were then disaggregated by fuel subtype using the market share of each fuel blend in each county, so that speciation profiles can be accurately assigned. After this step, emissions were normalized and aggregated to calculate the percentage of total NonHAPTOG and (for nonroad) PM emissions that should be speciated by each profile for each SMOKE SCC and process. Finally, these percentages were applied in SMOKE-MOVES to all counties based on their representative county. A MOVES post-processing tool was then used to generate the needed data for preparing speciation cross-references (GSREFs) for SMOKE from the outputs of the inventory mode runs. Although they are similar in nature and outcome, the post-processing tools used for onroad and nonroad emissions output from MOVES are different.

To generate onroad emissions and to perform the subsequent speciation, SMOKE-MOVES was first run to estimate emissions and both the MEPROC and INVTABLE files were used to control which pollutants are processed and eventually integrated. From there, the NONHAPTOG emission factor tables produced by MOVES were speciated within SMOKE using the GSREF files output from the MOVES postprocessing and the NONHAPTOG GSPRO files generated by the S2S-Tool. Overall, this process allows most speciation to occur outside of MOVES, which better supports processing of onroad emissions for multiple chemical mechanisms without having to rerun the MOVES model. Further details on speciation methods involving MOVES can be found in the associated technical reports (EPA-420-R-22-017, EPA-420-R-23-006).[25]

3.3.4 Other Ancillary Files

SMOKE-MOVES requires several other types of ancillary files to prepare emissions for air quality modeling:

- Mobile county cross reference (MCXREF): Maps individual counties to representative counties.
- Mobile fuel month cross reference (MFMREF): Maps actual months to fuel months for each representative county. May through September are mapped to the July fuel month, and all other months to the January fuel month.
- MOVES lookup table list (MRCLIST): Lists emission factor table filenames for each representative county.
- Mobile emissions processes and pollutants (MEPROC): Lists which pollutants to include in the SMOKE run.
- Meteorological data for MOVES (METMOVES): Gridded daily minimum and maximum temperature data. This file is created by the SMOKE program Met4moves and is used for RatePerProfile (RPP) processing.

4 EGU Emissions Inventory Methodology

This section focuses on the approach and data sources used to develop gridded, hourly emissions for the electrical generating unit (EGU) or “power plant” sector that are suitable for input to an air quality model in terms of the format, grid resolution, and chemical species.

[25] https://www.epa.gov/moves/moves-onroad-technical-reports

4.1 Integrated Planning Model (IPM)

IPM is a linear programming model that accounts for variables and information such as energy demand, planned unit retirements, and planned rules to project unit-level energy production and configurations.

4.2 IPM 2022 Post-IRA

The version of IPM used to generate EGU inventories for the AQM analysis is the 2022 Post-IRA version with Final Good Neighbor Plan (GNP), which includes the Inflation Reduction Act Provisions reflecting supply-side impacts.[26]

The IRA provisions modeled within IPM included:

- Clean Electricity Production and Investment Tax Credits
- Existing Nuclear Production Tax Credit
- Carbon Capture and Storage 45Q Tax Credit

This modeling did not include other power sector impacts, such as demand impacts from higher levels of vehicle electrification or IRA energy efficiency provisions.

IPM was run for a set of years, including 2050, with 2055 as the furthest out year. We used the 2050 outputs, and assumed they are constant through 2055, to avoid end of timeframe issues. All inputs, outputs and full documentation of EPA's IPM Post-IRA 2022 Reference Case and the associated NEEDS version is available on the power sector modeling website. The inputs and outputs for the AQM reference and policy scenarios described in this Section are also available in the docket for the rule.[27]

4.2.1 AQM Reference Scenario and Incremental Demand Input Files

IPM requires an electricity demand, and the default electricity demand for the version of IPM used to run the LMDV AQM reference scenario is based on AEO 2021, which does not include the full forecasted zero emission vehicle (ZEV) adoption. Relative to AEO 2021, the LMDV AQM reference case has increased HD ZEV adoption (to account for California's Advanced Clean Trucks Regulation)[28] and LD BEV adoption (to account for EPA's Revised 2023 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions Standards (LD GHG 2023–2026)) final rule (86 FR 74434, December 30, 2021).[29] Therefore, we developed IPM input files specific to the demand of electric vehicles not captured by IPM's defaults, which we call

[26] https://www.epa.gov/power-sector-modeling/final-pm-naaqs

[27] Web-ready IPM files for the LMDV FRM AQM Reference scenario and LMDV FRM AQM Policy scenario.

[28] California Air Resources Board, Final Regulation Order – Advanced Clean Trucks Regulation. Filed March 15, 2021. Available at: https://ww2.arb.ca.gov/sites/default/files/barcu/regact/2019/act2019/fro2.pdf.

[29] Beardsley, Megan. 2023. "Updates to MOVES for the Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles." Memorandum to the Docket EPA-HQ-OAR-2022-0829.

incremental demand input files. The IPM incremental demand for LD and HD is the NPRM No-Action case, detailed in Chapter 5 of the Draft RIA for the proposal.[30]

4.2.1.1 Light-duty incremental demand

Charging profiles for light-duty PEVs were sourced from the Electric Vehicle Infrastructure Projection Tool (EVI-Pro) Lite developed by the National Renewable Energy Laboratory in collaboration with others.[31] EVI-Pro Lite allows users to generate charging profiles[32] for different scenarios based on the number[33] and mix of vehicles, daily vehicle miles traveled, ambient temperature, and availability and preference for certain charging types and charging strategies. While full customization isn't possible in the tool, we generally tried to make selections among the available options most consistent with our reference case where applicable, using default selections for other variables.[34] The resulting weekday and weekend charging profiles[35] are shown in Figure 4-1.

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[30] US EPA, 2023. Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles – Draft Regulatory Impact Analysis. EPA-420-D-23-003. See Table 5-2. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P10175J2.pdf

[31] U.S. Department of Energy, Alternative Fuels Data Center. 2023. "Electric Vehicle Infrastructure Projection Tool (EVI-Pro) Lite." Available at: https://afdc.energy.gov/evi-pro-lite/load-profile.

[32] The tool asks users to select a city or urban area, which changes default selections for average ambient temperature and vehicle miles traveled. Since we use the resulting profiles nationwide, we made selections (e.g., 50°F) intended to reflect that.

[33] We selected 30,000 PEVs (the highest default option available in the tool). However, it is important to note that we do not use the charging profiles from EVI-Pro Lite to estimate the amount of PEV demand. Rather, we use the profiles only to distribute our estimate of PEV demand for the Reference and Regulatory cases by hour of day.

[34] We made the following selections: average daily miles traveled per vehicle: 35 miles; average ambient temperature: 50°F; PEVs that are all-electric: 75% (highest available option); PEVs that are sedans: 50%; mix of workplace charging: 20% Level 1 and 80% Level 2; access to home charging: 75%; mix of home charging: 50% Level 1 and 50% Level 2; preference for home charging: 100%; home charging strategy: immediate - as fast as possible; work charging strategy: immediate – as fast as possible.

[35] Profiles from the EVI-Pro Lite tool are generated in 15-minute increments. Here we have aggregated to hourly shares for use in IPM. We also normalized profiles such that the sum of hourly demand shares totals 100%.

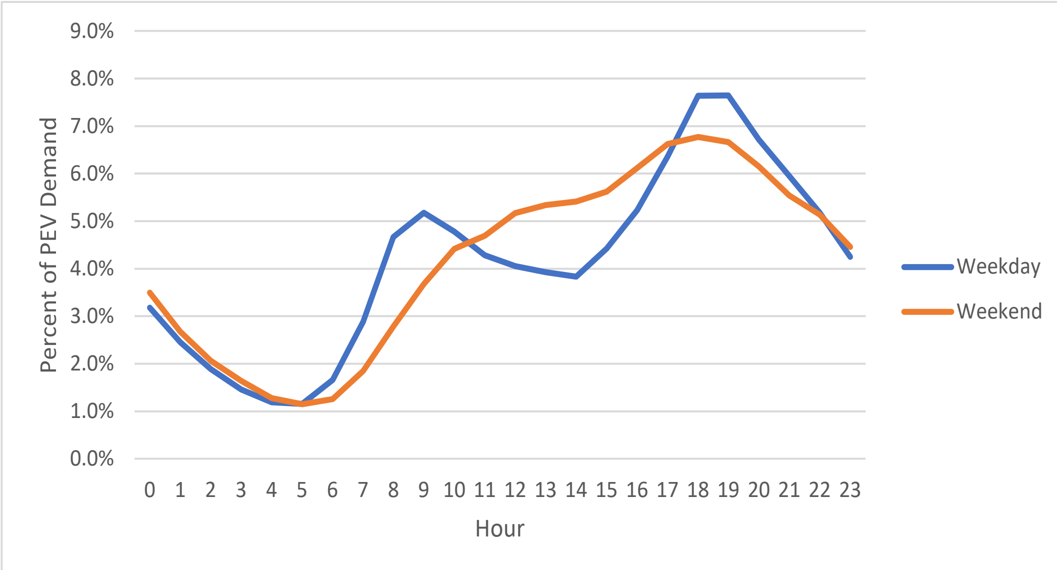

Figure 4-1: Charging profiles for light-duty PEV demand in the reference Case[36]

4.2.1.2 Heavy-duty incremental demand

We used the output of national MOVES3.R1 runs to develop the set of IPM incremental heavy-duty demand input files. Electricity demand was calculated using the MOVES national modeling domain, with output by each type of day (i.e., for an average weekday and weekend). IPM requires grid demand to be specified by day type, by each of IPM's geographic regions, and by each hour of the day.

IPM requires grid demand to be geographically allocated by IPM region. We developed regional allocation factors based on county-level CO_2 emissions in the 2016v2 emissions modeling platform.[37,38] We used CO_2 emissions as our basis for regional allocation because CO_2 scales well with VMT while capturing differing fleet characteristics in different counties. IPM includes a mapping of each county to an IPM region, which we used to aggregate county allocation factors by IPM region.

Inputs to the IPM model include not only the anticipated electricity demand from plug-in electric vehicles (PEVs), but also how that demand is distributed by time of day. This will depend on when PEVs charge. We develop and apply charging profiles to reflect the share of demand from PEV charging that we assume occurs each hour on weekdays and weekends.

[36] We use light-duty charging profiles to distribute PEV demand for cars, passenger trucks, and light commercial trucks (MOVES vehicle types 21, 31, and 32, see Table 3-1).

[37] The emissions modeling platform is a product of the National Emissions Inventory Collaborative consistent of more than 245 employees of state and regional air agencies, EPA, and Federal Land Management agencies. It includes a full suite of base year (2016) and projection year emission inventories modeled using EPA's full suite of emissions modeling tools, including MOVES, SMOKE, and CMAQ.

[38] U.S. EPA. "2016v2 Platform". January 23, 2023. Available online: https://www.epa.gov/air-emissions-modeling/2016v2-platform

Heavy-duty vehicles comprise a broad spectrum of vehicle types and applications, and we would expect charging patterns to vary accordingly. For this reason, we develop individual charging profiles for seven vehicle categories: transit buses, school buses, other buses, refuse trucks, single unit short-haul trucks, combination short-haul trucks, and motorhomes. We start from data on vehicle soaks (or times when vehicles are not operating) in MOVES3.R1 for each of the above categories. For our analysis, we considered only soak lengths that were greater than or equal to 12 hours, using this as a proxy for when vehicles may be parked at a depot, warehouse, or other off-shift location and may have an opportunity to charge. How long a particular vehicle will take to charge will depend on a variety of factors including the vehicle's daily electricity consumption and the power level of the charging equipment. The time that charging occurs will also depend on the charging preferences of BEV owners or operators. Some may choose to start charging as soon as the vehicle is parked, while others may delay charging to accommodate other vehicles in a fleet, take advantage of time-of-use electricity rates, or for other reasons. In developing national, fleetwide profiles, we made the simplifying assumption that charging demand would be evenly distributed across the 12 hours before vehicles start daily operation, i.e. when the soak periods end.

As a final step, we weighted the seven individual charging profiles by the relative share of electricity demand for each vehicle category in MOVES3.R1. The resulting aggregate weekday and weekend profiles are shown in Figure 4-2.

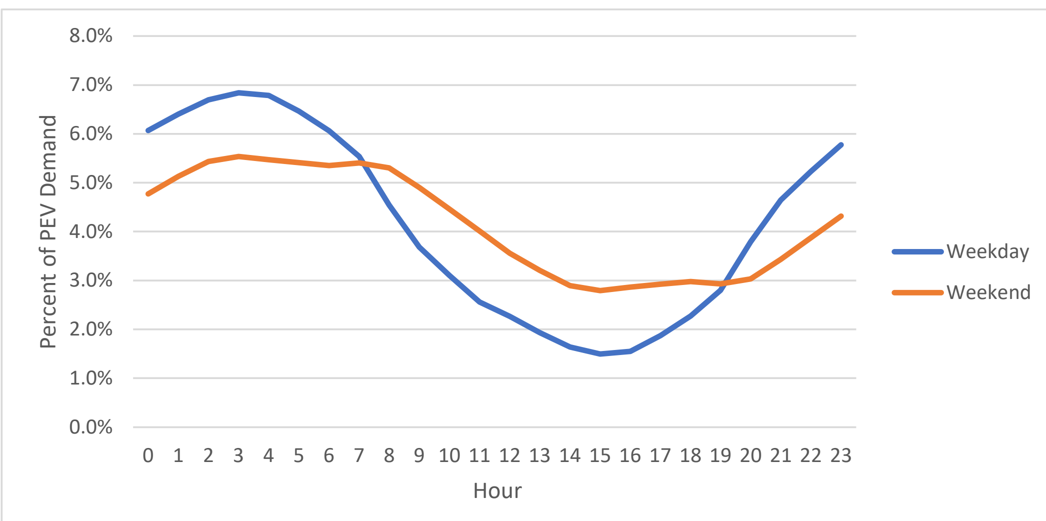

Figure 4-2: Charging profiles for heavy-duty PEV demand in the reference case[39]

Finally, upstream emissions that would be incurred for fuel cell electric vehicles (FCEVs) due to the production of hydrogen are not captured by MOVES. We made a simplifying assumption that all hydrogen used to fuel FCEVs is produced via the electrolysis of water, and thus in this

[39] We use heavy-duty charging profiles to distribute demand for PEVs of MOVES vehicle type 41 and higher (see Table 3-1).

analysis, all hydrogen production is represented as additional demand to EGUs and the emissions are modeled using IPM. Hydrogen in the U.S. today is primarily produced via steam methane reforming (SMR) largely in support of petroleum refining and ammonia production. New transportation demand and economic incentives may shift how hydrogen is produced, and electrolysis is a key mature technology for hydrogen production. The relative emissions impact of hydrogen production via SMR versus electrolysis depends on the source of electricity generation, and this varies significantly by region across the country. Electrolysis powered by electricity from the grid on average in the U.S. may overestimate the upstream emissions impacts that are attributable to HD FCEVs in the near-term.

We developed yearly scalar multipliers which were applied to MOVES FCEV energy consumption to represent total grid demand from the hydrogen production necessary to support the projected levels of FCEVs. First, we assumed hydrogen is produced by a series of decentralized, grid-powered polymer electrolyte membrane (PEM) electrolyzer systems, each with a hydrogen production capacity around 1,500 kilograms per day.[40,41] Next, we assumed the gaseous hydrogen is compressed and pre-cooled for delivery to vehicles using grid-powered electrical equipment. Finally, we assumed a linear improvement between our estimated current and future efficiency for hydrogen production. The linear interpolation is between current values that start in 2025 and future values represented for 2055, assuming a period of diffusion for more efficient electrolysis technology improvements to spread. The final scaling factors range from 1.748 in 2025 to 1.616 in 2055.

4.2.2 AQM Policy Scenario and incremental demand inputs

The default electricity demand for the version of IPM[42] used to run the LMDV AQM policy scenario is based on AEO 2021, which does not include the full forecasted zero emission vehicle (ZEV) adoption. As mentioned above, we developed light- and medium-duty incremental demand input files for the LMDV AQM reference case and in addition to those files, described in Section 4.2.1.1, the incremental light-duty demand input files for the policy scenario also included light- and medium-duty EV demand to represent the NPRM Action case. The light- and medium-duty demand associated with the NPRM action case is detailed in Chapter 5.2.3 of the Draft RIA for the proposal.[43] We used regional profiles, generated using EVI-X, for the light-duty PEV demand in our policy case, see Chapter 5.1 and 5.3 in the DRIA for more detail on EVI-X.

We also developed heavy-duty incremental demand input files for the LMDV AQM policy case. We used the output of national MOVES3.R1 runs to develop the set of IPM incremental heavy-duty demand input files. Electricity demand was calculated using the MOVES national modeling domain, with output by each type of day (i.e., for an average weekday and weekend).

[40] This is based on assumptions from the Hydrogen Analysis Production (H2A) Model from the National Renewable Energy Laboratory (NREL).

[41] National Renewable Energy Laboratory (NREL). “H2A: Hydrogen Analysis Production Model: Version 3.2018”. Available online: https://www.nrel.gov/hydrogen/h2a-production-archive.html

[42] https://www.epa.gov/power-sector-modeling/post-ira-2022-reference-case

[43] US EPA, 2023. Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles – Draft Regulatory Impact Analysis. EPA-420-D-23-003. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P10175J2.pdf

The heavy-duty EV charging profiles were the same for the reference and policy cases, see Section 4.2.1.1.2.

4.3 Air Quality Model-Ready EGU inventory generation

The EGU emissions are calculated for the AQM inventory using the output of the IPM model for the forecast year. Units that are identified to have a primary fuel of landfill gas, fossil waste, non-fossil waste, residual fuel oil, or distillate fuel oil may be missing emissions values for certain pollutants in the generated inventory flat file. Units with missing emissions values are gapfilled using projected base year values.

The projections are calculated using the ratio of the future year seasonal generation in the IPM parsed file and the base year seasonal generation at each unit for each fuel type in the unit as derived from the 2018 EIA923 tables and the 2018 NEI. New controls identified at a unit in the IPM parsed file are accounted for with appropriate emissions reductions in the gapfill projection values. When base year unit-level generation data cannot be obtained no gapfill value is calculated for that unit. Additionally, some units, such as landfill gas, may not be assigned a valid SCC in the initial flat file. The SCCs for these units are updated based on the base year SCC for the unit-fuel type. Combined cycle units produce some of their energy from process steam that turns a steam turbine. The IPM model assigns a fraction of the total combined cycle production to the steam turbine. When the emissions are calculated these steam units are assigned emissions values that come from the combustion portion of the process. In the base year NEI steam turbines are usually implicit to the total combined cycle unit. To achieve the proper plume rise for the total combined cycle emissions, the stack parameters for the steam turbine units are updated with the parameters from the combustion release point. Large EGUs in the IPM-derived flat file inventory are associated with hourly CEMS data for NO_X and SO_2 emissions values in the base year. To maintain a temporal pattern consistent with the 2016 base year, the NO_X and SO_2 values in the hourly CEMS inventories are projected to match the total seasonal emissions values in the future years.

5 Petroleum Sector Emissions Inventory Methodology

This section focuses on the approach and data sources used to develop adjusted gridded, hourly emissions for some of the sectors related to producing petroleum liquid fuels for mobile sources. While the emission factors used to develop emissions for the reference and policy scenarios differed, the approach and data sources used to calculate emissions for both scenarios were consistent.

Emission sources related to producing petroleum liquid fuels for mobile sources include extracting, transporting, and storing crude oil; extracting, transporting, and storing natural gas; and refining, transporting, and storing finished fuels like gasoline and diesel. These sources are described in the emissions modeling platform TSD in Section 2.1.2 (point oil and gas) and 2.2.4 (nonpoint oil and gas).44

More details on the modeling of the petroleum sector emissions are in the following subsections, and national emission summaries for key pollutants are provided in Section 6. The

[44] U.S. EPA (2023) Technical Support Document: Preparation of Emissions Inventories for the 2016v3 North American Emissions Modeling Platform. https://www.epa.gov/air-emissions-modeling/2016-version-3-technical-support-document.

docketed spreadsheet "LMDV FRM AQM petroleum adjustment factors.xlsx" presents the calculations described in this Section.

5.1 Refinery Emissions

5.1.1 Projection of Refinery Emissions to 2050/2055

The 2016v3 emissions modeling platform, which includes projection years 2023 and 2026, was the starting point for the air quality analysis to develop refinery inventories.[45] The 2026 refinery inventory from the 2016v3 emissions modeling platform was projected to 2050 using AEO 2023 growth factors.[46,47] We assumed no change in refinery emissions between 2050 and 2055. The national total refinery inventory is presented in Table 5-1, and see docketed spreadsheet "2050 national refinery summary for OTAQ FRM.xlsx".

Table 5-1 2016v3 Emissions Modeling Platform Refinery Inventory Projected to 2026 and 2055

Pollutant	Projected emissions in 2026 (tons/yr)	Projected emissions in 2055 (tons/yr)
NOx	76,447	81,607
$PM_{2.5}$	18,231	19,243
SO_2	25,164	26,287
VOC	63,033	64,091

5.1.2 Identifying Refineries to Adjust for Air Quality Analysis

To isolate the impact of this rule on refinery emissions, only refineries that produce gasoline or diesel fuel for onroad vehicles were adjusted in the air quality modeling. For the NPRM illustrative air quality analysis, eligible refineries were identified from the 2016v2 emissions modeling platform refineries report, and those that did not produce gasoline or diesel fuel for onroad vehicles were excluded (see docketed spreadsheet, "2016v2 platform refineries report.xlsx"). In preparation for the final rule, the same approach was applied to new refineries that had been added to the 2016v3 emissions modeling platform (see docketed spreadsheet "refineries in 2016v3 not 2016v2.xlsx"). Ultimately, 118 refineries that produce onroad fuel were adjusted in the air quality modeling.

5.1.3 Apportioning Total Refinery Emissions to Gasoline and Diesel Fuel Production

Scaling factors were calculated to apportion total refinery emissions to the refining of gasoline and diesel versus other refined fuels and refinery operations. The scaling factors are based on the

[45] https://www.epa.gov/air-emissions-modeling/2016v3-platform

[46] Specifically, a projection packet was prepared for 2026->2050 using AEO 2023 for refineries. AEO categories were mapped to SCCs and SCC+NAICS combinations (with SCC+NAICS taking precedence if a mapping exists for the refinery NAICS, which are 32411/324110) using the usual industrial source AEO-SCC and AEO-SCC-NAICS xrefs from past platforms. Only refineries NAICS and SCCs which have refinery emissions were included when making the packet, so the 2026-2050 packet is not something that can be used to project the entire ptnonipm sector. Each record in the packet references the refineries NAICS so that it can be applied to the entire ptnonipm sector without changing any non-refineries.

[47] https://www.eia.gov/outlooks/aeo/tables_ref.php

relative energy demand of refining various fuels calculated by Wang et al.[48] Wang et al. expressed the energy demand of refining fuels in terms of mass and included outputs that are not refinery products (i.e., fuel gas), so we removed non-refinery products and adjusted the energy demand factors to be based on volume instead of mass.

Relative emissions related to the refining of various products are determined primarily by the energy needed to refine those products, but also depend on pollutant-specific emissions from refining those products. For example, the refining of gasoline causes higher methane emissions than an equivalent volume of diesel. We developed pollutant-specific apportionment factors based on relative emissions of refining gasoline, diesel, and other products using emission factors from GREET 2021.[49] We use the apportionment factors to calculate the portion of the refinery inventory attributable to the refining of each fuel type. Final apportionment factors for each pollutant that we modeled in our refinery analysis appear in Table 5-2.

Table 5-2 Refinery emission apportionment factors by fuel type

Pollutant	**Refinery Emissions Apportionment Factor**		
	Gasoline	**Diesel**	**Other**
Carbon Dioxide (CO_2)	0.591	0.061	0.348
Methane (CH_4)	0.640	0.053	0.307
Nitrous Oxide (N_2O)	0.583	0.063	0.354
Nitrogen Oxides (NO_X)	0.610	0.056	0.334
Particulate Matter ($PM_{2.5}$)	0.620	0.054	0.326
Sulfur Dioxide (SO_2)	0.596	0.058	0.346
Volatile Organic Compounds (VOC)	0.570	0.058	0.372

Table 5-3 shows how we estimated 2050 refinery emissions that are attributable to the refining of gasoline and diesel fuel. We began with the total refinery inventory, which was reduced to only represent refineries that produce onroad fuels (see Section 5.1.2.). Then, we further apportioned emissions to be specific to the refining of gasoline or the refining of diesel.

Table 5-3 2050 refinery emission inventory apportioned by refinery type and fuel type

Pollutant	**Emission Inventory by Refinery Group (U.S. Tons)**		**Inventory Apportioned by Fuel Type (U.S. Tons)**	
	All Refineries	**Refineries that produce gasoline and diesel**	**Gasoline**	**Diesel**
Nitrogen Oxides (NO_X)	81,607	77,830	47,437	4,335
Particulate Matter ($PM_{2.5}$)	19,243	18,253	11,324	605
Sulfur Dioxide (SO_2)	26,287	23,501	14,017	819
Volatile Organic Compounds (VOC)	64,091	57,829	32,972	1,924

[48] Wang, M., Lee, H. & Molburg, J. Allocation of energy use in petroleum refineries to petroleum products. Int J LCA 9, 34–44 (2004). https://doi.org/10.1007/BF02978534

[49] Wang, Michael, Elgowainy, Amgad, Lee, Uisung, Bafana, Adarsh, Banerjee, Sudhanya, Benavides, Pahola T., Bobba, Pallavi, Burnham, Andrew, Cai, Hao, Gracida, Ulises, Hawkins, Troy R., Iyer, Rakesh K., Kelly, Jarod C., Kim, Taemin, Kingsbury, Kathryn, Kwon, Hoyoung, Li, Yuan, Liu, Xinyu, Lu, Zifeng, Ou, Longwen, Siddique, Nazib, Sun, Pingping, Vyawahare, Pradeep, Winjobi, Olumide, Wu, May, Xu, Hui, Yoo, Eunji, Zaimes, George G., and Zang, Guiyan. Greenhouse gases, Regulated Emissions, and Energy use in Technologies Model ® (2021 Excel). Computer Software. U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy (EERE). 11 Oct. 2021. Web. doi:10.11578/GREET-Excel-2021/dc.20210902.1.

5.1.4 Total Refined Fuel and Onroad Fuel Consumed Associated with AQM Cases

We estimated total reference case refinery activity in terms of gasoline and diesel produced. The total refined fuel supplied in 2050 was obtained from AEO 2023 Table 11[50,51] and is presented here in Table 5-4. We assume that 2050 projected volumes stay constant through 2055. It is important to note that an error was made in interpreting the total refined fuel supplied that is presented in AEO 2023 Table 11. "Product suppled" was assumed to be the volume of fuel refined in the United States; however, after the AQM was underway, we learned that this value presented in AEO 2023 Table 11 does not include fuel that was refined and exported. The United States is a net exporter of gasoline and diesel and therefore, the total refinery activity that was assumed for the reference case is underestimated. We estimate that this error has had a relatively small impact on the air quality modeling results compared to the total emission reductions from the policy scenario; its implications are discussed further in Section 5.1.7.

Table 5-4 Total Refined Fuel Supplied in 2050 from AEO 2023 Reference Case (billion gallons/yr)

	Total Refined Fuel Supplied[a]
Gasoline	113.92
Diesel	49.12

[a] Total refined fuel supplied from Table 11 of AEO 2023, with units converted from million barrels per day

The fuel demanded in 2055 by onroad vehicles (gallons of gasoline and gallons of diesel) in the policy scenario was generated using MOVES (see docketed spreadsheets "FRM reference petroelumconsumption.xlsx" and "FRM policy petroelumconsumption.xlsx").

There are methodological differences in how onroad fuel demand is calculated by MOVES and by AEO. An adjustment factor to account for the difference between MOVES4.R1 and AEO 2023 reference was applied to the MOVES onroad fuel demand numbers to make them more consistent with AEO 2023, see Table 5-5.

Table 5-5 Factor to apply to MOVES fuel demand to make consistent with AEO fuel demand

	MOVES adjustment factor
Gasoline	1.01
Diesel	0.93

The adjusted MOVES onroad fuel demand was then used to calculate the change in fuel demand from the reference onroad fuel demand obtained from AEO 2023 Table 36 ('Transportation Energy Use: Light-Duty Vehicle: Total').[52] The reduction in onroad fuel demand due to the policy scenario was calculated separately for gasoline and for diesel by

[50] https://www.eia.gov/outlooks/aeo/data/browser/#/?id=11-AEO2023&cases=ref2023&sourcekey=0

[51] From the Annual Energy Outlook 2023 Table 11 'Petroleum and Other Liquids Supply and Disposition

Case: Reference case', "Product Supplied – by Fuel – Motor Gasoline" in 2050 was used as the total refined gasoline supplied, and "Product Supplied – by Fuel – Distillate Fuel Oil – of which: Diesel" in 2050 was used as the total refined diesel supplied.

[52] https://www.eia.gov/outlooks/aeo/data/browser/#/?id=46-AEO2023&cases=ref2023&sourcekey=0

subtracting the fuel demands in Table 5-6, in which the MOVES policy case estimates have been adjusted to account for AEO/MOVES methodological differences.

Table 5-6 2055 Onroad Fuel Demand for Air Quality Analysis Scenarios (billion gallons/yr)

	Reference Onroad Fuel Demand	**LMDV Policy Onroad Fuel Demand**
Gasoline	105.55	55.60
Diesel	36.95	31.41

5.1.5 Projected Change in U.S. Refinery Activity Related to Decreased Domestic Demand

We estimate the change in refinery activity by assuming a reduction in onroad fuel demand will lead to a reduction in the total amount of fuel refined. However, U.S. refineries can theoretically respond to lower domestic demand by increasing volumes of exported liquid fuels, thus allowing them to refine at the same volume and leaving refinery emissions unchanged.

In the NPRM air quality analysis, we assumed that 7% of the reduced domestic demand for refined fuels would be made up by an increase in exports, based on a comparison of the reference case and low economic growth case in AEO 2023. We received comments from several organizations that refineries would increase exports more than we assumed.

There are several reasons to expect refineries to increase exports in the case that domestic demand for refined fuels drops in the future. First, most refineries refine products in addition to onroad fuels. In fact, the refining of gasoline and diesel fuel produces coproducts that have economic value of their own, so refineries may continue refinery activity but focus on other products. Second, it can be economically advantageous to refine crude oil in the United States because feedstock prices tend to be lower, thus leading to higher profit margins.

Despite the favorable economic conditions for refiners in the United States, there have been some refinery closures and conversions in recent years, often at least partially in response to lower domestic fuel demand from the COVID-19 pandemic and the desire for low-carbon fuels.

The closure or conversion of some U.S. refineries in recent years suggests that the closure or conversion of additional refineries is likely as domestic demand for gasoline and diesel fuel declines, especially for those that have lower margins or face other issues. The extent to which U.S. refineries keep operating, shut down, or are converted is difficult to project, since it depends on the economics of individual refineries, the economic condition of the parent company, and the long-term strategy pursued by each company’s board for providing a return to its shareholders.

After carefully taking into consideration stakeholder comments, the more desirable economic conditions for refiners in the U.S., and the recent closures and conversions of some U.S. refineries, we have updated our projection of how refineries will be impacted by this rulemaking. For the final rule, we estimated refinery emissions by assuming that U.S. refineries would increase exports to offset half of the projected reductions in domestic demand for liquid fuels. Thus, the total decrease in refinery activity, measured in gallons of gasoline and diesel refined, is half of the estimated drop in domestic fuel demand (see Table 5-7). However, there remains significant uncertainty in how U.S. refineries will respond to lower demand for liquid onroad fuels. Therefore, we performed a sensitivity analysis in which we estimate emission impacts if refineries had no change in activity as a result of reduced domestic demand from this rule. In the sensitivity analysis, presented in Chapter 7 of the RIA, we present total emission impacts of the policy scenario with no change in refinery emissions from the reference case.

Table 5-7 Reductions in Onroad Fuel Demand and Refinery Activity for 2050 Policy Scenario (billions gallons/year)

	Reductions in Onroad Fuel Demand	Reductions in Refined Gasoline and Diesel
Gasoline	49.94	24.97
Diesel	5.54	2.77

5.1.6 Generation of Adjustment Factors

The reduced gallons of onroad gasoline and diesel that would be refined domestically (Table 5-7) was subtracted from the total refined fuel supplied in Table 5-4 and used to create an adjustment factor to be applied to the gasoline and diesel portions of the 2050 onroad refinery inventory. Adjustment factors of 0.78 and 0.94 were applied to gasoline and diesel portions, respectively. The resulting emissions, associated with refining gasoline and diesel fuel only, are presented in Table 5-8.

Table 5-8 Projected 2055 Emissions from Refineries Associated with Producing Gasoline and Diesel Only

Scenario		NO_X (tons/yr)	$PM_{2.5}$ (tons/yr)	SO_2 (tons/yr)	VOC (tons/yr)
LMDV Policy	**gasoline**	37,039	8,842	10,944	25,744
	diesel	4,091	571	773	1,815

The total refinery emissions in the policy scenario is estimated as the total refinery emissions in the reference case less the projected reductions in gas and diesel refining associated with this rule. A final adjustment factor, equal to the ratio of the total refinery emissions in the regulatory case to the total refinery emissions in the reference case, was then calculated for each of the pollutants included in air quality analysis (see Table 5-9). These adjustment factors were applied in air quality modeling to each of the refineries that produce onroad fuel (see Section 5.1.2).

Table 5-9 Adjustment Factor to Apply to 2050 Refinery Inventory

Scenario	NO_X	$PM_{2.5}$	SO_2	VOC
LMDV Policy	0.86	0.86	0.87	0.87

5.1.7 Limitations of Modeling Impacts on Refinery Emissions

5.1.7.1 Uncertainty in impact on refinery activity

As noted in Section 5.1.5, we recognize that there is significant uncertainty in the impact that reduced domestic demand for gasoline and diesel fuel will have on refinery emissions and that the refinery industry could respond differently than how we have predicted in our air quality analysis. For example, many US refineries may continue their production of refined products and instead import less refined product because they experience lower crude oil and natural gas prices than refineries elsewhere. Some refineries may also increase exports of US refined products. If refineries employ these strategies and their production is unaffected by lower domestic demand, we would project no emission reductions from refineries rather than those associated with the adjustment factors presented in Table 5-9.

5.1.7.2 Overestimation of reduction in refinery inventory

As mentioned in Section 5.1.4, we underestimated the total refined fuel in the reference case by not including fuel that was refined in the US and then exported. Therefore, the adjustment factors we applied in the air quality analysis overestimate the relative reduction in the refinery inventory between the reference and policy cases. This error was discovered after air quality modeling was already underway, so we were unable to correct it due to time constraints. However, we have estimated its impact on the total refinery emissions and the total emissions across all sectors in the policy case, and we conclude that although the overestimate of emissions reductions is non-negligible, it is relatively small.

To quantify the magnitude of the overestimate, we first estimated exports of gasoline and diesel in the reference case. Growth factors for exports were estimated for 2050 versus 2022 using the projected net exports provided in Table 11 of AEO 2023.[53] These growth factors were then applied to apportioned exports of refined fuels measured by EIA in 2022 to estimate net exports of gasoline and diesel in 2050. The projected net exports were added to the total refined fuel that had been used for the reference case, and the method for estimating adjustment factors for the regulatory scenario refinery emissions was repeated using the updated estimate of total refined fuel that included net exports of gasoline and diesel in 2050.[54] Compared to the adjustment factors that were applied to relevant refineries in the AQM (see Table 5-9), the corrected adjustment factors after the addition of refined fuels exports were ~2 percentage points higher (see Table 5-10). We then applied the corrected adjustment factor to the emissions inventories for all refineries that produce onroad fuel and compared the estimated refinery emissions impacts against those calculated from the uncorrected adjustment factors to quantify the magnitude of the error on projected refinery emissions impacts (see Table 5-11). Using this method, we conclude that the exclusion of net exports from the initial adjustment factor calculations has likely resulted in an overestimate of refinery emissions reductions of 16%. Finally, to understand the impact that this overestimate had on the total projected emissions impacts from all sources, we reduced the refinery-related emissions impacts by 16% and summed new, corrected total emissions reductions (see Table 5-12). Note that the uncorrected emissions reductions presented in Table 5-12 represent projected changes in refinery activity among the 48 contiguous United States, whereas the reductions presented in Table 5-11 also include refineries in Alaska and Hawaii (see Section 5.1.1).

[53] https://www.eia.gov/outlooks/aeo/data/browser/#/?id=11-AEO2023&cases=ref2023&sourcekey=0

[54] The calculations are provided on docketed spreadsheet "LMDV FRM AQM petroleum adjustment factors with exports for refinery corrections.xlsx".

Table 5-10 Corrected Adjustment Factors with Addition of Net Exported Refined Fuels

Pollutant	Uncorrected	Corrected
NOx	0.86	0.89
$PM_{2.5}$	0.86	0.88
SO_2	0.87	0.89
VOC	0.87	0.89

[a]Here, 'uncorrected' maintains the error that was made prior to AQM. These data represent what was used as AQM inputs.
[b]The corrected emissions were recalculated with the inclusion of net exports of refined fuels to address the overestimating error.

Table 5-11 Corrected Refinery Emissions Impacts with Addition of Net Exported Refined Fuels

Pollutant	Uncorrected[a]	Corrected[b]	Difference	% difference
		Refineries Emissions Only		
$PM_{2.5}$	2,516	2,112	404	16%
NO_X	10,643	8,913	1,730	16%
SO_2	3,119	2,616	503	16%
VOC	7,336	6,155	1,181	16%

[a]Here, 'uncorrected' maintains the error that was made prior to AQM. These data represent what was used as AQM inputs.
[b]The corrected emissions were recalculated with the inclusion of net exports of refined fuels to address the overestimating error.

Table 5-12 Corrected Emissions Impacts with Addition of Net Exported Refined Fuels

	Sector (48 states)	Uncorrected	Corrected	Difference	% difference
$PM_{2.5}$	Onroad Total	-8,326	-8,326	-	-
	Upstream Total	-1,393	-996	397	28%
	EGU	1,039	1,039	-	-
	Refinery	-2,467	-2,070	397	16%
	Crude Production Wells	-102	-102	-	-
	Natural Gas Production Wells	137	137	-	-
$PM_{2.5}$	Total	-9,719	-9,322	397	4%
NOx	Onroad Total	-84,692	-84,692	-	-
	Upstream Total	-9,643	-7,942	1,701	18%
	EGU	1,605	1,605	-	-
	Refinery	-10,468	-8,767	1,701	16%
	Crude Production Wells	-4,778	-4,778	-	-
	Natural Gas Production Wells	3,999	3,999	-	-
NOx	Total	-94,335	-92,634	1,701	2%
SO_2	Onroad Total	-2,334	-2,334	-	-
	Upstream Total	-2,929	-2,435	494	17%
	EGU	1,946	1,946	-	-
	Refinery	-3,067	-2,573	494	16%
	Crude Production Wells	-1,867	-1,867	-	-
	Natural Gas Production Wells	59	59	-	-

	Sector (48 states)	Uncorrected	Corrected	Difference	% difference
SO_2	Total	-5,263	-4,769	494	9%
VOC	Onroad Total	-165,159	-165,159	-	-
	Upstream Total	-29,029	-27,869	1,160	4%
	EGU	467	467	-	-
	Refinery	-7,205	-6,045	1,160	16%
	Crude Production Wells	-33,343	-33,343	-	-
	Natural Gas Production Wells	11,052	11,052	-	-
VOC	Total	-194,188	-193,028	1,160	0.6%

5.1.7.3 Uniform application of adjustment factor

Lastly, because we are unable to predict the potential impact that this rule will have on individual refineries, we have used an adjustment factor method that applies the projected impact of reduced demand evenly across all relevant refineries, as a scalar of emissions.

5.2 Crude production well and pipeline emissions

5.2.1 Reference Case Crude Production Well Site and Pipeline Inventories for 2050/2055

The emission inventories for crude production wells and associated pipelines in the 2016v3 emissions modeling platform for the year 2026 are projected to the year 2050 using AEO 2023 reference case production forecast data in the year 2050 relative to that in the year 2026. These reference case crude production well and pipeline inventories were assumed to remain constant from 2050 to 2055.

5.2.2 Policy Scenario and Associated Crude Demand

The reference case 2050/2055 crude production well and pipeline inventories for 2055 needed to be adjusted to reflect the impact of the policy scenario which reduced the domestic demand for liquid fuel, see Table 5-7.[55] The total reduced gallons of refined fuel consumed for each scenario were adjusted to account for refinery efficiency, using factors from Forman, et al (2014), to get reduced gallons of crude-equivalent finished fuel.[56,57] Then the gallons of reduced crude-equivalent finished fuel were converted to gallons of reduced crude using the energy density of crude and gasoline and diesel fuel.[58]

[55] The calculations are provided on docketed spreadsheet “LMDV FRM AQM petroleum adjustment factors.xlsx”.

[56] Forman et al, 2014 dx.doi.org/10.1021/es501035a

[57] The conversion of crude oil to products may be more efficient that this value as this value represents the overall refinery efficiency, not the efficiency for converting crude oil into products.

[58] Energy densities came from EIA, https://www.eia.gov/energyexplained/units-and-calculators/

5.2.3 Projected Change in U.S. Crude Production Activity Related to Decreased Domestic Demand

It was necessary to project how the reduced crude demand associated with the policy scenario would affect U.S. crude production well and pipeline emissions since U.S. crude demand is also satisfied by imports, not just domestic production. We projected how the change in crude demand would affect U.S. crude production based on a comparison generated for the NPRM AQM analysis using the AEO 2021 Reference case and Low Economic Growth case, and we retained this factor for the FRM AQM analysis.[59] The reduced domestic demand (gallons of crude) is multiplied by 8% to estimate the reduction in domestically produced crude.[60]

5.2.4 Generation of Crude Production Well and Pipeline Adjustment Factors

The reduced gallons of crude that would be domestically produced was subtracted from the total crude produced in the AEO 2023 reference case and used to create an adjustment factor, 0.98, to be applied to the crude production well and pipeline inventories.

Equation 1

$$\boldsymbol{CrudeProduction\ adjustment\ factor} = \frac{\begin{array}{c}\boldsymbol{AEO2023\ reference\ case\ Bgal\ crude\ produced\ domestically\ in\ 2050 -}\\ \boldsymbol{reduced\ crude\ produced\ domestically\ due\ to\ additional\ EV\ penetration}\end{array}}{\boldsymbol{AEO2023\ reference\ case\ Bgal\ crude\ produced\ domestically\ in\ 2050}}$$

5.2.5 Limitations of Modeling Impacts on Crude Production Wells and Pipeline Pumps

Because we are unable to predict the potential impact that this rule will have on individual production wells, we have used an adjustment factor method that applies the projected impact of reduced demand evenly across all relevant production sites and pipeline pumps, as a scalar of emissions.

5.3 Natural gas production wells and pipeline pumps emissions

5.3.1 Reference Case Natural Gas Production Well Site and Pipeline Inventories for 2050/2055

Emission inventories for natural gas production wells and associated pipelines in the 2016v3 emissions modeling platform were projected from 2026 to 2050 using AEO 2023 reference case production forecast data. We assumed no change in refinery emissions between 2050 and 2055.

[59] US EPA, 2023. Illustrative Air Quality Analysis for the Light and Medium Duty Vehicle Multipollutant Proposed Rule - Technical Support Document (TSD). April 2023, EPA-420-D-23-002.

[60] An error was made in the NPRM analysis and the AEO 2021 reference case and AEO 2021 low economic growth case comparison was done for 2030-2050 instead of 2027-2050. It should have started in 2027 as that is the first year that the rule is implemented. The impact of the error means that the reduced domestic demand should have been multiplied by 7% instead of 8%. The impact of this error was small enough that it did not change the adjustment factor that was calculated for crude production wells and pipeline pumps.

5.3.2 Policy Scenario and Associated Natural Gas Demand

The reference case natural gas production well and pipeline inventories needed to be adjusted to reflect the impact of the LMDV policy scenario, which will increase the domestic demand for electricity, leading to more demand for natural gas.[61] Natural gas use projections (trillion cubic feet) from IPM are presented in Table 5-13, and AEO 2023 reference case projections of the amount of produced natural gas going to EGUs are presented in Table 5-14.

Table 5-13 IPM projections of Natural Gas Usage, trillion cubic feet, in 2050

	Natural Gas Usage (Tcf)
Reference Case	6.10
LMDV Policy Case	6.50

Table 5-14 Projections of Natural Gas, in trillion cubic feet, in 2050 Reference Case, from AEO 2023 Table 13

	Natural Gas (Tcf)
Total Dry Gas Production	42.07
Consumption of Natural Gas by EGUs	7.74

5.3.3 Generation of Natural Gas Production Well and Pipeline Adjustment Factors

Based on the increased natural gas usage by EGUs indicated in Table 5-13, the LMDV policy case has 6.6% more natural gas usage than the reference case. The AEO projections from Table 5-14 indicate that 18% of the natural gas projected to be produced domestically in 2050 goes towards EGUs. The growth factor applied to the reference case natural gas well site and pipeline pump emission inventories to get the policy scenario natural gas well and pipeline pump emission inventories was 1.01, see Equation 2.

Equation 2

$$\text{Growth factor} = (1-0.18) + (0.18*1.07)$$

5.3.4 Limitations of Modeling Impacts on Natural Gas Production Wells and Pipeline Pumps

Because we are unable to predict the potential impact that this rule will have on individual production wells, we have used an adjustment factor method that applies the projected impact of increased demand evenly across all relevant production sites and pipeline pumps, as a scalar of emissions.

[61] The calculations are provided on docketed spreadsheet “LMDV FRM AQM petroleum adjustment factors.xlsx”.

6 Inventory Summary Tables

This section includes summary tables of emission inventories used in the AQM analysis and described in this document.

Table 6-1 Modeled $PM_{2.5}$, NO_X, SO_2, and VOC Annual Emissions Used in AQ Modeling (short tons)

Pollutant	Sector	2016 Base Year	2055 Cases Reference	2055 Cases Regulatory	Regulatory Impact[b]
$PM_{2.5}$	Onroad Total[a]	114,519	34,667	26,342	-8,326
	Upstream Total[a]	167,795	64,115	62,722	-1,393
	EGU	133,570	26,420	27,459	1,039
	Refinery	19,958	18,867	16,399	-2,467
	Crude Production Wells + Pipeline Pumps	3,393	5,102	5,000	-102
	Natural Gas Production Wells + Pipeline Pumps	10,875	13,726	13,863	137
$PM_{2.5}$	Total	282,315	98,782	89,063	-9,719
NOx	Onroad Total[a]	3,722,735	403,861	319,169	-84,692
	Upstream Total[a]	2,067,563	814,881	805,238	-9,643
	EGU	1,319,734	95,934	97,539	1,605
	Refinery	78,332	80,188	69,720	-10,468
	Crude Production Wells + Pipeline Pumps	161,605	238,895	234,117	-4,778
	Natural Gas Production Wells + Pipeline Pumps	507,891	399,863	403,862	3,999
NOx	Total	5,790,298	1,218,742	1,124,407	-94,335
SO_2	Onroad Total[a]	25,009	6,458	4,124	-2,334
	Upstream Total[a]	1,637,501	142,170	139,241	-2,929
	EGU	1,565,675	17,117	19,063	1,946
	Refinery	30,065	25,846	22,779	-3,067
	Crude Production Wells + Pipeline Pumps	37,095	93,330	91,464	-1,867
	Natural Gas Production Wells + Pipeline Pumps	4,665	5,876	5,935	59
SO_2	Total	1,662,510	148,628	143,365	-5,263
VOC	Onroad Total[a]	1,380,318	502,643	337,484	-165,159
	Upstream Total[a]	2,415,830	2,852,174	2,823,145	-29,029
	EGU	33,763	17,023	17,490	467
	Refinery	67,853	62,842	55,637	-7,205
	Crude Production Wells + Pipeline Pumps	1,229,169	1,667,134	1,633,791	-33,343
	Natural Gas Production Wells + Pipeline Pumps	1,085,046	1,105,175	1,116,227	11,052
VOC	Total	3,796,149	3,354,817	3,160,629	-194,188

[a]Sectors are for the 48 contiguous United States
[b]Calculated as the difference between the 2055 Reference Case and the 2055 Regulatory Case emissions values

Table 6-2 Modeled 48-state Onroad Emissions (short tons)

Pollutant	2016 Base Year	2055 Cases		2016 Base vs. 2055 Reference		Reference vs. Regulatory	
		Reference	Regulatory	Difference	% Change	Difference	% Change
$PM_{2.5}$	114,519	34,667	26,342	79,852	70%	8,326	24%
NO_X	3,722,735	403,861	319,169	3,318,874	89%	84,692	21%
SO_2	25,009	6,458	4,124	18,551	74%	2,334	36%
VOC	1,380,318	502,643	337,484	877,675	64%	165,159	33%
CO	19,218,852	5,035,912	3,248,848	14,182,940	74%	1,787,063	35%
Acrolein	1,480	205	120	1,275	86%	85	41%
Acetaldehyde	13,989	3,285	2,043	10,704	77%	1,242	38%
Benzene	26,255	7,722	4,574	18,533	71%	3,148	41%
1,3-Butadiene	3,694	852	459	2,842	77%	393	46%
Ethylbenzene	20,312	8,046	5,365	12,265	60%	2,682	33%
Formaldehyde	19,539	2,420	1,628	17,120	88%	791	33%
Naphthalene	2,527	316	184	2,210	87%	133	42%

Table 6-3 Modeled 48-state Nonroad Emissions (short tons)

Pollutant	Year	
	2016	2055
$PM_{2.5}$	106,184	55,891
NO_X	1,108,985	667,652
SO_2	1,451	1,248
VOC	1,155,551	954,103
CO	11,257,608	15,083,974
Acrolein	2,067	590
Acetaldehyde	11,099	5,481
Benzene	28,803	28,095
1,3-Butadiene	4,547	4,838
Ethylbenzene	20,239	17,065
Formaldehyde	28,249	13,210
Naphthalene	1,928	1,399

Table 6-4 Modeled 48-state Fugitive Dust Emissions (short tons)

	Year	
Pollutant	2016	2055
$PM_{2.5}$	880,002	921,877

7 Air Quality Modeling Methodology

7.1 Air Quality Model – CMAQ

CMAQ is a non-proprietary computer model that simulates the formation and fate of photochemical oxidants, primary and secondary PM concentrations, acid deposition, and air toxics over regional and urban spatial scales for given inputs of meteorological conditions and emissions. CMAQ includes numerous science modules that simulate the emission, production, decay, deposition and transport of organic and inorganic gas-phase and particle pollutants in the atmosphere. The CMAQ model is a well-known and well-respected tool and has been used in numerous national and international applications.[62] The air quality modeling completed for the final rulemaking used the 2016v3 platform with the most recent multi-pollutant CMAQ code available at the time of air quality modeling (CMAQ version 5.4).[63] The 2016 CMAQ runs utilized the CB6r3 chemical mechanism (Carbon Bond with linearized halogen chemistry) for gas-phase chemistry, and AERO7 (aerosol model with non-volatile primary organic aerosol) for aerosols. The CMAQ model is regularly peer-reviewed; CMAQ versions 5.2 and 5.3 beta were most recently peer-reviewed in 2019 for the U.S. EPA.[64]

7.2 CMAQ Domain and Configuration

The CMAQ modeling analyses used a domain covering the continental United States (CONUS) and large portions of Canada and Mexico, as shown in Figure 7-1, using 12 km × 12 km horizontal grid spacing. The 2016 simulation used a Lambert Conformal map projection centered at (-97, 40) with true latitudes at 33 and 45 degrees north. The model extends vertically from the surface to 50 millibars (approximately 17,600 meters) using a sigma-pressure coordinate system with 35 vertical layers. Table 7-1 provides some basic geographic information regarding the CMAQ domains and Table 7-2 provides the vertical layer structure for the CMAQ domain.

Table 7-1 Geographic elements of domains used in air quality modeling

	CMAQ Modeling Configuration
Grid Resolution	12 km National Grid
Map Projection	Lambert Conformal Projection
Coordinate Center	97 deg W, 40 deg N
True Latitudes	33 deg N and 45 deg N
Dimensions	396 × 246 × 35
Vertical extent	35 Layers: Surface to 50 millibar level (See Table 7-2)

[62] More information available at: https://www.epa.gov/cmaq.

[63] Model code for CMAQ v5.4 is available from the Community Modeling and Analysis System (CMAS) at: http://www.cmascenter.org.

[64] The Sixth External Peer Review of the Community Multiscale Air Quality (CMAQ) Modeling System. Available online at: https://www.epa.gov/sites/production/files/2019-08/documents/sixth_cmaq_peer_review_comment_report_6.19.19.pdf.

Table 7-2 Vertical layer structure for CMAQ domain

Vertical Layers	Sigma P	Pressure (mb)	Approximate Height (m)
35	0.0000	50.00	17,556
34	0.0500	97.50	14,780
33	0.1000	145.00	12,822
32	0.1500	192.50	11,282
31	0.2000	240.00	10,002
30	0.2500	287.50	8,901
29	0.3000	335.00	7,932
28	0.3500	382.50	7,064
27	0.4000	430.00	6,275
26	0.4500	477.50	5,553
25	0.5000	525.00	4,885
24	0.5500	572.50	4,264
23	0.6000	620.00	3,683
22	0.6500	667.50	3,136
21	0.7000	715.00	2,619
20	0.7400	753.00	2,226
19	0.7700	781.50	1,941
18	0.8000	810.00	1,665
17	0.8200	829.00	1,485
16	0.8400	848.00	1,308
15	0.8600	867.00	1,134
14	0.8800	886.00	964
13	0.9000	905.00	797
12	0.9100	914.50	714
11	0.9200	924.00	632
10	0.9300	933.50	551
9	0.9400	943.00	470
8	0.9500	952.50	390
7	0.9600	962.00	311
6	0.9700	971.50	232
5	0.9800	981.00	154
4	0.9850	985.75	115
3	0.9900	990.50	77
2	0.9950	995.25	38
1	0.9975	997.63	19
0	1.0000	1000.00	0

Figure 7-1 Map of the CMAQ 12 km modeling domain (noted by the purple box)

7.3 CMAQ Inputs

The key inputs to the CMAQ model include emissions from anthropogenic and biogenic sources, meteorological data, and initial and boundary conditions.

The emissions inputs are summarized in earlier sections of this document.

The CMAQ meteorological input files were derived from simulations of the Weather Research and Forecasting Model (WRF) version 3.8 for the entire 2016 year.[65,66] The WRF

[65] Skamarock, W.C., et al. (2008) A Description of the Advanced Research WRF Version 3. https://opensky.ucar.edu/islandora/object/technotes:500.

[66] USEPA (2019). Meteorological Model Performance for Annual 2016 Simulation WRF v3.8 https://nepis.epa.gov/Exe/ZyPDF.cgi/P100YD39.PDF?Dockey=P100YD39.PDF.

Model is a state-of-the-science mesoscale numerical weather prediction system developed for both operational forecasting and atmospheric research applications.[67] The meteorological outputs from WRF were processed to create 12 km model-ready inputs for CMAQ using the Meteorology-Chemistry Interface Processor (MCIP) version 4.3. These inputs included hourly varying horizontal wind components (i.e., speed and direction), temperature, moisture, vertical diffusion rates, and rainfall rates for each grid cell in each vertical layer.[68]

The boundary and initial species concentrations were provided by a northern hemispheric CMAQ modeling platform for the year 2016.[69,70] The hemispheric-scale platform uses a polar stereographic projection at 108 km resolution to completely and continuously cover the northern hemisphere for 2016. Meteorology is provided by WRF v3.8. Details on the emissions used for hemispheric CMAQ can be found in the 2016 hemispheric emissions modeling platform TSD.[71] The atmospheric processing (transformation and fate) was simulated by CMAQ (v5.2.1) using the CB6r3 and the aerosol model with non-volatile primary organic carbon (AE6nvPOA). The CMAQ model also included the on-line windblown dust emission sources (excluding agricultural land), which are not always included in the regional platform but are important for large-scale transport of dust.

7.4 CMAQ Model Performance Evaluation

An operational model performance evaluation for ozone, $PM_{2.5}$ and its related speciated components, specific air toxics (i.e., formaldehyde, acetaldehyde, and benzene), as well as nitrate and sulfate deposition were conducted using 2016 state/local monitoring sites data in order to estimate the ability of the CMAQ modeling system to replicate the base year concentrations for the 12 km CONUS domain (Section 7.2, Figure 7-1). Included in this evaluation are statistical measures of model versus observed data that were paired in space and time on a daily or weekly basis, depending on the sampling frequency of each network (i.e., measured data). For certain time periods with missing ozone, $PM_{2.5}$, air toxic, and nitrate and sulfate deposition observations we excluded the CMAQ predictions from those time periods in our calculations. It should be noted when pairing model and observed data that each CMAQ concentration represents a grid-cell volume-averaged value, while the ambient network measurements are made at specific locations.

Model performance statistics were calculated for several spatial scales and temporal periods (statistics are defined in Section 7.4.2). Statistics were calculated for individual monitoring sites and for each of the nine National Oceanic and Atmospheric Administration (NOAA) climate

[67] https://www.mmm.ucar.edu/models/wrf.

[68] Byun, D.W., Ching, J. K.S. (1999). Science algorithms of EPA Models-3 Community Multiscale Air Quality (CMAQ) modeling system, EPA/600/R-99/030, Office of Research and Development. Please also see: https://www.cmascenter.org/.

[69] Henderson, B., et al. (2018) Hemispheric-CMAQ Application and Evaluation for 2016, Presented at 2019 CMAS Conference, available https://cmascenter.org/conference//2018/slides/0850_henderson_hemispheric-cmaq_application_2018.pptx.

[70] Mathur, R., et al. (2017) Extending the Community Multiscale Air Quality (CMAQ) modeling system to hemispheric scales: overview of process considerations and initial applications, Atmos. Chem. Phys., 17, 12449-12474, https://doi.org/10.5194/acp-17-12449-2017.

[71] USEPA (2019). Technical Support Document: Preparation of Emissions Inventories for the Version 7.1 2016 Hemispheric Emissions Modeling Platform. Office of Air Quality Planning and Standards.

regions of the 12-km U.S. modeling domain (Figure 7-2).[72] The regions include the Northeast, Ohio Valley, Upper Midwest, Southeast, South, Southwest, Northern Rockies, Northwest and West[73,74] as were originally identified in Karl and Koss (1984).[75] The statistics for each site and climate region were calculated by season ("winter" is defined as average of December, January, and February; "spring" is defined as average of March, April, and May; "summer" is defined as average of June, July, and August; and "fall" is defined as average of September, October, and November). For 8-hour daily maximum ozone, we also calculated performance statistics by region for the April through September ozone season.[76] In addition to the performance statistics, we prepared several graphical presentations of model performance. These graphical presentations include regional maps which show the mean bias, mean error, normalized mean bias and normalized mean error calculated for each season at individual monitoring sites.

[72] NOAA, National Centers for Environmental Information scientists have identified nine climatically consistent regions within the contiguous U.S., http://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php.

[73] The nine climate regions are defined by States where: Northeast includes CT, DE, ME, MA, MD, NH, NJ, NY, PA, RI, and VT; Ohio Valley includes IL, IN, KY, MO, OH, TN, and WV; Upper Midwest includes IA, MI, MN, and WI; Southeast includes AL, FL, GA, NC, SC, and VA; South includes AR, KS, LA, MS, OK, and TX; Southwest includes AZ, CO, NM, and UT; Northern Rockies includes MT, NE, ND, SD, WY; Northwest includes ID, OR, and WA; and West includes CA and NV.

[74] Note most monitoring sites in the West region are located in California (see Figure 7-2), therefore statistics for the West will be mostly representative of California ozone air quality.

[75] Karl, T. R. and Koss, W. J., 1984: "Regional and National Monthly, Seasonal, and Annual Temperature Weighted by Area, 1895-1983." Historical Climatology Series 4-3, National Climatic Data Center, Asheville, NC, 38 pp.

[76] In calculating the ozone season statistics, we limited the data to those observed and predicted pairs with observations that exceeded 60 ppb in order to focus on concentrations at the upper portion of the distribution of values.

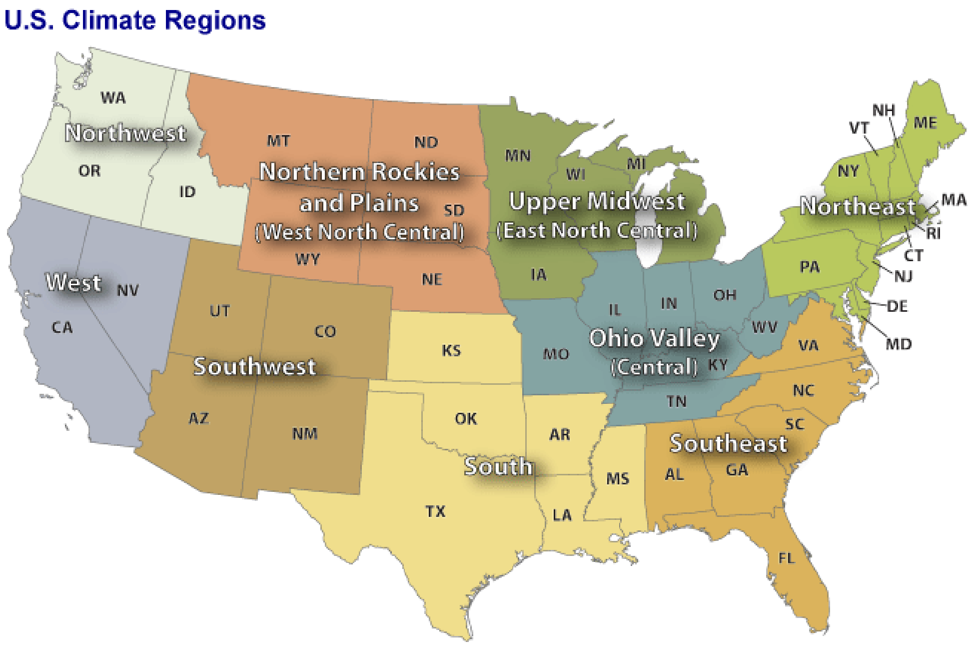

Figure 7-2 NOAA Nine Climate Regions (source: http://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php#references)

7.4.1 Monitoring Networks

The model evaluation for ozone was based upon comparisons of model predicted 8-hour daily maximum concentrations to the corresponding ambient measurements for 2016 at monitoring sites in the EPA Air Quality System (AQS) and the Clean Air Status and Trends Network (CASTNet). The observed ozone data were measured and reported on an hourly basis. The $PM_{2.5}$ evaluation focuses on concentrations of $PM_{2.5}$ total mass and its components including sulfate (SO_4), nitrate (NO_3), total nitrate (TNO_3), ammonium (NH_4), elemental carbon (EC), and organic carbon (OC) as well as wet deposition for nitrate and sulfate. The $PM_{2.5}$ performance statistics were calculated for each season (e.g., “winter” is defined as December, January, and February). $PM_{2.5}$ ambient measurements for 2016 were obtained from the following networks: Chemical Speciation Network (CSN), Interagency Monitoring of PROtected Visual Environments (IMPROVE), Clean Air Status and Trends Network (CASTNet), and National Acid Deposition Program/National Trends (NADP/NTN). NADP/NTN collects and reports wet deposition measurements as weekly average data. The pollutant species included in the evaluation for each monitoring network are listed in Table 7-3. For $PM_{2.5}$ species that are measured by more than one network, we calculated separate sets of statistics for each network. The CSN and IMPROVE networks provide 24-hour average concentrations on a 1 in every 3-day, or 1 in every 6-day sampling cycle. The $PM_{2.5}$ species data at CASTNet sites are weekly integrated samples. In this analysis we use the term “urban sites” to refer to CSN sites; “suburban/rural sites” to refer to CASTNet sites; and “rural sites” to refer to IMPROVE sites.

Table 7-3 $PM_{2.5}$ monitoring networks and pollutants species included in the CMAQ performance evaluation

Ambient Monitoring Networks	Particulate Species							Wet Deposition Species	
	$PM_{2.5}$ Mass	SO_4	NO_3	TNO_3[a]	EC	OC	NH_4	SO_4	NO_3
IMPROVE	X	X	X		X	X			
CASTNet		X		X			X		
CSN	X	X	X		X	X	X		
NADP								X	X

[a] $TNO_3 = (NO_3 + HNO_3)$

The air toxics evaluation focuses on specific species relevant to this rulemaking, i.e., formaldehyde, acetaldehyde, and benzene. Similar to the $PM_{2.5}$ evaluation, the air toxics performance statistics were calculated for each season to estimate the ability of the CMAQ modeling system to replicate the base year concentrations for the 12 km continental U.S. domain. Toxic measurements for 2016 were obtained from the air toxics archive, https://www.epa.gov/amtic/amtic-air-toxics-data-ambient-monitoring-archive. While most of the data in the archive are from the AQS database including the National Air Toxics Trends Stations (NATTS), additional data (e.g., special studies) are included in the archive but not reported in the AQS.

7.4.2 Model Performance Statistics

The Atmospheric Model Evaluation Tool (AMET) was used to conduct the evaluation described in this document.[77] There are various statistical metrics available and used by the science community for model performance evaluation. For this evaluation of the 2016 CMAQ modeling platform, we have selected the mean bias, mean error, normalized mean bias, and normalized mean error to characterize model performance, which are consistent with the recommendations in Simon et al. (2012)[78] and the photochemical air quality modeling guidance.[79]

Mean bias (MB) is the average difference in the predicted and observed values, calculated as the sum of the difference (predicted-observed) divided by the total number of replicates (n). MB is given in units of ppb and is defined as:

[77] Appel, K.W., Gilliam, R.C., Davis, N., Zubrow, A., and Howard, S.C.: Overview of the Atmospheric Model Evaluation Tool (AMET) v1.1 for evaluating meteorological and air quality models, *Environ. Modell. Softw.*,26, 4, 434-443, 2011. (http://www.cmascenter.org/).

[78] Simon, H., Baker, K., Phillips, S., 2012: Compilation and interpretation of photochemical model performance statistics published between 2006 and 2012. Atmospheric Environment 61, 124-139.

[79] U.S. Environmental Protection Agency (US EPA), Modeling Guidance for Demonstrating Attainment of Air Quality Goals for Ozone, $PM_{2.5}$, and Regional Haze. November 2018, U.S. EPA, Research Triangle Park, NC, 27711, 454/R-18-009, 205pp. https://www.epa.gov/sites/default/files/2020-10/documents/o3-pm-rh-modeling_guidance-2018.pdf.

$$\text{MB} = \frac{1}{n}\sum_{1}^{n}(P - O)$$, where P = predicted and O = observed concentrations

Mean error (ME) calculates the absolute value of the difference (predicted – observed) divided by the total number of replicates (*n*). ME is given in units of ppb and is defined as:

$$\text{ME} = \frac{1}{n}\sum_{1}^{n}|P - O|$$

Normalized mean bias (NMB) is used to facilitate a range of concentration magnitudes. This statistic normalizes the difference (predicted – observed) by the sum of observed values. NMB is a useful model performance indicator because it avoids over-inflating the observed range of values, especially at low concentrations. NMB is given in percentage units and is defined as:

$$\text{NMB} = \frac{\sum_{1}^{n}(P - O)}{\sum_{1}^{n}(O)} * 100$$

Normalized mean error (NME) is similar to NMB, in that the performance statistic is a normalization of the mean error. NME is calculated as the absolute value of the difference (predicted – observed) over the sum of observed values. NME is given in percentage units and is defined as:

$$\text{NME} = \frac{\sum_{1}^{n}|P - O|}{\sum_{1}^{n}(O)} * 100$$

The "acceptability" of model performance was judged by comparing our CMAQ 2016 performance results to the range of performance found in recent regional ozone and $PM_{2.5}$ model applications.[80,81,82,83,84,85,86,87,88,89] These other modeling studies represent a wide range of modeling analyses that cover various models, model configurations, domains, years and/or episodes, chemical mechanisms, and aerosol modules. Overall, the ozone and $PM_{2.5}$ model performance results for the 2016 CMAQ simulations are within the range found in other recent peer-reviewed and regulatory applications. The model performance results, as described in this document, demonstrate that our applications of CMAQ using this 2016 modeling platform provide a scientifically credible approach for assessing ozone and $PM_{2.5}$ concentrations for the purposes of this final rulemaking.

7.4.3 Evaluation for 8-hour Daily Maximum Ozone

The 8-hour ozone model performance bias and error statistics for each climate region, for each season defined above, and for each monitor network (AQS and CASTNet) are provided in Table 7-4. As indicated by the statistics in Table 7-4, bias and error for 8-hour daily maximum ozone are low in each climate region. Spatial plots of the MB, ME, NMB, and NME for individual monitors are shown in Figure 7-3 through Figure 7-6. The statistics shown in these figures were calculated over the ozone season using paired data on days with observed 8-hour ozone $\geq$ 60 ppb. Figure 7-3 shows MB for 8-hour ozone $\geq$ 60 ppb during the ozone season in the range of ±15 ppb at the majority of ozone AQS and CASTNet measurement sites. At both AQS and CASTNet sites, NMB is within the range of ±20 percent (Figure 7-5). ME for 8-hour

[80] National Research Council (NRC), 2002. Estimating the Public Health Benefits of Proposed Air Pollution Regulations, Washington, DC: National Academies Press.

[81] Appel, K.W., Roselle, S.J., Gilliam, R.C., and Pleim, J.E, 2010: Sensitivity of the Community Multiscale Air Quality (CMAQ) model v4.7 results for the eastern United States to MM5 and WRF meteorological drivers. Geoscientific Model Development, 3, 169-188.

[82] Foley, K.M., Roselle, S.J., Appel, K.W., Bhave, P.V., Pleim, J.E., Otte, T.L., Mathur, R., Sarwar, G., Young, J.O., Gilliam, R.C., Nolte, C.G., Kelly, J.T., Gilliland, A.B., and Bash, J.O., 2010: Incremental testing of the Community multiscale air quality (CMAQ) modeling system version 4.7. Geoscientific Model Development, 3, 205-226.

[83] Hogrefe, G., Civeroio, K.L., Hao, W., Ku, J-Y., Zalewsky, E.E., and Sistla, G., Rethinking the Assessment of Photochemical Modeling Systems in Air Quality Planning Applications. Air & Waste Management Assoc., 58:1086-1099, 2008.

[84] Phillips, S., K. Wang, C. Jang, N. Possiel, M. Strum, T. Fox, 2007. Evaluation of 2002 Multi-pollutant Platform: Air Toxics, Ozone, and Particulate Matter, 7th Annual CMAS Conference, Chapel Hill, NC, October 6-8, 2008. (http://www.cmascenter.org/conference/2008/agenda.cfm).

[85] Simon, H., Baker, K.R., and Phillips, S., 2012. Compilation and interpretation of photochemical model performance statistics published between 2006 and 2012. Atmospheric Environment 61, 124-139. http://dx.doi.org/10.1016/j.atmosenv.2012.07.012.

[86] Tesche, T.W., Morris, R., Tonnesen, G., McNally, D., Boylan, J., Brewer, P., 2006. CMAQ/CAMx annual 2002 performance evaluation over the eastern United States. Atmospheric Environment 40, 4906-4919.

[87] U.S. Environmental Protection Agency; Technical Support Document for the Final Clean Air Interstate Rule: Air Quality Modeling; Office of Air Quality Planning and Standards; RTP, NC; March 2005 (CAIR Docket OAR-2005-0053-2149).

[88] U.S. Environmental Protection Agency, Proposal to Designate an Emissions Control Area for Nitrogen Oxides, Shttps://19january2017snapshot.epa.gov/sites/production/files/2016-09/documents/420r09007.pdfent. EPA-420-R-007, 329pp., 2009. (https://nepis.epa.gov/Exe/ZyPDF.cgi/P1003E8M.PDF?Dockey=P1003E8M.PDF).

[89] U.S. Environmental Protection Agency, 2010, Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis. EPA-420-R-10-006. February 2010. Sections 3.4.2.1.2 and 3.4.3.3. Docket EPA-HQ-OAR-2009-0472-11332.

maximum ozone ≥ 60 ppb, as seen in Figure 7-4, is 20 ppb or less at most of the sites across the modeling domain.

Table 7-4 Daily Maximum 8-hour Ozone Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Monitor Network	Season	No. of Obs	MB (ppb)	ME (ppb)	NMB (%)	NME (%)
Northeast	AQS	Winter	11,462	-2.4	4.7	-7.3	14.4
		Spring	15,692	-5.8	7.2	-13.1	16.3
		Summer	16,686	1.4	6.3	3.2	13.9
		Fall	13,780	0.8	4.9	2.4	14.1
	CASTNet	Winter	1,238	-3.1	4.7	-8.9	13.6
		Spring	1,336	-6.4	7.4	-14.2	16.5
		Summer	1,315	0.7	5.8	1.7	13.6
		Fall	1,306	0.9	4.8	2.7	14.2
Ohio Valley	AQS	Winter	4,178	-0.6	4.4	-1.9	14.5
		Spring	15,498	-3.3	5.9	-7.2	12.9
		Summer	20,495	3.7	7.0	8.1	15.4
		Fall	14,025	2.1	5.7	5.4	13.1
	CASTNet	Winter	1,574	-1.1	4.3	-3.4	13.2
		Spring	1,600	-4.0	6.1	-8.7	13.1
		Summer	1,551	2.9	6.4	6.4	14.6
		Fall	1,528	-0.2	4.9	-0.4	12.3
Upper Midwest	AQS	Winter	1,719	-1.1	4.5	-3.6	14.4
		Spring	6,892	-6.0	7.4	-13.3	16.6
		Summer	9,742	0.5	5.8	1.2	13.8
		Fall	6,050	2.4	4.6	7.5	14.6
	CASTNet	Winter	435	-2.2	4.5	-6.7	13.4
		Spring	434	-7.5	8.2	-16.7	18.2
		Summer	412	-4.6	5.2	-3.8	12.5
		Fall	426	0.2	4.3	0.6	13.7
Southeast	AQS	Winter	7,128	-3.4	5.2	-9.5	14.5
		Spring	14,569	-3.9	6.0	-8.5	12.9

Climate Region	Monitor Network	Season	No. of Obs	MB (ppb)	ME (ppb)	NMB (%)	NME (%)
		Summer	15,845	3.1	5.9	7.9	15.0
		Fall	12,583	0.6	4.9	1.6	12.0
	CASTNet	Winter	887	-3.9	5.2	-10.4	14.0
		Spring	947	-5.6	6.8	-11.7	14.3
		Summer	926	2.5	5.8	6.4	14.8
		Fall	928	-0.9	5.3	-2.1	12.9
South	AQS	Winter	11,432	-3.1	5.5	-9.2	16.4
		Spring	13,093	-2.7	6.6	-6.3	15.0
		Summer	12,829	1.7	6.3	4.3	16.4
		Fall	12,443	-0.3	5.1	-0.7	13.0
	CASTNet	Winter	523	-3.3	5.2	-9.2	14.3
		Spring	532	-3.8	6.7	-8.5	14.7
		Summer	508	0.3	7.2	0.7	18.5
		Fall	528	-0.2	4.7	-0.6	12.1
Southwest	AQS	Winter	9,990	-4.6	6.4	-11.8	16.3
		Spring	11,381	-7.7	8.5	-15.1	16.5
		Summer	12,027	-6.7	8.2	-12.4	15.3
		Fall	11,097	-2.3	4.7	-5.7	11.4
	CASTNet	Winter	757	-6.8	7.1	-15.1	15.9
		Spring	810	-8.2	8.6	-15.5	16.3
		Summer	812	-5.7	6.9	-10.6	12.9
		Fall	791	-2.8	4.2	-6.4	9.6
Northern Rockies	AQS	Winter	4,719	-2.8	5.0	13.5	-9.5
		Spring	4,975	-5.3	6.5	-12.2	14.9
		Summer	5,054	-2.6	5.3	-5.6	11.4
		Fall	4,876	0.1	4.4	0.2	13.0
	CASTNet	Winter	666	-3.8	6.1	-9.6	15.6
		Spring	696	-7.0	7.7	-15.1	16.5
		Summer	693	-3.9	5.6	-8.1	11.6

Climate Region	Monitor Network	Season	No. of Obs	MB (ppb)	ME (ppb)	NMB (%)	NME (%)
		Fall	605	-1.2	4.9	-3.1	13.1
Northwest	AQS	Winter	677	-3.3	6.0	-10.2	18.6
		Spring	1,288	-6.7	8.2	-16.5	20.4
		Summer	2,444	-1.8	6.2	-4.7	16.5
		Fall	1,236	0.6	5.2	2.0	16.5
	CASTNet	Winter	30	-3.8	5.0	-10.3	13.5
		Spring	-	-	-	-	-
		Summer	-	-	-	-	-
		Fall	63	-1.3	4.4	-4.2	14.0
West	AQS	Winter	14,539	-4.3	6.3	-12.5	18.3
		Spring	17,191	-7.7	8.4	-16.8	18.3
		Summer	18,132	-7.3	9.6	-13.7	18.0
		Fall	16,211	-4.9	7.1	-11.3	16.5
	CASTNet	Winter	506	-3.6	5.3	-9.2	13.5
		Spring	519	-7.6	8.0	-15.8	16.6
		Summer	526	-10.2	11.0	-16.8	18.2
		Fall	530	-5.1	6.3	-10.8	13.5

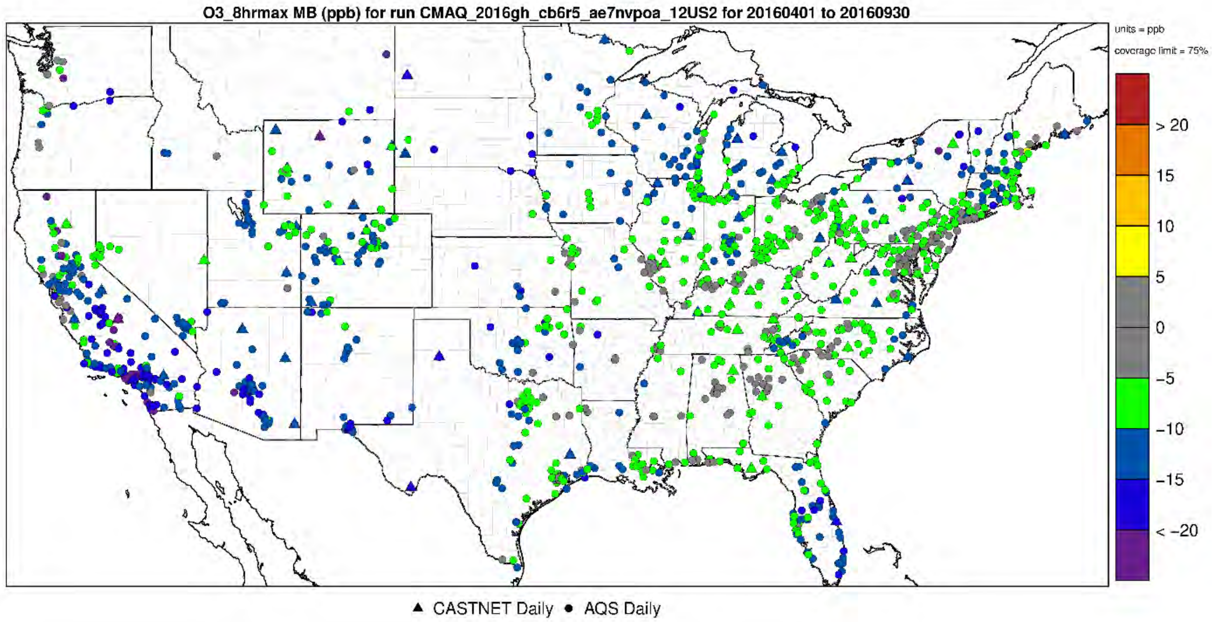

Figure 7-3 Mean Bias (ppb) of 8-hour daily maximum ozone greater than 60 ppb over the period April-September 2016 at AQS and CASTNet monitoring sites in the modeling domain

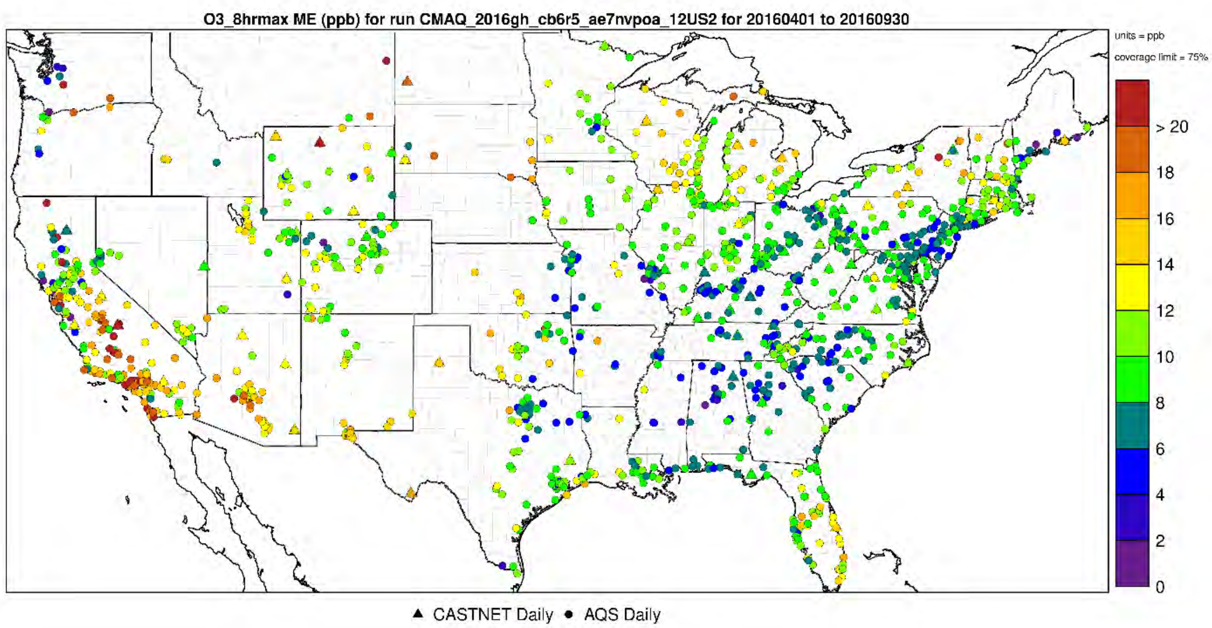

Figure 7-4 Mean Error (ppb) of 8-hour daily maximum ozone greater than 60 ppb over the period April-September 2016 at AQS and CASTNet monitoring sites in the modeling domain

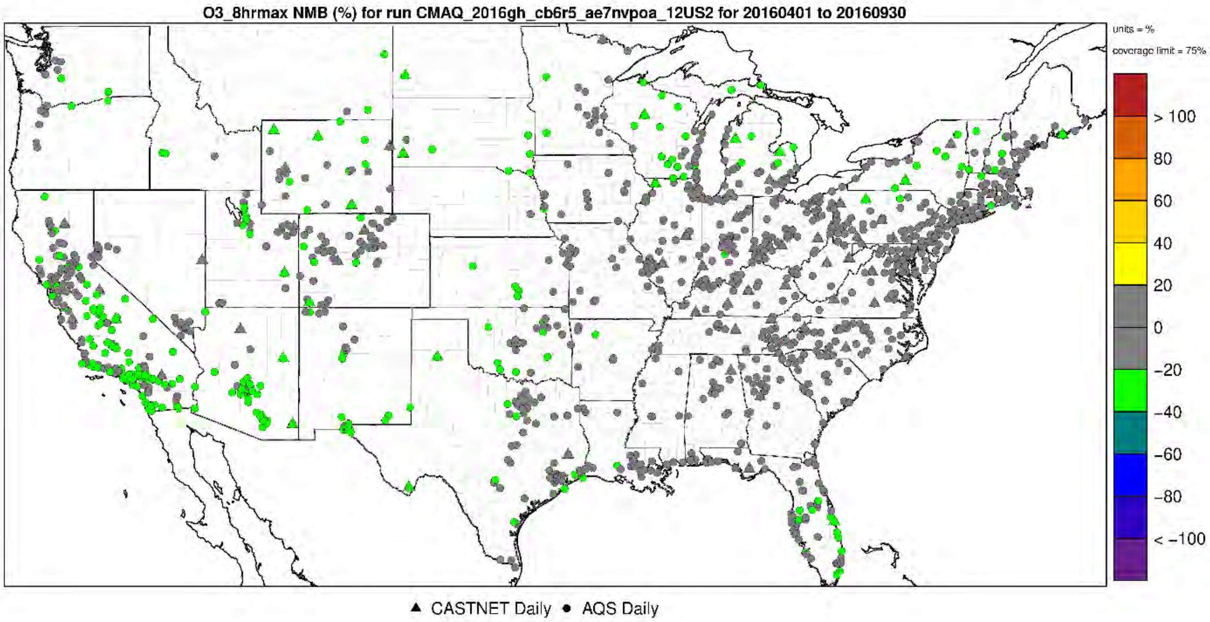

Figure 7-5 Normalized Mean Bias (%) of 8-hour daily maximum ozone greater than 60 ppb over the period April-September AQS and CASTNet 2016 at monitoring sites in the modeling domain

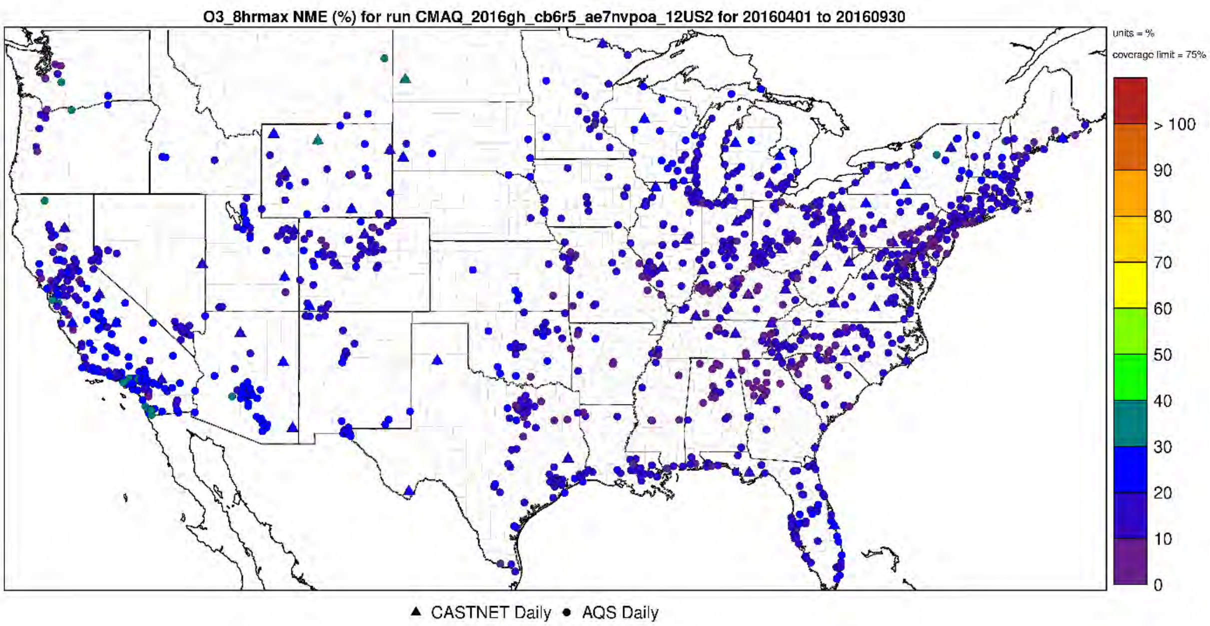

Figure 7-6 Normalized Mean Error (%) of 8-hour daily maximum ozone greater than 60 ppb over the period April-September AQS and CASTNet 2016 at monitoring sites in the modeling domain

7.4.4 Seasonal Evaluation of $PM_{2.5}$ Component Species

The evaluation of 2016 model predictions for $PM_{2.5}$ covers the performance for the individual $PM_{2.5}$ component species (i.e., sulfate, nitrate, organic carbon, elemental carbon, and ammonium). Performance results are provided for each $PM_{2.5}$ species. As indicated above, for each species we present tabular summaries of bias and error statistics by climate region for each season. These statistics are based on the set of observed-predicted pairs of data for the particular season at monitoring sites within the nine NOAA climate regions. Separate statistics are provided for each monitoring network, as applicable for the particular species measured. For sulfate and nitrate we also provide a more refined temporal and spatial analysis of model performance that includes spatial maps that show the MB, ME, NMB, and NME =by site, aggregated by season.

7.4.4.1 Seasonal Evaluation for Sulfate

The model performance bias and error statistics for sulfate for each climate region and each season by monitor network are provided in Table 7-5. Spatial plots of the NMB and NME by season for individual monitors are shown in Figure 7-7 through Figure 7-22.

Table 7-5 Sulfate Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	IMPROVE	Winter	431	-0.1	0.2	-18.1	32.6
		Spring	477	-0.1	0.2	-19.1	28.7
		Summer	486	-0.2	0.3	-29.7	38.6
		Fall	456	-0.1	0.2	-17.9	34.2
	CSN	Winter	716	-0.1	0.4	-6.5	40.3
		Spring	768	-0.0	0.3	-5.2	35.2
		Summer	782	-0.3	0.4	-29.5	36.4
		Fall	736	-0.0	0.3	-3.3	37.9
	CASTNet	Winter	221	-0.3	0.3	-33.2	33.5
		Spring	242	-0.3	0.3	-32.9	33.4
		Summer	252	-0.4	0.4	-41.4	41.7
		Fall	242	-0.3	0.3	-32.6	33.3
Ohio Valley	IMPROVE	Winter	220	-0.3	0.4	-25.2	35.3
		Spring	244	-0.4	0.4	38.2	-28.8
		Summer	239	-0.6	0.7	-38.4	44.3
		Fall	227	-0.4	0.5	-31.5	35.9

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
	CSN	Winter	546	-0.3	0.5	-20.1	36.1
		Spring	562	-0.1	0.4	34.6	-4.9
		Summer	553	-0.3	0.6	-20.8	36.3
		Fall	541	-0.1	0.4	-11.5	32.2
	CASTNet	Winter	212	-0.5	0.5	-36.4	36.9
		Spring	228	-0.5	0.5	-37.7	38.2
		Summer	224	-0.7	0.7	-41.5	41.5
		Fall	226	-0.5	0.5	-36.8	36.8
Upper Midwest	IMPROVE	Winter	200	-0.1	0.2	-14.2	30.4
		Spring	208	-0.1	0.2	-12.4	31.6
		Summer	210	-0.2	0.3	-31.7	39.5
		Fall	215	-0.1	0.2	-18.7	36.9
	CSN	Winter	326	0.0	0.3	4.2	34.6
		Spring	354	0.1	0.3	12.8	36.9
		Summer	314	-0.1	0.4	-7.0	36.8
		Fall	310	0.1	0.3	18.0	42.8
	CASTNet	Winter	59	-0.3	0.3	-31.1	31.6
		Spring	63	-0.2	0.2	-21.3	22.3
		Summer	63	-0.3	0.3	-31.7	31.9
		Fall	57	-0.2	0.2	-30.0	30.6
Southeast	IMPROVE	Winter	342	-0.2	0.4	-20.1	37.3
		Spring	379	-0.4	0.5	-34.9	37.7
		Summer	394	-0.6	0.6	-47.0	48.2
		Fall	366	-0.3	0.3	-28.3	32.9
	CSN	Winter	512	-0.0	0.3	-2.5	35.9
		Spring	551	-0.2	0.4	-20.2	31.5
		Summer	523	-0.4	0.4	-34.7	39.4
		Fall	505	-0.1	0.3	-13.6	27.2
	CASTNet	Winter	150	-0.4	0.4	-37.2	38.2

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Spring	164	-0.6	0.6	-45.6	45.7
		Summer	164	-0.7	0.7	-53.5	53.5
		Fall	154	-0.5	0.5	-40.3	40.3
South	IMPROVE	Winter	240	-0.0	0.2	-6.3	32.1
		Spring	273	-0.3	0.4	-28.9	41.5
		Summer	252	-0.8	0.8	-52.3	54.2
		Fall	264	-0.3	0.4	-29.4	37.2
	CSN	Winter	326	-0.1	0.5	-5.0	42.5
		Spring	351	-0.5	0.7	-31.4	47.8
		Summer	336	-0.7	0.8	-42.2	49.5
		Fall	329	-0.3	0.5	-21.2	36.6
	CASTNet	Winter	92	-0.4	0.4	-34.1	34.8
		Spring	102	-0.6	0.6	-45.3	45.5
		Summer	96	-1.0	1.0	-56.9	56.9
		Fall	102	-0.5	0.5	-39.6	39.7
Southwest	IMPROVE	Winter	910	0.1	0.2	41.2	70.7
		Spring	991	0.1	0.2	35.6	52.1
		Summer	985	-0.3	0.3	-45.9	52.7
		Fall	962	-0.1	0.2	-24.1	43.7
	CSN	Winter	246	-0.1	0.4	-10.6	69.3
		Spring	255	0.2	0.2	44.6	56.1
		Summer	250	-0.3	0.4	-41.6	50.2
		Fall	260	-0.0	0.2	-8.6	42.4
	CASTNet	Winter	101	-0.1	0.1	24.6	51.2
		Spring	115	0.1	0.1	18.8	29.3
		Summer	114	-0.3	0.3	-44.8	46.5
		Fall	115	-0.1	0.2	-27.2	37.8
Northern Rockies	IMPROVE	Winter	542	0.1	0.2	16.7	57.2
		Spring	573	0.1	0.2	17.6	43.1

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Summer	603	-0.0	0.1	-4.3	36.4
		Fall	574	0.0	0.1	2.8	41.4
	CSN	Winter	139	0.2	0.4	42.0	67.3
		Spring	151	0.1	0.3	26.9	51.6
		Summer	153	0.0	0.2	6.9	42.2
		Fall	136	0.1	0.3	30.5	57.4
	CASTNet	Winter	126	-0.1	0.1	-20.0	37.2
		Spring	139	-0.0	0.1	-1.0	21.5
		Summer	138	-0.1	0.1	-23.7	27.8
		Fall	129	-0.1	0.1	-14.2	27.3
Northwest	IMPROVE	Winter	427	0.1	0.1	50.1	79.5
		Spring	505	0.1	0.2	33.2	50.5
		Summer	519	-0.0	0.2	-5.7	45.3
		Fall	499	0.0	0.1	15.8	59.0
	CSN	Winter	156	0.2	0.3	72.9	>100
		Spring	161	0.3	0.3	64.9	71.3
		Summer	166	0.0	0.3	4.7	46.9
		Fall	161	0.2	0.3	58.4	83.4
	CASTNet	Winter	12	0.0	0.1	22.2	40.8
		Spring	13	0.0	0.1	14.0	21.4
		Summer	13	-0.0	0.0	-8.9	13.4
		Fall	13	-0.0	0.1	-5.0	25.6
West	IMPROVE	Winter	565	0.1	0.2	64.4	97.0
		Spring	608	0.0	0.3	8.1	51.4
		Summer	603	-0.2	0.3	-33.9	47.0
		Fall	576	-0.1	0.2	-13.8	46.1
	CSN	Winter	340	0.1	0.3	18.4	62.3
		Spring	352	-0.1	0.4	-12.6	45.3
		Summer	349	-0.7	0.7	-47.0	51.1

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Fall	330	-0.2	0.4	-25.4	43.7
	CASTNet	Winter	69	0.0	0.2	16.2	58.1
		Spring	73	-0.2	0.3	-25.9	39.1
		Summer	75	-0.5	0.5	-53.3	54.0
		Fall	77	-0.2	0.3	-36.8	43.3

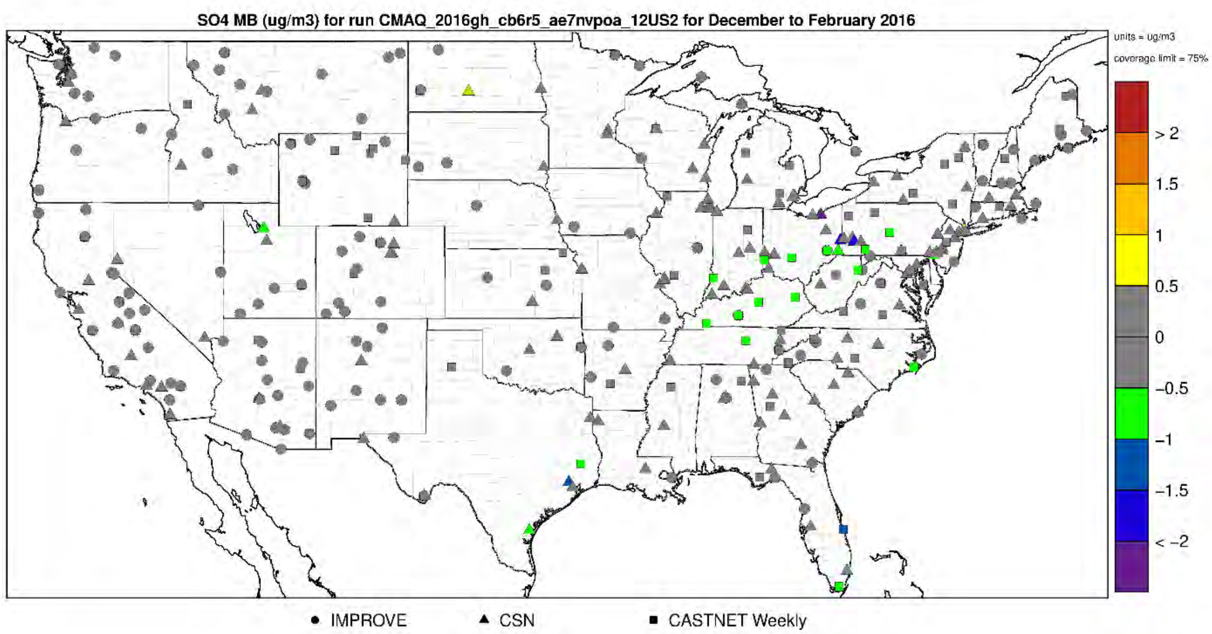

Figure 7-7 Mean Bias (µg/m^3) of sulfate during winter 2016 at monitoring sites in the modeling domain

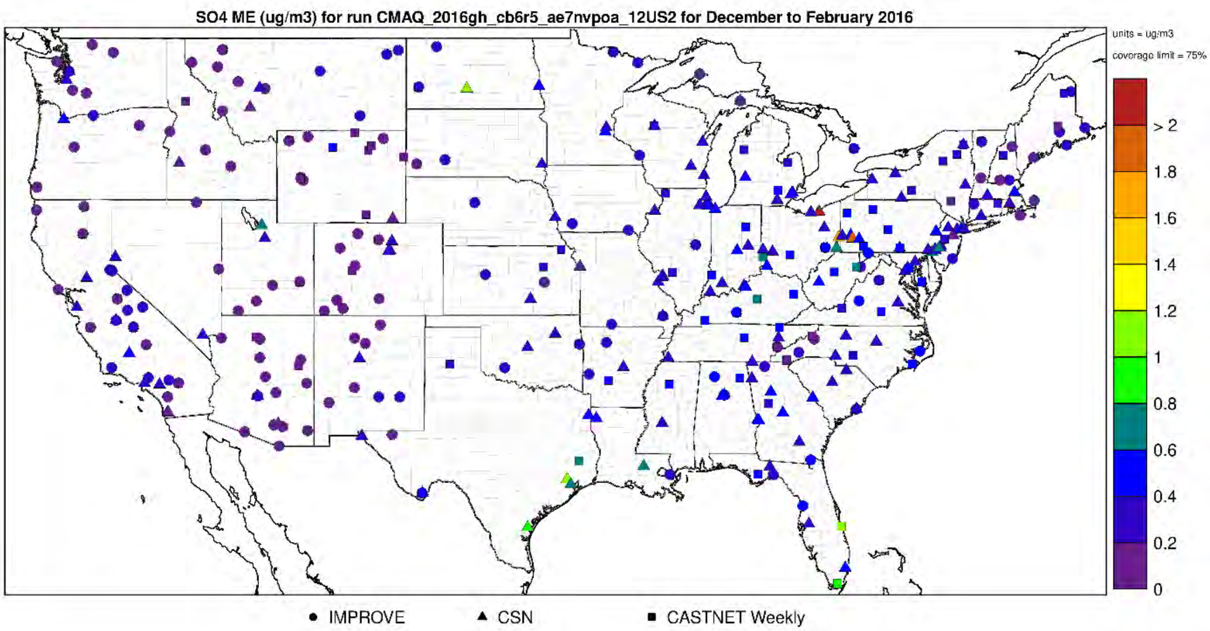

Figure 7-8 Mean Error (µg/m^3) of sulfate during winter 2016 at monitoring sites in the modeling domain

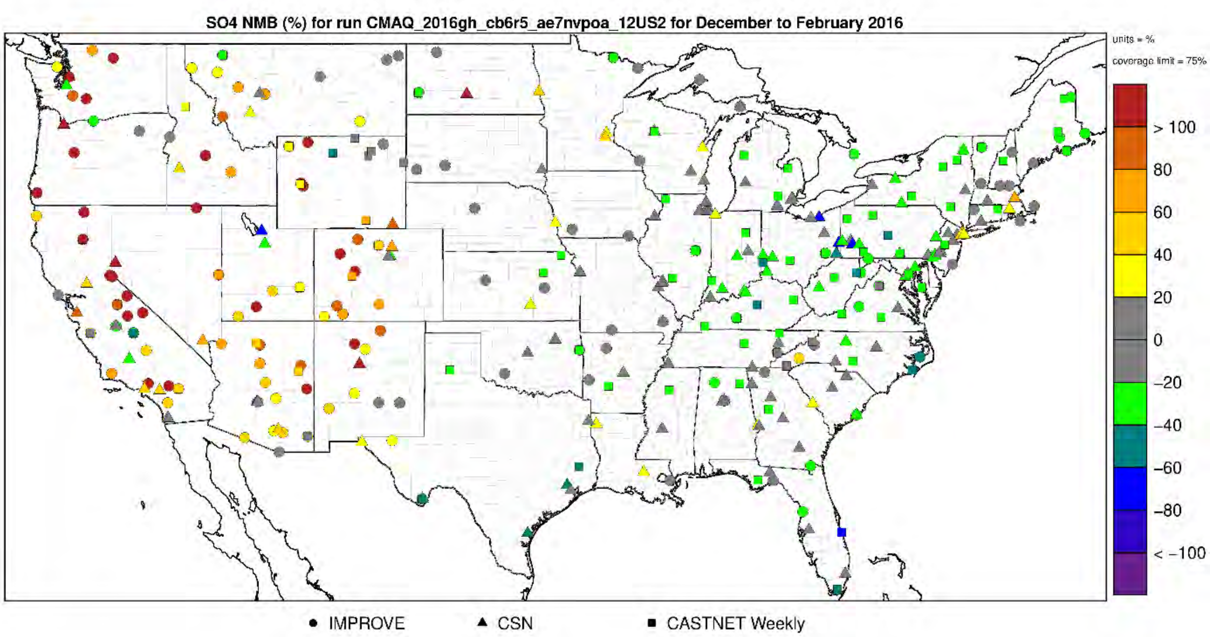

Figure 7-9 Normalized Mean Bias (%) of sulfate during winter 2016 at monitoring sites in the modeling domain

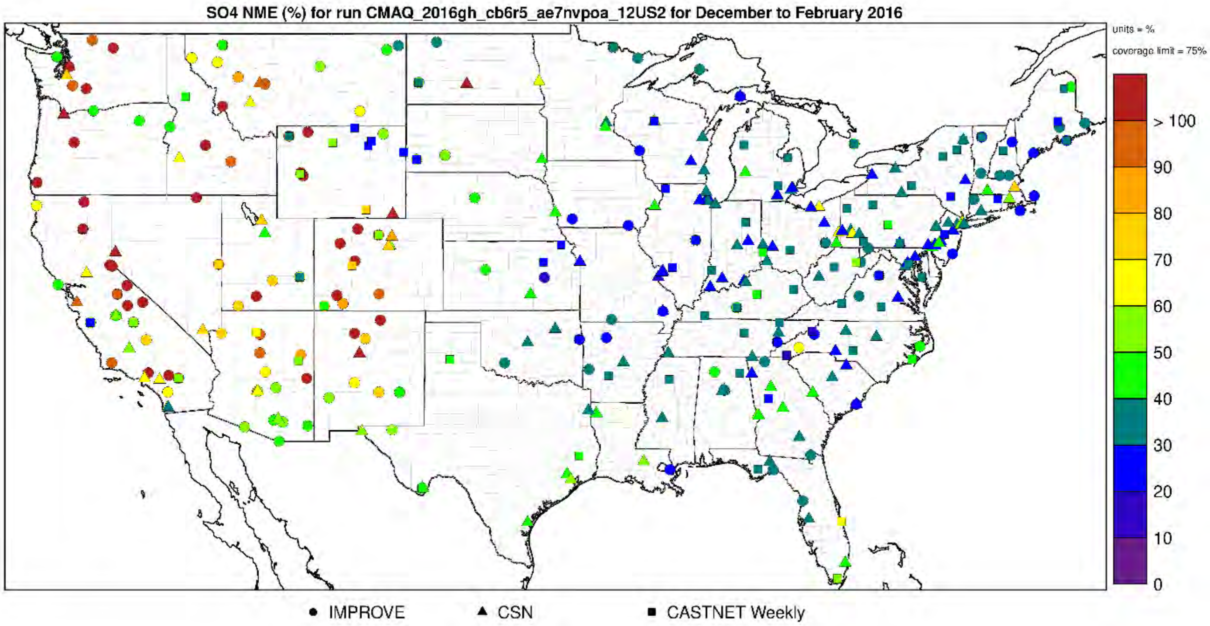

Figure 7-10 Normalized Mean Error (%) of sulfate during winter 2016 at monitoring sites in the modeling domain

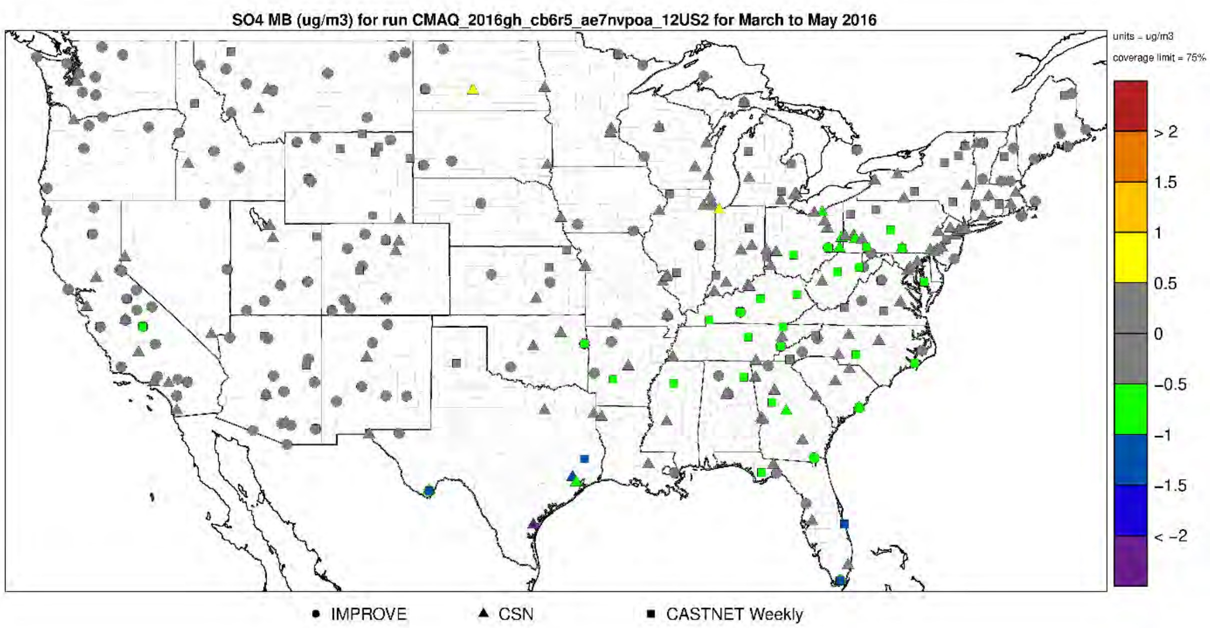

Figure 7-11 Mean Bias (µg/m^3) of sulfate during spring 2016 at monitoring sites in the modeling domain

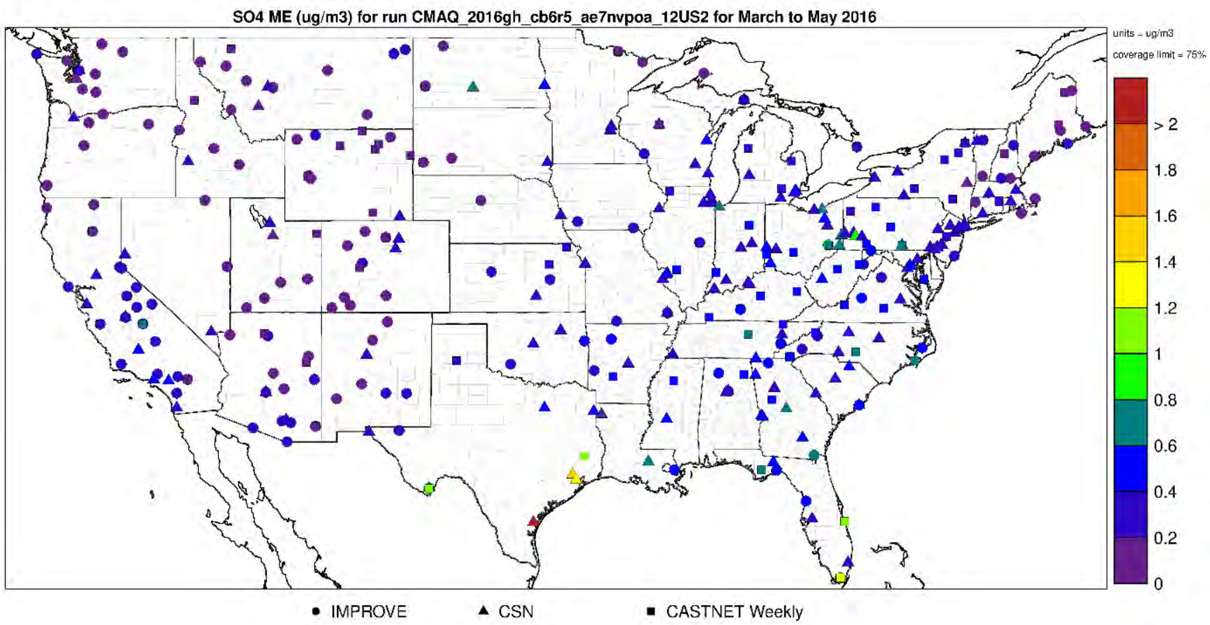

Figure 7-12 Mean Error (μg/m^3) of sulfate during spring 2016 at monitoring sites in the modeling domain

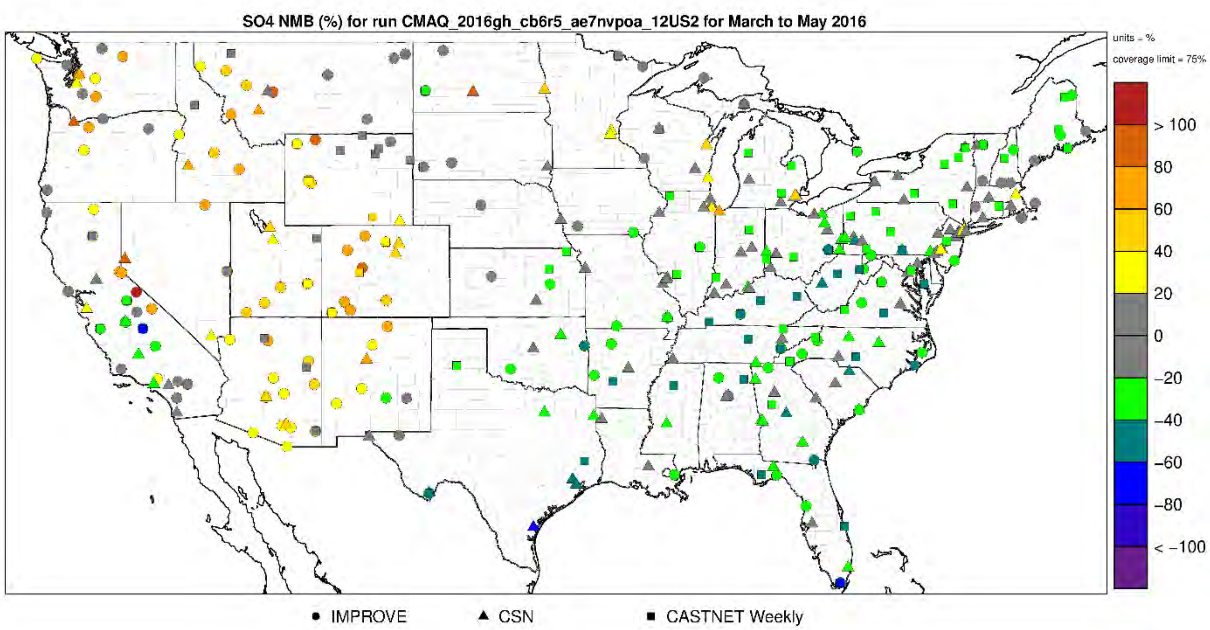

Figure 7-13 Normalized Mean Bias (%) of sulfate during spring 2016 at monitoring sites in the modeling domain

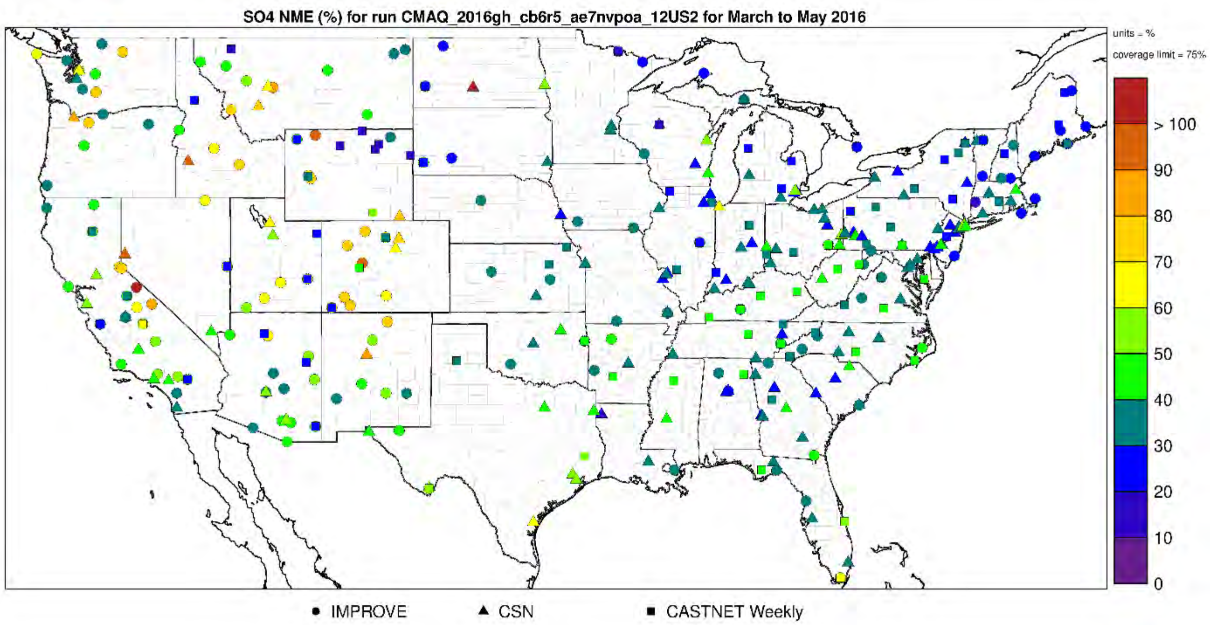

Figure 7-14 Normalized Mean Error (%) of sulfate during spring 2016 at monitoring sites in the modeling domain

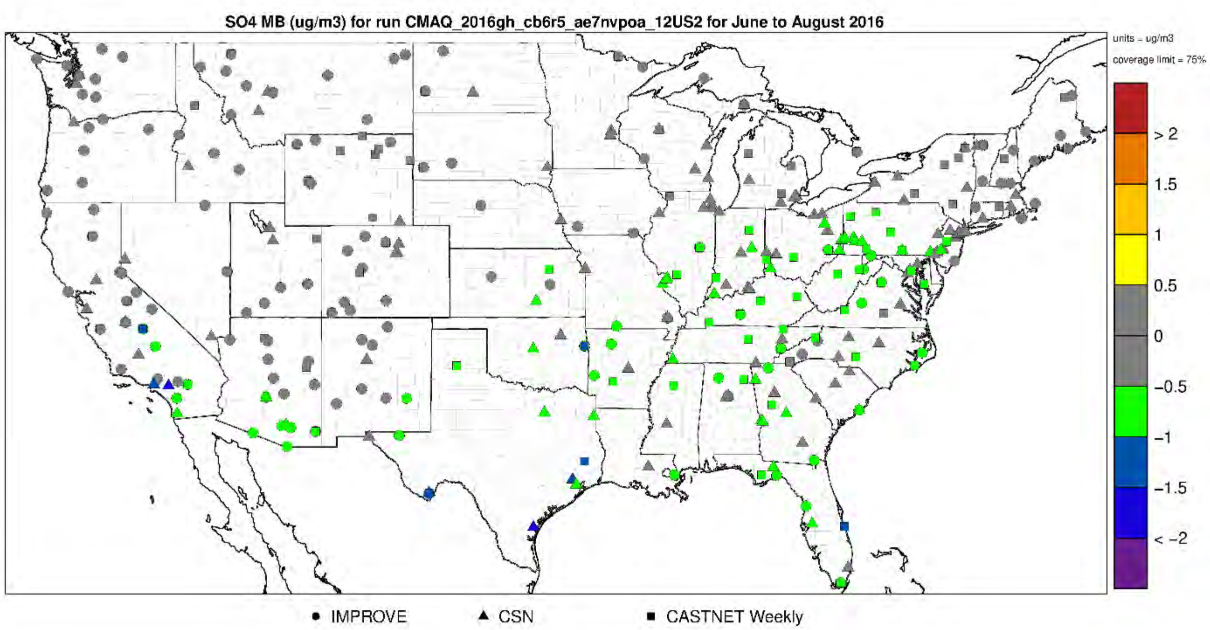

Figure 7-15 Mean Bias (µg/m^3) of sulfate during summer 2016 at monitoring sites in the modeling domain

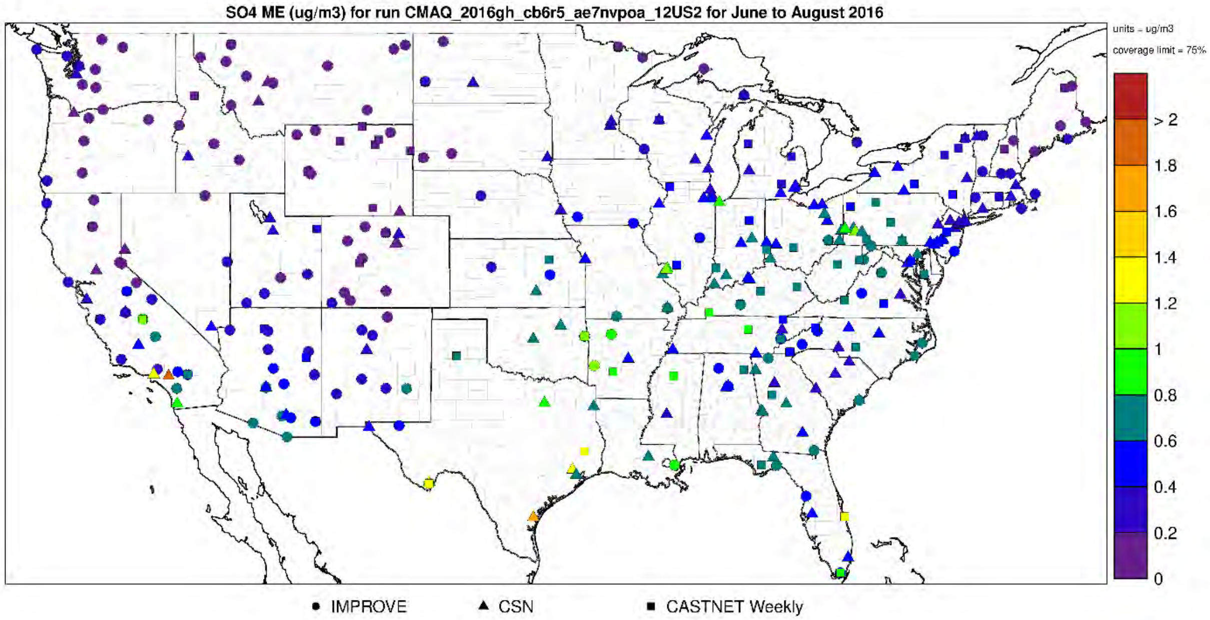

Figure 7-16 Mean Error (μg/m^3) of sulfate during summer 2016 at monitoring sites in the modeling domain

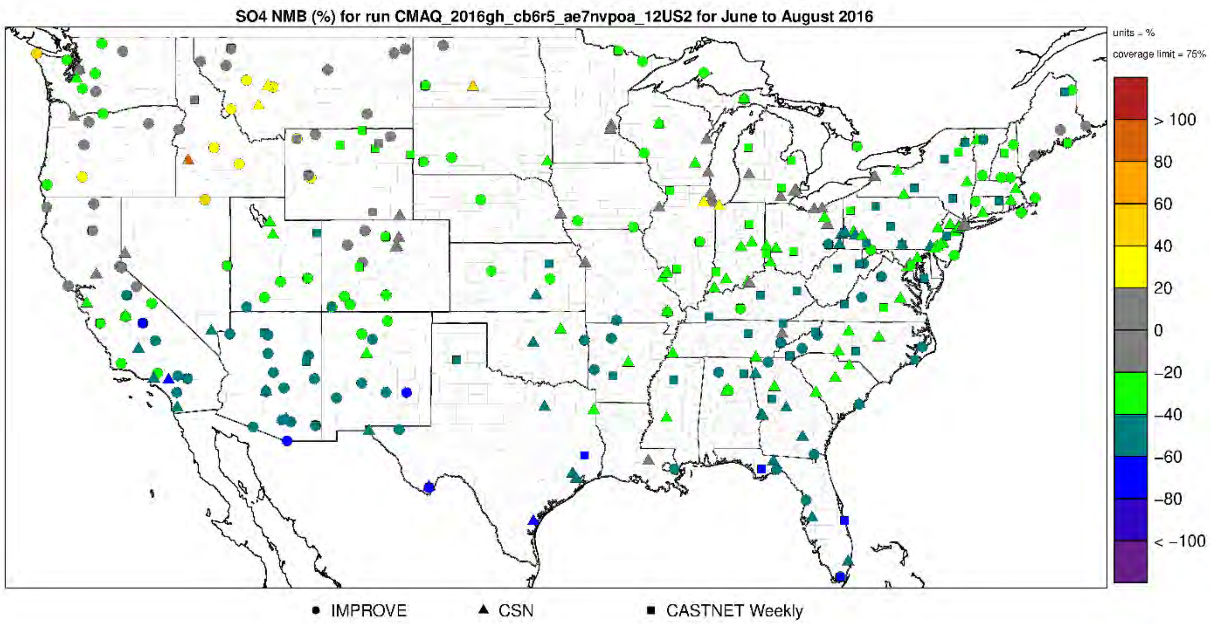

Figure 7-17 Normalized Mean Bias (%) of sulfate during summer 2016 at monitoring sites in the modeling domain

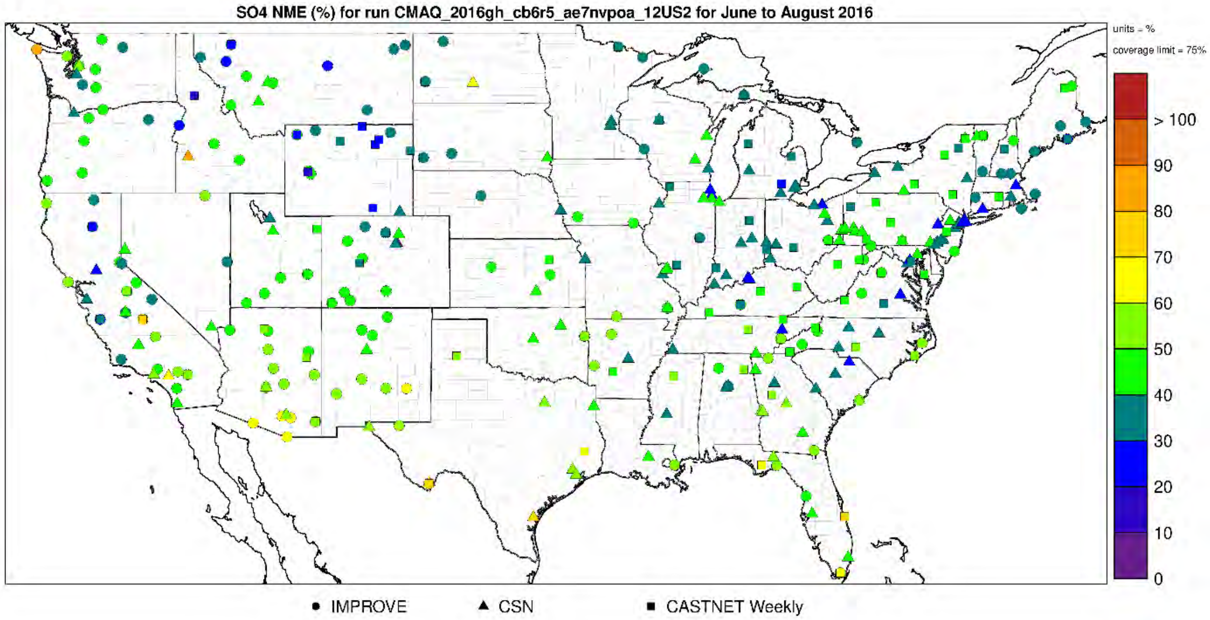

Figure 7-18 Normalized Mean Error (%) of sulfate during summer 2016 at monitoring sites in the modeling domain

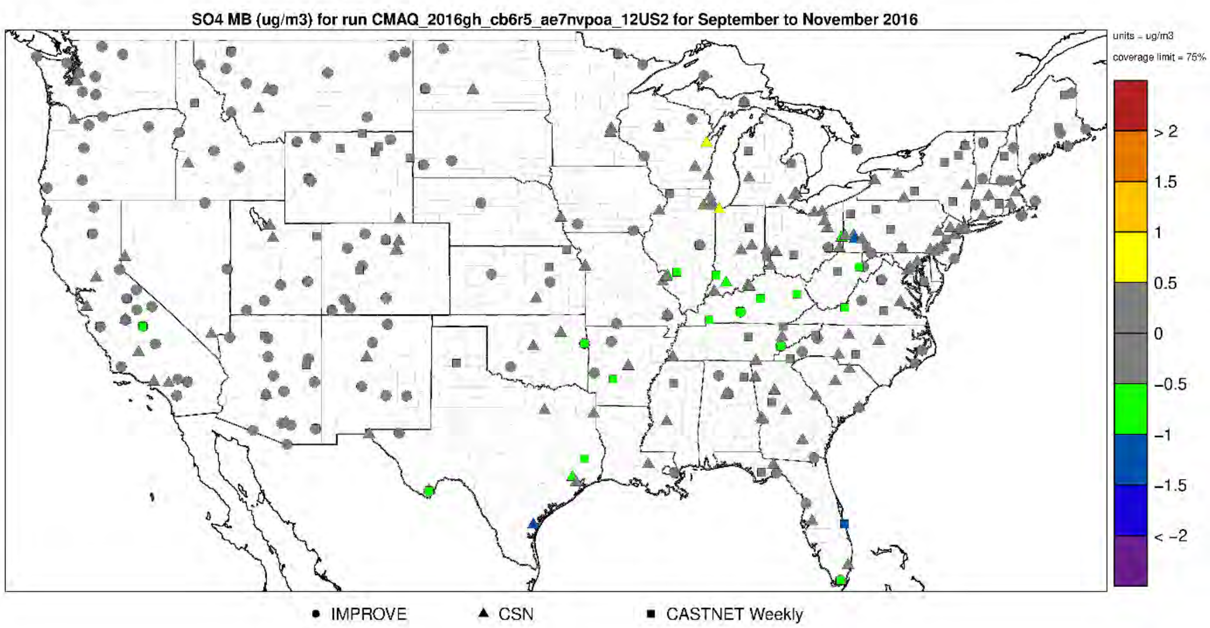

Figure 7-19 Mean Bias (μg/m^3) of sulfate during fall 2016 at monitoring sites in the modeling domain

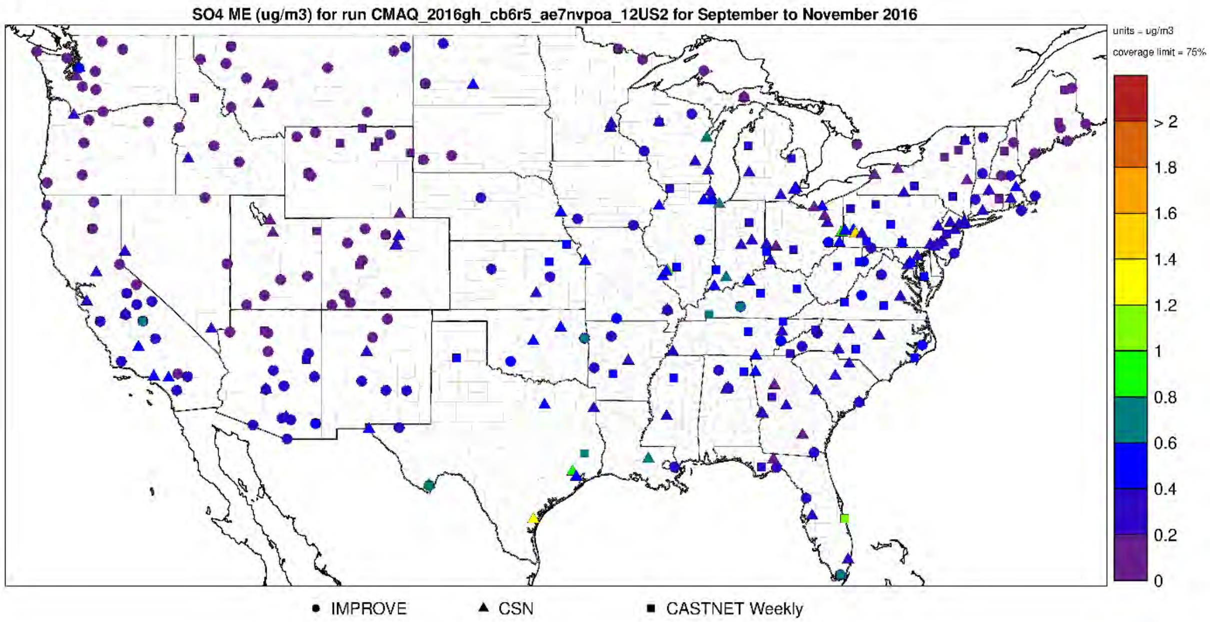

Figure 7-20 Mean Error (µg/m^3) of sulfate during fall 2016 at monitoring sites in the modeling domain

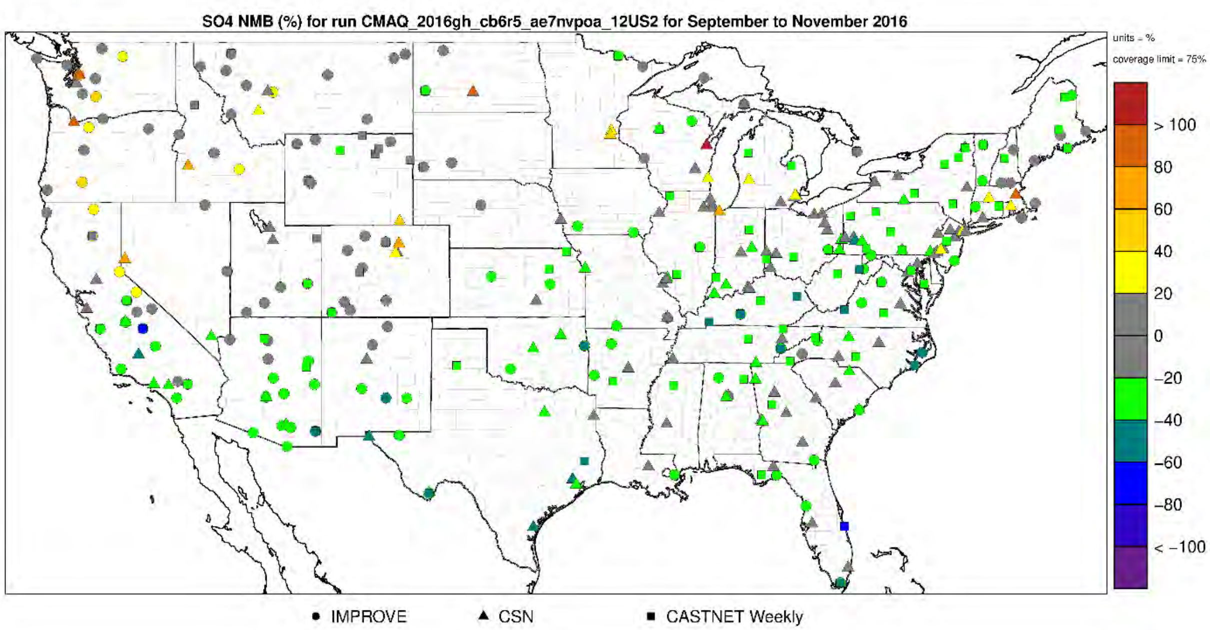

Figure 7-21 Normalized Mean Bias (%) of sulfate during fall 2016 at monitoring sites in the modeling domain

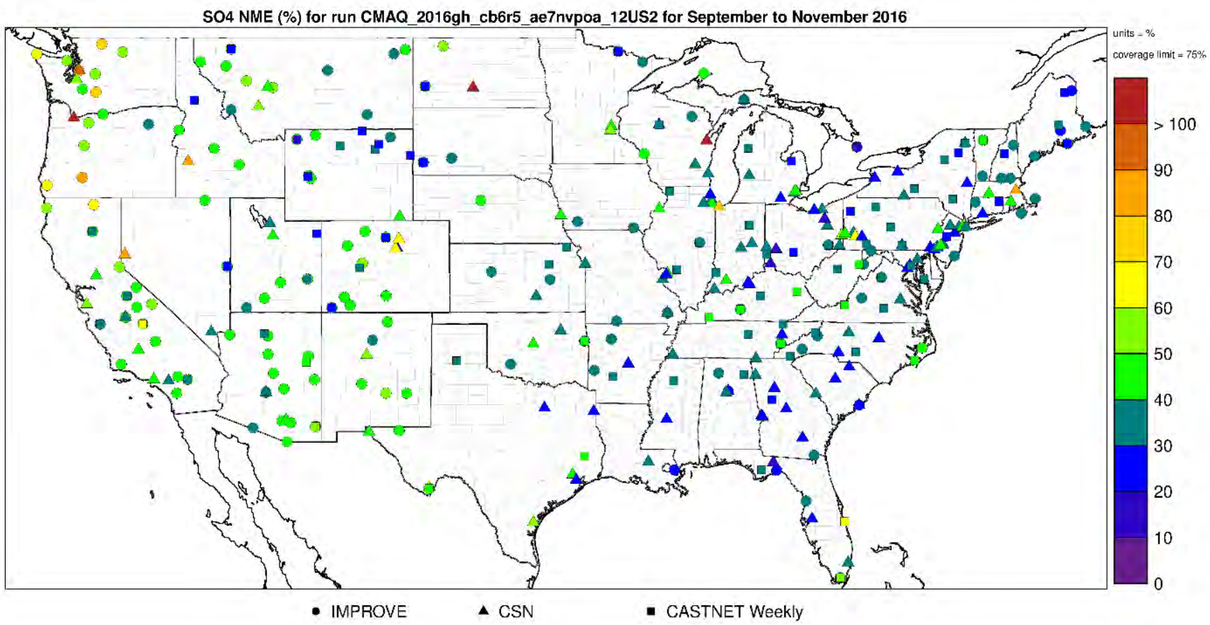

Figure 7-22 Normalized Mean Error (%) of sulfate during fall 2016 at monitoring sites in the modeling domain

7.4.4.2 Seasonal Evaluation for Nitrate

The model performance bias and error statistics for nitrate for each climate region and season are provided in Table 7-6. This table includes statistics for both particulate nitrate, as measured at CSN and IMPROVE sites, and total nitrate ($TNO_3=NO_3+HNO_3$), as measured at CASTNet sites. Spatial plots of the MB, ME, NMB, and NME by season for individual monitors are shown in Figure 7-23 through Figure 7-54.

Table 7-6 Nitrate and Total Nitrate Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	IMPROVE (NO_3)	Winter	431	0.8	0.8	>100	>100
		Spring	477	0.1	0.2	24.8	76.5
		Summer	486	0.0	0.2	29.0	>100
		Fall	456	0.2	0.3	63.0	>100
	CSN (NO_3)	Winter	715	1.2	1.4	73.1	84.5
		Spring	770	0.3	0.6	32.3	67.7
		Summer	778	-0.1	0.2	-36.1	67.6
		Fall	737	0.3	0.5	48.2	81.4
	CASTNet	Winter	221	0.5	0.5	31.0	34.4

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
	(TNO_3)	Spring	242	0.0	0.3	1.5	25.7
		Summer	252	0.1	0.3	11.5	29.2
		Fall	242	0.2	0.3	20.6	35.2
Ohio Valley	IMPROVE (NO_3)	Winter	220	-0.1	0.7	-7.4	55.2
		Spring	244	-0.2	0.3	-41.5	62.3
		Summer	239	-0.1	0.2	-30.5	87.2
		Fall	227	-0.1	0.3	-27.6	65.9
	CSN (NO_3)	Winter	543	0.2	1.1	7.8	46.0
		Spring	562	0.1	0.6	9.0	68.5
		Summer	552	0.0	0.3	1.8	87.2
		Fall	538	0.1	0.5	16.4	66.2
	CASTNet (TNO_3)	Winter	212	-0.1	0.5	-5.0	21.4
		Spring	228	-0.2	0.4	-13.2	24.3
		Summer	224	0.1	0.4	9.7	30.6
		Fall	226	0.1	0.5	6.3	32.5
Upper Midwest	IMPROVE (NO_3)	Winter	200	-0.2	0.7	-16.4	49.0
		Spring	208	-0.2	0.3	-34.0	59.0
		Summer	210	-0.0	0.1	-9.7	83.1
		Fall	215	-0.1	0.2	-29.2	65.4
	CSN (NO_3)	Winter	326	0.2	1.0	6.4	40.3
		Spring	354	0.1	0.7	11.2	62.0
		Summer	313	0.0	0.3	1.3	87.4
		Fall	307	0.1	0.4	14.4	57.7
	CASTNet (TNO_3)	Winter	59	-0.3	0.6	-14.1	23.6
		Spring	63	-0.1	0.4	-5.7	29.0
		Summer	63	0.1	0.3	6.6	30.3
		Fall	57	-0.0	0.3	-3.1	28.1
Southeast	IMPROVE (NO_3)	Winter	342	0.2	0.4	49.5	84.4
		Spring	379	-0.1	0.2	-36.9	67.6

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Summer	394	-0.1	0.1	-28.2	75.7
		Fall	366	-0.0	0.2	-13.5	71.9
	CSN (NO_3)	Winter	573	0.8	0.9	>100	>100
		Spring	643	-0.0	0.3	-10.2	75.8
		Summer	608	-0.1	0.2	-25.3	80.4
		Fall	560	0.1	0.3	39.9	96.0
	CASTNet (TNO_3)	Winter	150	0.2	0.5	13.6	40.1
		Spring	164	-0.4	0.5	-32.5	39.4
		Summer	164	-0.1	0.3	-14.6	36.2
		Fall	154	-0.0	0.5	-1.5	39.7
South	IMPROVE (NO_3)	Winter	240	0.0	0.6	0.2	62.4
		Spring	273	-0.1	0.2	-34.8	70.2
		Summer	252	-0.1	0.2	-69.3	85.0
		Fall	264	-0.1	0.2	-39.3	67.5
	CSN (NO_3)	Winter	326	0.2	0.6	27.2	68.2
		Spring	349	-0.1	0.2	-29.5	70.8
		Summer	335	-0.1	0.2	-33.3	81.0
		Fall	330	-0.0	0.3	84.0	-36.4
	CASTNet (TNO_3)	Winter	92	-0.1	0.5	-9.0	28.8
		Spring	102	-0.3	0.3	-27.2	29.2
		Summer	96	-0.4	0.5	-32.0	39.0
		Fall	102	-0.1	0.3	-7.3	29.9
Southwest	IMPROVE (NO_3)	Winter	910	-0.1	0.2	-46.5	75.7
		Spring	991	-0.1	0.1	-56.7	84.9
		Summer	985	-0.1	0.1	-93.2	95.7
		Fall	962	-0.1	0.1	-70.2	84.5
	CSN (NO_3)	Winter	247	-1.6	1.8	-64.4	72.3
		Spring	255	-0.2	0.3	-50.6	66.7
		Summer	250	-0.2	0.3	-74.3	97.6

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Fall	257	-0.3	0.5	-54.1	81.8
	CASTNet (TNO_3)	Winter	92	-0.1	0.5	-9.0	28.8
		Spring	102	-0.3	0.3	-27.2	29.2
		Summer	96	-0.4	0.5	-32.0	39.0
		Fall	102	-0.1	0.3	-7.3	29.9
Northern Rockies	IMPROVE (NO_3)	Winter	542	-0.2	0.3	-41.0	69.8
		Spring	573	-0.1	0.1	-41.4	73.7
		Summer	603	-0.1	0.1	-76.2	85.8
		Fall	574	-0.0	0.1	-24.2	83.9
	CSN (NO_3)	Winter	139	-0.1	0.7	-9.4	55.8
		Spring	151	-0.1	0.3	-25.6	53.6
		Summer	153	-0.1	0.1	-48.7	74.7
		Fall	135	-0.0	0.2	-4.6	62.8
	CASTNet (TNO_3)	Winter	126	-0.3	0.3	38.0	47.6
		Spring	139	-0.1	0.1	-19.6	29.7
		Summer	138	-0.2	0.2	-24.3	27.8
		Fall	129	-0.1	0.1	-13.3	28.7
Northwest	IMPROVE (NO_3)	Winter	427	-0.1	0.3	-19.2	97.6
		Spring	505	0.1	0.2	53.2	>100
		Summer	519	0.1	0.2	73.0	>100
		Fall	499	0.1	0.2	36.7	>100
	CSN (NO_3)	Winter	157	-0.0	1.1	-3.3	93.5
		Spring	161	0.9	1.0	>100	>100
		Summer	166	1.2	1.3	>100	>100
		Fall	161	0.7	0.9	>100	>100
	CASTNet (TNO_3)	Winter	-	-	-	-	-
		Spring	-	-	-	-	-
		Summer	-	-	-	-	-
		Fall	-	-	-	-	-

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
West	IMPROVE (NO_3)	Winter	565	-0.1	0.3	-26.1	60.7
		Spring	608	-0.1	0.2	-25.3	58.0
		Summer	603	-0.2	0.3	-62.0	86.5
		Fall	576	-0.2	0.3	-47.6	71.5
	CSN (NO_3)	Winter	341	-7.8	2.0	-53.6	61.3
		Spring	352	-0.8	0.9	-50.1	57.7
		Summer	348	-0.7	0.8	-58.7	67.0
		Fall	332	-1.2	1.4	-61.5	73.0
	CASTNet (TNO_3)	Winter	69	-0.3	0.4	-32.5	47.3
		Spring	73	-0.3	0.4	-35.8	37.9
		Summer	75	-0.7	0.8	-43.2	44.8
		Fall	77	-0.4	0.5	-37.2	43.0

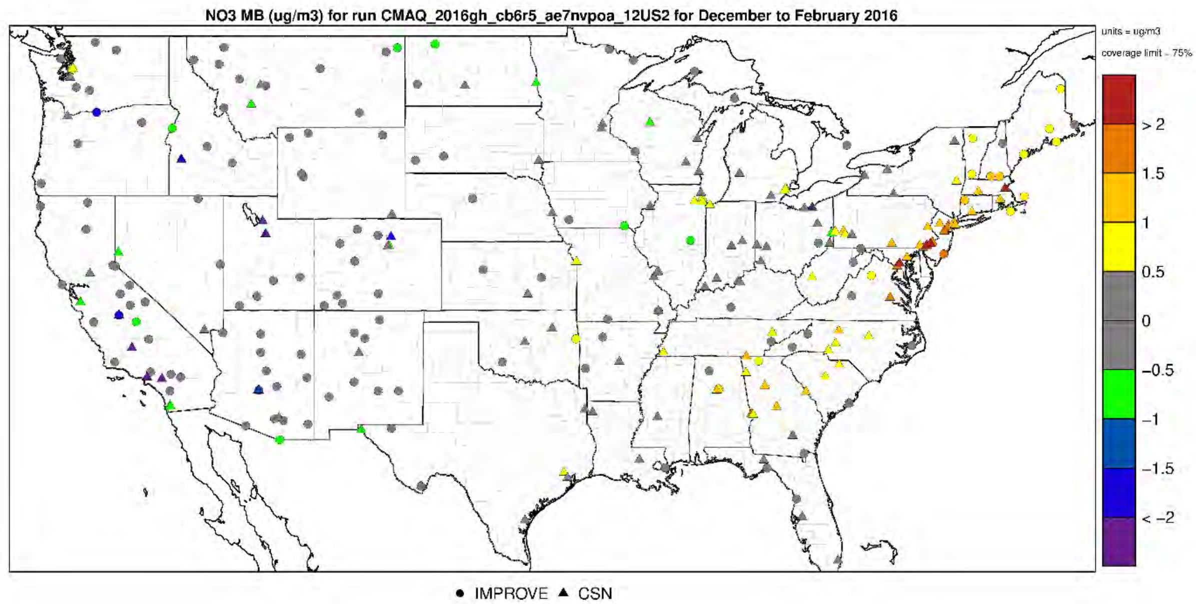

Figure 7-23 Mean Bias (µg/m³) for nitrate during winter 2016 at monitoring sites in the modeling domain

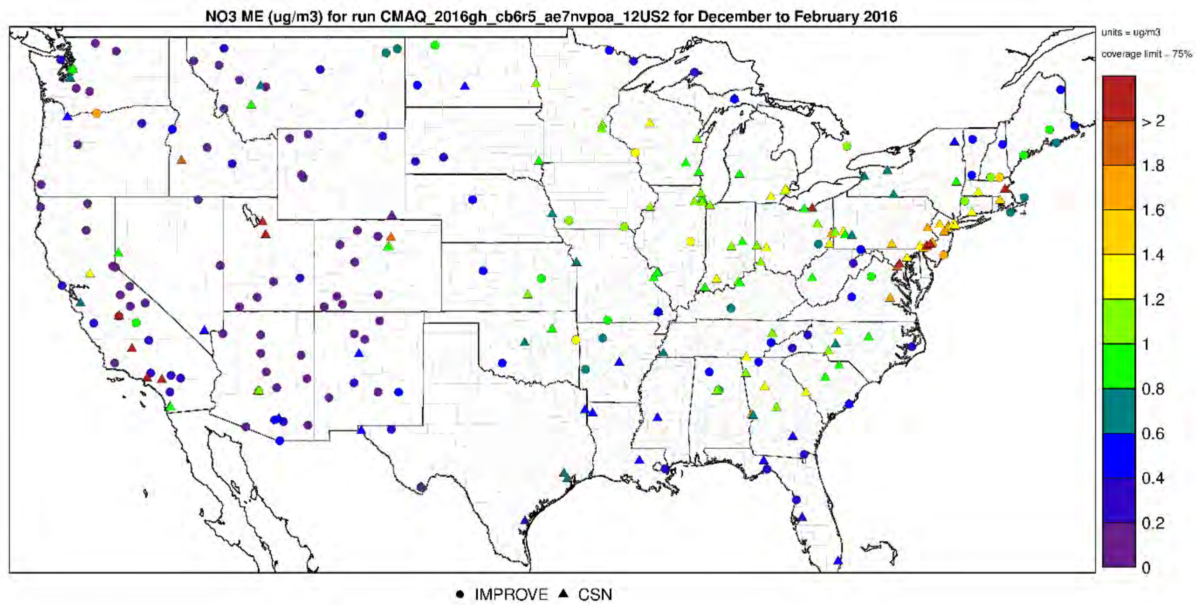

Figure 7-24 Mean Error (µg/m³) for nitrate during winter 2016 at monitoring sites in the modeling domain

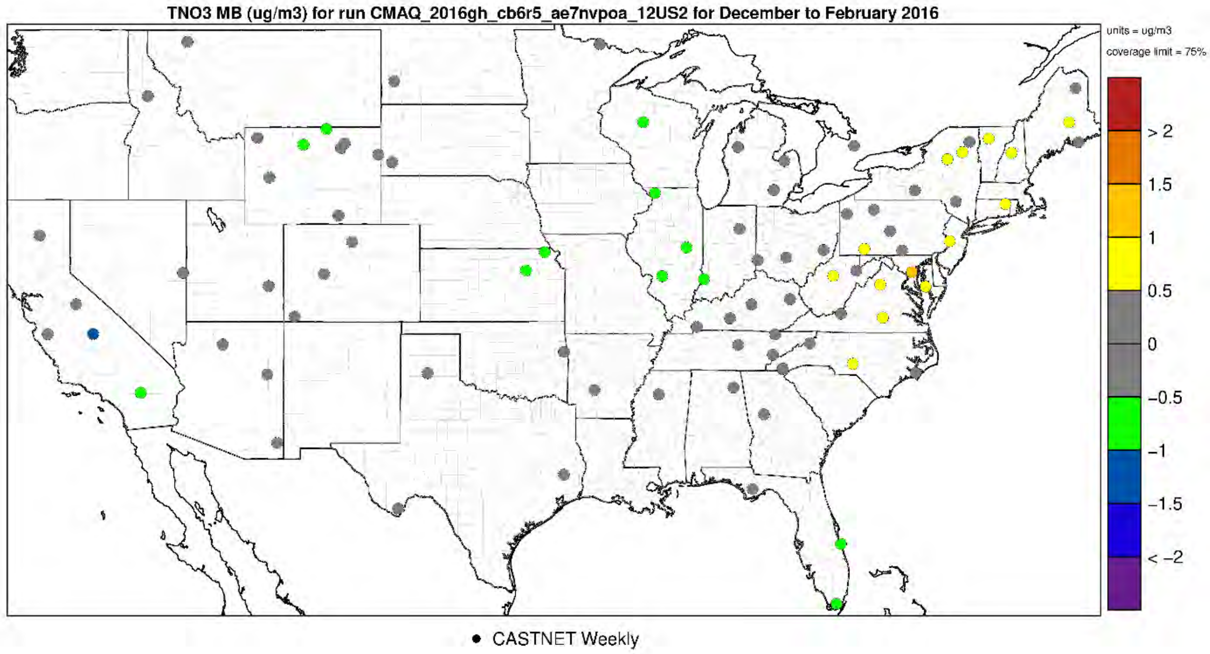

Figure 7-25 Mean Bias (µg/m³) for total nitrate during winter 2016 at monitoring sites in the modeling domain

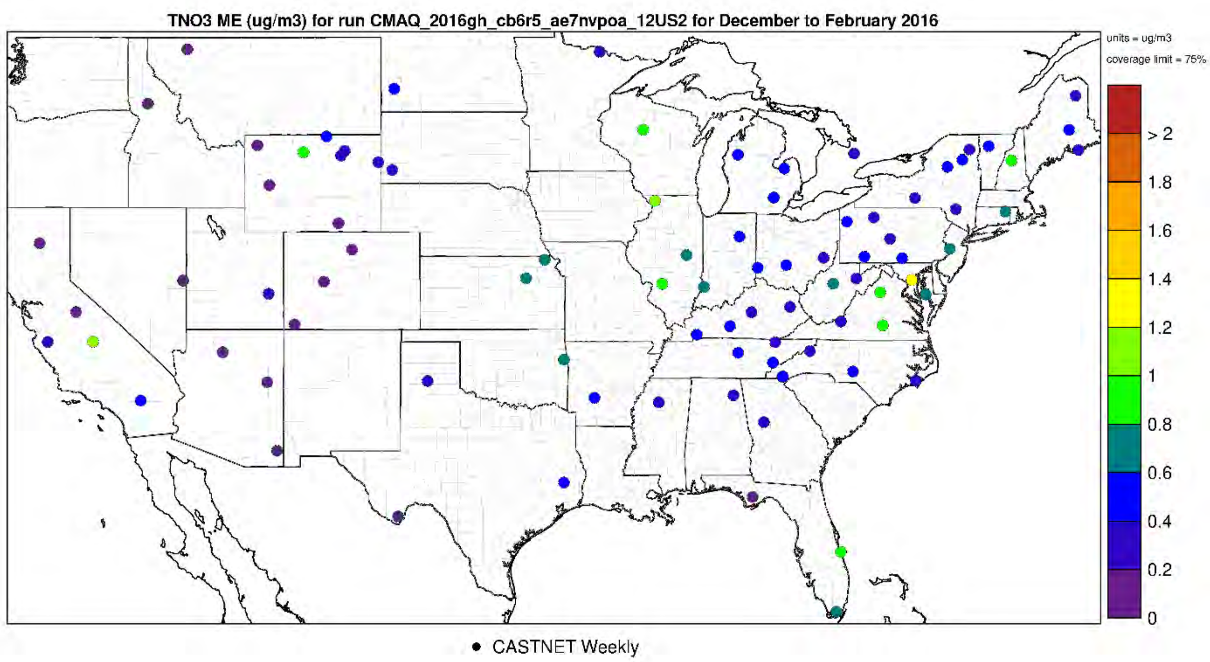

Figure 7-26 Mean Error (µg/m³) for total nitrate during winter 2016 at monitoring sites in the modeling domain

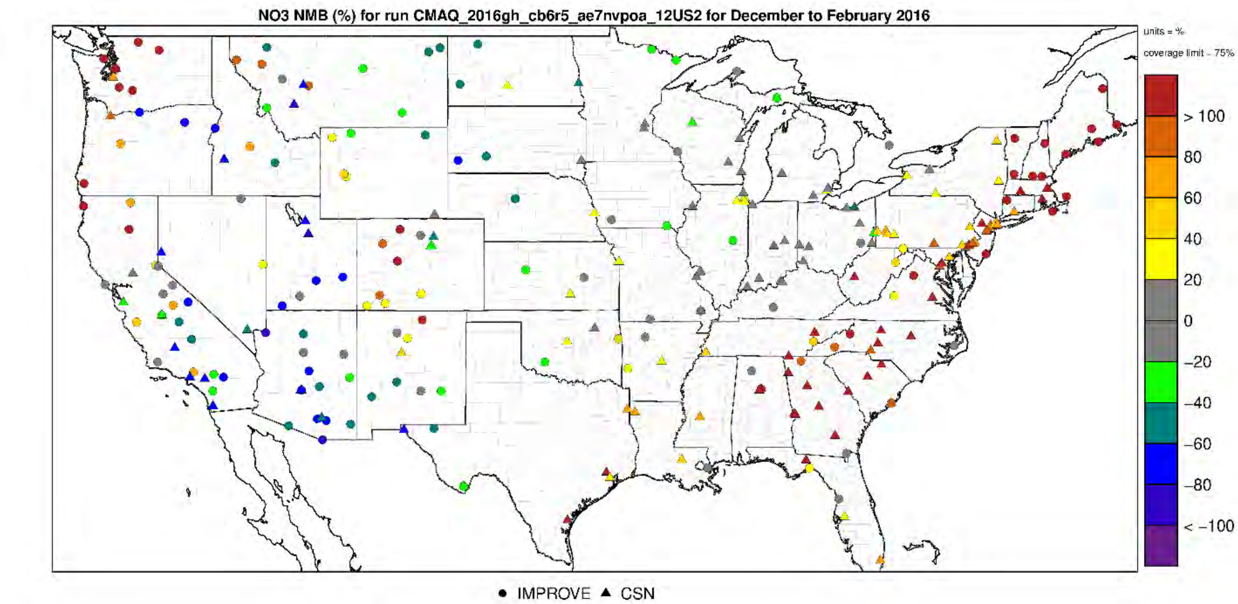

Figure 7-27 Normalized Mean Bias (%) for nitrate during winter 2016 at monitoring sites in the modeling domain

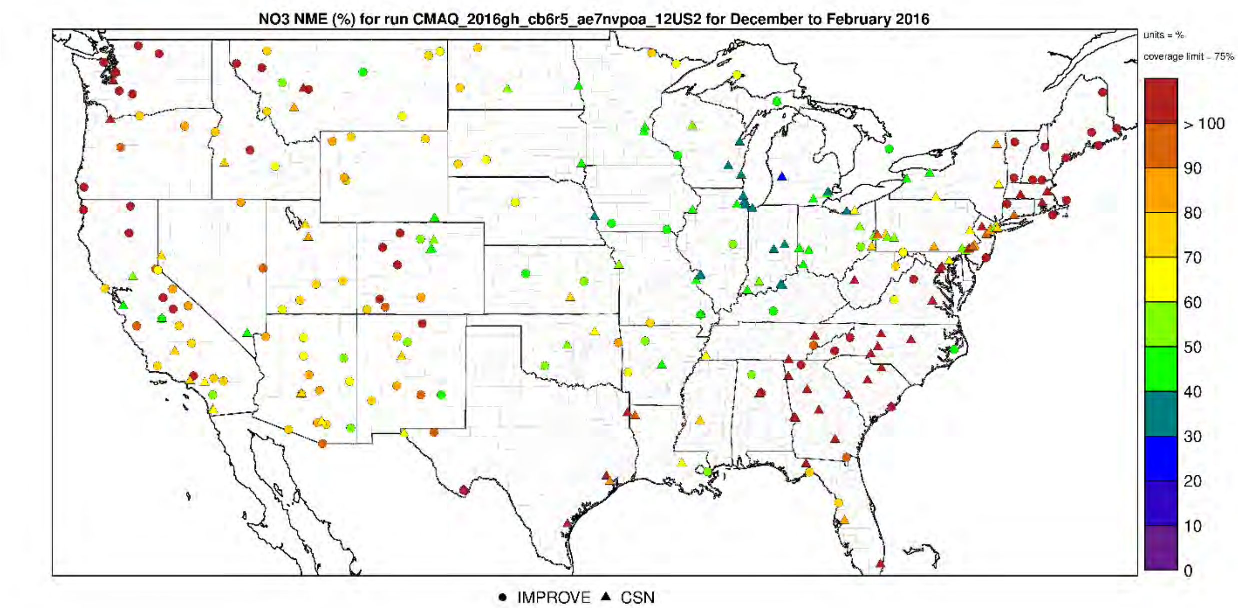

Figure 7-28 Normalized Mean Error (%) for nitrate during winter 2016 at monitoring sites in the modeling domain

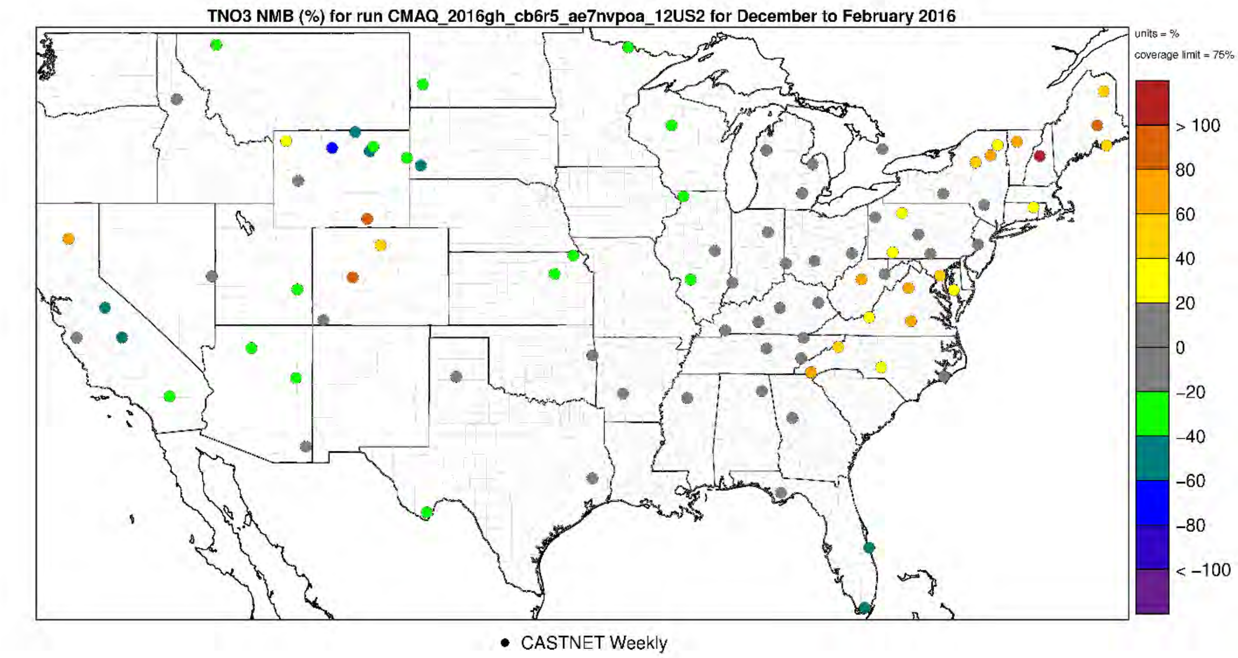

Figure 7-29 Normalized Mean Bias (%) for total nitrate during winter 2016 at monitoring sites in the modeling domain

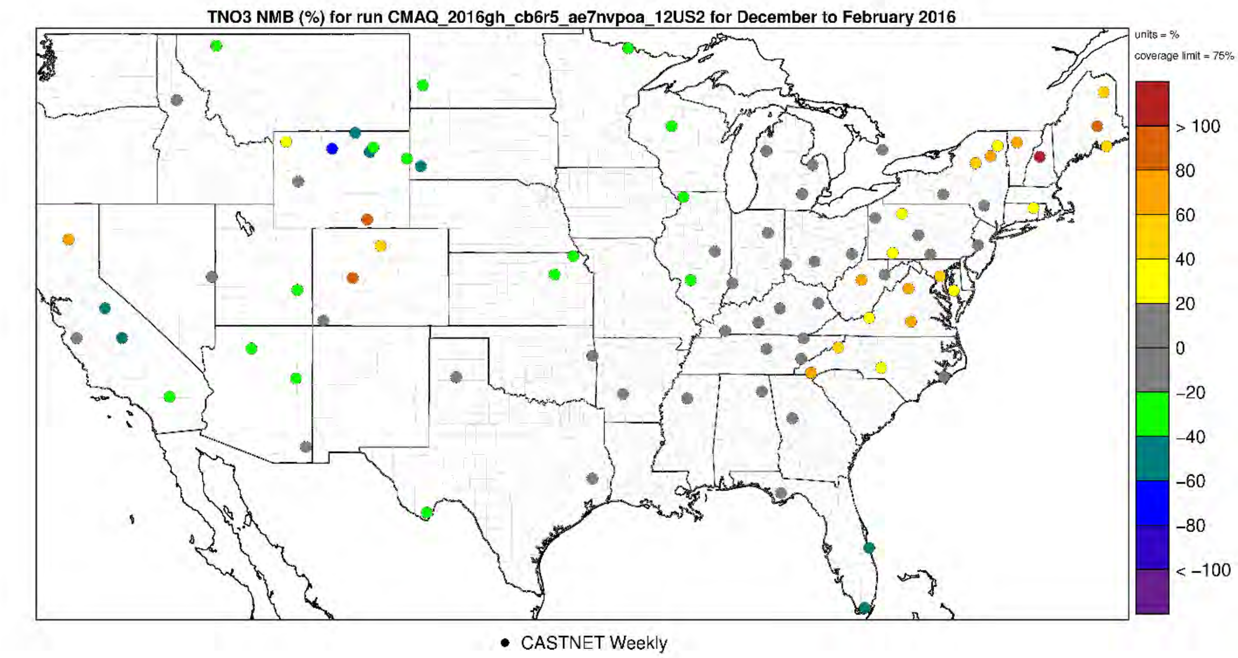

Figure 7-30 Normalized Mean Error (%) for total nitrate during winter 2016 at monitoring sites in the modeling domain

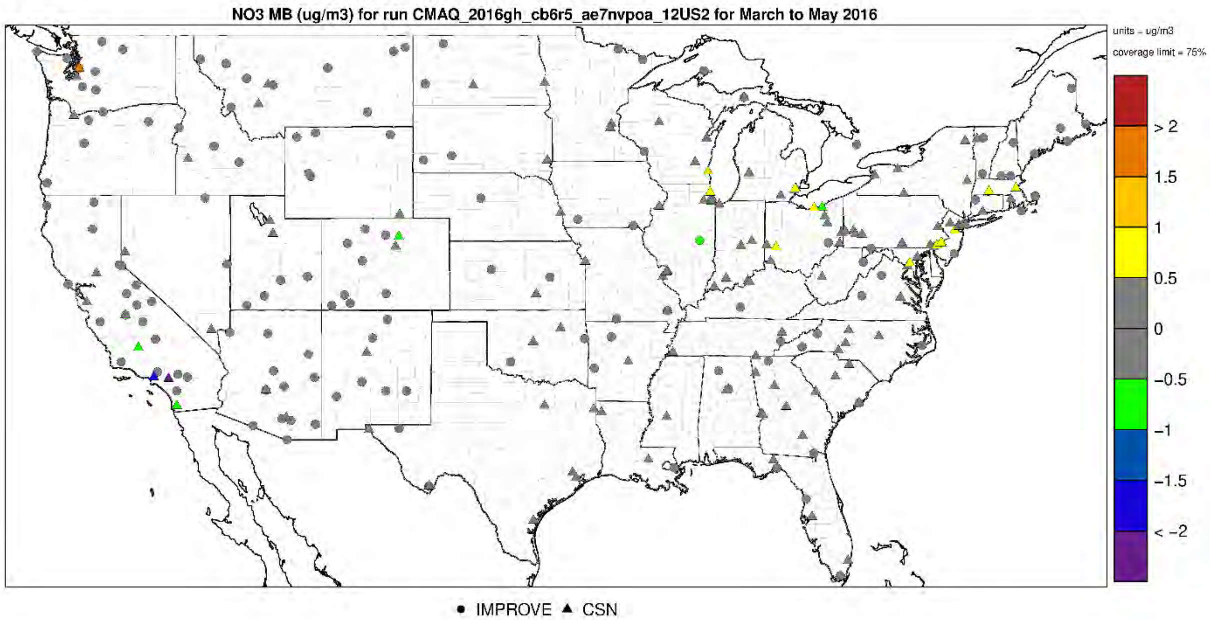

Figure 7-31 Mean Bias (µg/m^3) for nitrate during spring 2016 at monitoring sites in the modeling domain

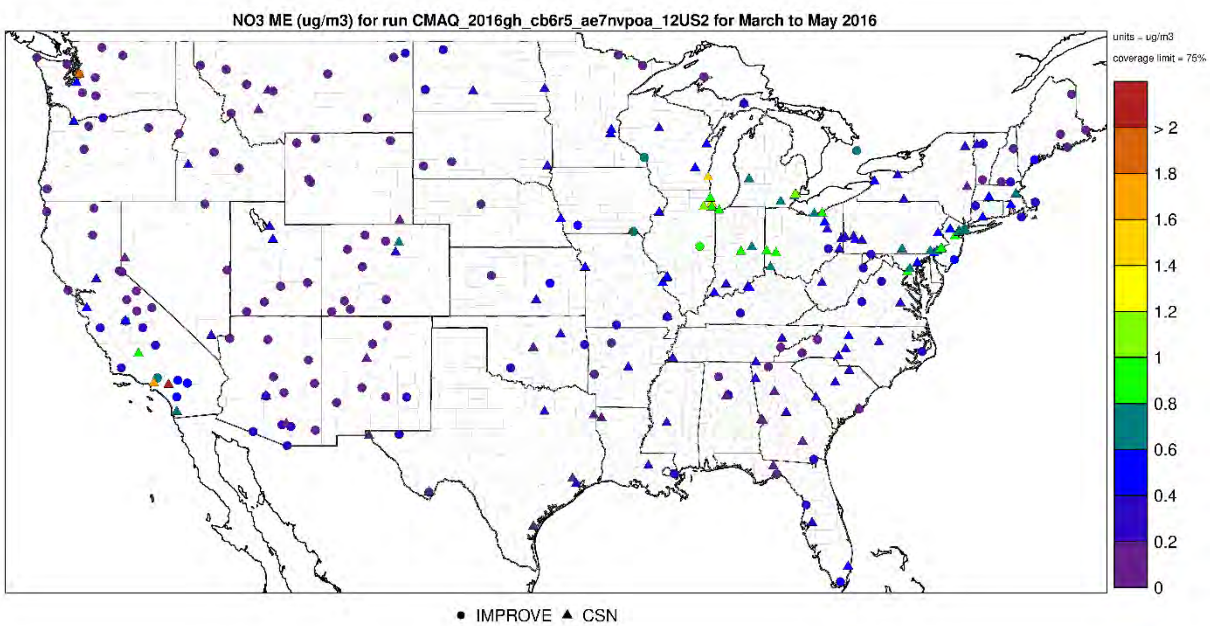

Figure 7-32 Mean Error (µg/m^3) for nitrate during spring 2016 at monitoring sites in the modeling domain

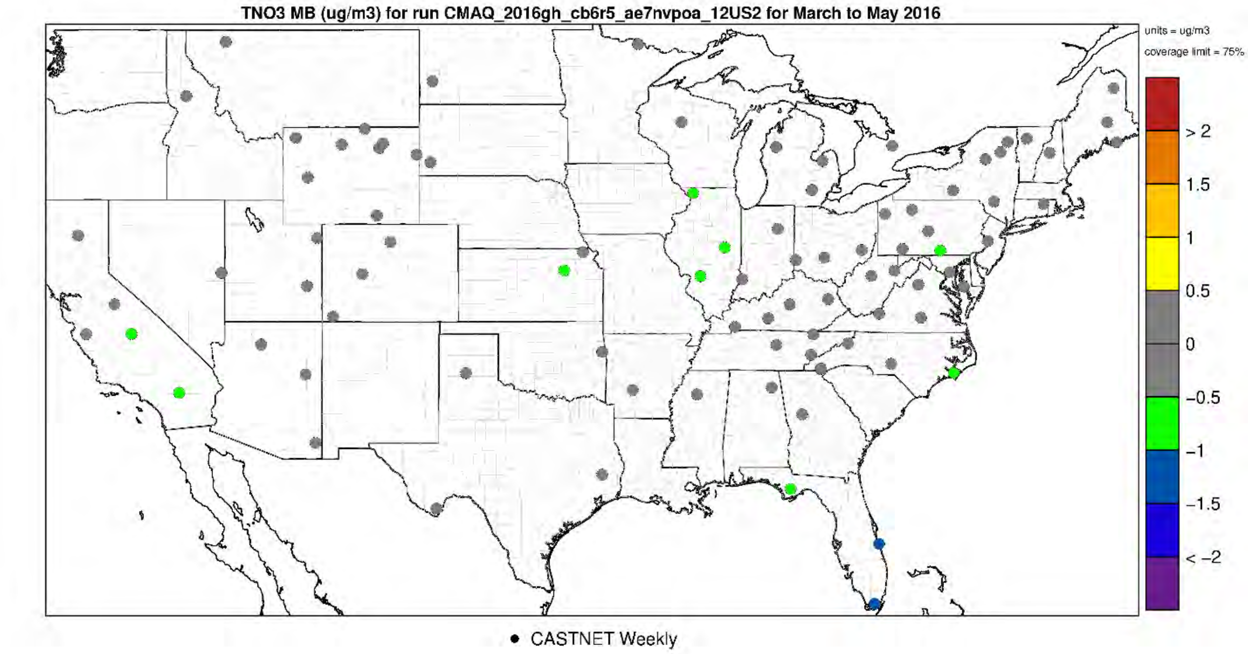

Figure 7-33 Mean Bias (µg/m^3) for total nitrate during spring 2016 at monitoring sites in the modeling domain

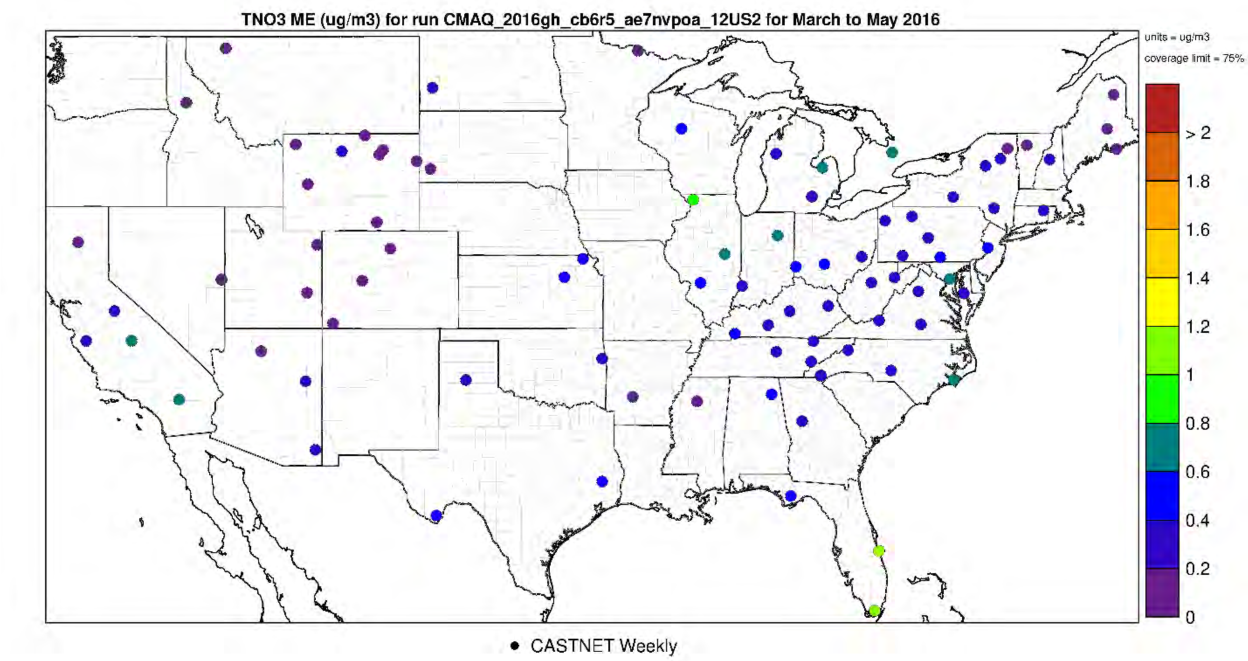

Figure 7-34 Mean Error (µg/m^3) for total nitrate during spring 2016 at monitoring sites in the modeling domain

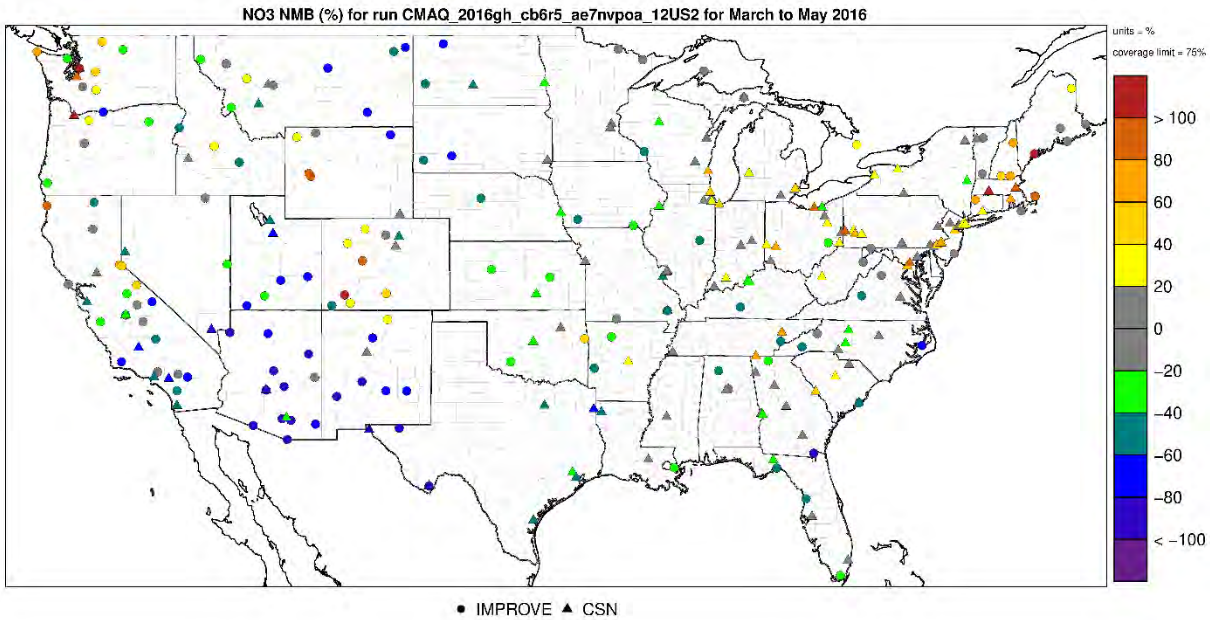

Figure 7-35 Normalized Mean Bias (%) for nitrate during spring 2016 at monitoring sites in the modeling domain

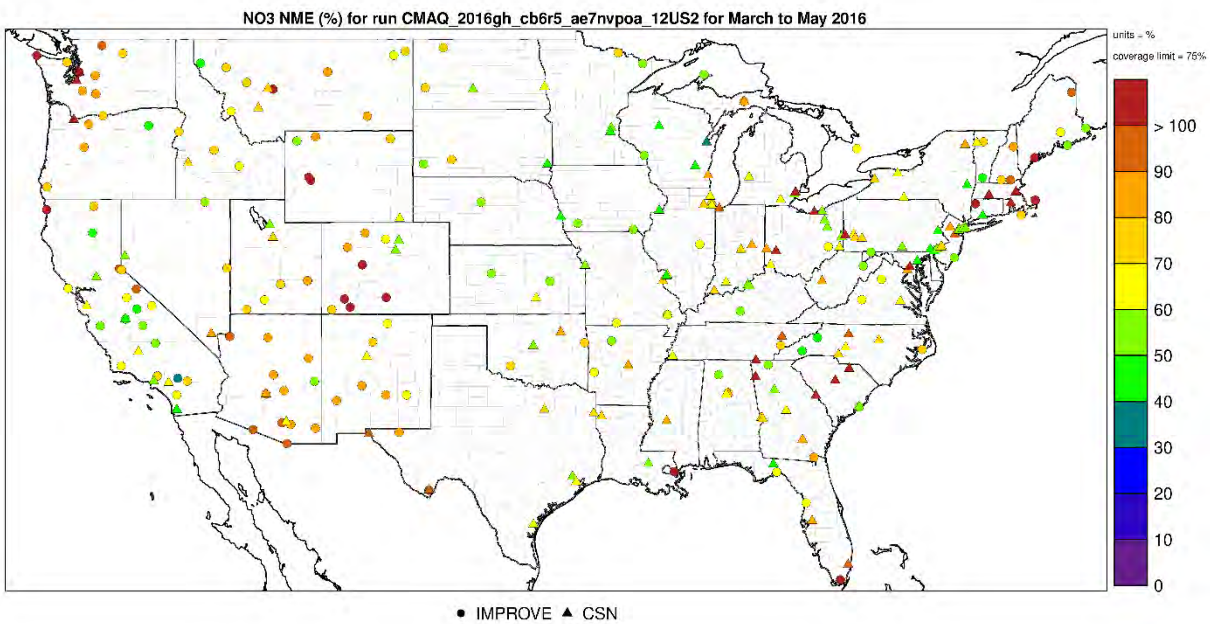

Figure 7-36 Normalized Mean Error (%) for nitrate during spring 2016 at monitoring sites in the modeling domain

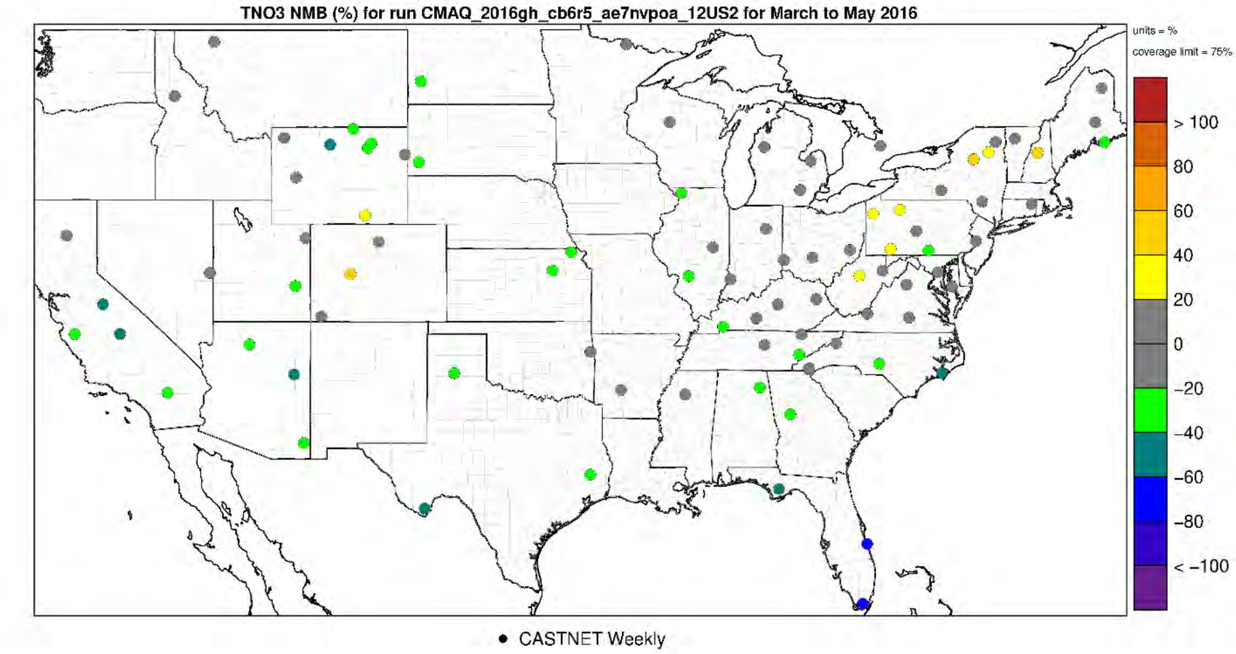

Figure 7-37 Normalized Mean Bias (%) for total nitrate during spring 2016 at monitoring sites in the modeling domain

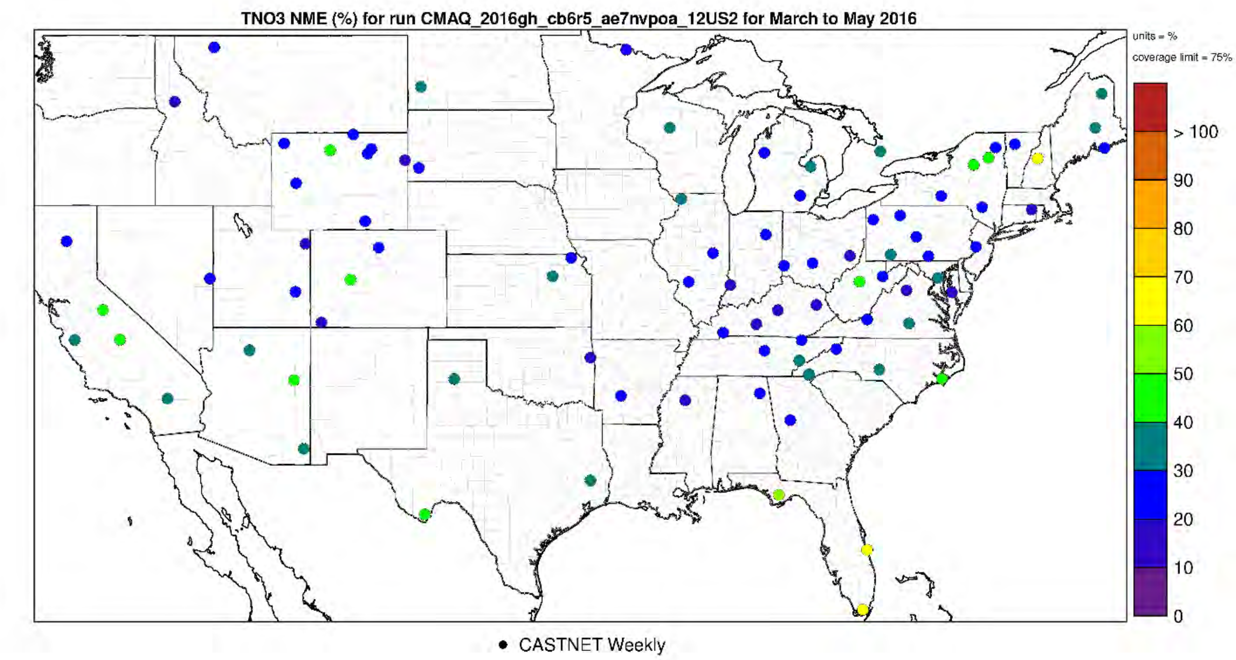

Figure 7-38 Normalized Mean Error (%) for total nitrate during spring 2016 at monitoring sites in the modeling domain

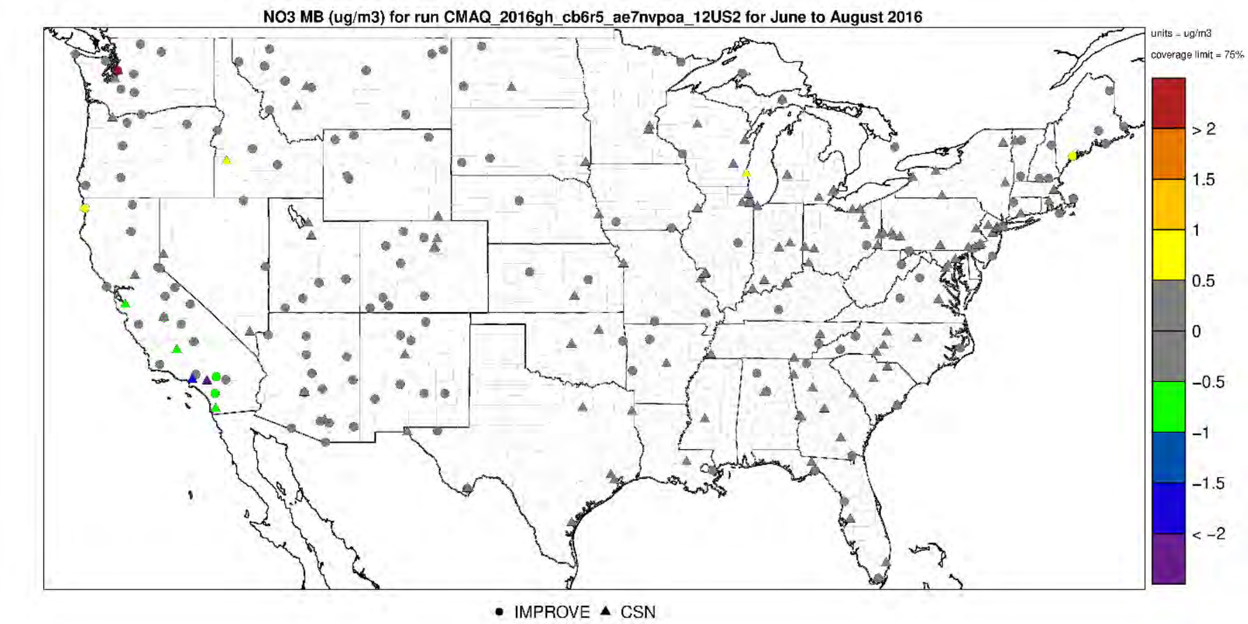

Figure 7-39 Mean Bias (µg/m^3) for nitrate during summer 2016 at monitoring sites in the modeling domain

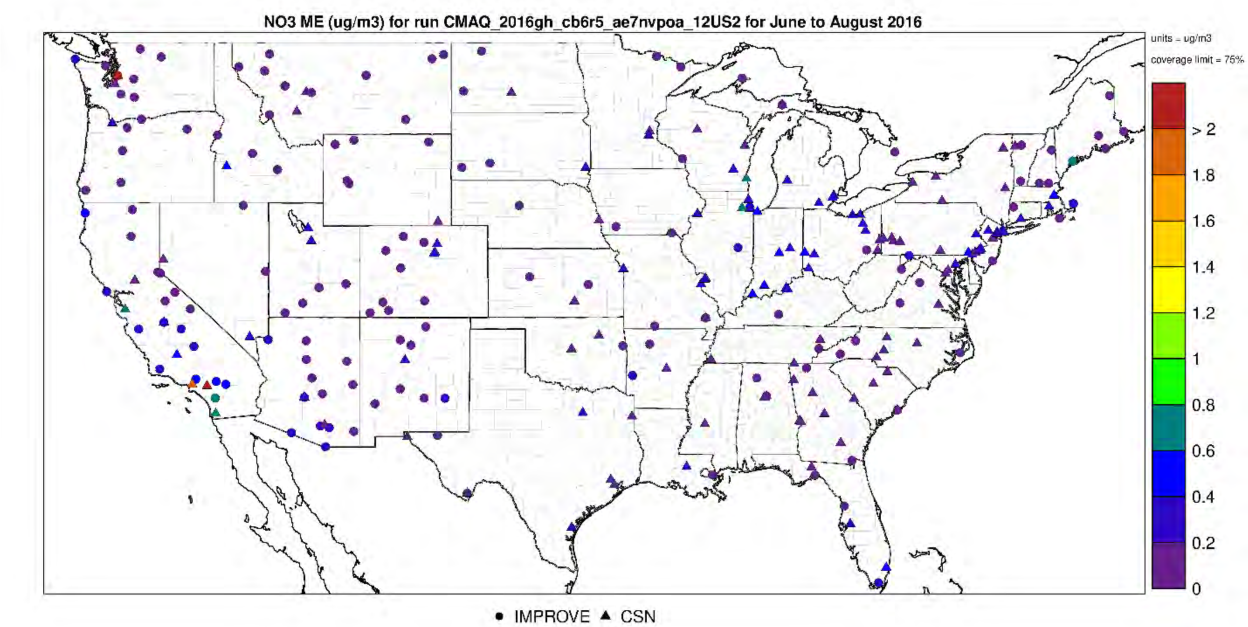

Figure 7-40 Mean Error (µg/m^3) for nitrate during summer 2016 at monitoring sites in the modeling domain

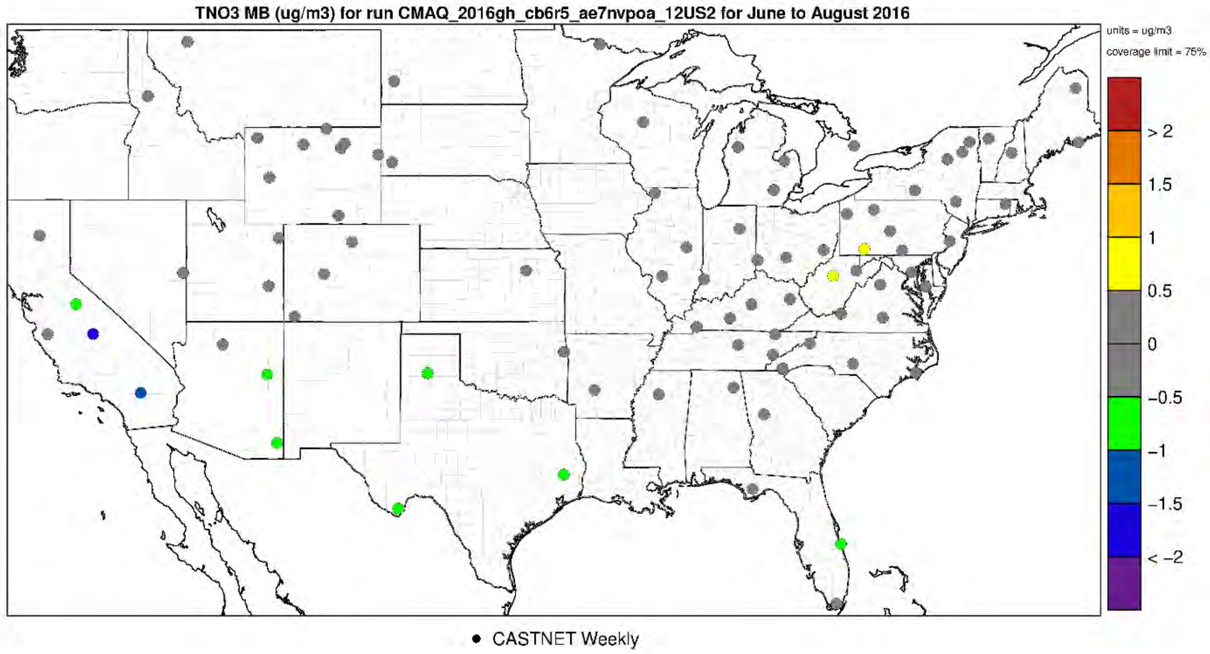

Figure 7-41 Mean Bias (µg/m^3) for total nitrate during summer 2016 at monitoring sites in the modeling domain

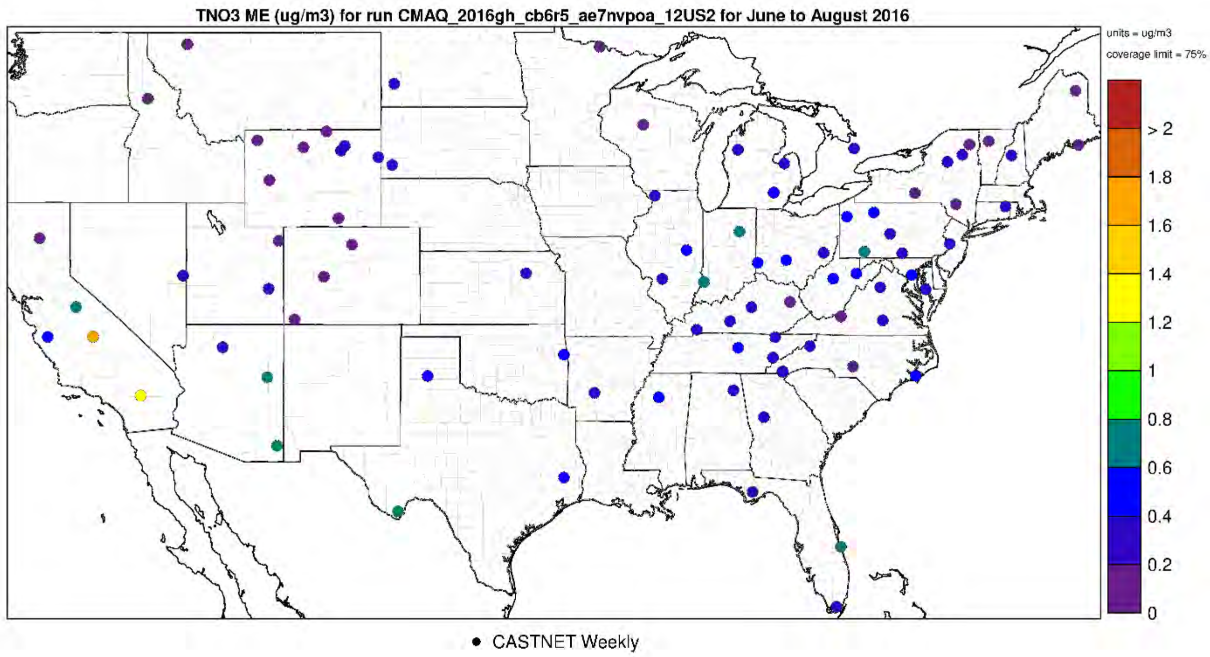

Figure 7-42 Mean Error (µg/m^3) for total nitrate during summer 2016 at monitoring sites in the modeling domain

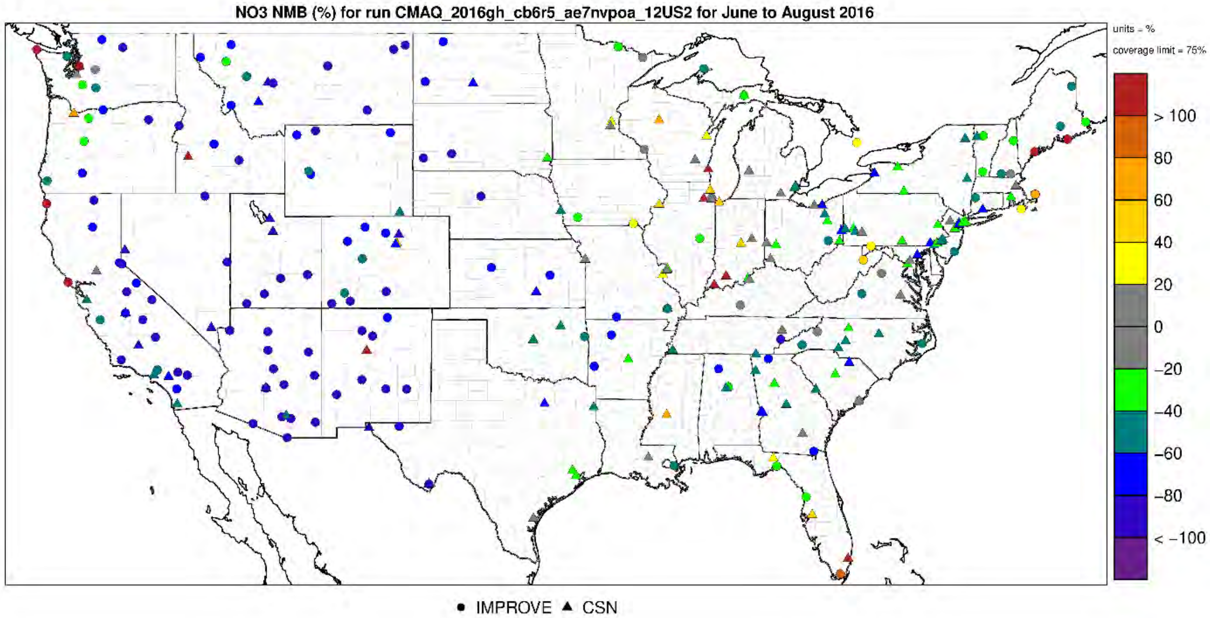

Figure 7-43 Normalized Mean Bias (%) for nitrate during summer 2016 at monitoring sites in the modeling domain

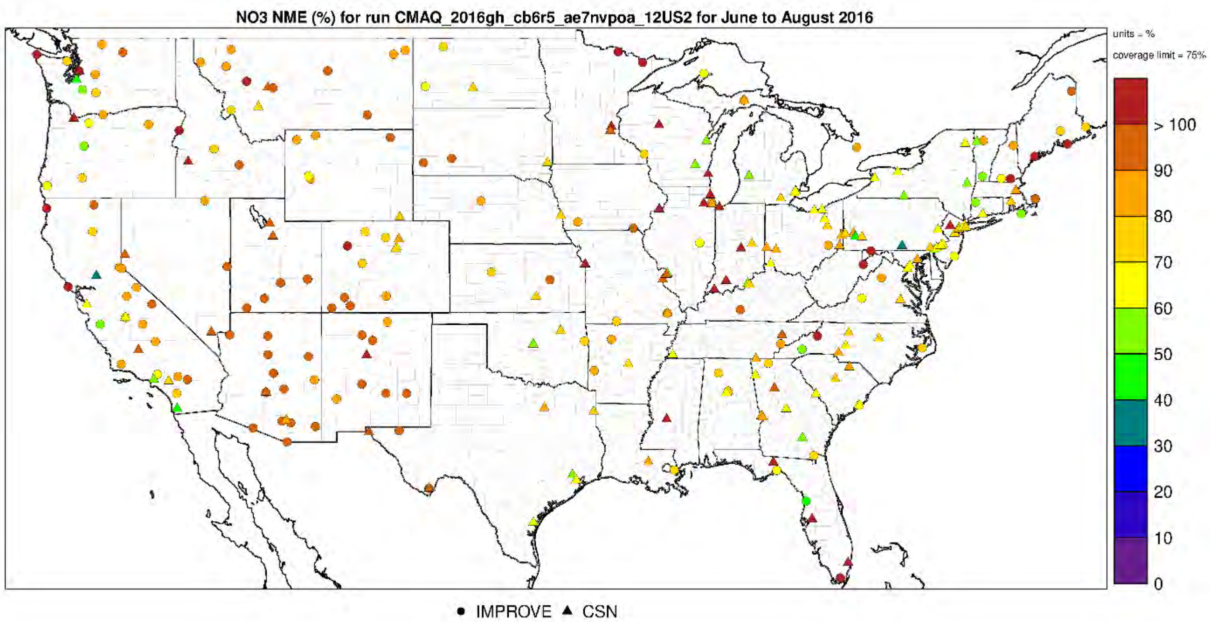

Figure 7-44 Normalized Mean Error (%) for nitrate during summer 2016 at monitoring sites in the modeling domain

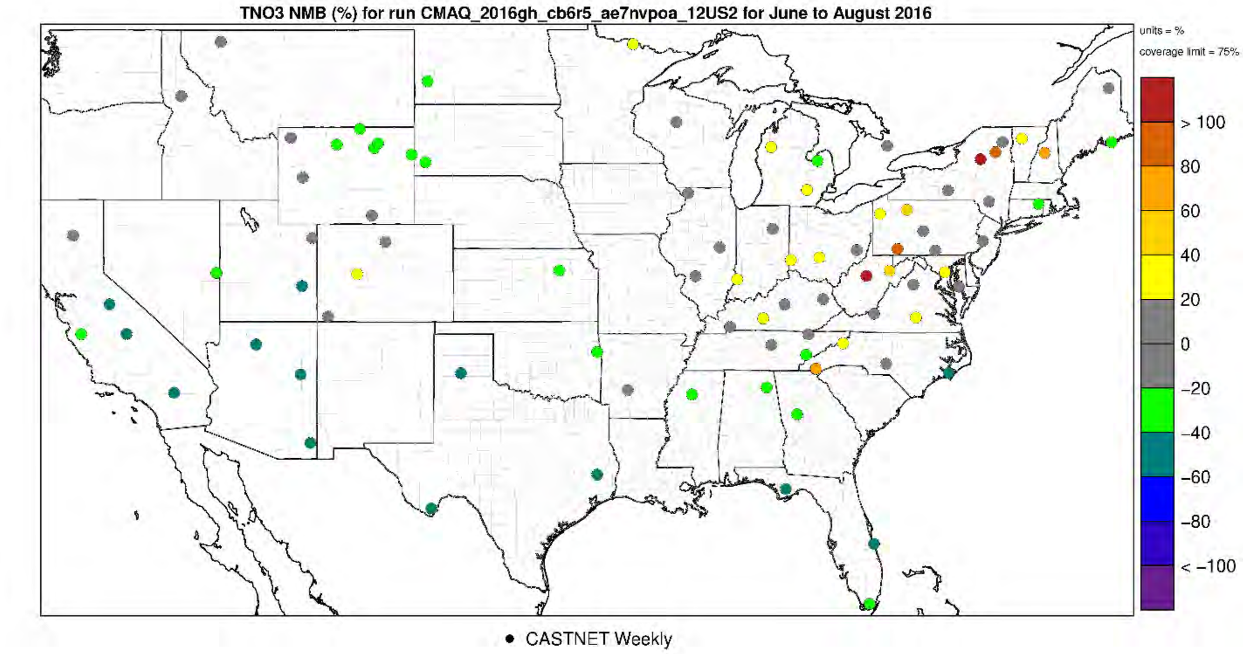

Figure 7-45 Normalized Mean Bias (%) for total nitrate during summer 2016 at monitoring sites in the modeling domain

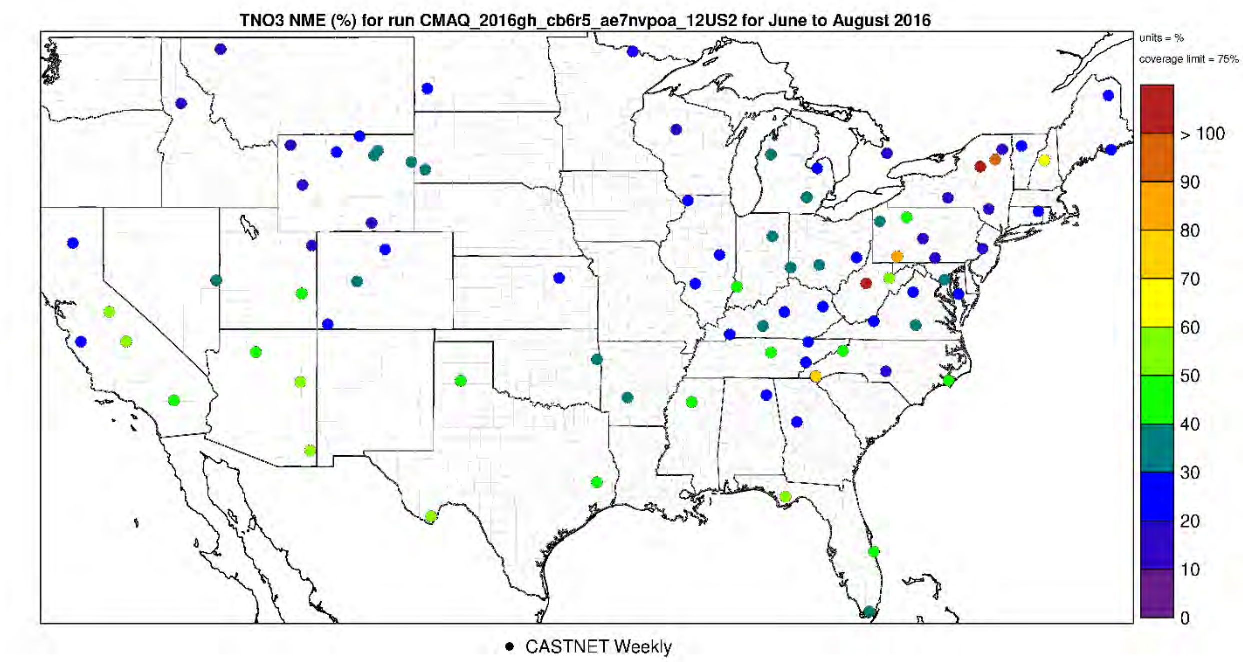

Figure 7-46 Normalized Mean Error (%) for total nitrate during summer 2016 at monitoring sites in the modeling domain

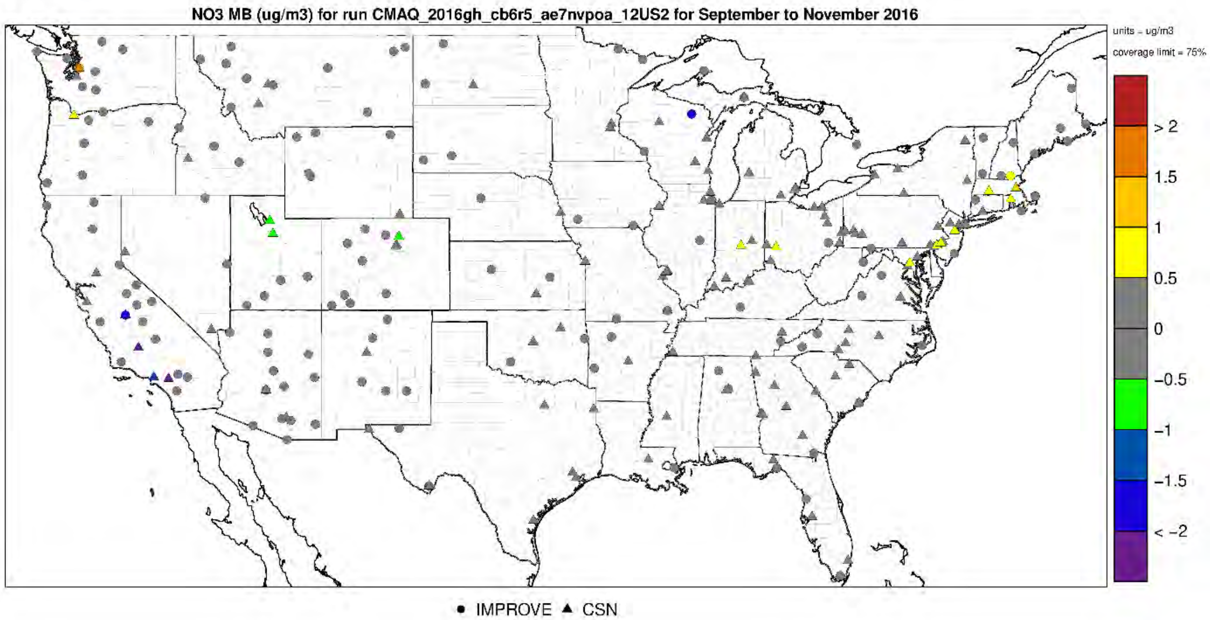

Figure 7-47 Mean Bias (µg/m^3) for nitrate during fall 2016 at monitoring sites in the modeling domain

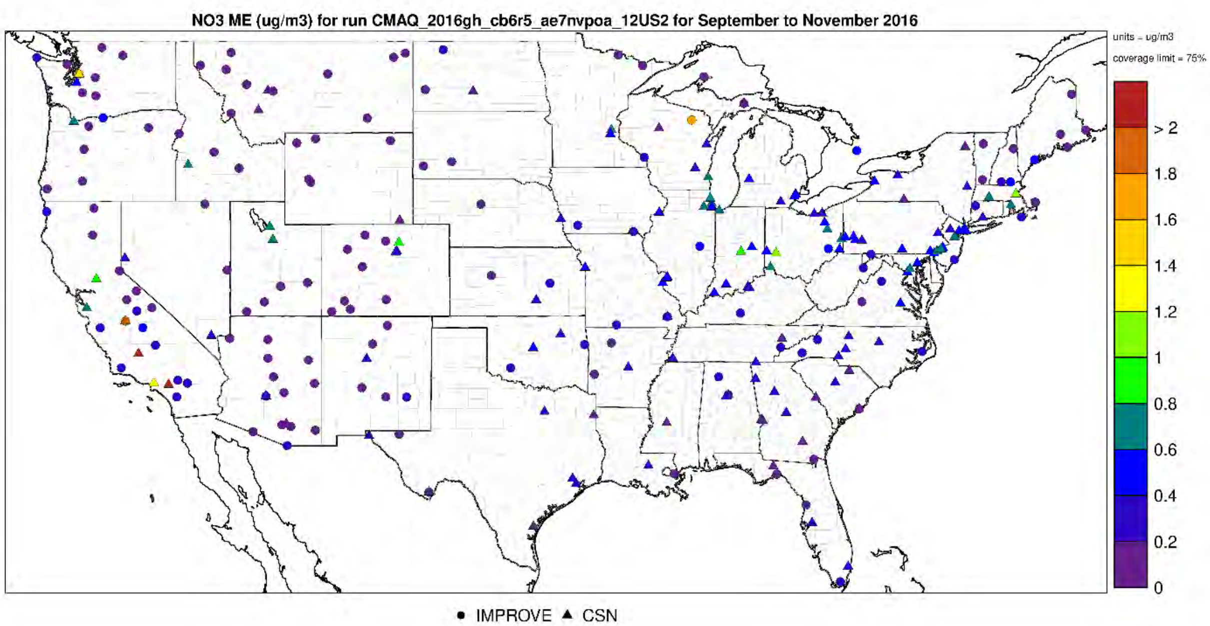

Figure 7-48 Mean Error (µg/m^3) for nitrate during fall 2016 at monitoring sites in the modeling domain

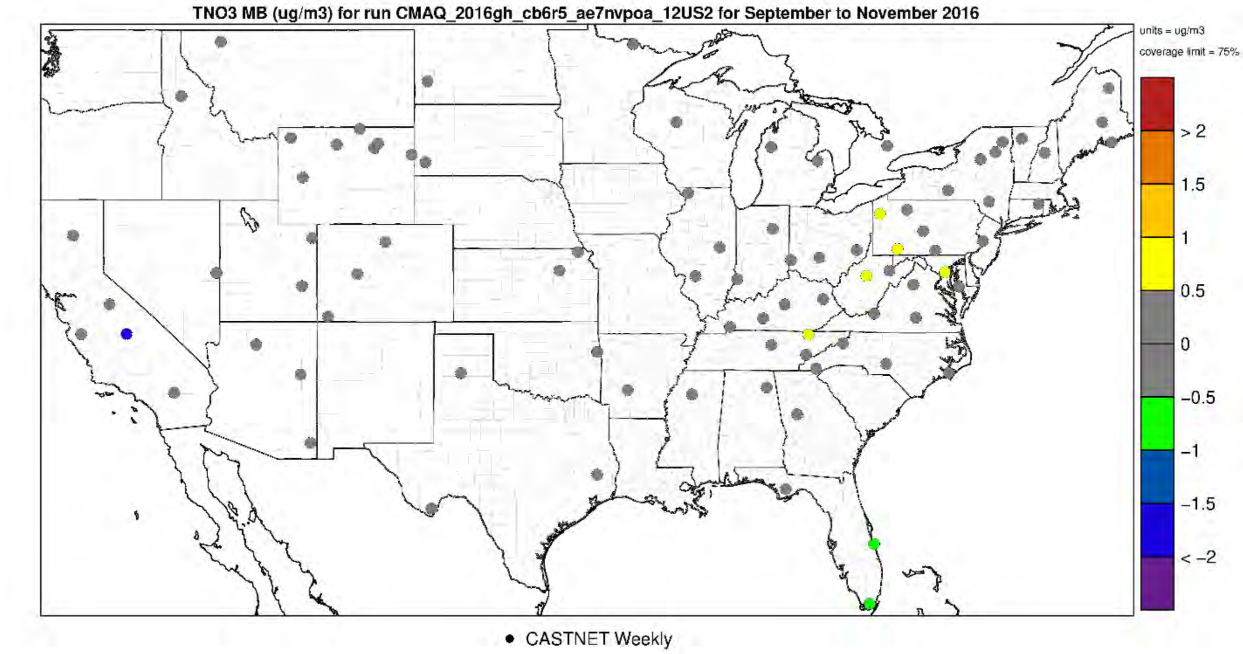

Figure 7-49 Mean Bias (µg/m^3) for total nitrate during fall 2016 at monitoring sites in the modeling domain

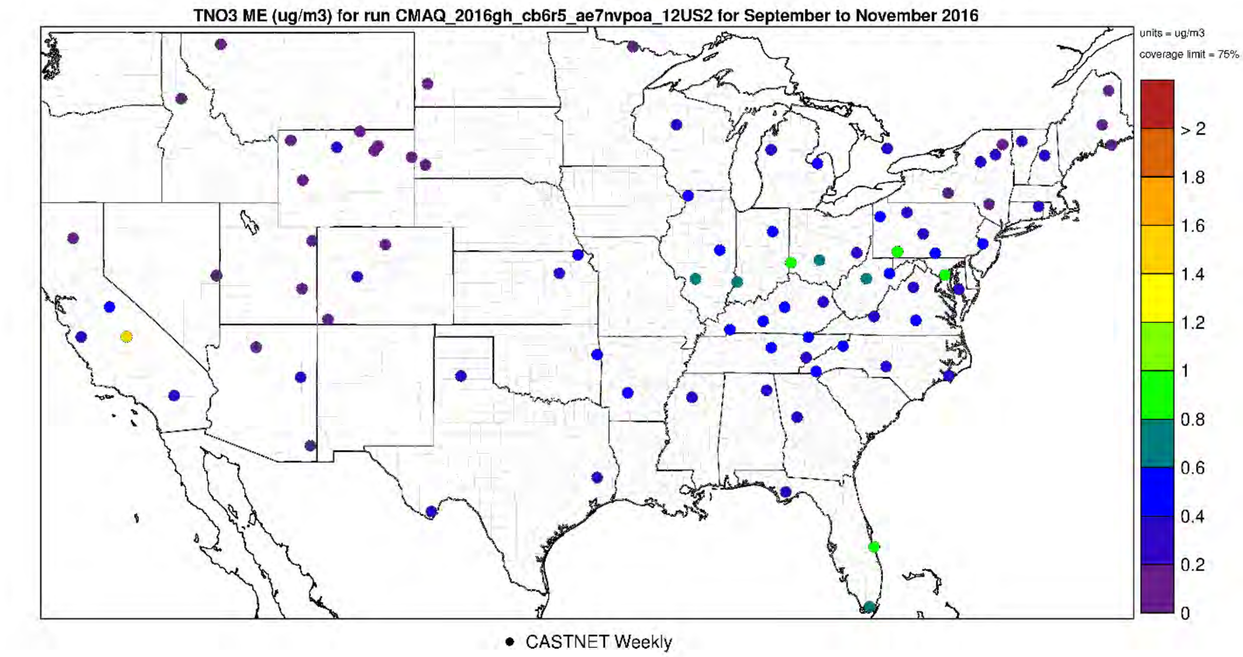

Figure 7-50 Mean Error (µg/m^3) for total nitrate during fall 2016 at monitoring sites in the modeling domain

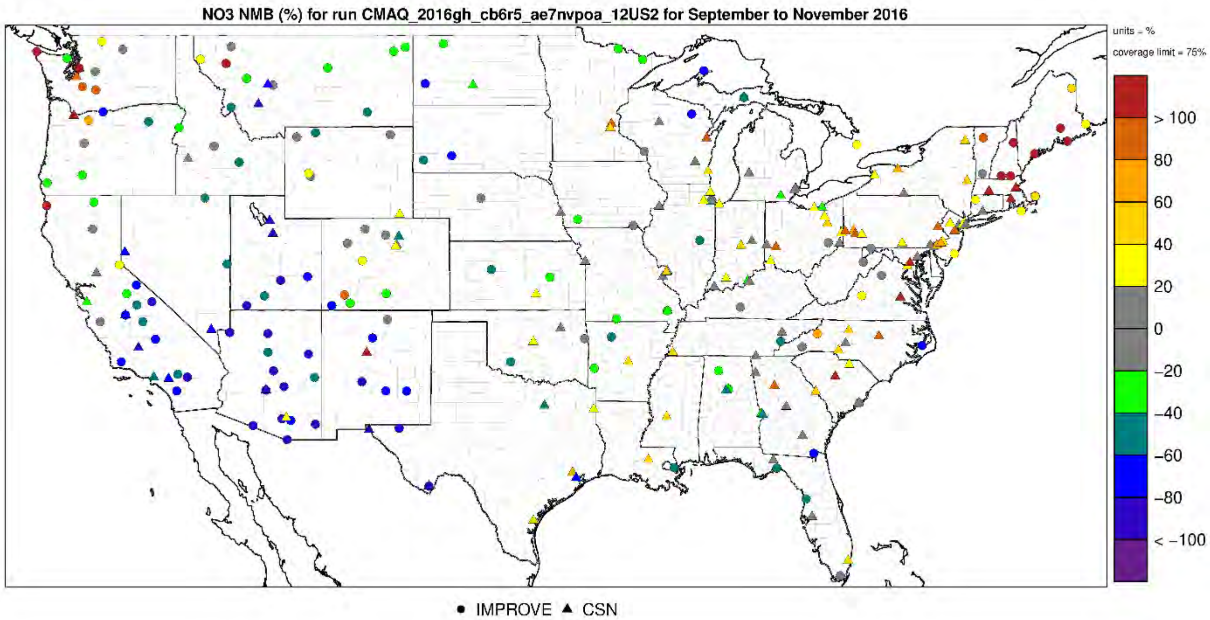

Figure 7-51 Normalized Mean Bias (%) for nitrate during fall 2016 at monitoring sites in the modeling domain

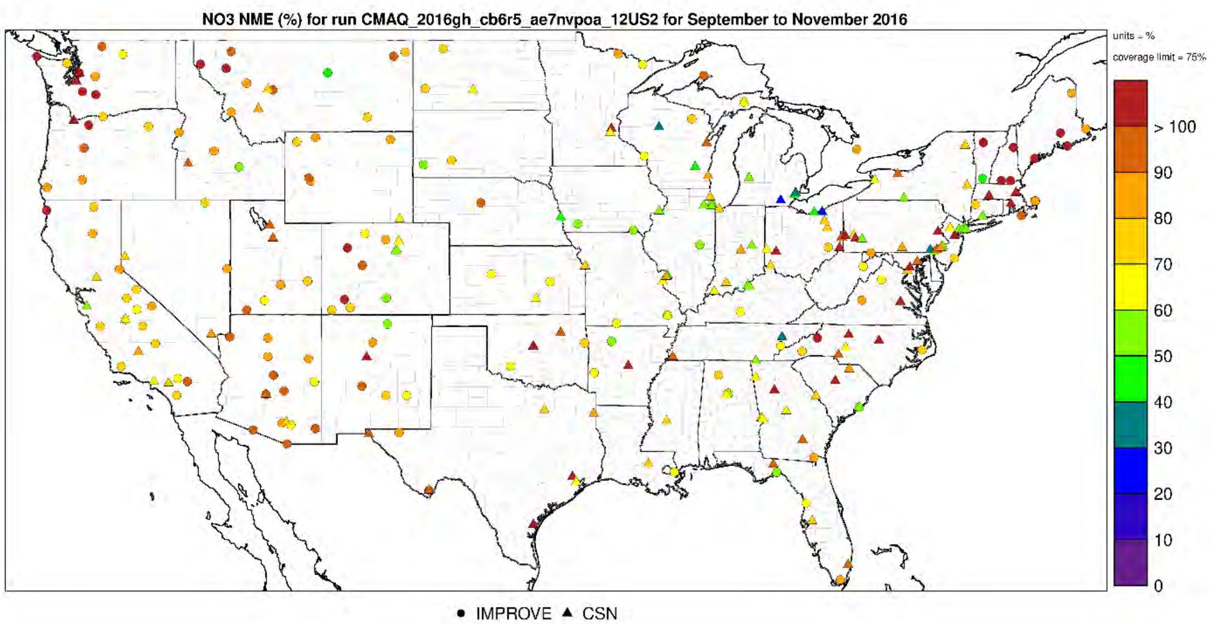

Figure 7-52 Normalized Mean Error (%) for nitrate during fall 2016 at monitoring sites in the modeling domain

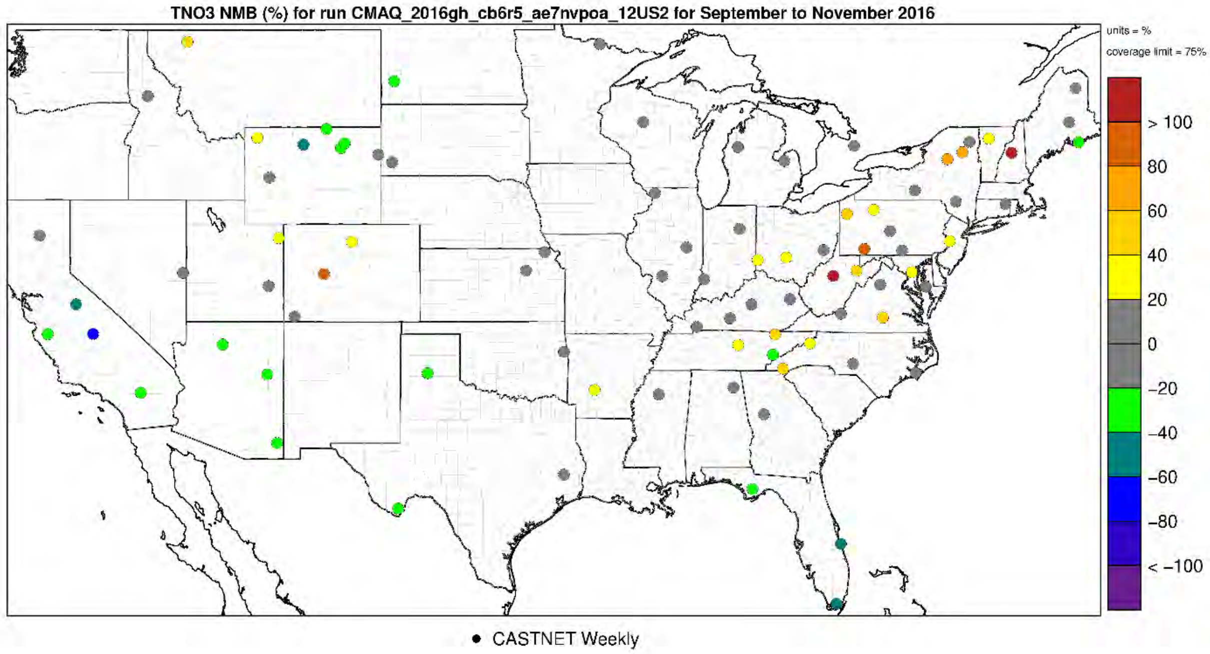

Figure 7-53 Normalized Mean Bias (%) for total nitrate during fall 2016 at monitoring sites in the modeling domain

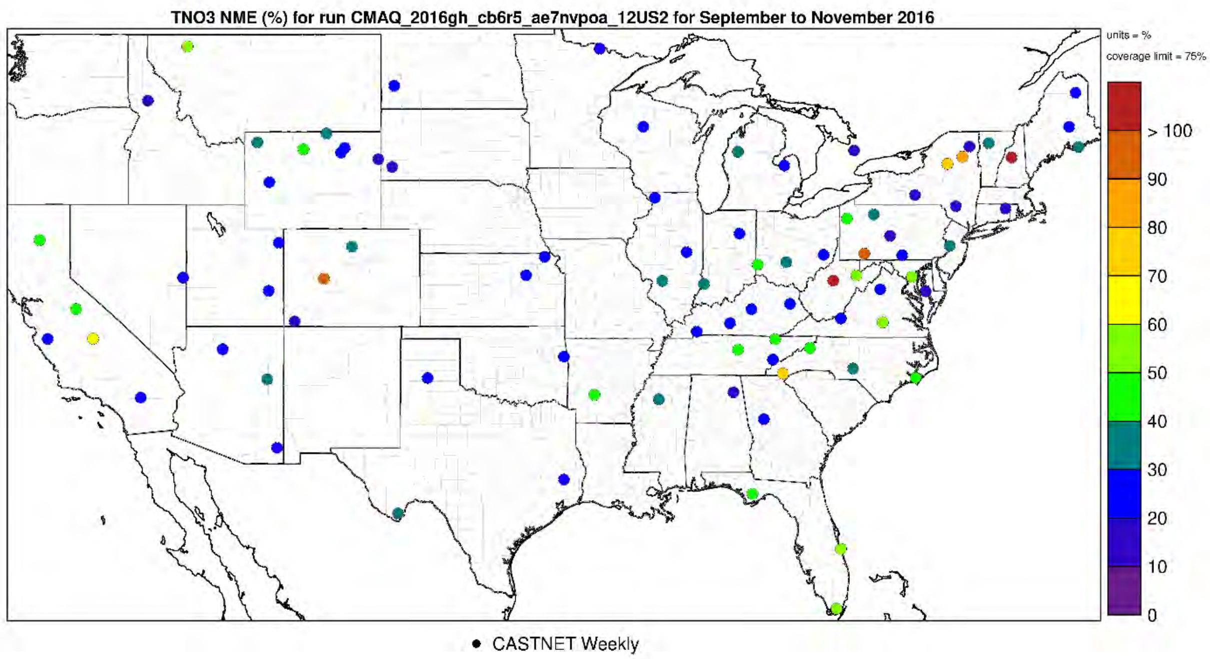

Figure 7-54 Normalized Mean Error (%) for total nitrate during fall 2016 at monitoring sites in the modeling domain

7.4.4.3 Seasonal Ammonium Performance

The model performance bias and error statistics for ammonium for each climate region and season are provided in Table 7-7. Spatial plots of the MB, ME, NMB, and NME by season for individual monitors are shown in Figure 7-55 through Figure 7-70.

Table 7-7 Ammonium Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	CSN	Winter	718	0.6	0.7	>100	>100
		Spring	770	0.2	0.3	82.6	>100
		Summer	782	-0.0	0.1	-5.1	60.2
		Fall	737	0.2	0.3	77.9	>100
	CASTNet	Winter	221	0.1	0.1	12.2	28.0
		Spring	242	-0.1	0.1	-26.2	34.7
		Summer	252	-0.2	0.2	-45.9	46.2
		Fall	242	-0.1	0.1	-23.6	37.0
Ohio Valley	CSN	Winter	547	0.2	0.5	26.6	65.0
		Spring	562	0.1	0.3	34.6	80.3
		Summer	554	0.0	0.2	6.4	64.8
		Fall	541	0.1	0.3	14.8	67.8
	CASTNet	Winter	212	-0.2	0.2	-21.4	27.9
		Spring	228	-0.2	0.3	-40.3	44.4
		Summer	224	-0.2	0.2	-40.4	41.5
		Fall	226	-0.2	0.2	-36.4	39.9
Upper Midwest	CSN	Winter	326	0.3	0.5	43.5	66.0
		Spring	354	0.2	0.3	43.2	80.6
		Summer	314	0.1	0.2	45.9	86.0
		Fall	310	0.2	0.3	80.8	>100
	CASTNet	Winter	59	-0.2	0.3	-25.5	30.7
		Spring	63	-0.1	0.2	-14.9	38.3
		Summer	63	-0.1	0.1	-38.2	39.1
		Fall	57	-0.1	0.2	-34.5	38.8

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Southeast	CSN	Winter	513	0.3	0.4	95.4	>100
		Spring	551	-0.1	0.2	-28.7	60.9
		Summer	524	-0.1	0.2	-41.9	66.3
		Fall	503	-0.0	0.2	-6.8	67.7
	CASTNet	Winter	150	-0.0	0.1	-3.1	28.0
		Spring	164	-0.2	0.2	-52.4	53.1
		Summer	164	-0.2	0.2	-58.1	58.1
		Fall	154	-0.2	0.2	-38.9	42.0
South	CSN	Winter	327	0.2	0.3	45.0	90.8
		Spring	351	-0.1	0.3	-42.2	77.5
		Summer	336	-0.1	0.2	-38.7	82.9
		Fall	331	-0.1	0.2	-21.4	62.3
	CASTNet	Winter	92	-0.1	0.2	-16.2	36.6
		Spring	102	-0.2	0.2	-51.7	56.1
		Summer	96	-0.2	0.2	-56.5	57.6
		Fall	102	-0.2	0.2	-41.2	45.6
Southwest	CSN	Winter	247	-0.4	0.5	-56.9	82.8
		Spring	255	-0.0	0.1	-16.4	>100
		Summer	250	-0.1	0.1	-56.4	99.2
		Fall	260	-0.1	0.2	-43.0	>100
	CASTNet	Winter	101	-0.1	0.1	-42.6	56.0
		Spring	115	-0.0	0.1	-35.9	48.4
		Summer	114	-0.1	0.1	-64.5	64.5
		Fall	115	-0.1	0.1	-50.9	53.9
Northern Rockies	CSN	Winter	143	0.2	0.3	96.9	>100
		Spring	151	0.1	0.2	92.6	>100
		Summer	153	0.1	0.1	>100	>100
		Fall	139	0.1	0.1	>100	>100
	CASTNet	Winter	126	-0.1	0.1	-52.9	56.2

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Spring	139	-0.1	0.1	-45.6	51.3
		Summer	138	-0.1	0.1	-60.2	60.2
		Fall	129	-0.1	0.1	-50.9	54.3
Northwest	CSN	Winter	157	0.1	0.3	31.5	>100
		Spring	161	0.2	0.2	>100	>100
		Summer	166	0.2	0.2	>100	>100
		Fall	161	0.2	0.2	>100	>100
	CASTNet	Winter	12	-0.0	0.0	-15.5	33.7
		Spring	13	-0.1	0.1	-66.3	66.5
		Summer	13	-0.1	0.1	-81.8	81.8
		Fall	13	-0.1	0.1	-68.6	68.7
West	CSN	Winter	341	-0.4	0.6	-44.3	71.7
		Spring	352	-0.2	0.3	-47.3	73.6
		Summer	349	-0.2	0.3	-61.0	71.3
		Fall	332	-0.3	0.4	-56.4	79.7
	CASTNet	Winter	69	-0.1	0.1	-34.5	56.4
		Spring	73	-0.1	0.1	-56.4	58.2
		Summer	75	-0.3	0.3	-81.1	81.1
		Fall	77	-0.1	0.1	-59.6	62.5

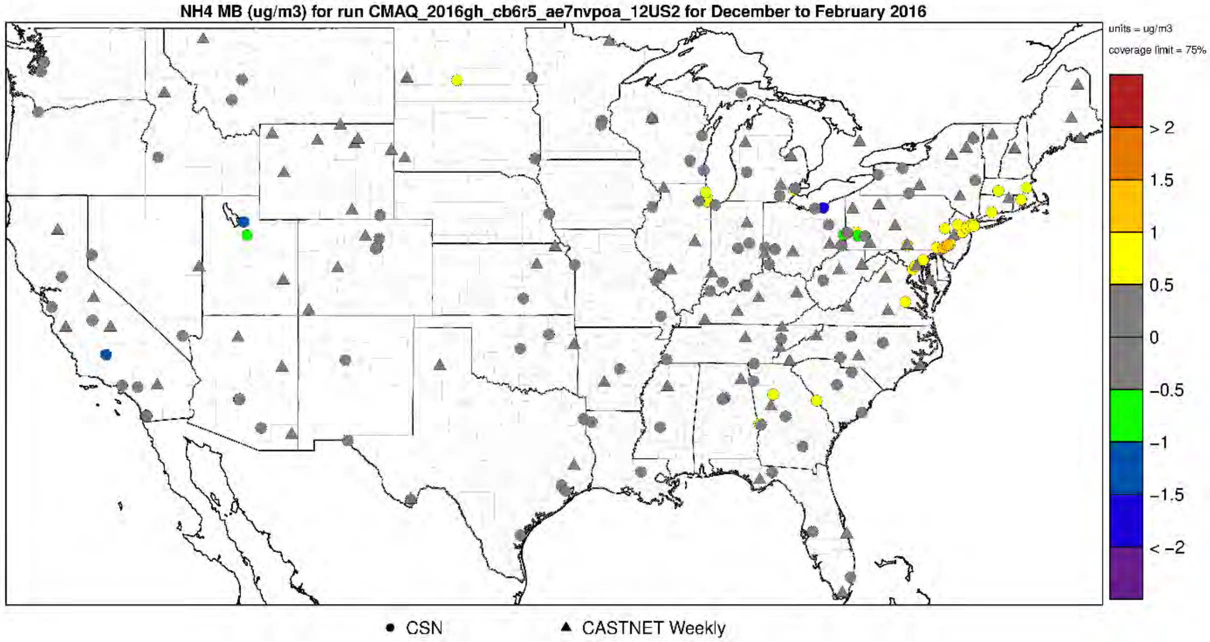

Figure 7-55 Mean Bias (µg/m^3) of ammonium during winter 2016 at monitoring sites in the modeling domain

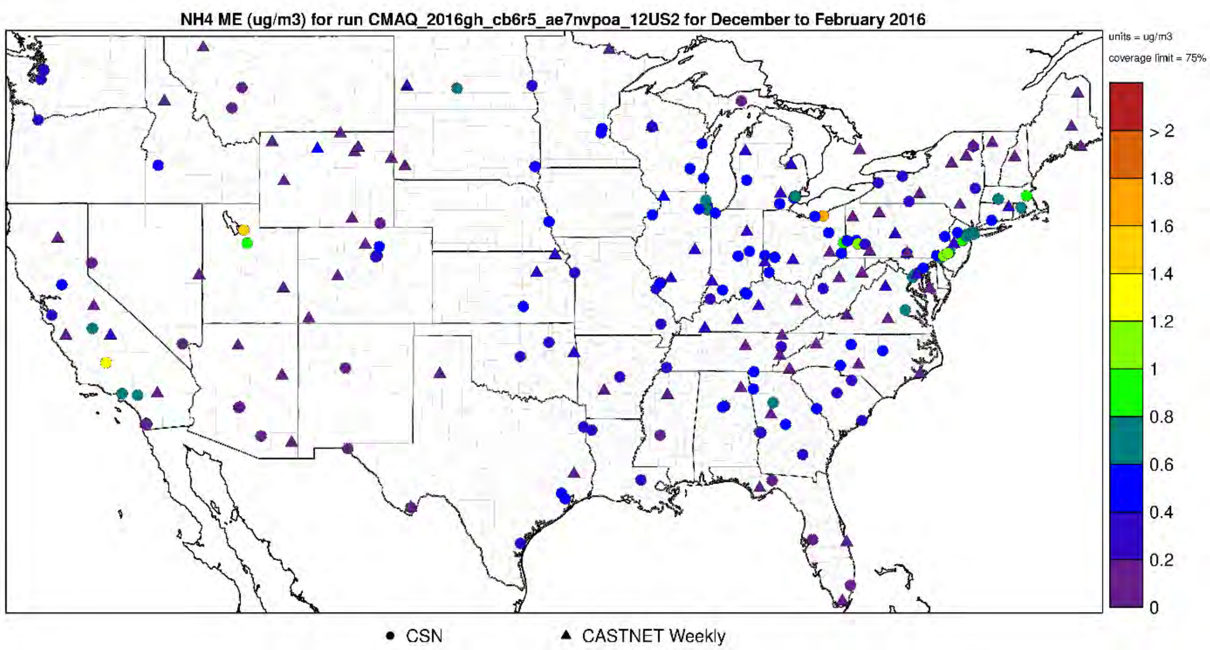

Figure 7-56 Mean Error (µg/m^3) of ammonium during winter 2016 at monitoring sites in the modeling domain

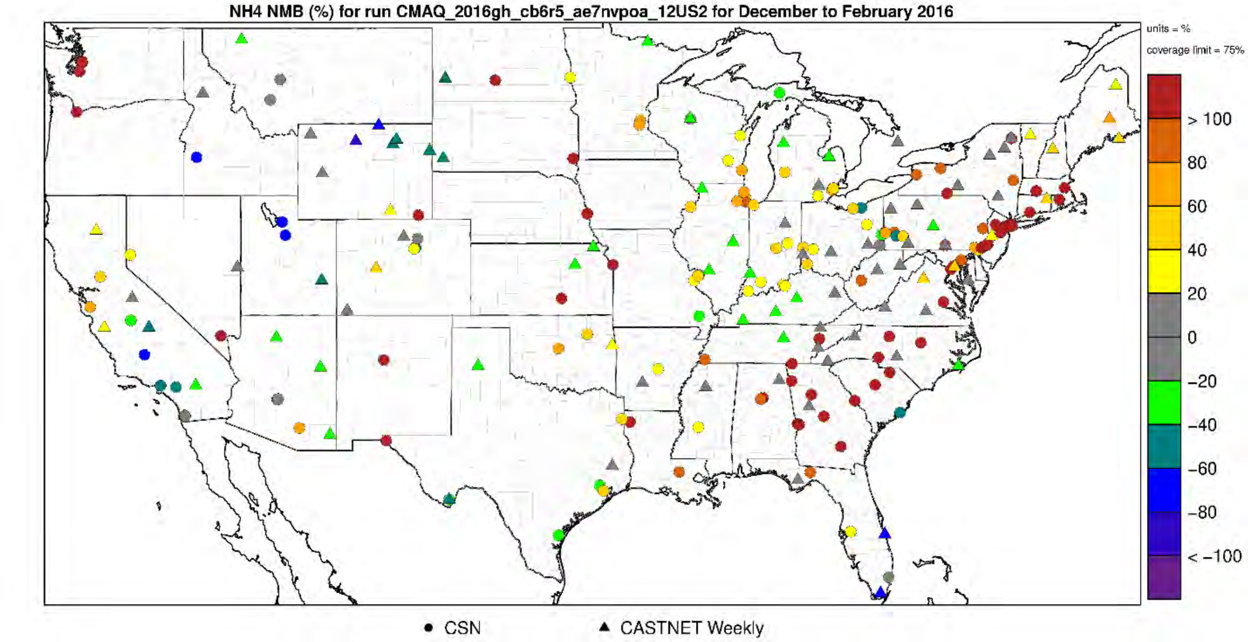

Figure 7-57 Normalized Mean Bias (%) of ammonium during winter 2016 at monitoring sites in the modeling domain

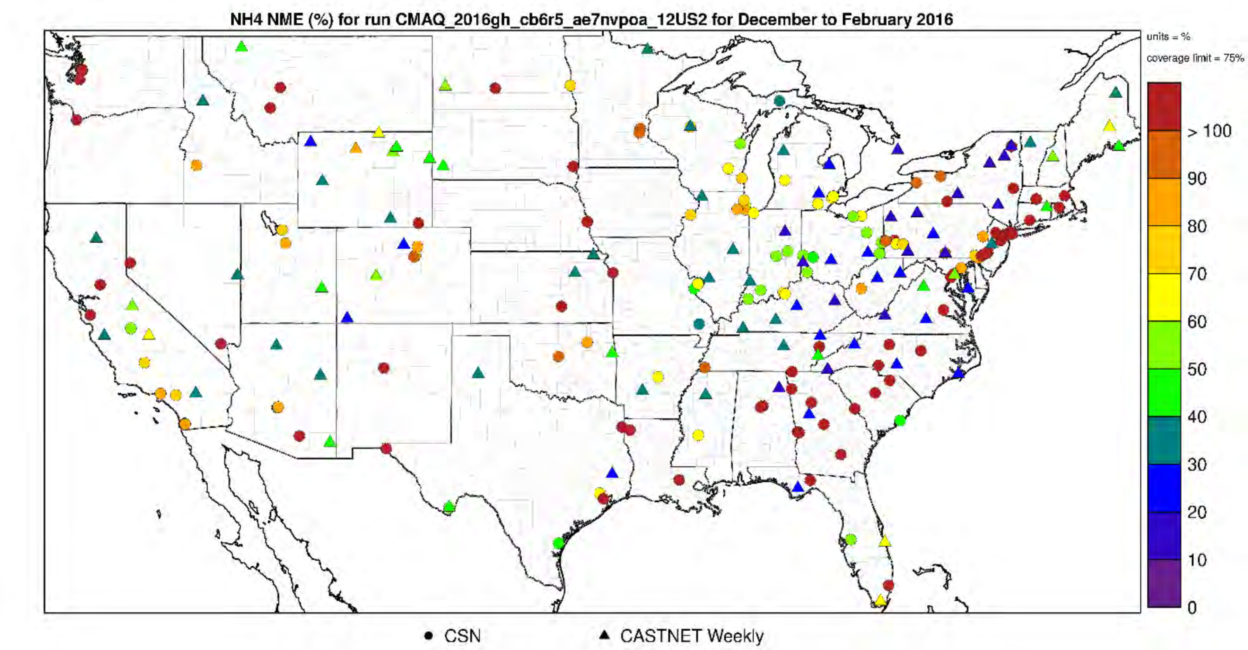

Figure 7-58 Normalized Mean Error (%) of ammonium during winter 2016 at monitoring sites in the modeling domain

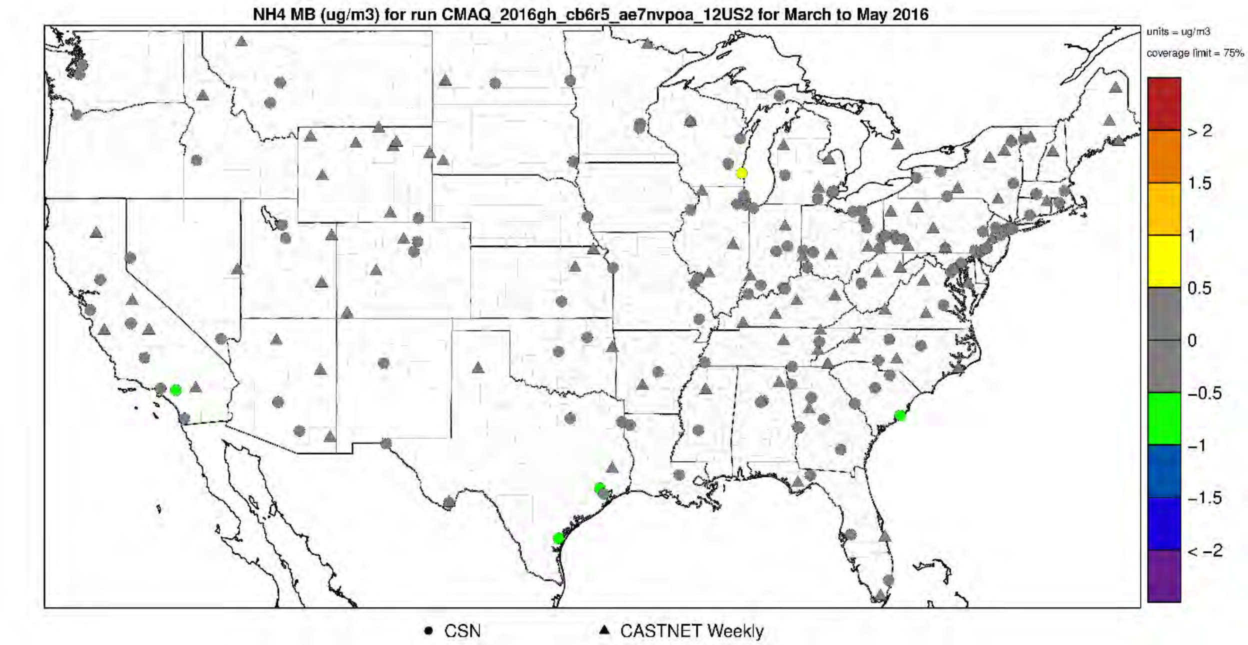

Figure 7-59 Mean Bias (µg/m^3) of ammonium during spring 2016 at monitoring sites in the modeling domain

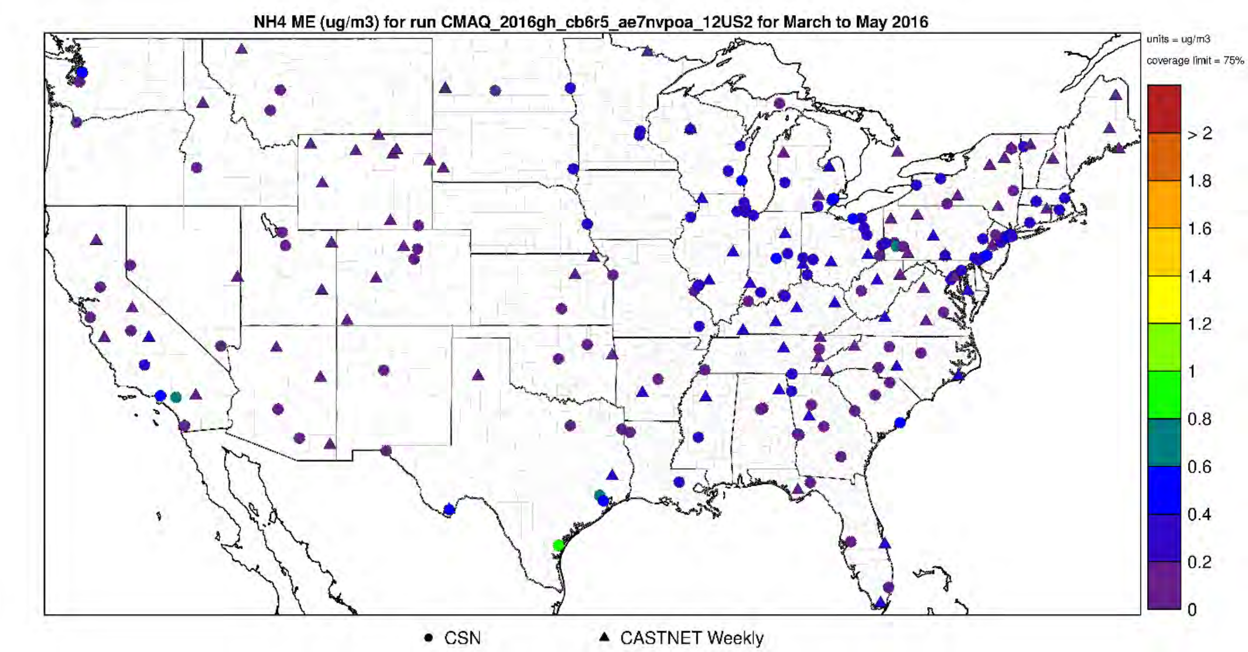

Figure 7-60 Mean Error (µg/m^3) of ammonium during spring 2016 at monitoring sites in the modeling domain

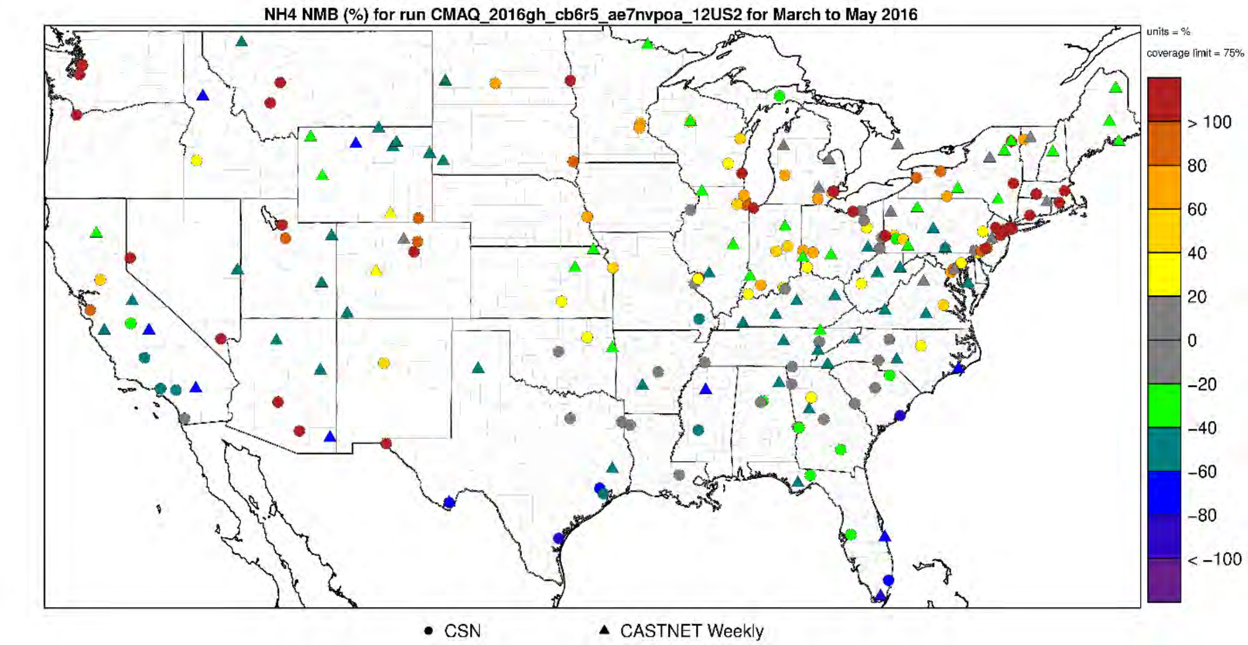

Figure 7-61 Normalized Mean Bias (%) of ammonium during spring 2016 at monitoring sites in the modeling domain

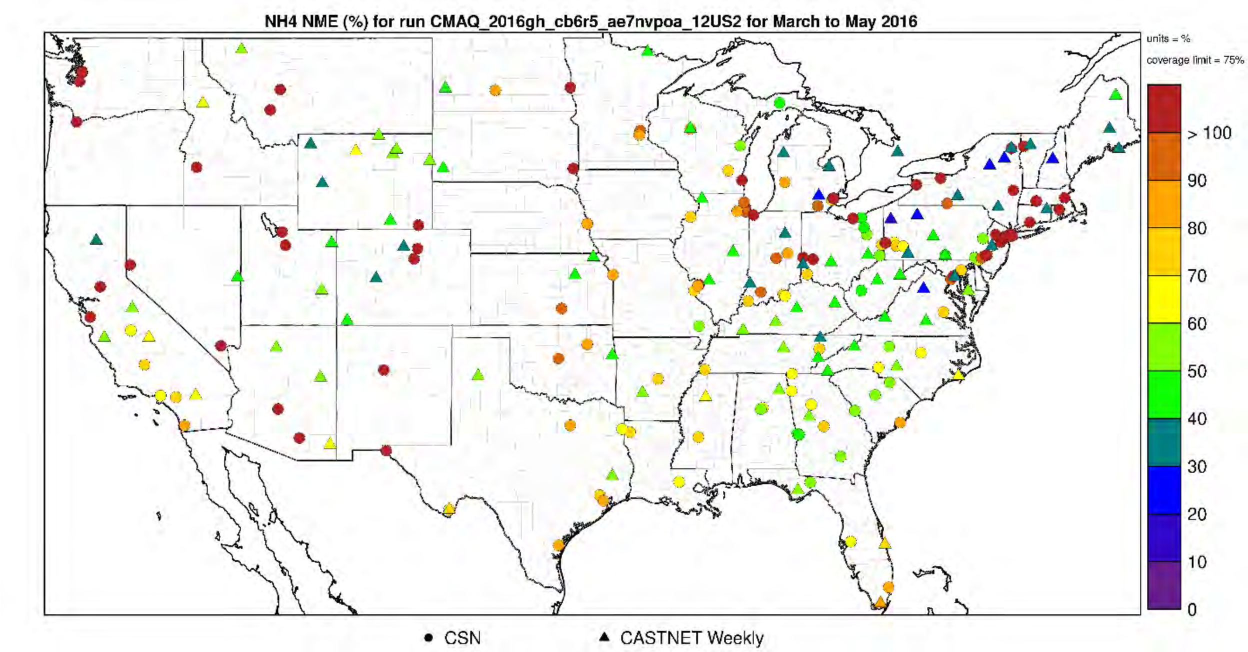

Figure 7-62 Normalized Mean Error (%) of ammonium during spring 2016 at monitoring sites in the modeling domain

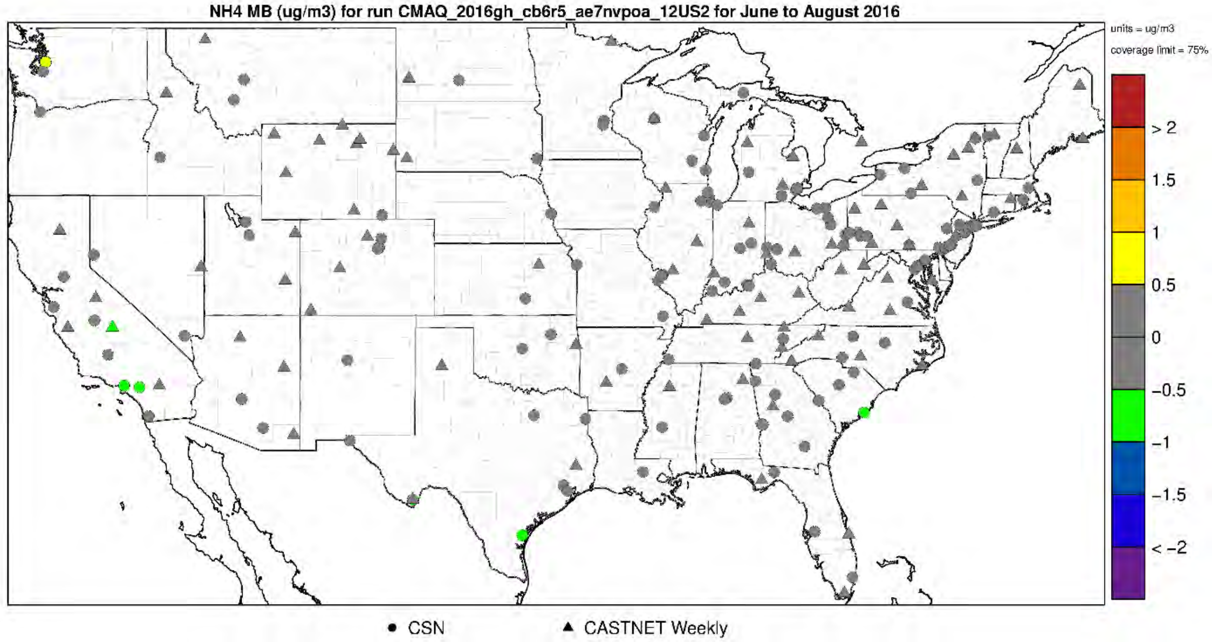

Figure 7-63 Mean Bias (µg/m³) of ammonium during summer 2016 at monitoring sites in the modeling domain

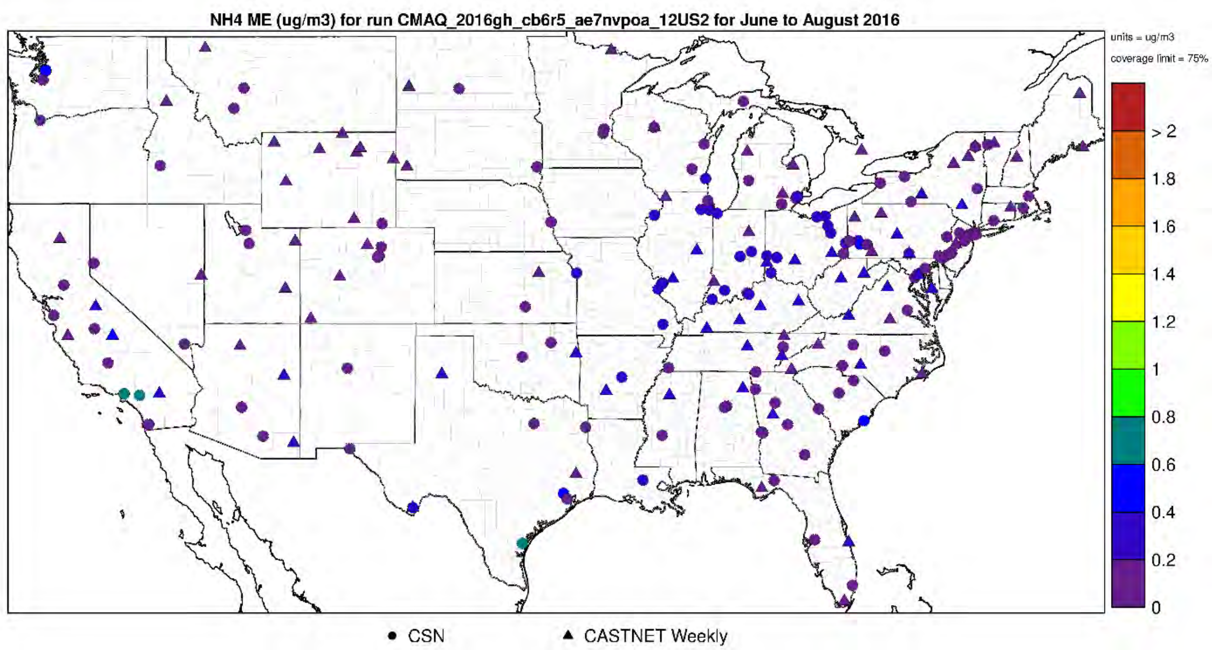

Figure 7-64 Mean Error (µg/m³) of ammonium during summer 2016 at monitoring sites in the modeling domain

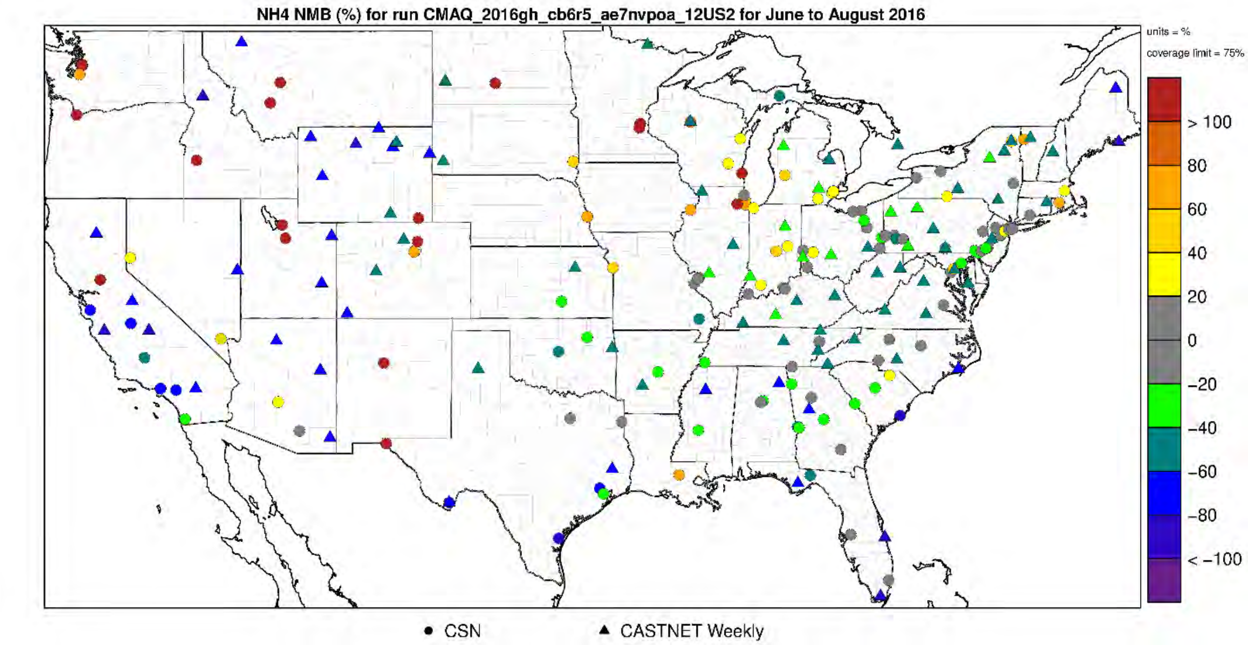

Figure 7-65 Normalized Mean Bias (%) of ammonium during summer 2016 at monitoring sites in the modeling domain

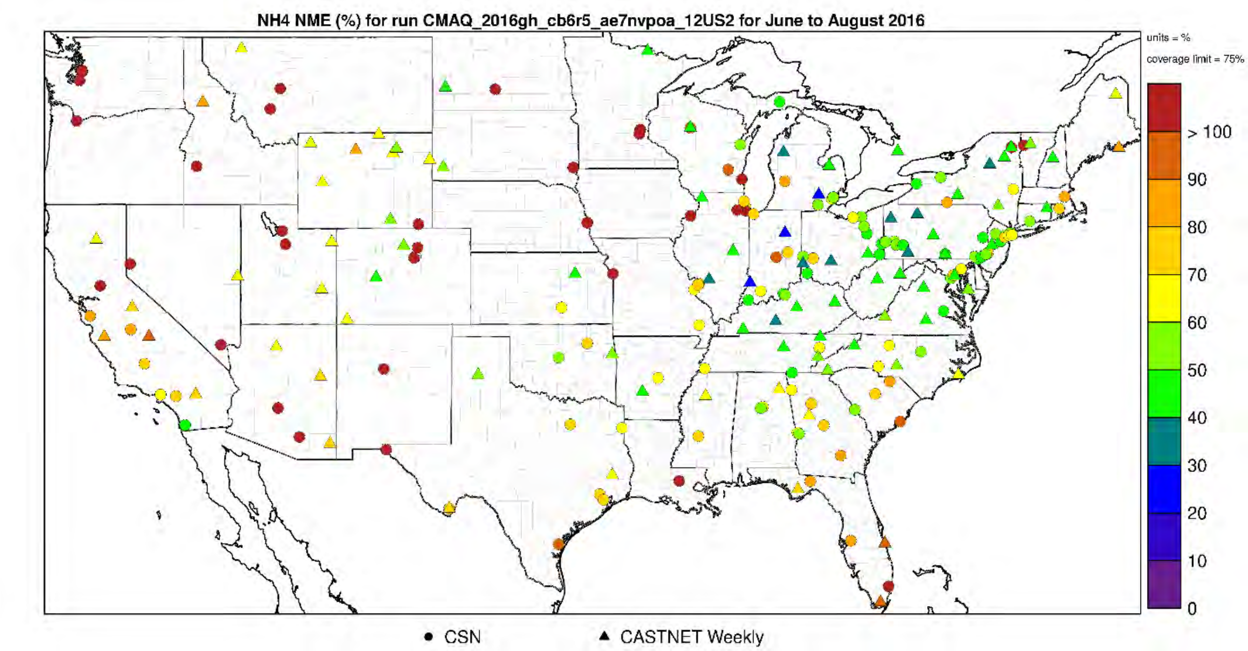

Figure 7-66 Normalized Mean Error (%) of ammonium during summer 2016 at monitoring sites in the modeling domain

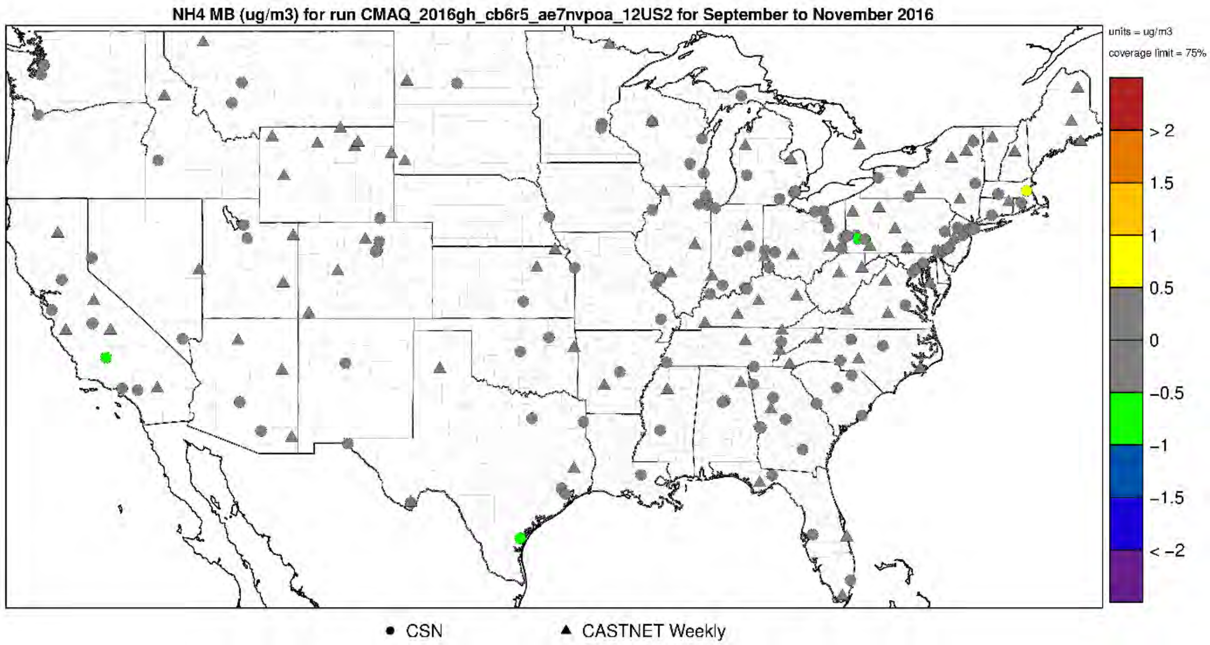

Figure 7-67 Mean Bias (µg/m³) of ammonium during fall 2016 at monitoring sites in the modeling domain

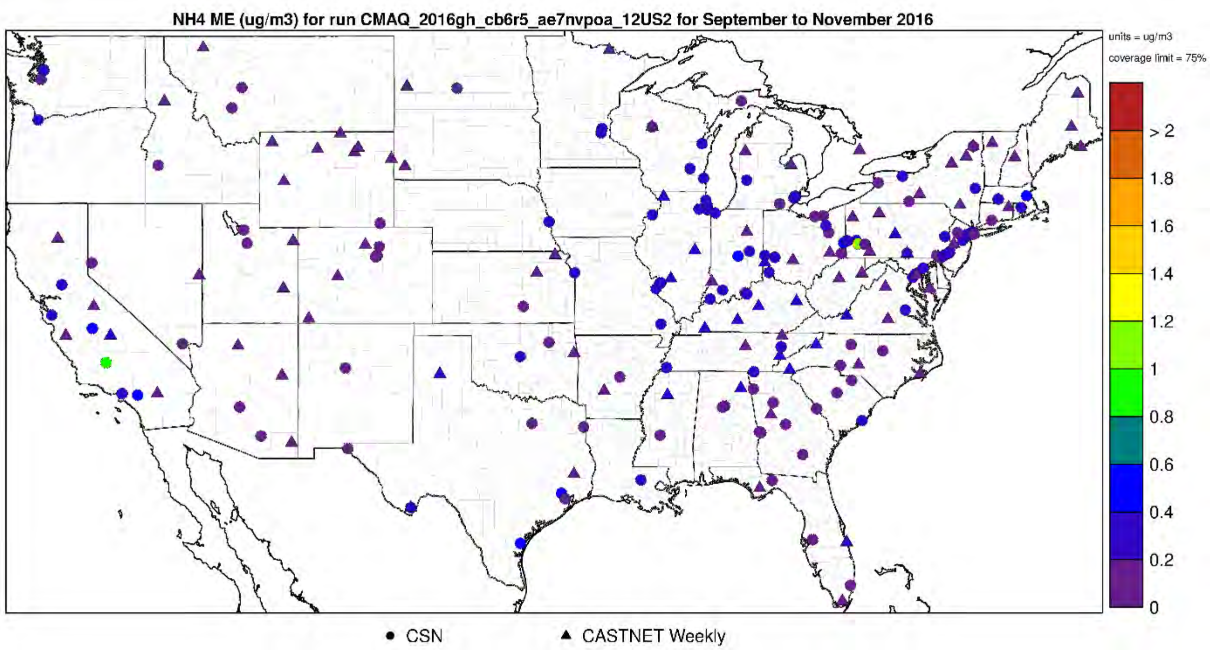

Figure 7-68 Mean Error (µg/m³) of ammonium during fall 2016 at monitoring sites in the modeling domain

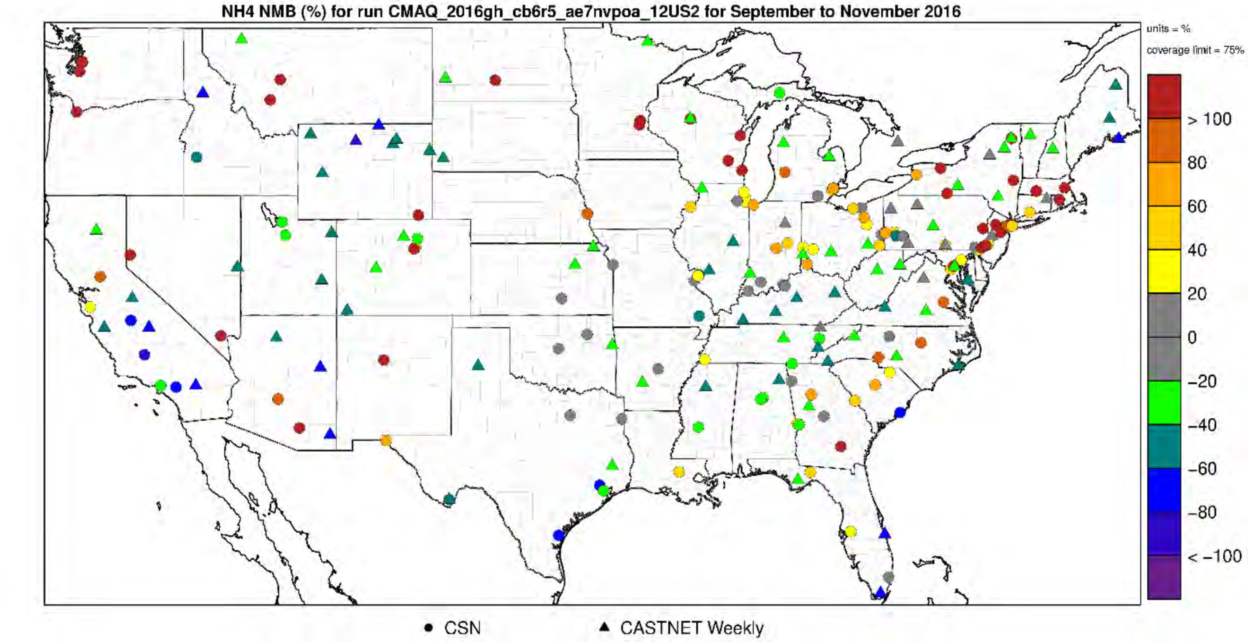

Figure 7-69 Normalized Mean Bias (%) of ammonium during fall 2016 at monitoring sites in the modeling domain

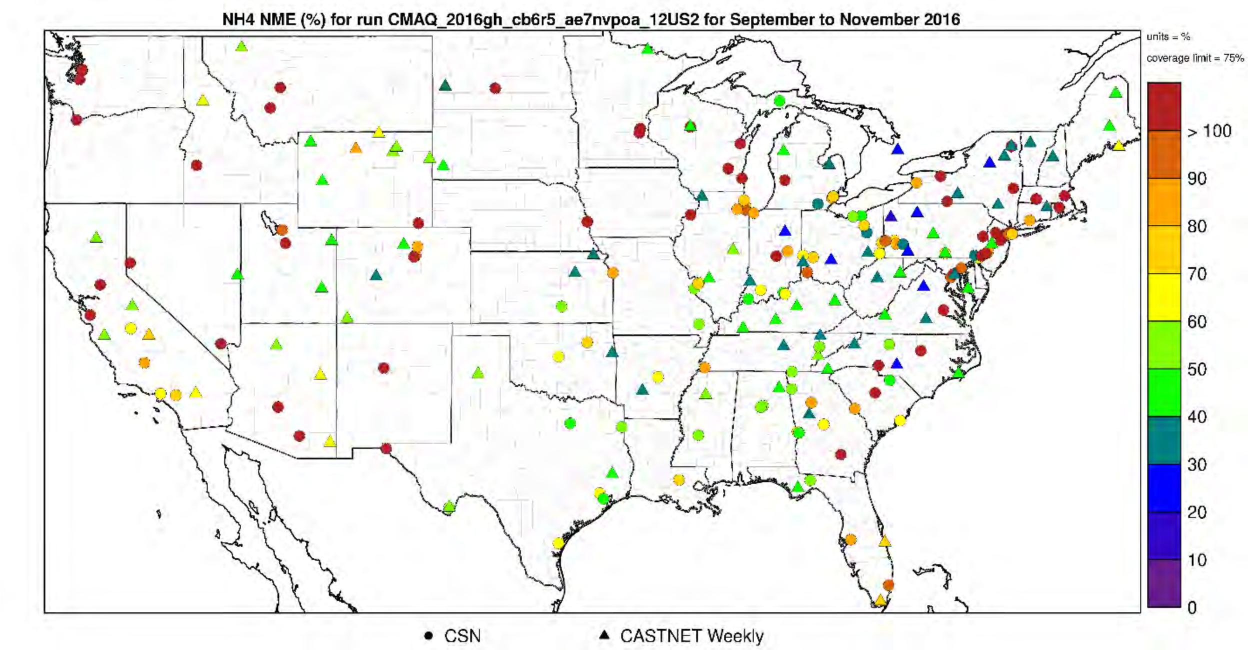

Figure 7-70 Normalized Mean Error (%) of ammonium during fall 2016 at monitoring sites in the modeling domain

7.4.4.4 Seasonal Elemental Carbon Performance

The model performance bias and error statistics for elemental carbon for each of climate region and season are provided in Table 7-8. The statistics show clear at urban and rural sites in most climate regions. Spatial plots of the MB, ME, NMB, and NME by season for individual monitors are shown in Figure 7-71 through Figure 7-86.

Table 7-8 Elemental Carbon Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	IMPROVE	Winter	429	0.1	0.1	46.2	60.5
		Spring	478	0.0	0.1	13.4	44.7
		Summer	479	-0.0	0.1	-6.5	39.1
		Fall	456	0.0	0.1	9.5	43.6
	CSN	Winter	722	0.1	0.4	21.7	56.3
		Spring	785	-0.0	0.3	-3.2	44.7
		Summer	788	-0.1	0.2	-13.2	41.1
		Fall	780	0.1	0.3	14.8	50.0
Ohio Valley	IMPROVE	Winter	217	0.0	0.1	7.6	46.2
		Spring	242	-0.1	0.1	-23.9	49.9
		Summer	241	-0.1	0.1	-36.1	40.1
		Fall	232	-0.1	0.1	-28.7	38.3
	CSN	Winter	535	0.1	0.2	17.8	46.8
		Spring	571	-0.1	0.2	-15.1	39.4
		Summer	532	-0.1	0.2	-20.0	38.7
		Fall	535	-0.0	0.2	-7.0	35.1
Upper Midwest	IMPROVE	Winter	222	0.1	0.1	37.0	53.7
		Spring	239	-0.0	0.1	-17.3	45.2
		Summer	236	-0.1	0.1	-30.9	44.4
		Fall	243	-0.0	0.1	-12.7	44.0
	CSN	Winter	334	0.2	0.2	53.8	73.7
		Spring	347	-0.0	0.2	-0.1	48.6
		Summer	332	-0.0	0.2	-9.7	46.4

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Fall	338	0.0	0.2	7.0	47.5
Southeast	IMPROVE	Winter	398	-0.0	0.1	-8.1	49.0
		Spring	446	-0.2	0.2	-46.8	58.3
		Summer	442	-0.1	0.1	-29.9	48.7
		Fall	422	-0.1	0.1	-31.1	40.8
	CSN	Winter	436	-0.0	0.2	-3.7	41.5
		Spring	478	-0.1	0.2	-25.9	42.9
		Summer	445	-0.0	0.2	-10.3	49.6
		Fall	430	-0.1	0.3	-19.8	41.1
South	IMPROVE	Winter	240	-0.0	0.1	-5.2	41.1
		Spring	272	-0.0	0.1	-14.3	52.7
		Summer	242	-0.0	0.1	-30.2	42.8
		Fall	262	-0.1	0.1	-33.5	42.6
	CSN	Winter	272	-0.0	0.2	-5.1	40.6
		Spring	297	-0.1	0.2	-16.5	38.7
		Summer	251	-0.0	0.2	-3.4	52.1
		Fall	238	-0.0	0.2	-2.3	45.4
Southwest	IMPROVE	Winter	890	-0.1	0.1	-34.3	58.1
		Spring	981	-0.0	0.1	-2.2	65.6
		Summer	962	-0.0	0.1	-22.9	57.1
		Fall	945	-0.0	0.1	-24.7	58.9
	CSN	Winter	228	0.0	0.4	3.1	42.1
		Spring	254	0.2	0.2	48.5	61.1
		Summer	237	0.1	0.1	25.7	48.9
		Fall	240	0.1	0.3	18.7	49.1
Northern Rockies	IMPROVE	Winter	557	0.0	0.0	12.5	75.0
		Spring	594	-0.0	0.1	-17.2	76.3
		Summer	616	0.0	0.1	16.1	76.6
		Fall	585	-0.0	0.1	-19.6	61.3

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
	CSN	Winter	141	-0.0	0.2	-0.7	96.8
		Spring	145	-0.0	0.1	-12.8	58.6
		Summer	161	-0.0	0.1	-18.0	45.7
		Fall	146	-0.0	0.2	-13.5	70.9
Northwest	IMPROVE	Winter	434	0.0	0.1	54.0	>100
		Spring	505	0.1	0.1	>100	>100
		Summer	504	0.1	0.2	79.8	>100
		Fall	474	0.1	0.2	>100	>100
	CSN	Winter	140	0.3	0.6	42.1	84.2
		Spring	150	0.7	0.8	>100	>100
		Summer	158	1.0	1.0	>100	>100
		Fall	155	0.8	1.0	>100	>100
West	IMPROVE	Winter	540	-0.0	0.1	-12.3	62.5
		Spring	600	0.0	0.1	17.5	69.2
		Summer	601	-0.0	0.1	-10.1	65.4
		Fall	565	0.0	0.1	2.2	60.8
	CSN	Winter	286	0.0	0.5	4.6	42.6
		Spring	294	0.2	0.3	49.9	61.3
		Summer	290	0.2	0.2	42.1	54.6
		Fall	277	0.2	0.4	36.6	55.1

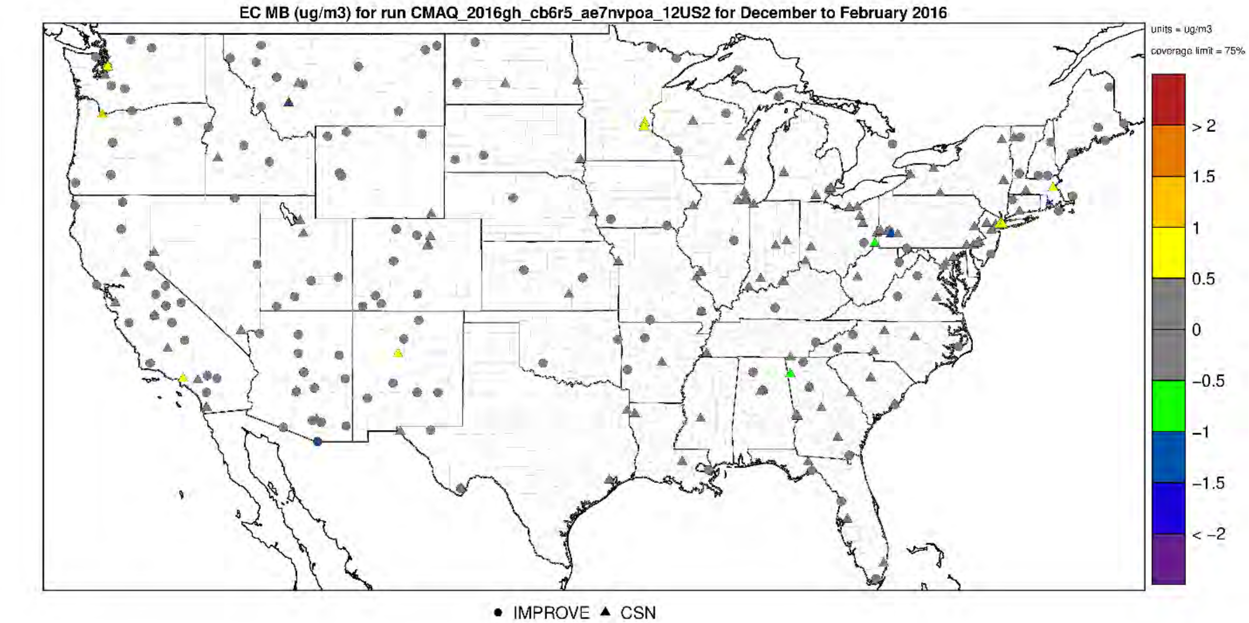

Figure 7-71 Mean Bias (µg/m^{3}3) of elemental carbon during winter 2016 at monitoring sites in the modeling domain

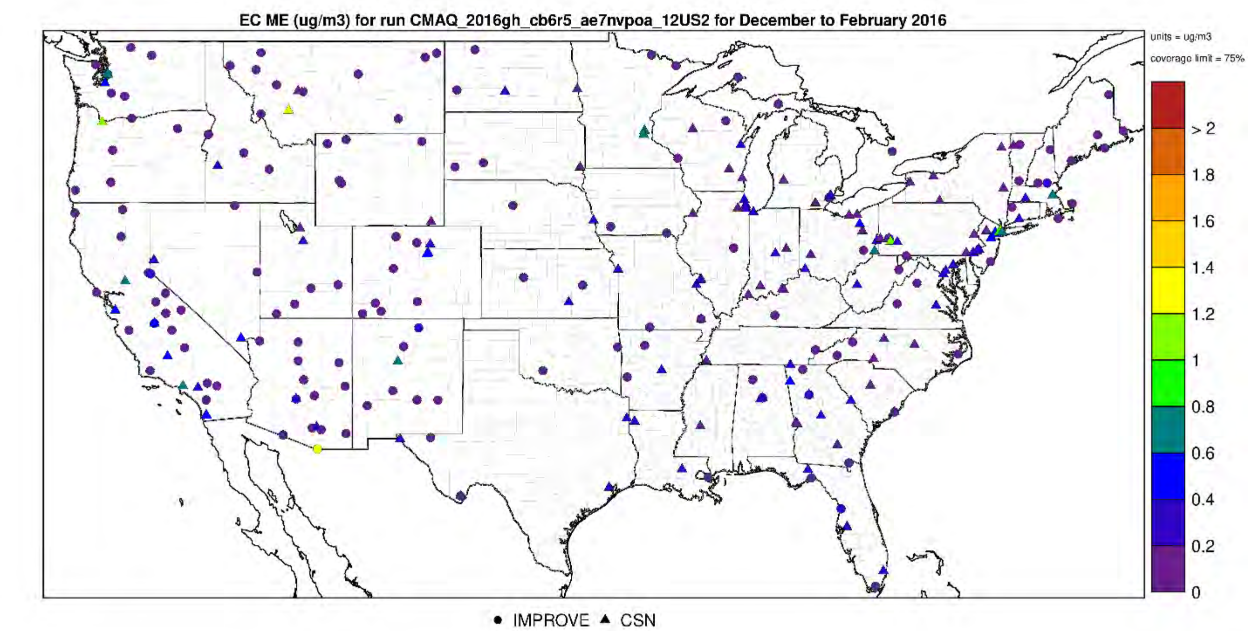

Figure 7-72 Mean Error (µg/m^3) of elemental carbon during winter 2016 at monitoring sites in the modeling domain

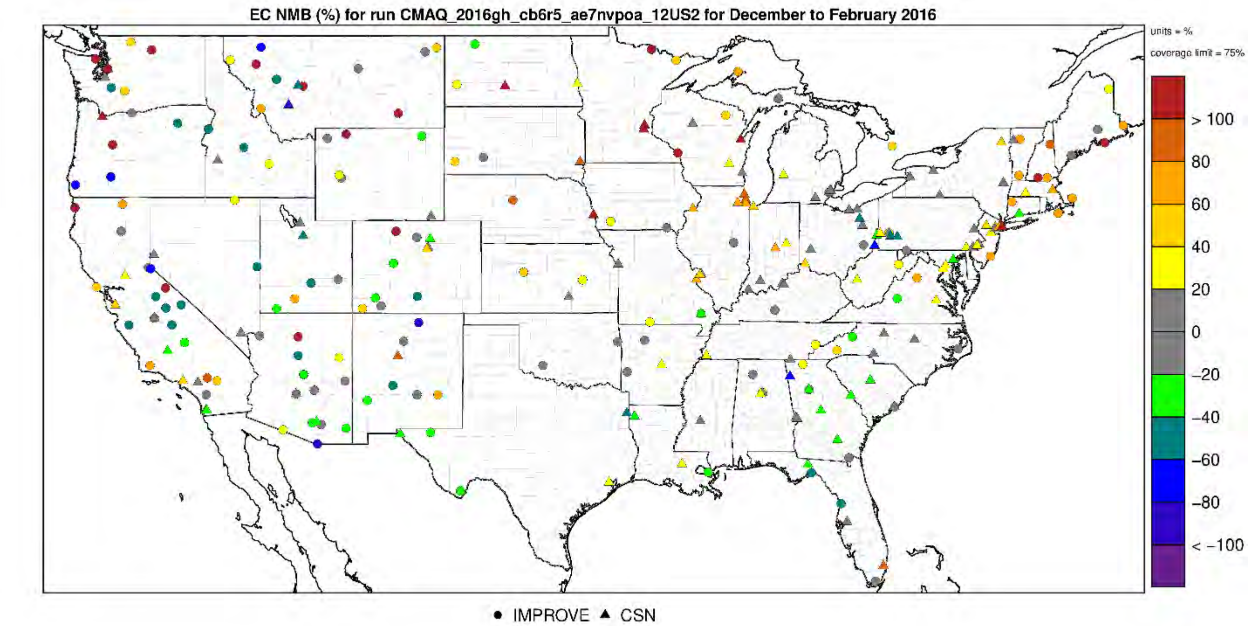

Figure 7-73 Normalized Mean Bias (%) of elemental carbon during winter 2016 at monitoring sites in the modeling domain

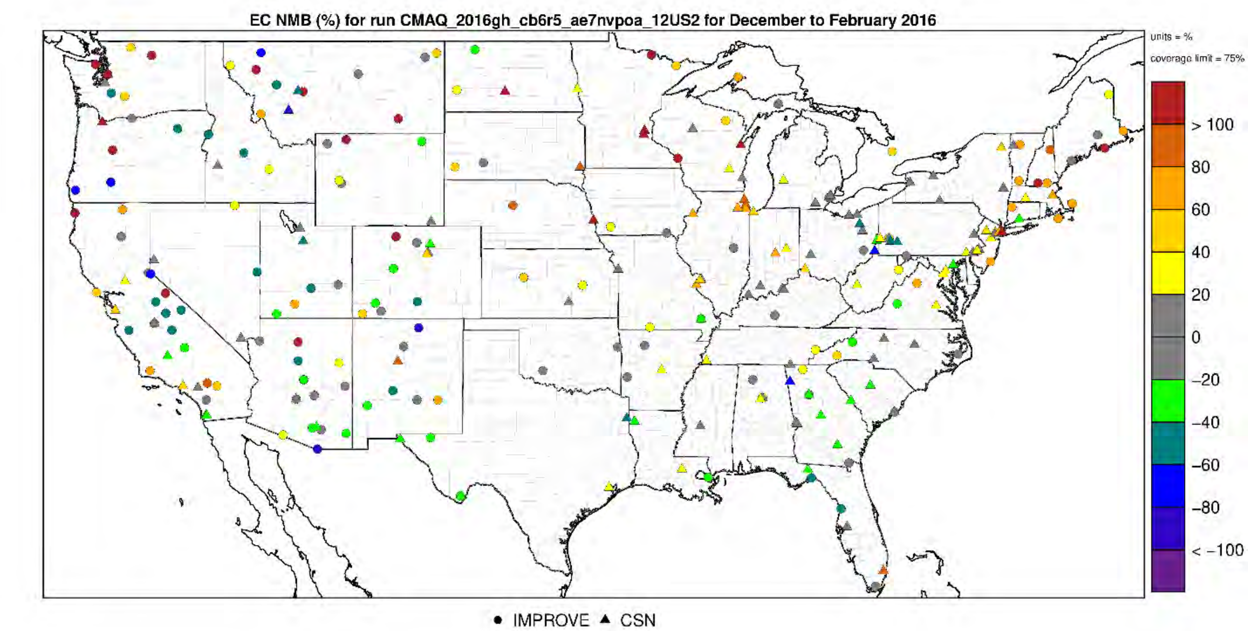

Figure 7-74 Normalized Mean Error (%) of elemental carbon during winter 2016 at monitoring sites in the modeling domain

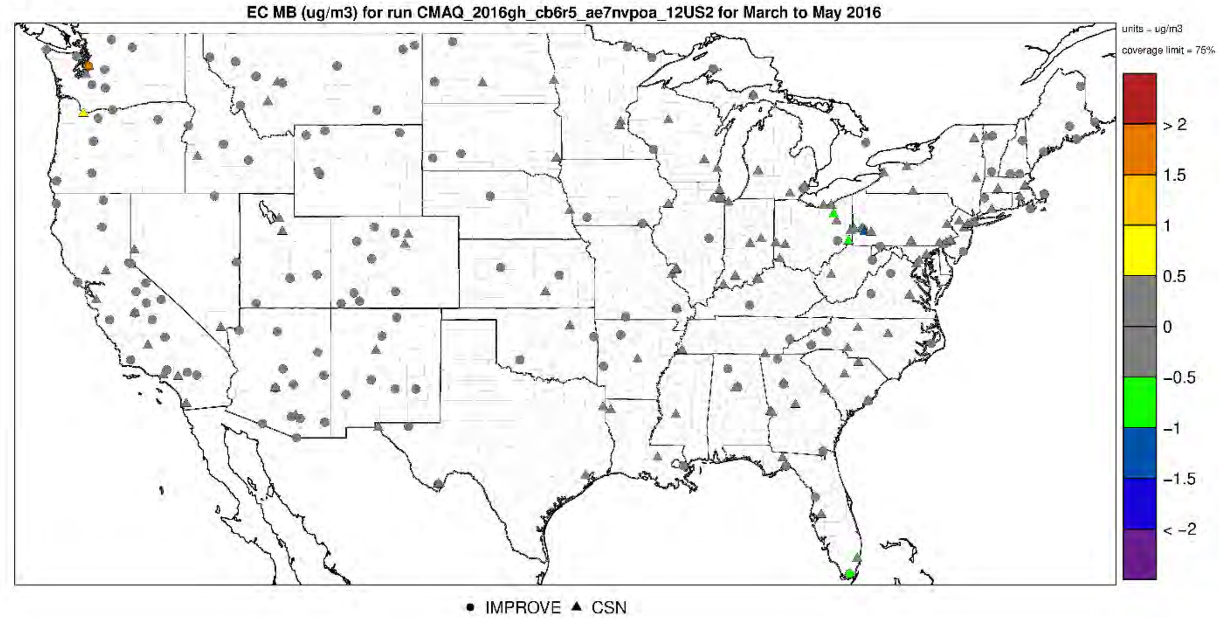

Figure 7-75 Mean Bias (µg/m^3) of elemental carbon during spring 2016 at monitoring sites in the modeling domain

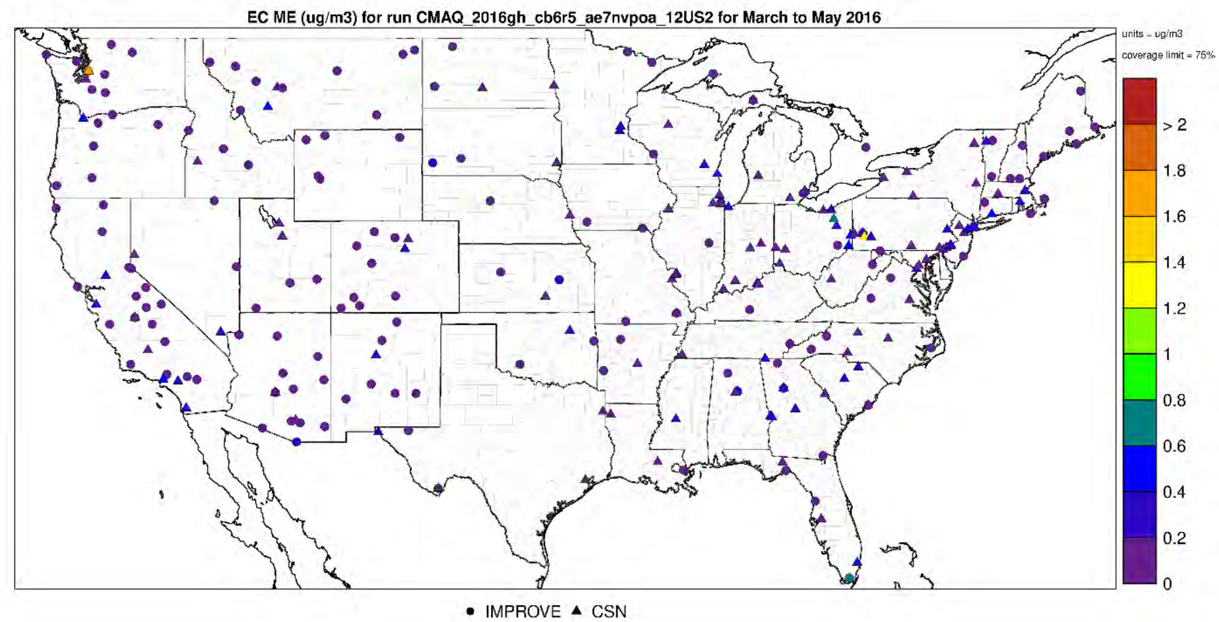

Figure 7-76 Mean Error (µg/m^3) of elemental carbon during spring 2016 at monitoring sites in the modeling domain

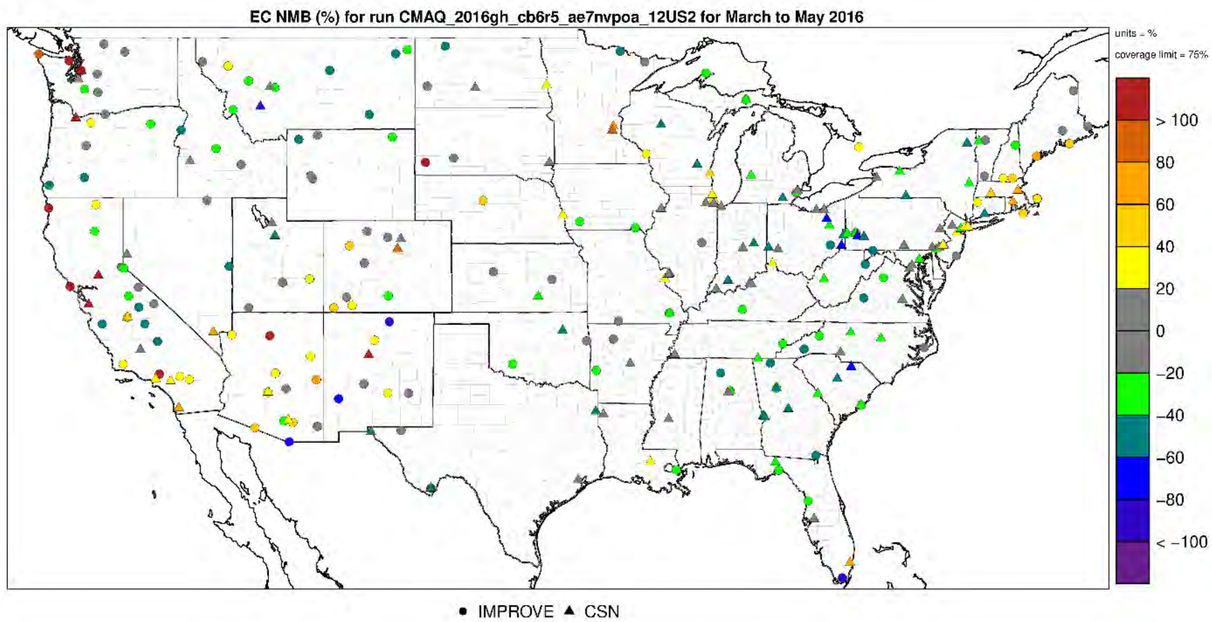

Figure 7-77 Normalized Mean Bias (%) of elemental carbon during spring 2016 at monitoring sites in the modeling domain

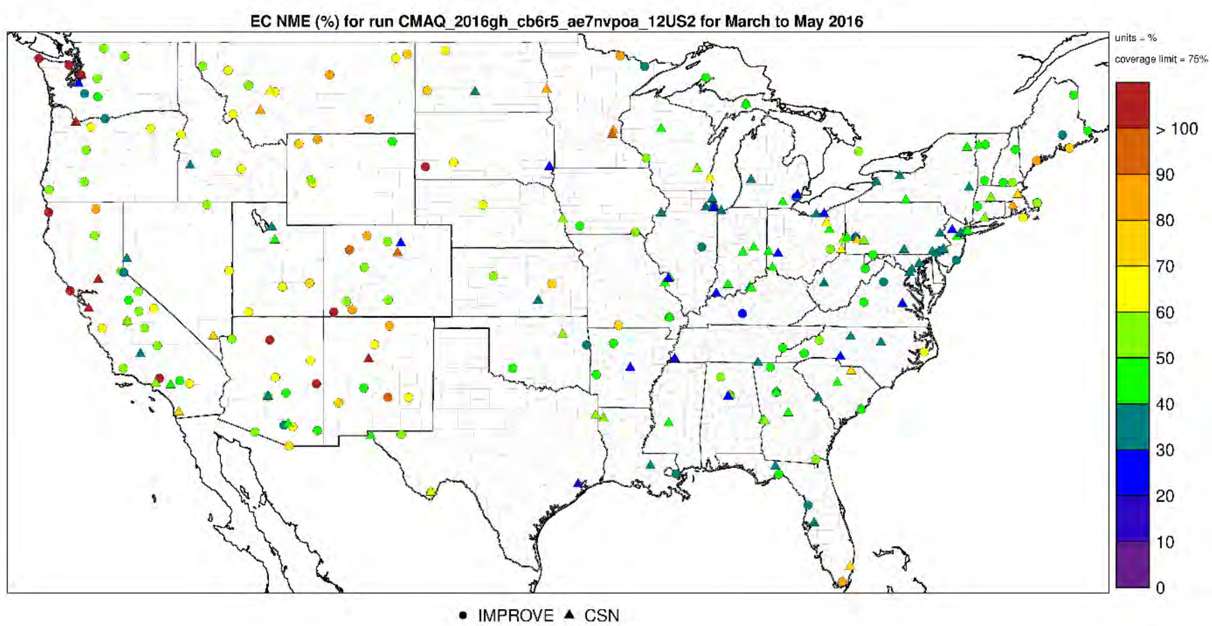

Figure 7-78 Normalized Mean Error (%) of elemental carbon during spring 2016 at monitoring sites in the modeling domain

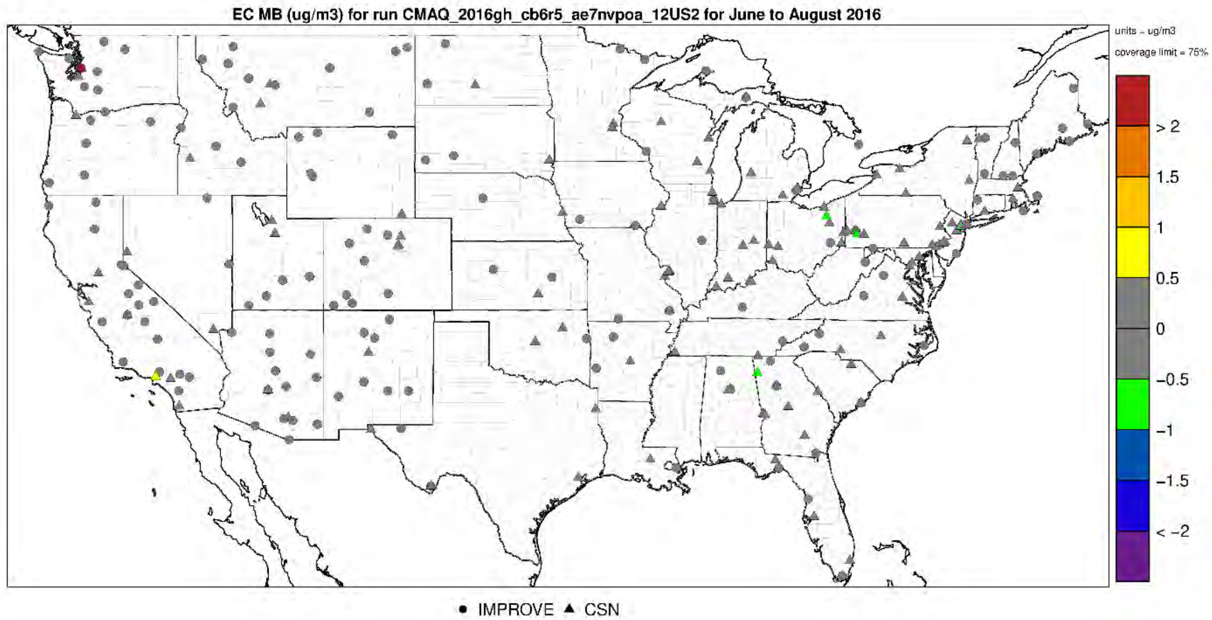

Figure 7-79 Mean Bias (µg/m^3) of elemental carbon during summer 2016 at monitoring sites in the modeling domain

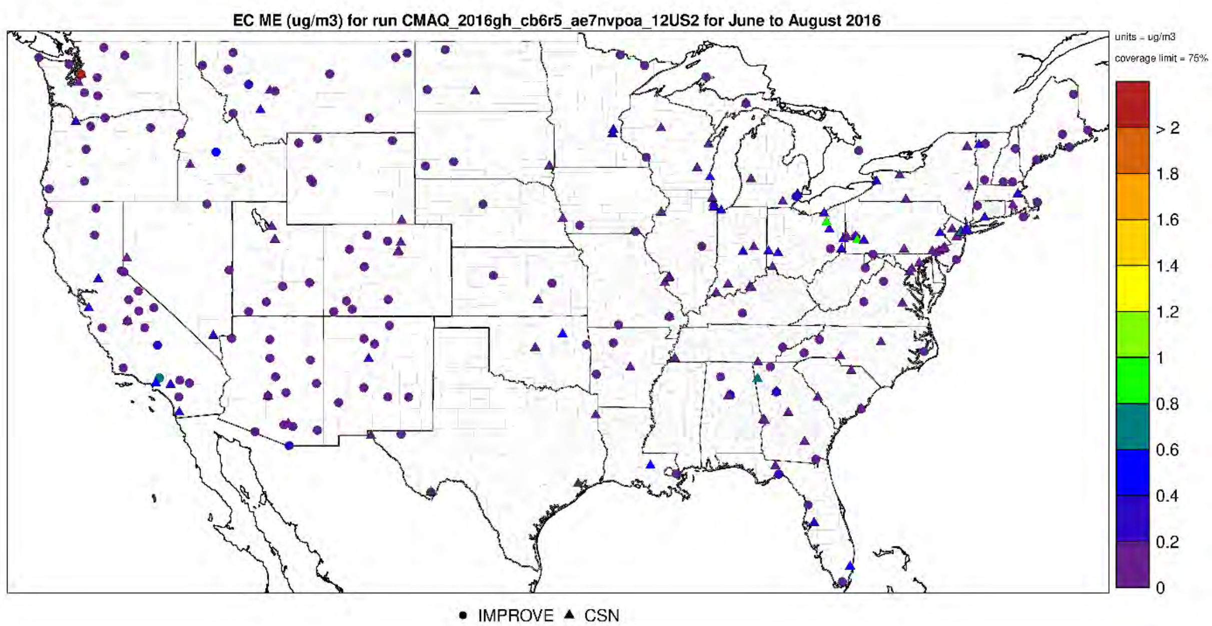

Figure 7-80 Mean Error (µg/m^3) of elemental carbon during summer 2016 at monitoring sites in the modeling domain

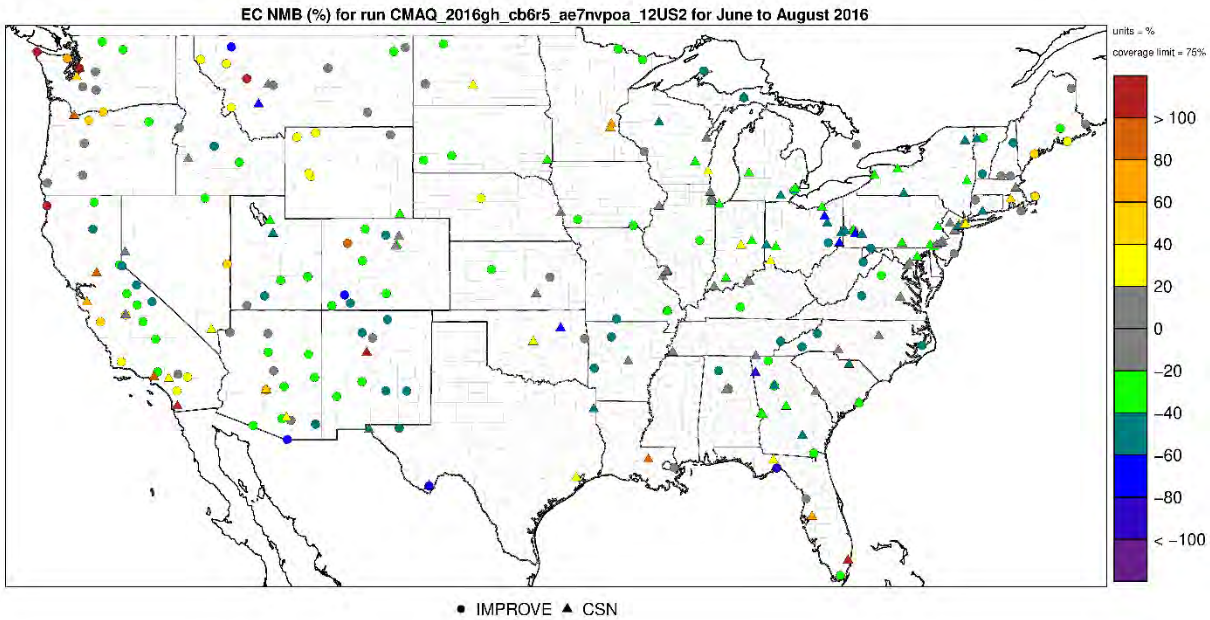

Figure 7-81 Normalized Mean Bias (%) of elemental carbon during summer 2016 at monitoring sites in the modeling domain

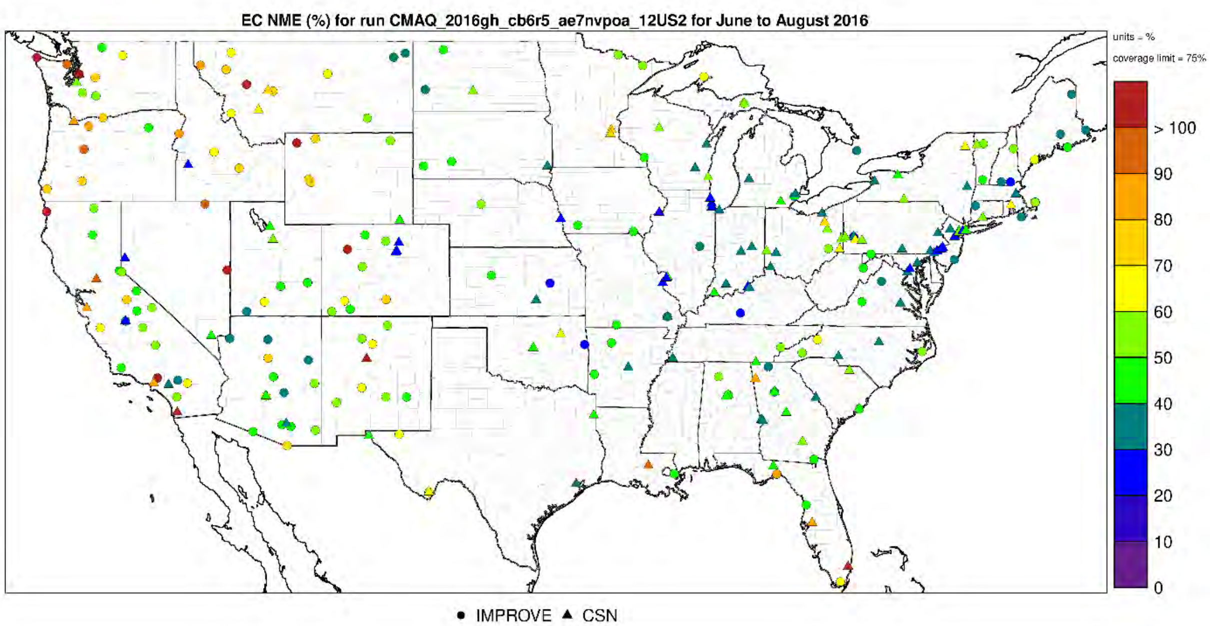

Figure 7-82 Normalized Mean Error (%) of elemental carbon during summer 2016 at monitoring sites in the modeling domain

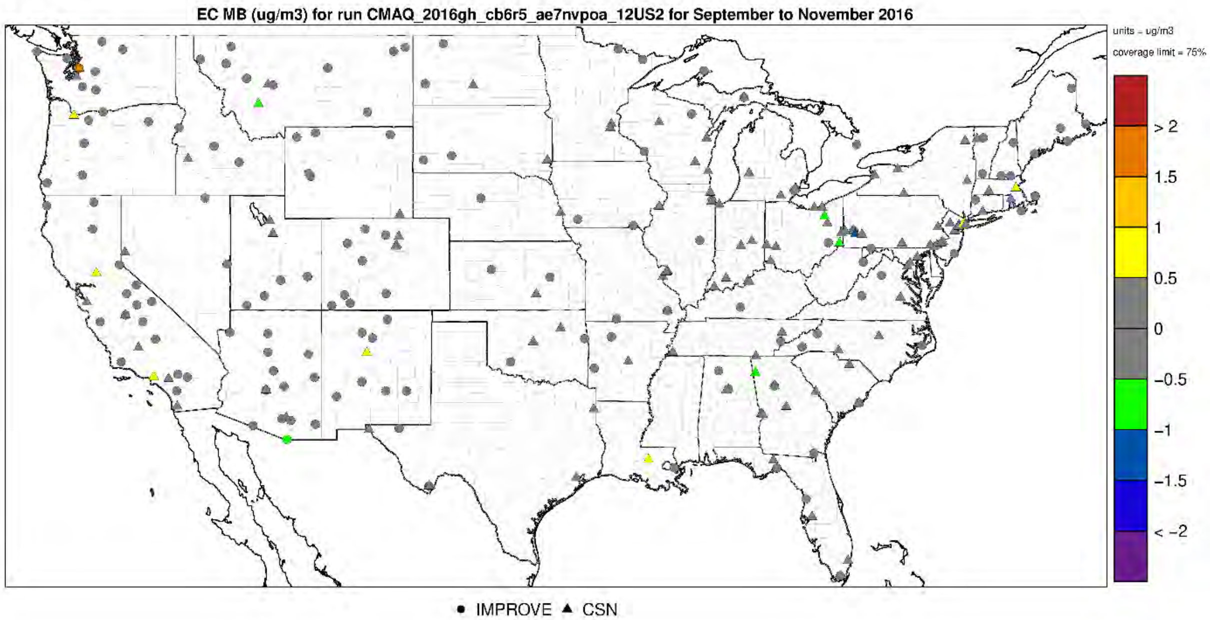

Figure 7-83 Mean Bias (µg/m^3) of elemental carbon during fall 2016 at monitoring sites in the modeling domain

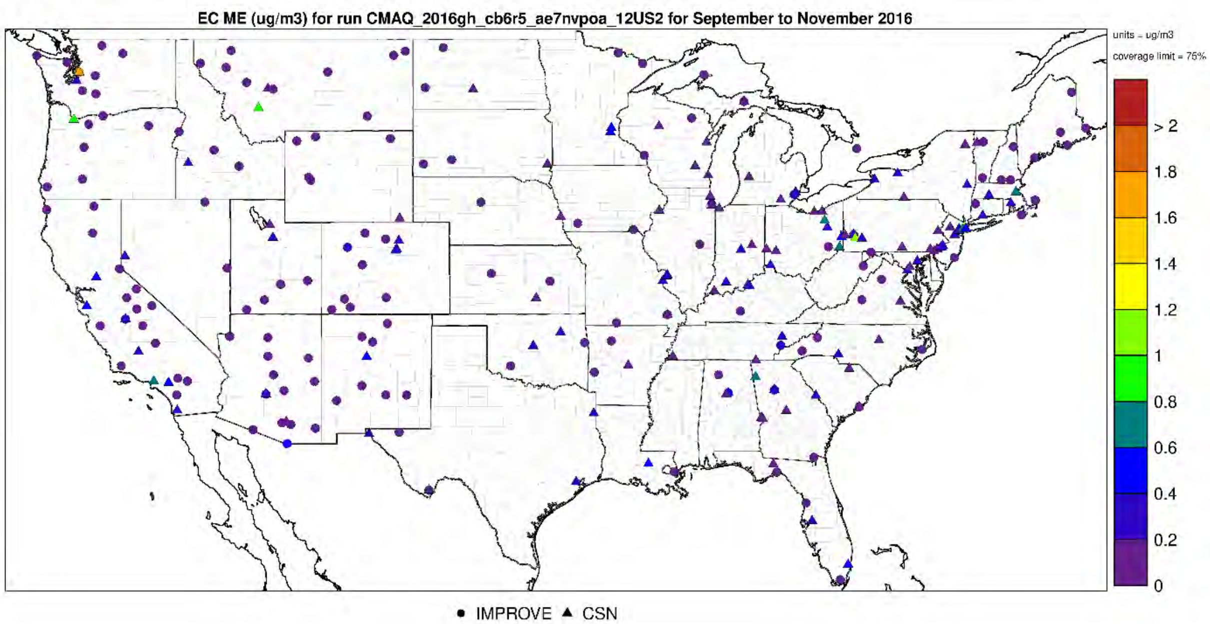

Figure 7-84 Mean Error (µg/m^3) of elemental carbon during fall 2016 at monitoring sites in the modeling domain

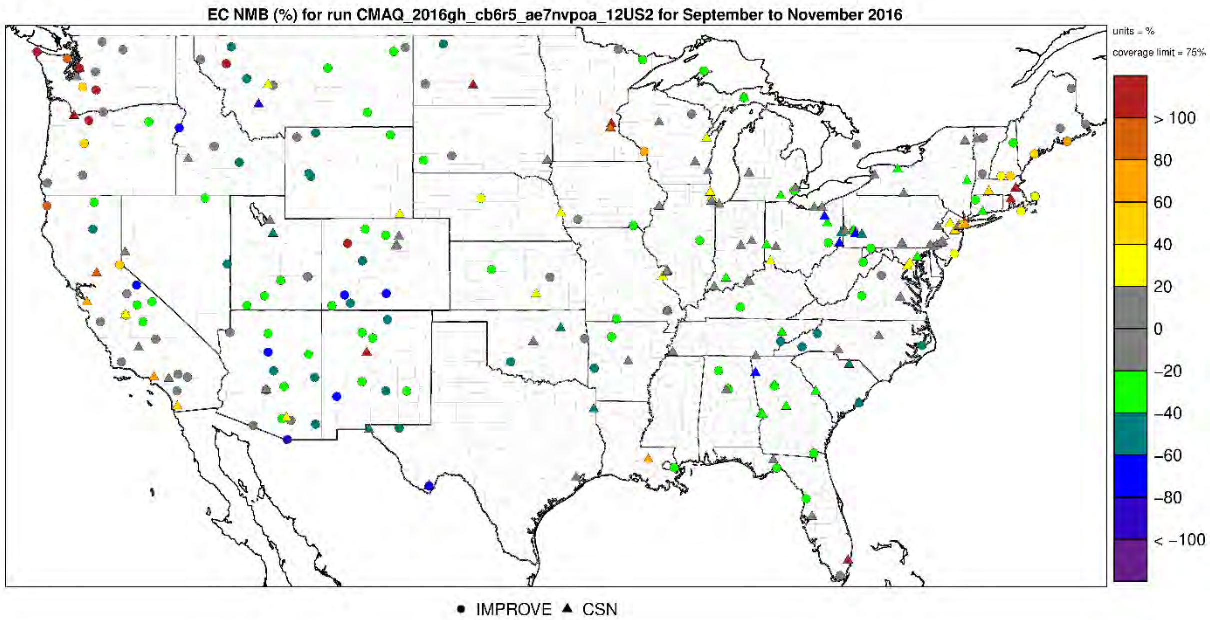

Figure 7-85 Normalized Mean Bias (%) of elemental carbon during fall 2016 at monitoring sites in the modeling domain

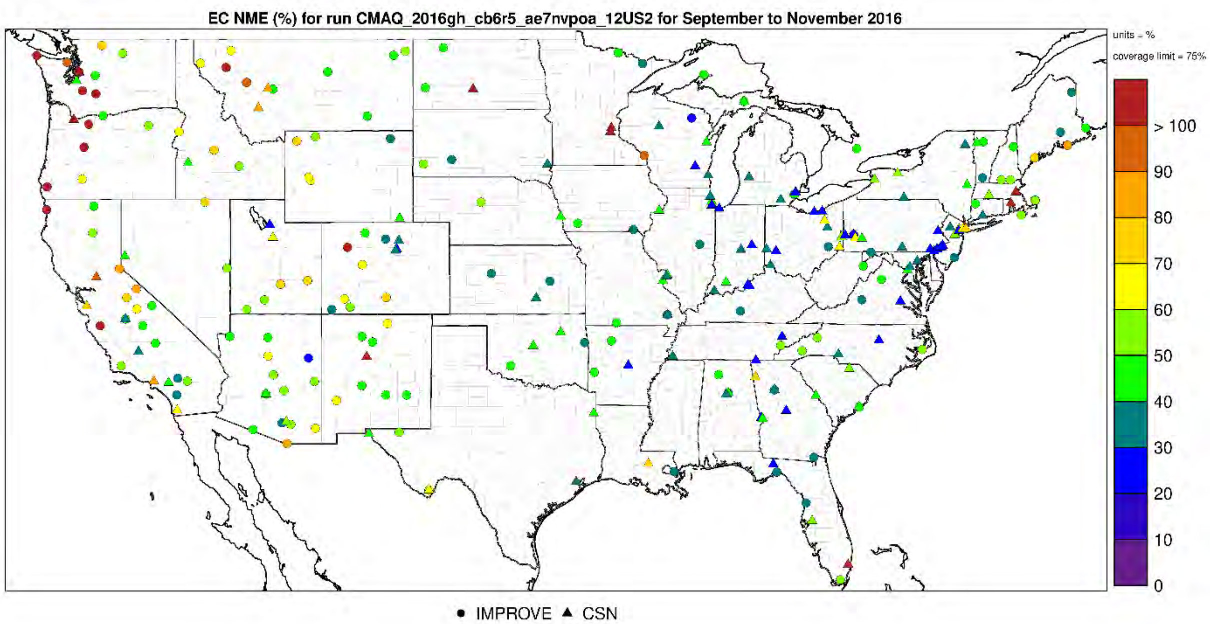

Figure 7-86 Normalized Mean Error (%) of elemental carbon during fall 2016 at monitoring sites in the modeling domain

7.4.4.5 *Seasonal Organic Carbon Performance*

The model performance bias and error statistics for organic carbon for each climate region and season are provided in Table 7-9. The statistics in this table indicate a tendency for the modeling platform to observed organic carbon concentrations during most seasons and climate regions except in the Northern Rockies and the Western U.S. Spatial plots of the MB, ME, NMB, and NME by season for individual monitors are shown in Figure 7-87 through Figure 7-102.

Table 7-9 Organic Carbon Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	IMPROVE	Winter	427	-0.1	0.3	-12.7	34.2
		Spring	477	-0.3	0.3	-40.8	46.3
		Summer	482	-0.5	0.6	-43.9	49.1
		Fall	459	-0.2	0.4	-26.9	40.4
	CSN	Winter	722	-0.1	0.8	-7.0	48.1
		Spring	785	-0.4	0.7	-24.5	42.4
		Summer	788	-0.4	0.7	-20.6	38.0
		Fall	780	-0.1	0.8	-7.99	40.7
Ohio Valley	IMPROVE	Winter	217	-0.4	0.6	-37.7	60.5
		Spring	242	-0.5	0.7	-42.0	64.3
		Summer	242	-0.1	0.6	-8.5	43.3
		Fall	232	-0.6	0.9	-31.8	50.0
	CSN	Winter	535	-0.6	0.7	-35.0	42.0
		Spring	571	-0.7	0.7	-41.8	45.9
		Summer	431	-0.2	0.8	-12.9	41.3
		Fall	532	-0.8	1.0	-32.8	42.3
Upper Midwest	IMPROVE	Winter	226	-0.1	0.2	-20.8	40.8
		Spring	238	-0.5	0.6	-58.1	63.8
		Summer	237	-0.6	0.7	-51.6	57.8
		Fall	243	-0.4	0.4	-42.4	49.8
	CSN	Winter	333	-0.1	0.5	-7.3	42.3
		Spring	347	-0.6	0.8	-40.1	51.5

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Summer	331	-0.6	0.7	-34.3	42.8
		Fall	337	-0.4	0.6	-29.4	39.6
Southeast	IMPROVE	Winter	398	-0.5	0.7	-46.2	63.1
		Spring	447	-5.5	5.6	-88.7	90.1
		Summer	445	-0.4	0.7	-29.0	49.5
		Fall	423	-0.8	1.1	-40.9	54.8
	CSN	Winter	436	-0.9	0.9	-42.5	46.1
		Spring	478	-0.8	0.9	-40.4	44.4
		Summer	445	-0.1	0.7	-5.8	34.2
		Fall	430	-0.9	1.4	-30.4	47.9
South	IMPROVE	Winter	239	-0.4	0.5	-50.4	55.6
		Spring	272	-0.7	0.7	-66.1	68.1
		Summer	250	-0.5	0.6	-42.4	49.8
		Fall	264	-0.6	0.6	-49.4	54.8
	CSN	Winter	272	-0.9	1.0	-46.2	50.6
		Spring	297	-0.7	0.7	-46.0	51.4
		Summer	251	-0.3	0.7	-17.0	47.7
		Fall	237	-0.6	0.9	-28.5	44.9
Southwest	IMPROVE	Winter	881	-0.5	0.5	-71.7	73.2
		Spring	981	-0.3	0.3	-70.2	74.4
		Summer	978	-0.7	0.7	-76.8	80.0
		Fall	964	-0.4	0.5	-67.7	74.3
	CSN	Winter	228	-1.2	1.4	-46.3	56.8
		Spring	254	-0.4	0.6	-38.8	54.5
		Summer	237	-0.8	0.9	-59.9	60.9
		Fall	240	-0.7	0.8	-42.4	50.1
Northern Rockies	IMPROVE	Winter	549	-0.2	0.2	-50.4	61.2
		Spring	590	-0.5	0.5	-77.0	79.6
		Summer	631	-0.9	0.9	-71.7	77.2

Climate Region	Monitor Network	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
		Fall	600	-0.4	0.5	-68.7	72.8
	CSN	Winter	140	-0.5	0.6	-54.9	65.6
		Spring	145	-0.6	0.6	-68.2	71.1
		Summer	161	-1.1	1.1	-72.1	72.1
		Fall	146	-0.6	0.7	-61.7	64.4
Northwest	IMPROVE	Winter	407	-0.1	0.3	-25.9	78.0
		Spring	497	-0.2	0.4	-33.9	81.7
		Summer	494	-0.2	0.6	-29.3	76.2
		Fall	516	-0.6	1.0	-50.8	79.7
	CSN	Winter	139	-0.5	1.4	-21.9	57.9
		Spring	150	0.6	1.2	42.4	86.3
		Summer	155	0.4	1.3	20.5	67.5
		Fall	158	0.8	1.5	55.6	100
West	IMPROVE	Winter	552	-0.4	0.4	-63.4	66.8
		Spring	599	-0.4	0.4	-68.7	70.9
		Summer	608	-1.2	1.2	-69.3	71.2
		Fall	574	-0.7	0.7	-63.0	66.0
	CSN	Winter	285	-1.8	1.9	-48.2	50.5
		Spring	294	-0.6	0.7	-41.0	44.8
		Summer	289	-1.5	1.5	-60.8	61.1
		Fall	277	-1.3	1.4	-44.6	48.8

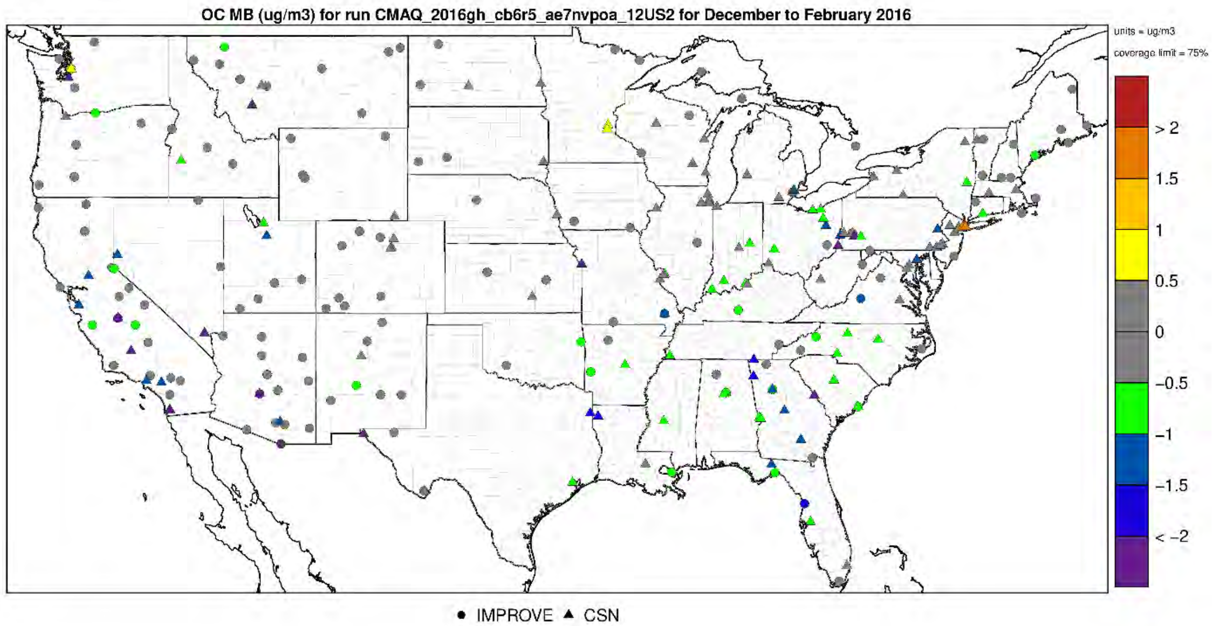

Figure 7-87 Mean Bias (µg/m³) of organic carbon during winter 2016 at monitoring sites in the modeling domain

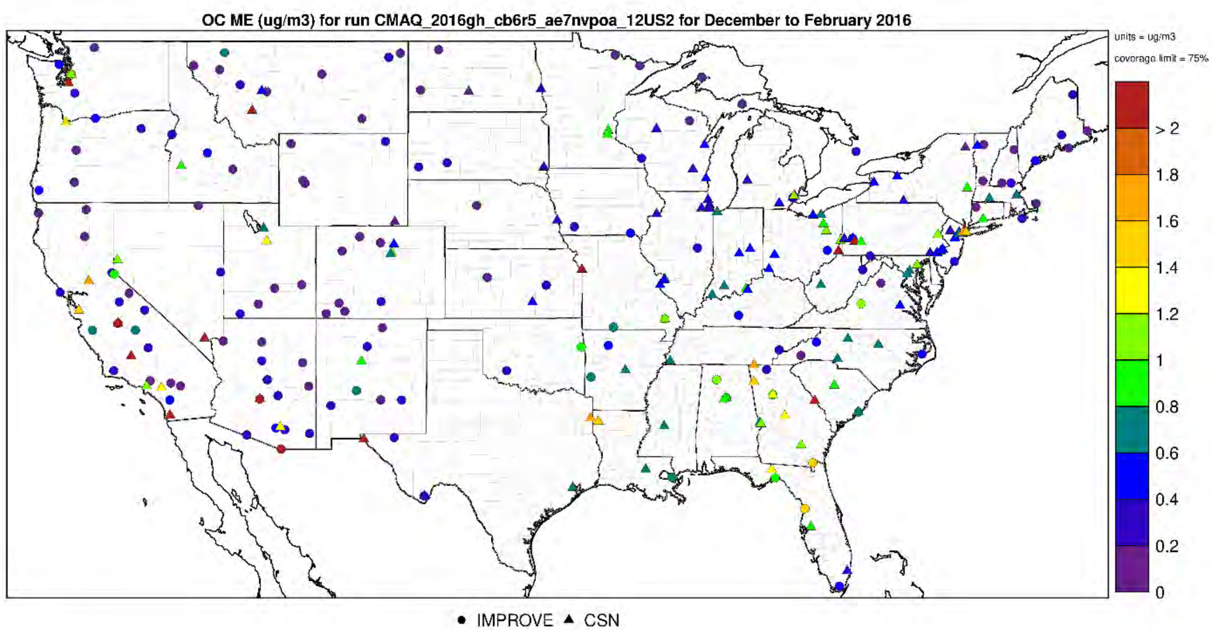

Figure 7-88 Mean Error (µg/m³) of organic carbon during winter 2016 at monitoring sites in the modeling domain

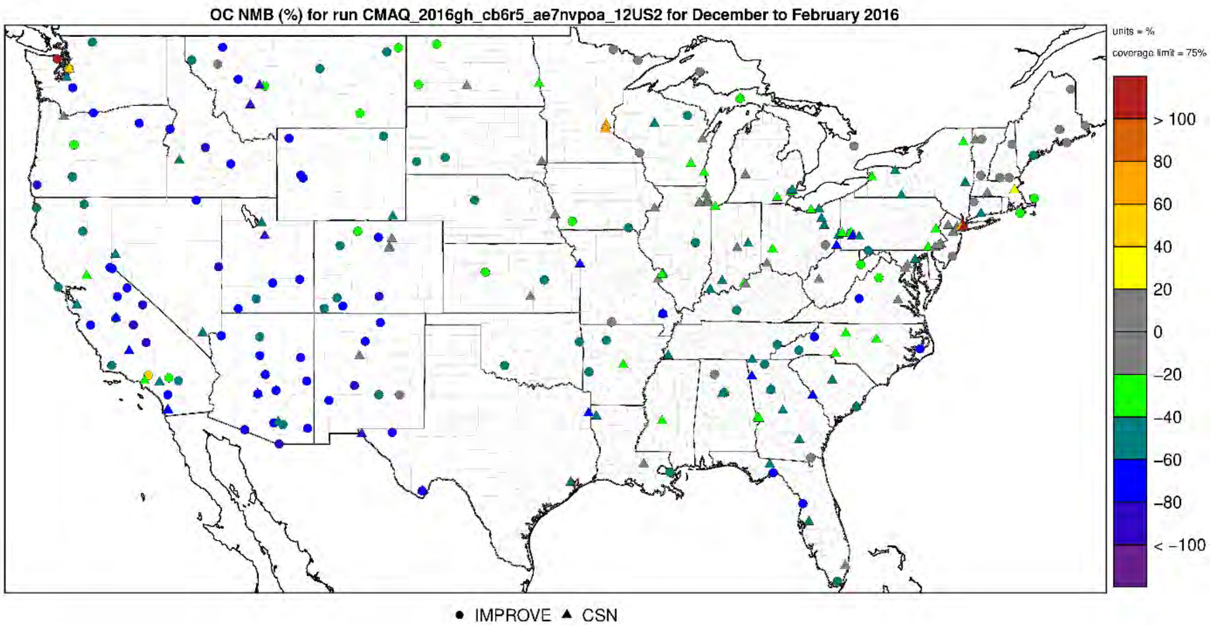

Figure 7-89 Normalized Mean Bias (%) of organic carbon during winter 2016 at monitoring sites in the modeling domain

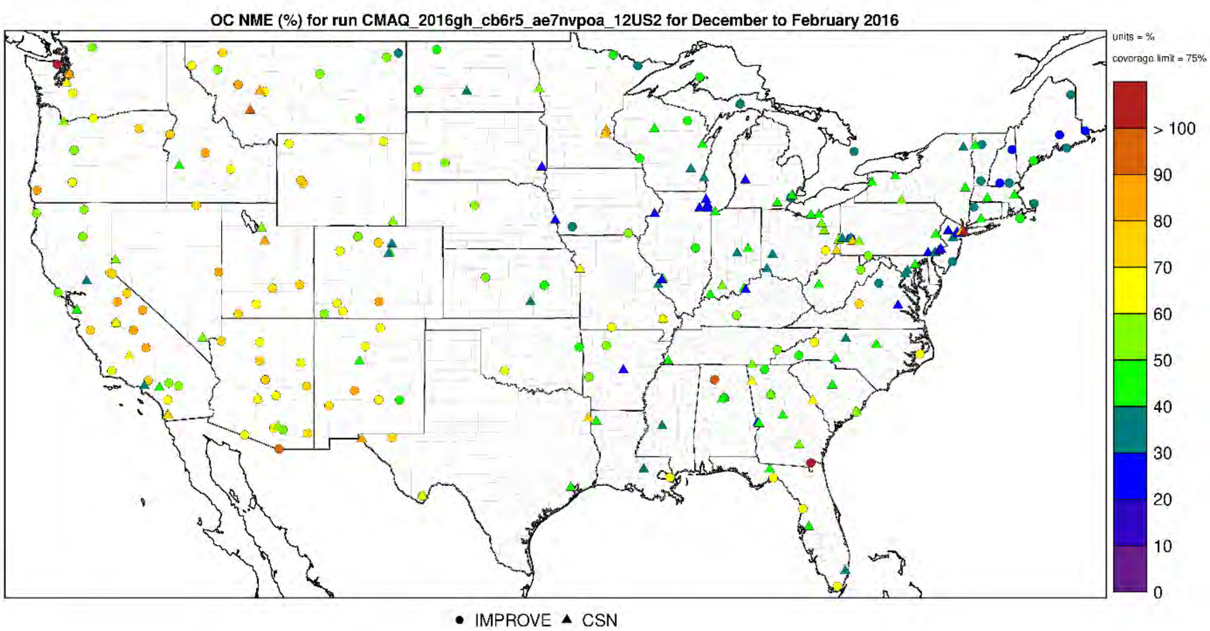

Figure 7-90 Normalized Mean Error (%) of organic carbon during winter 2016 at monitoring sites in the modeling domain

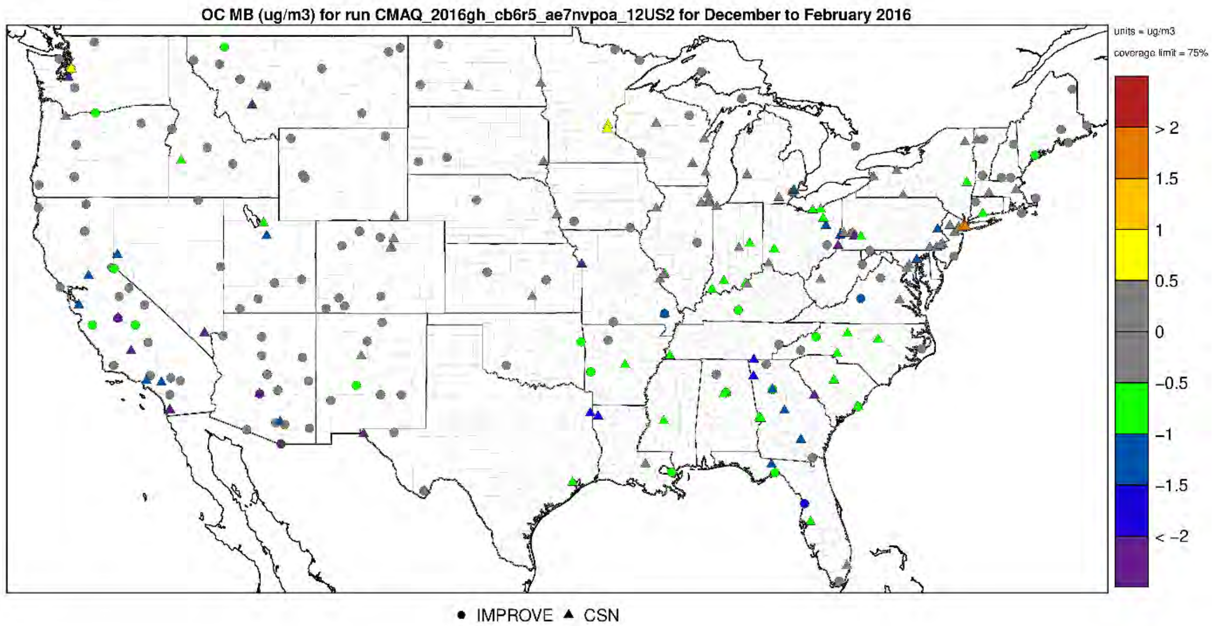

Figure 7-91 Mean Bias (µg/m^3) of organic carbon during spring 2016 at monitoring sites in the modeling domain

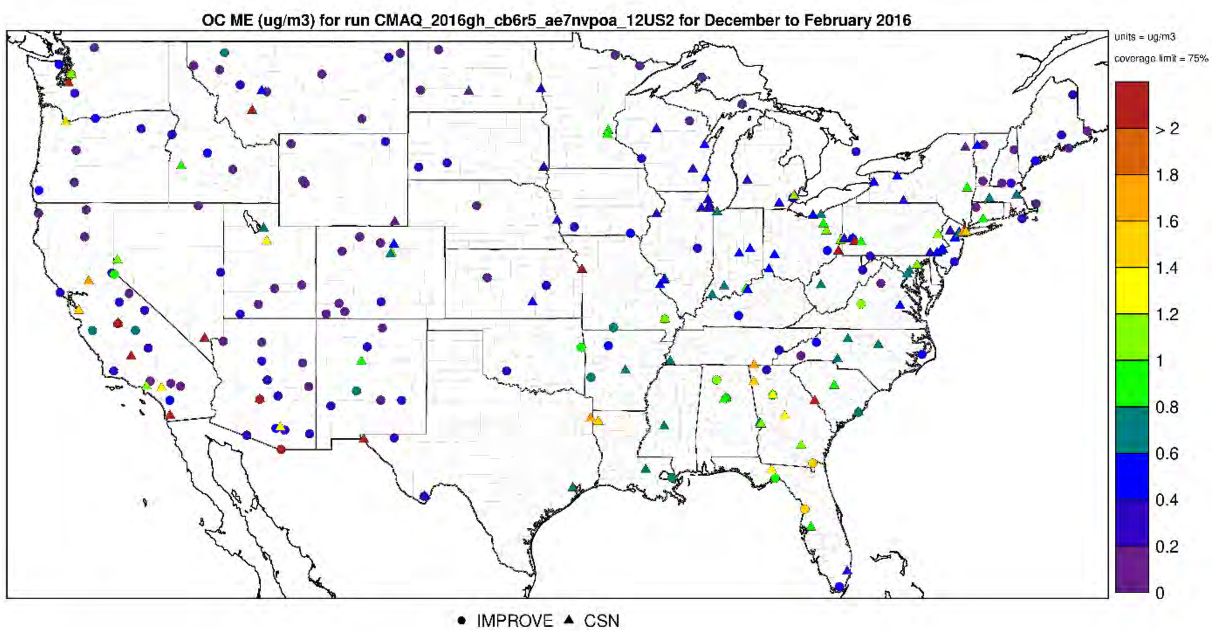

Figure 7-92 Mean Error (µg/m^3) of organic carbon during spring 2016 at monitoring sites in the modeling domain

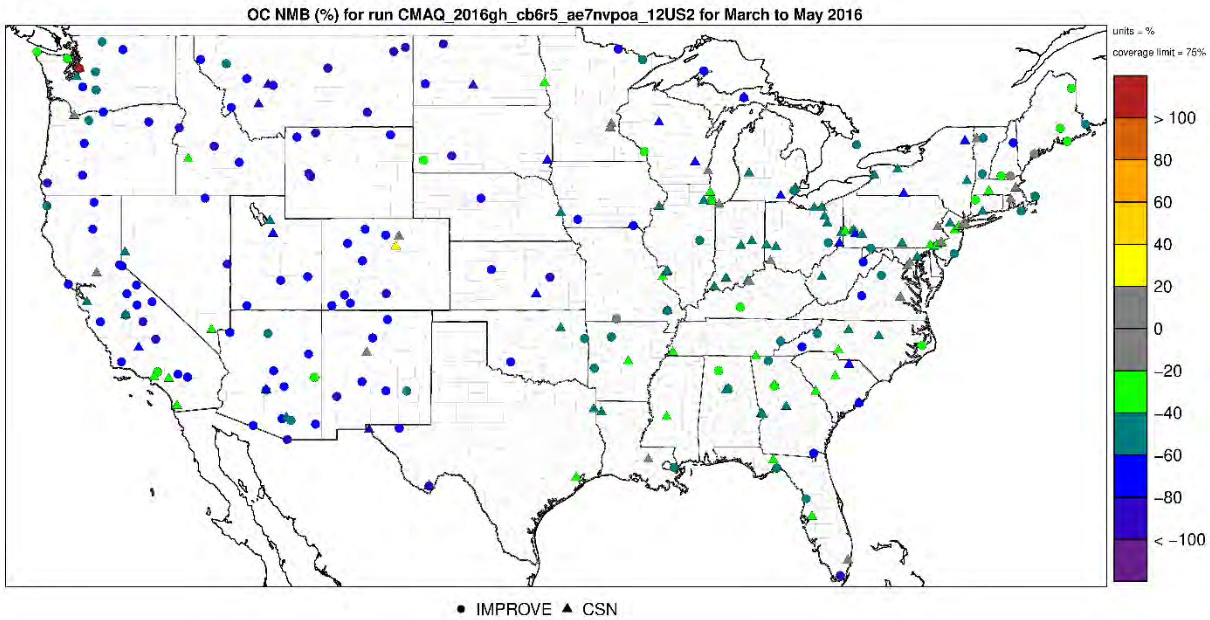

Figure 7-93 Normalized Mean Bias (%) of organic carbon during spring 2016 at monitoring sites in the modeling domain

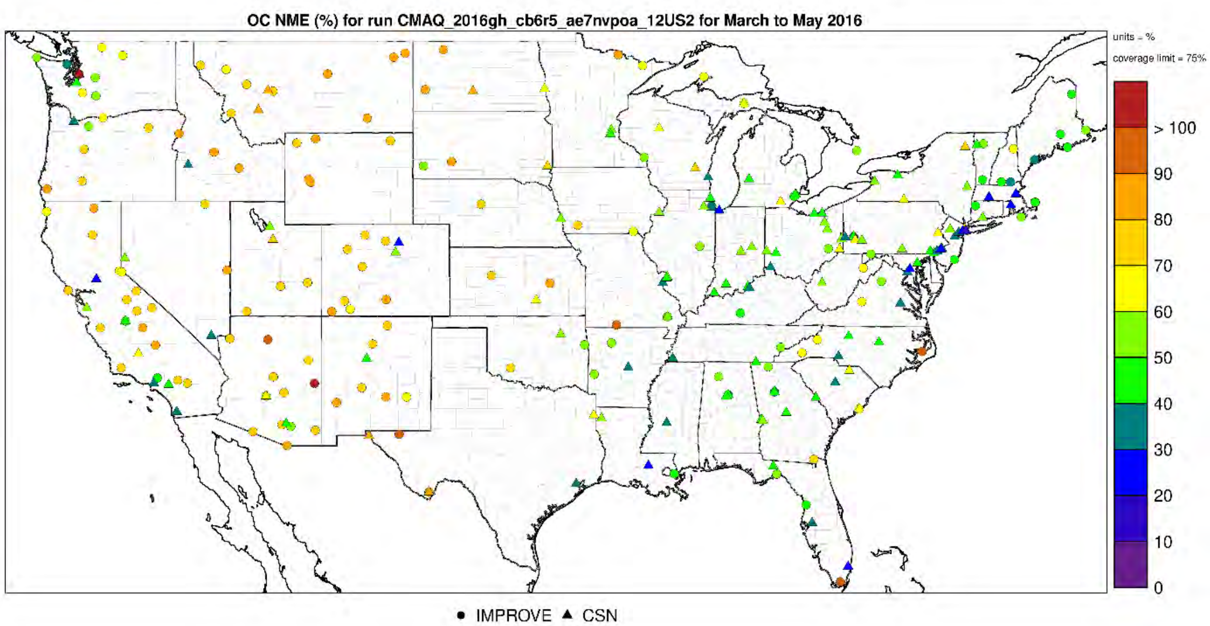

Figure 7-94 Normalized Mean Error (%) of organic carbon during spring 2016 at monitoring sites in the modeling domain

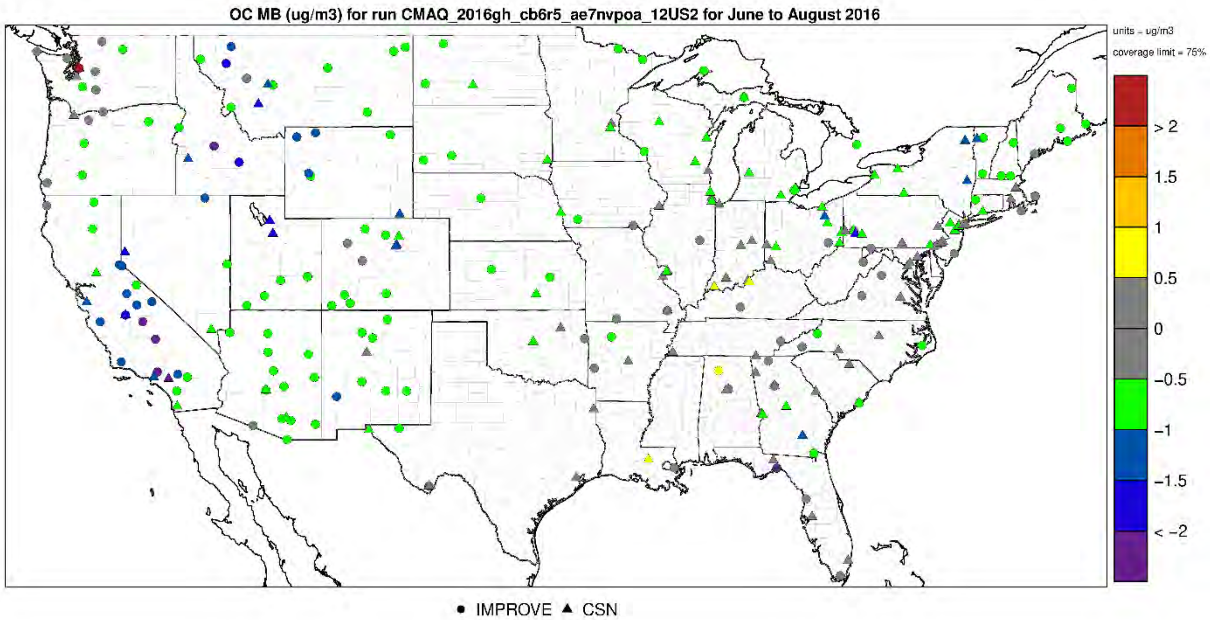

Figure 7-95 Mean Bias (µg/m^3) of organic carbon during summer 2016 at monitoring sites in the modeling domain

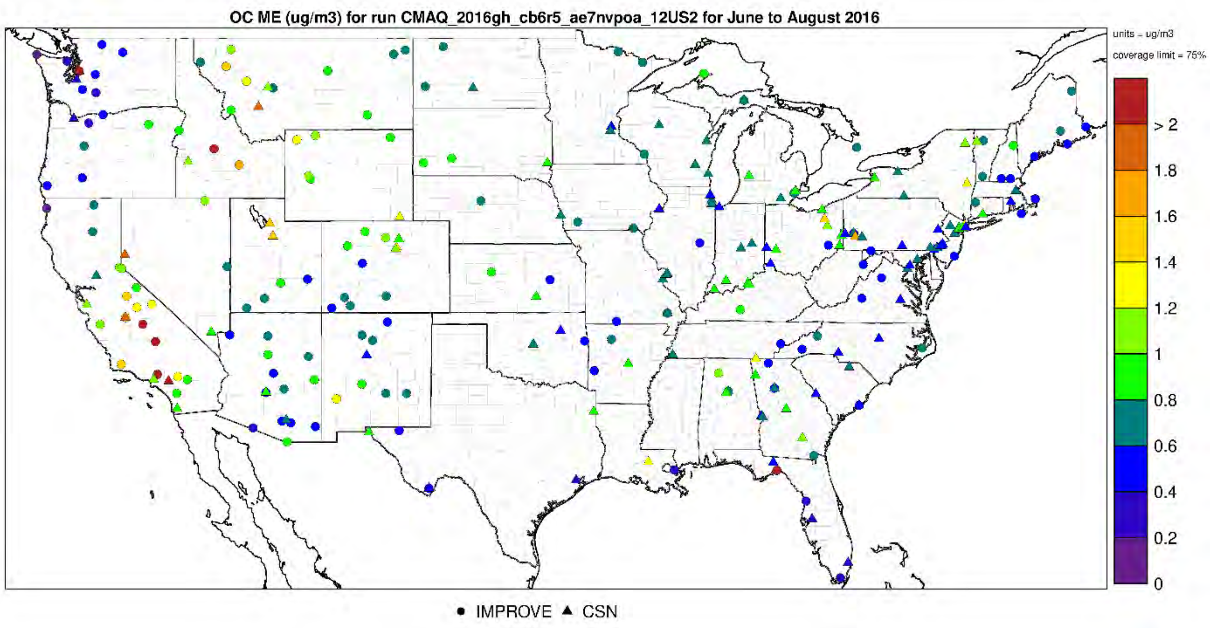

Figure 7-96 Mean Error (µg/m^3) of organic carbon during summer 2016 at monitoring sites in the modeling domain

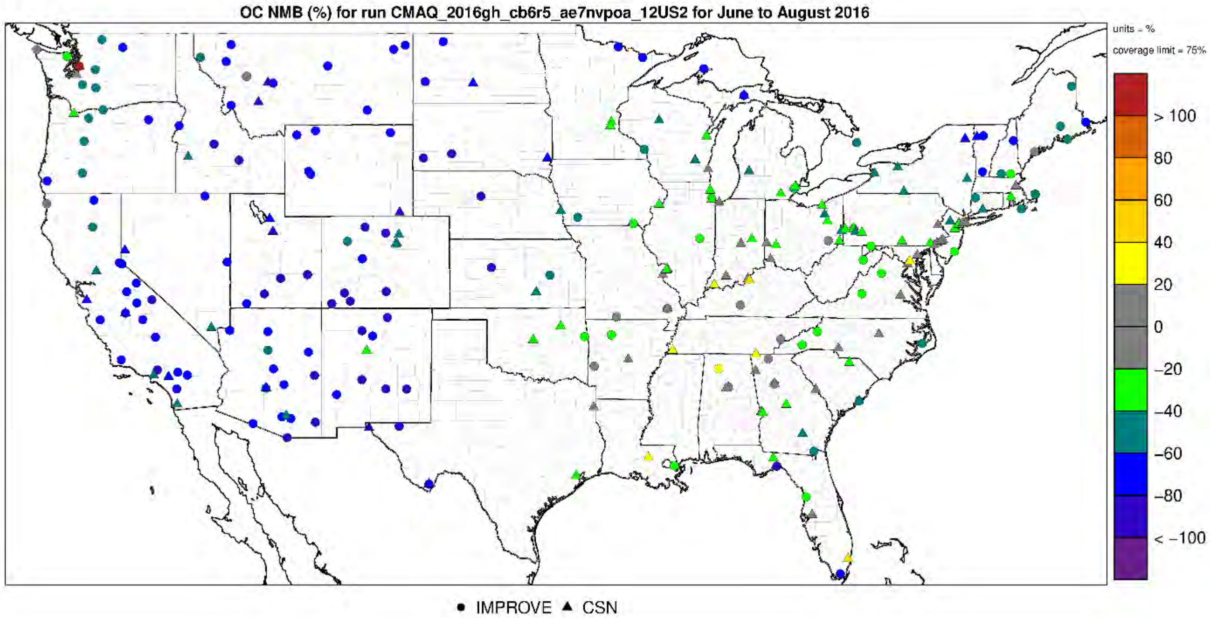

Figure 7-97 Normalized Mean Bias (%) of organic carbon during summer 2016 at monitoring sites in the modeling domain

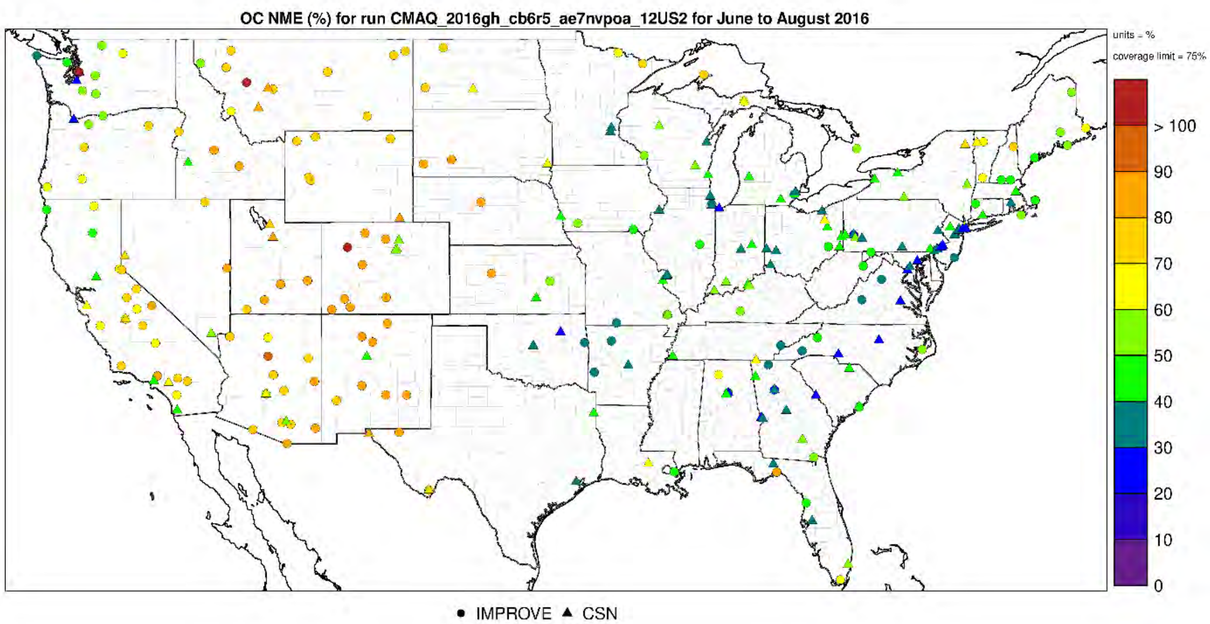

Figure 7-98 Normalized Mean Error (%) of organic carbon during summer 2016 at monitoring sites in the modeling domain

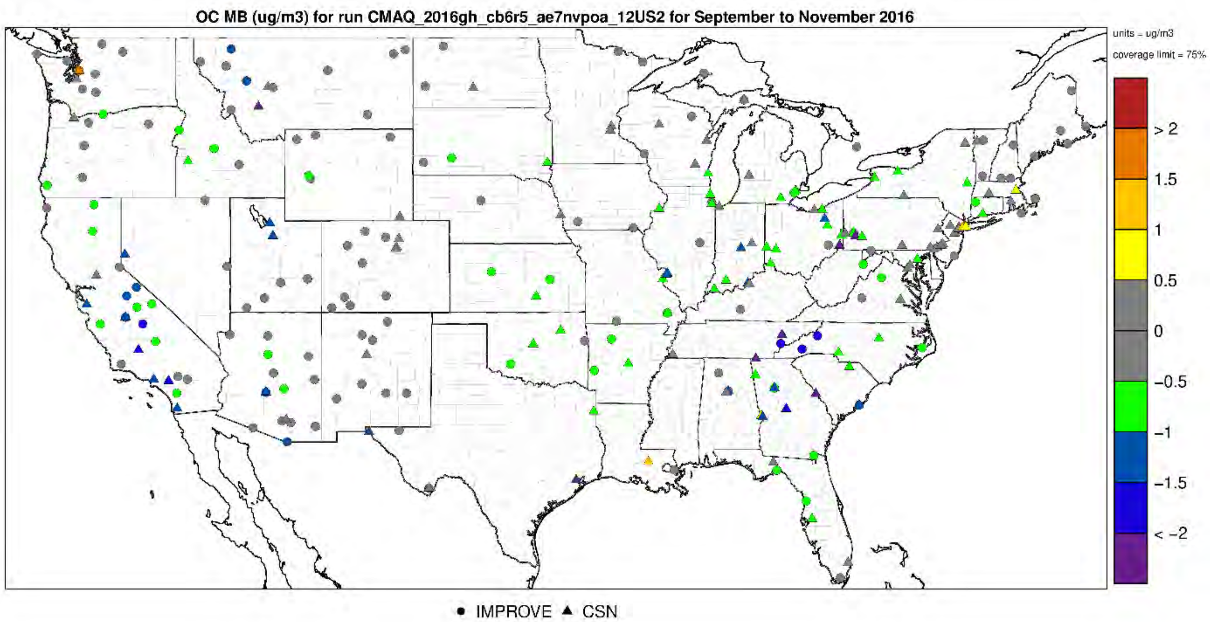

Figure 7-99 Mean Bias (µg/m³) of organic carbon during fall 2016 at monitoring sites in the modeling domain

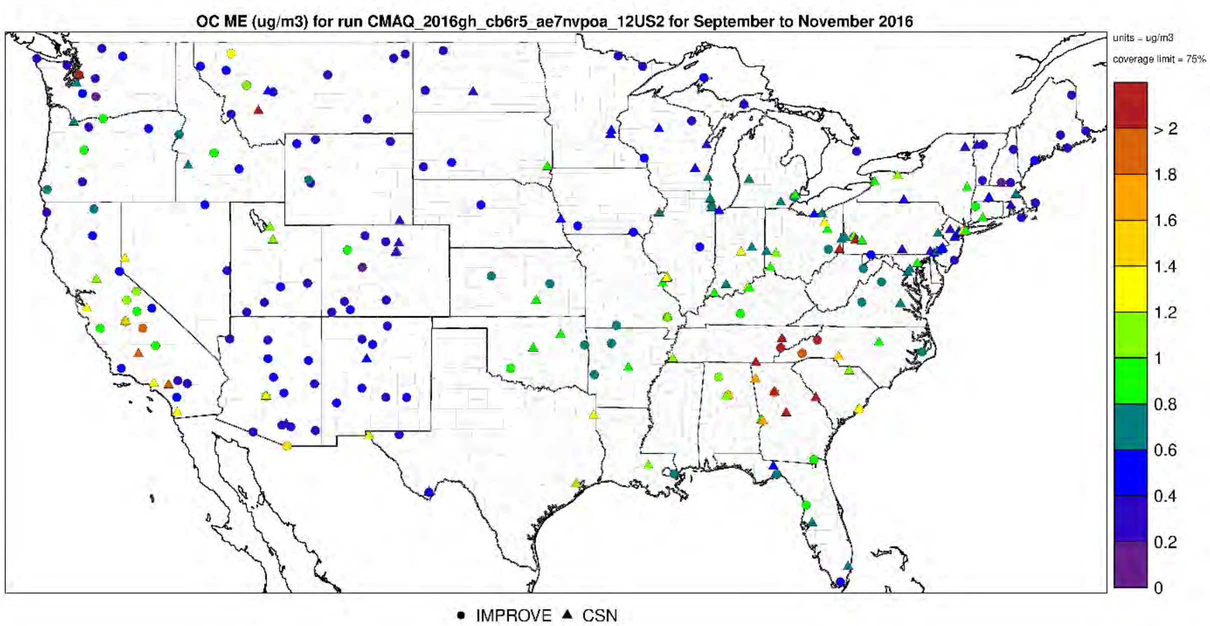

Figure 7-100 Mean Error (µg/m³) of organic carbon during fall 2016 at monitoring sites in the modeling domain

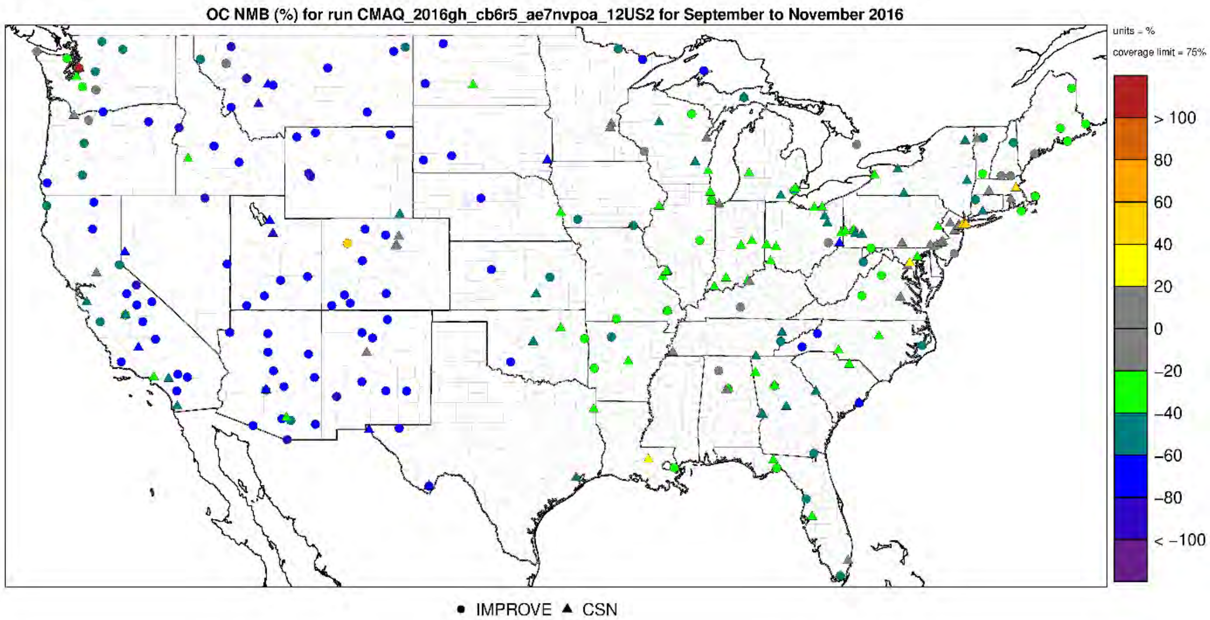

Figure 7-101 Normalized Mean Bias (%) of organic carbon during fall 2016 at monitoring sites in the modeling domain

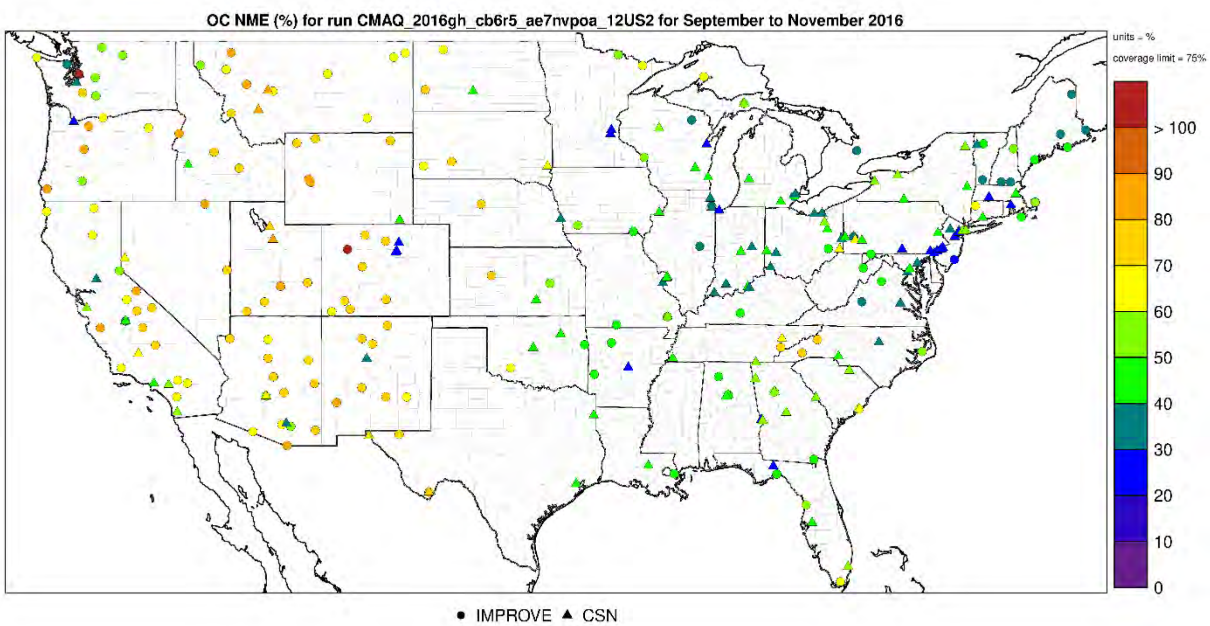

Figure 7-102 Normalized Mean Error (%) of organic carbon during fall 2016 at monitoring sites in the modeling domain

7.4.5 Seasonal Hazardous Air Pollutants Performance

A seasonal operational model performance evaluation for specific hazardous air pollutants (i.e., formaldehyde, acetaldehyde, and benzene) was conducted in order to estimate the ability of the CMAQ modeling system to replicate the base year concentrations for the 12 km CONUS domain. The seasonal model performance results for the 12 km modeling domain are presented below in Table 7-10. Toxic measurements included in the evaluation were taken from the 2016 air toxics archive, https://www.epa.gov/amtic/amtic-air-toxics-data-ambient-monitoring-archive. While most of the data in the archive are from the AQS database including the National Air Toxics Trends Stations (NATTS), additional data (e.g., special studies) are included in the archive but not reported in the AQS. Similar to $PM_{2.5}$ and ozone, the evaluation principally consists of statistical assessments of model versus observed data that were paired in time and space on a daily basis.

Model predictions of annual formaldehyde, acetaldehyde, and benzene showed relatively small to moderate bias and error percentages when compared to observations. Model performance for HAPs is not as good as model performance for ozone and $PM_{2.5}$. Technical issues in the HAPs data consist of (1) uncertainties in monitoring methods; (2) limited measurements in time/space to characterize ambient concentrations ("local in nature"); (3) ambient data below method detection limit (MDL); (4) commensurability issues between measurements and model predictions; (5) emissions and science uncertainty issues may also affect model performance; and (6) limited data for estimating intercontinental transport that effects the estimation of boundary conditions (i.e., boundary estimates for some species are much higher than predicted values inside the domain).

As with the national, annual $PM_{2.5}$ and ozone CMAQ modeling, the "acceptability" of model performance was judged by comparing our CMAQ 2016 performance results to the limited performance found in recent regional multi-pollutant model applications.[90,91] Overall, the mean bias and error (MB and ME), as well as the normalized mean bias and error (NMB and NME) statistics shown below in Table 7-10 indicate that CMAQ-predicted 2016 toxics (i.e., observation vs. model predictions) are within the range of recent regional modeling applications.

Table 7-10 Hazardous Air Toxics Performance Statistics by Season for the 2016 CMAQ Model Simulation

Air Toxic Species	Season	No. of Obs.	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Formaldehyde	Winter	1,184	-1.0	1.1	-61.0	63.1
	Spring	1,914	-1.3	1.3	-60.1	61.6
	Summer	2,318	-1.4	1.5	-43.4	47.7
	Fall	1,886	-1.1	1.2	-48.0	53.3
Acetaldehyde	Winter	1,818	-0.4	0.4	-52.6	57.1
	Spring	1,920	-0.5	0.5	-57.5	60.6

[90] Phillips, S., K. Wang, C. Jang, N. Possiel, M. Strum, T. Fox, 2007: Evaluation of 2002 Multi-pollutant Platform: Air Toxics, Ozone, and Particulate Matter, 7th Annual CMAS Conference, Chapel Hill, NC, October 6-8, 2008.

[91] Wesson, K., N. Fann, M. Morris, T. Fox, and B. Hubbell 2010: A Multi-pollutant, Risk-based Approach to the Air Quality Management: Case Study for Detroit, Atmospheric Pollution Research, 1 (4) (2010), pp. 296-304, 10.5094/APR.2010.037.

	Summer	2,316	-0.3	0.5	-31.1	49.9
	Fall	1,870	-0.4	0.5	-43.9	53.1
Benzene	Winter	3,991	-0.0	0.1	-18.0	42.0
	Spring	4,479	-0.1	0.1	-31.9	47.7
	Summer	5,907	-0.0	0.1	-21.2	54.6
	Fall	4,572	-0.1	0.1	-29.2	48.5

7.4.6 Seasonal Nitrate and Sulfate Deposition Performance

Seasonal nitrate and sulfate wet deposition performance statistics for the 12 km Continental U.S. domain are provided in Table 7-11 and Table 7-12. The model predictions for seasonal nitrate deposition generally show under prediction for the continental U.S. NADP sites (NMB values range from -0.6% to -83.7%). Sulfate deposition performance shows similar under predictions (NMB values range from -1.3% to 81.7%). The errors for both annual nitrate and sulfate are relatively moderate with most values ranging from 33% to 92% which reflect scatter in the model predictions versus observation comparison.

Table 7-11 Nitrate Wet Deposition Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	Winter	600	-0.1	0.1	-41.0	54.1
	Spring	649	-0.0	0.1	-12.1	44.5
	Summer	681	-0.0	0.1	-21.7	51.1
	Fall	679	-0.0	0.1	-0.6	48.9
Ohio Valley	Winter	297	-0.0	0.1	-5.2	49.7
	Spring	300	-0.0	0.1	-9.9	33.9
	Summer	309	-0.1	0.1	-32.1	51.8
	Fall	288	0.0	0.1	5.1	52.0
Upper Midwest	Winter	275	-0.0	0.1	-40.5	63.9
	Spring	277	-0.0	0.1	-28.1	46.7
	Summer	292	-0.1	0.1	-34.6	49.0
	Fall	301	-0.0	0.1	-17.7	47.8
Southeast	Winter	359	-0.0	0.0	-3.8	51.3
	Spring	376	-0.0	0.1	-14.8	45.8

Climate Region	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
	Summer	413	-0.1	0.1	-32.7	50.7
	Fall	385	-0.0	0.0	-13.0	59.9
South	Winter	236	0.0	0.0	9.3	56.2
	Spring	263	-0.0	0.1	-15.6	44.9
	Summer	281	-0.1	0.1	-39.5	56.0
	Fall	280	-0.0	0.0	-20.9	53.7
Southwest	Winter	300	-0.0	0.0	-78.5	83.1
	Spring	322	-0.0	0.1	-70.8	81.6
	Summer	292	-0.0	0.1	-39.7	56.9
	Fall	334	-0.0	0.0	-47.6	72.4
Northern Rockies	Winter	216	-0.0	0.0	-68.7	87.3
	Spring	251	-0.0	0.1	-43.9	68.0
	Summer	226	-0.0	0.1	-41.2	52.7
	Fall	237	-0.0	0.0	-37.1	63.6
Northwest	Winter	121	-0.0	0.0	-0.5	51.7
	Spring	141	-0.0	0.0	-7.0	59.3
	Summer	138	-0.0	0.0	-1.4	73.1
	Fall	145	0.0	0.0	22.7	66.1
West	Winter	151	-0.0	0.0	-27.1	57.0
	Spring	151	0.0	0.0	7.3	79.0
	Summer	161	-0.0	0.0	-83.7	93.1
	Fall	160	-0.0	0.0	-15.0	76.2

Table 7-12 Sulfate Wet Deposition Performance Statistics by Climate Region, by Season, and by Monitoring Network for the 2016 CMAQ Model Simulation

Climate Region	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
Northeast	Winter	600	-0.1	0.1	-51.1	59.8
	Spring	681	-0.0	0.1	-21.3	56.5
	Summer	679	-0.0	0.1	-26.7	53.3

Climate Region	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
	Fall	649	-0.0	0.1	-30.6	47.9
Ohio Valley	Winter	297	-0.0	0.1	-36.7	53.4
	Spring	300	-0.0	0.1	-26.2	38.8
	Summer	309	-0.0	0.1	-26.6	51.5
	Fall	288	-0.0	0.0	-20.3	52.3
Upper Midwest	Winter	275	-0.0	0.0	-46.7	61.3
	Spring	292	-0.0	0.1	-28.1	50.3
	Summer	277	-0.0	0.0	-37.3	51.4
	Fall	301	-0.0	0.1	-41.0	55.8
Southeast	Winter	359	-0.0	0.1	-34.3	52.5
	Spring	376	-0.0	0.1	-34.2	54.9
	Summer	413	-0.0	0.1	-33.2	54.1
	Fall	385	-0.0	0.0	-27.2	62.5
South	Winter	236	-0.0	0.0	-26.4	51.1
	Spring	263	-0.1	0.1	-48.2	57.1
	Summer	281	-0.1	0.1	-46.4	64.7
	Fall	280	-0.0	0.0	-42.4	62.2
Southwest	Winter	300	-0.0	0.0	-81.7	86.0
	Spring	322	-0.0	0.0	-71.3	81.4
	Summer	292	-0.0	0.0	-38.9	60.0
	Fall	334	-0.0	0.0	-67.9	76.3
Northern Rockies	Winter	216	-0.0	0.0	-74.8	86.8
	Spring	251	-0.0	0.0	-55.3	61.1
	Summer	226	-0.0	0.0	-32.4	54.0
	Fall	237	-0.0	0.0	-52.6	66.1
Northwest	Winter	121	0.0	0.0	80.1	62.8
	Spring	141	-0.0	0.0	-8.4	53.2
	Summer	138	0.0	0.0	18.0	89.3

Climate Region	Season	No. of Obs	MB (ug/m^3)	ME (ug/m^3)	NMB (%)	NME (%)
	Fall	145	0.0	0.0	22.9	77.4
West	Winter	151	0.0	0.0	46.7	92.9
	Spring	151	0.0	0.0	27.2	93.0
	Summer	161	-0.0	0.0	-80.7	93.0
	Fall	160	-0.0	0.0	-1.3	84.0

7.5 Model Simulation Scenarios

As part of our analysis for this rulemaking, the CMAQ modeling system was used to calculate annual $PM_{2.5}$ concentrations, 8-hour maximum average ozone season concentrations, annual NO_2, SO_2, and CO concentrations, annual and seasonal (summer and winter) air toxics concentrations, and annual nitrogen and sulfur deposition for each of the following emissions scenarios:

- 2016 base year
- 2055 reference
- 2055 light and medium duty regulatory scenario

We use the predictions from the CMAQ model in a relative sense by combining the 2016 base-year predictions with predictions from each future-year scenario and applying these modeled ratios to ambient air quality observations to estimate 8-hour ozone concentrations during the ozone season (May - Sept), daily and annual $PM_{2.5}$ concentrations, and visibility impairment for each of the 2055 scenarios. The ambient air quality observations are average conditions, on a site-by-site basis, for a period centered around the model base year (i.e., 2014-2018).

The projected annual $PM_{2.5}$ concentrations were calculated using the Speciated Modeled Attainment Test (SMAT) approach that utilizes a Federal Reference Method (FRM) mass construction methodology which results in reduced nitrates (relative to the amount measured by routine speciation networks), higher mass associated with sulfates (reflecting water included in FRM measurements), and a measure of organic carbonaceous mass that is derived from the difference between measured $PM_{2.5}$ and its non-carbon components. This characterization of $PM_{2.5}$ mass also reflects crustal material and other minor constituents. The resulting characterization provides a complete mass balance. It does not have any unknown mass that is sometimes presented as the difference between measured $PM_{2.5}$ mass and the characterized chemical components derived from routine speciation measurements. However, the assumption that all mass difference is organic carbon has not been validated in many areas of the U.S. The SMAT methodology uses the following $PM_{2.5}$ species components: sulfates, nitrates, ammonium, organic carbon mass, elemental carbon, crustal, water, and blank mass (a fixed value of 0.5 $\mu g/m^3$). More complete details of the SMAT procedures can be found in the report "Procedures for Estimating Future $PM_{2.5}$ Values for the CAIR Final Rule by Application of the (Revised) Speciated Modeled Attainment Test (SMAT)." For this analysis, several datasets and techniques were updated. These changes are fully described within the technical support document for the Final Transport Rule AQM TSD.

Additionally, we conducted an analysis to compare the absolute differences between the future year reference and regulatory scenario for annual and seasonal acetaldehyde, benzene, formaldehyde, and naphthalene, as well as annual NO_2, SO_2, CO, and nitrate/sulfate deposition. These data were not compared in a relative sense due to the limited observational data available.

8 Additional Results of Air Quality Analysis

EPA conducted an air quality modeling analysis of a regulatory scenario involving light- and medium-duty "onroad" vehicle emission reductions and corresponding changes in "upstream" emission sources like EGU (electric generating unit) emissions and refinery emissions.

The RIA includes maps that present the impact of the LMDV regulatory scenario on projected ozone, $PM_{2.5}$, NO_2, SO_2, CO, and air toxics concentrations, and projected nitrogen and sulfur deposition. In this TSD we present annual reference and LMDV regulatory scenario maps for ozone, $PM_{2.5}$, CO, NO_2, SO_2, air toxics, and nitrogen and sulfur deposition as well as seasonal difference maps for air toxics and visibility levels at Mandatory Class I Federal Areas.

8.1 Annual 2055 Reference, LMDV Regulatory, and Onroad-Only Scenario Maps

The following section presents maps of projected ambient concentrations of $PM_{2.5}$, ozone, CO, NO_2, SO_2, acetaldehyde, benzene, 1,3-butadiene, formaldehyde, and naphthalene, and total nitrogen and sulfur deposition in the 2055 reference case and the 2055 LMDV regulatory scenario and the 2055 onroad-only scenario.

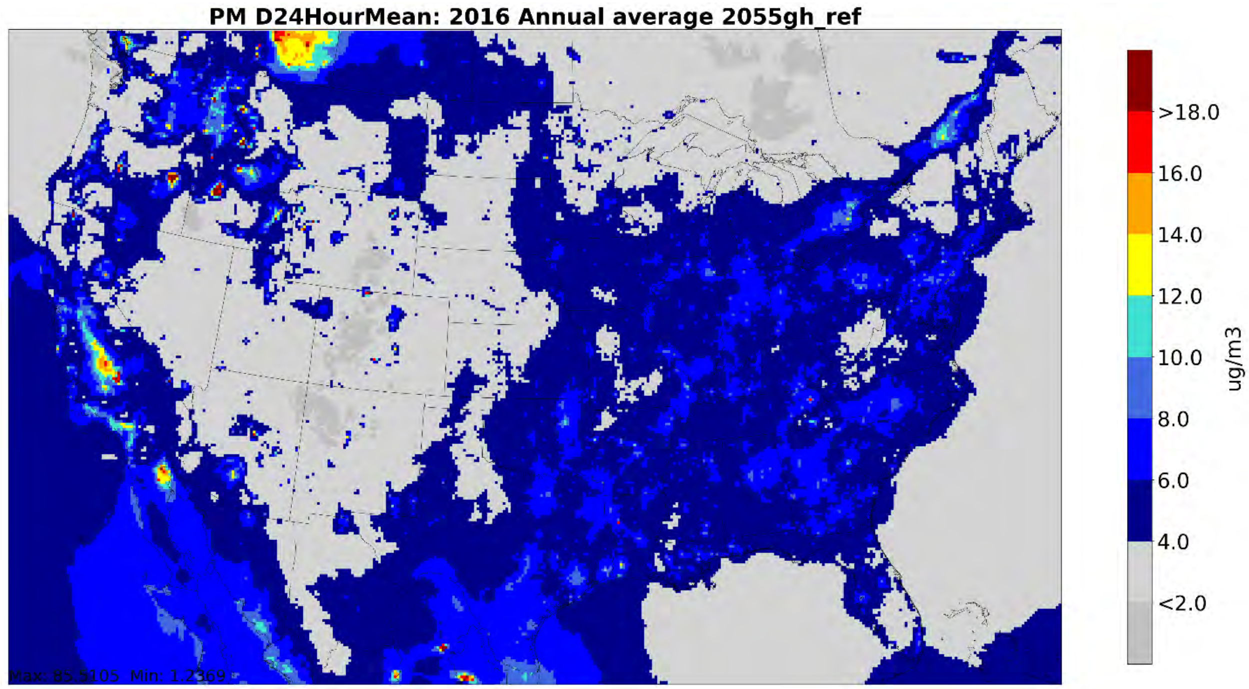

Figure 8-1 Projected Annual Average $PM_{2.5}$ Concentrations in 2055 Reference Case (ug/m^3)

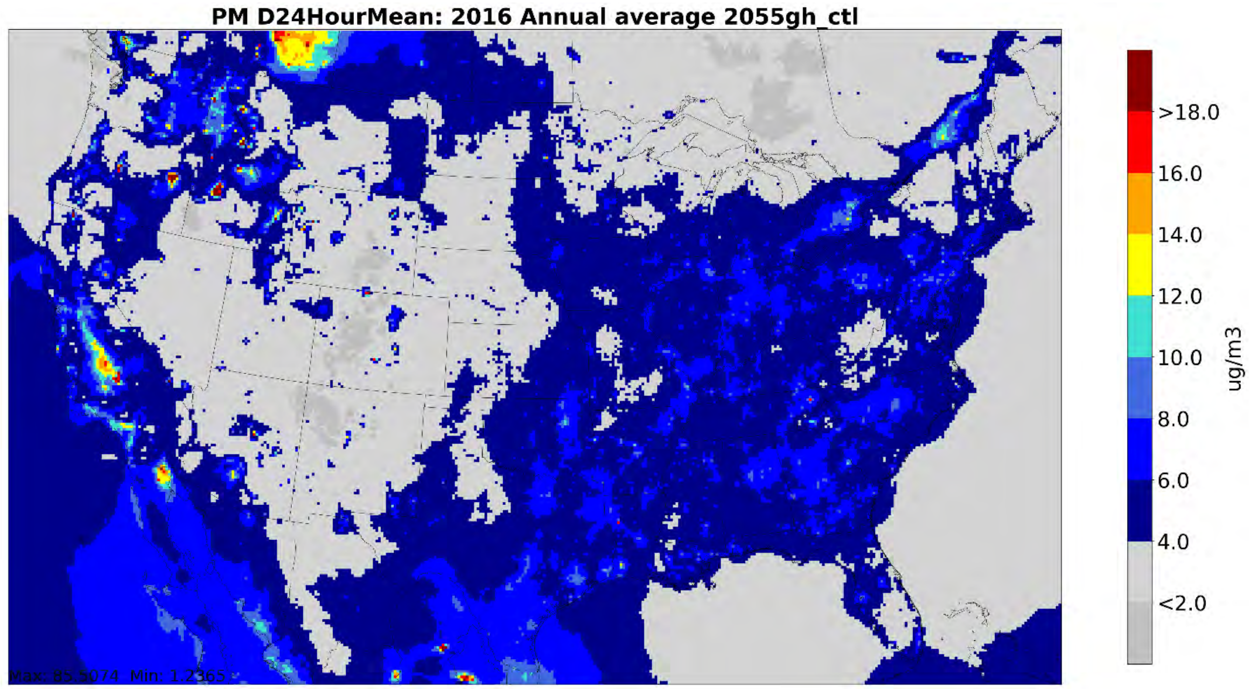

Figure 8-2 Projected Annual Average $PM_{2.5}$ Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

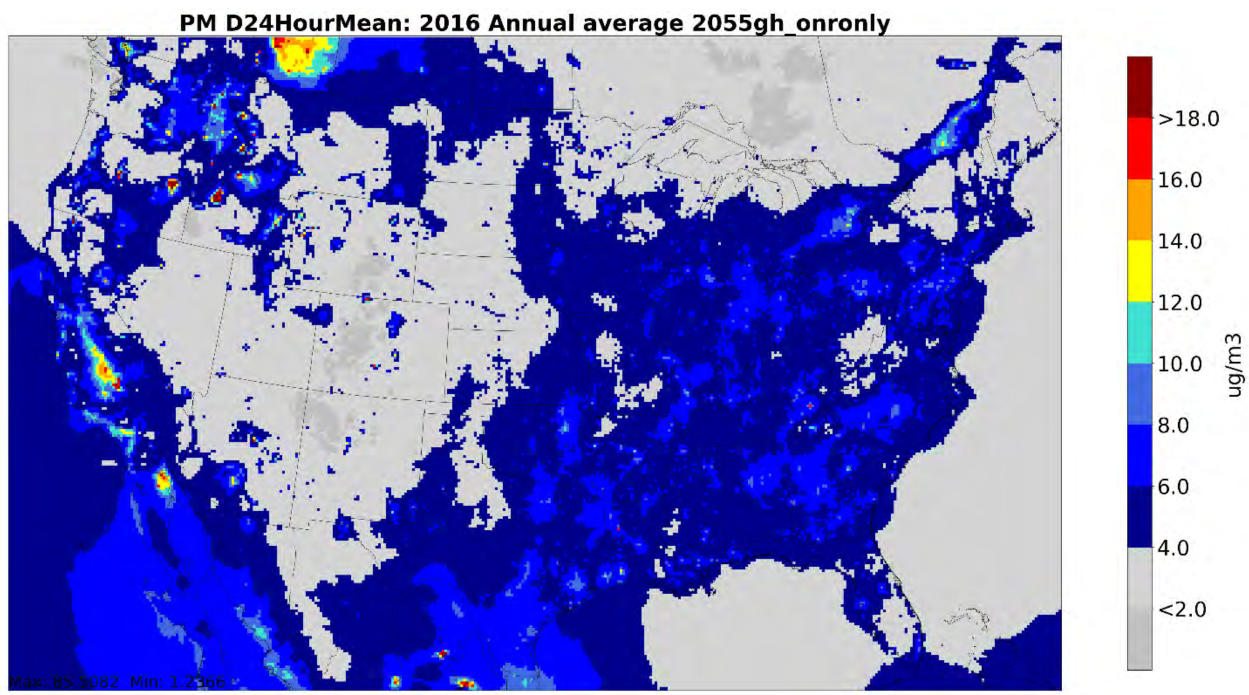

Figure 8-3 Projected Annual Average $PM_{2.5}$ Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

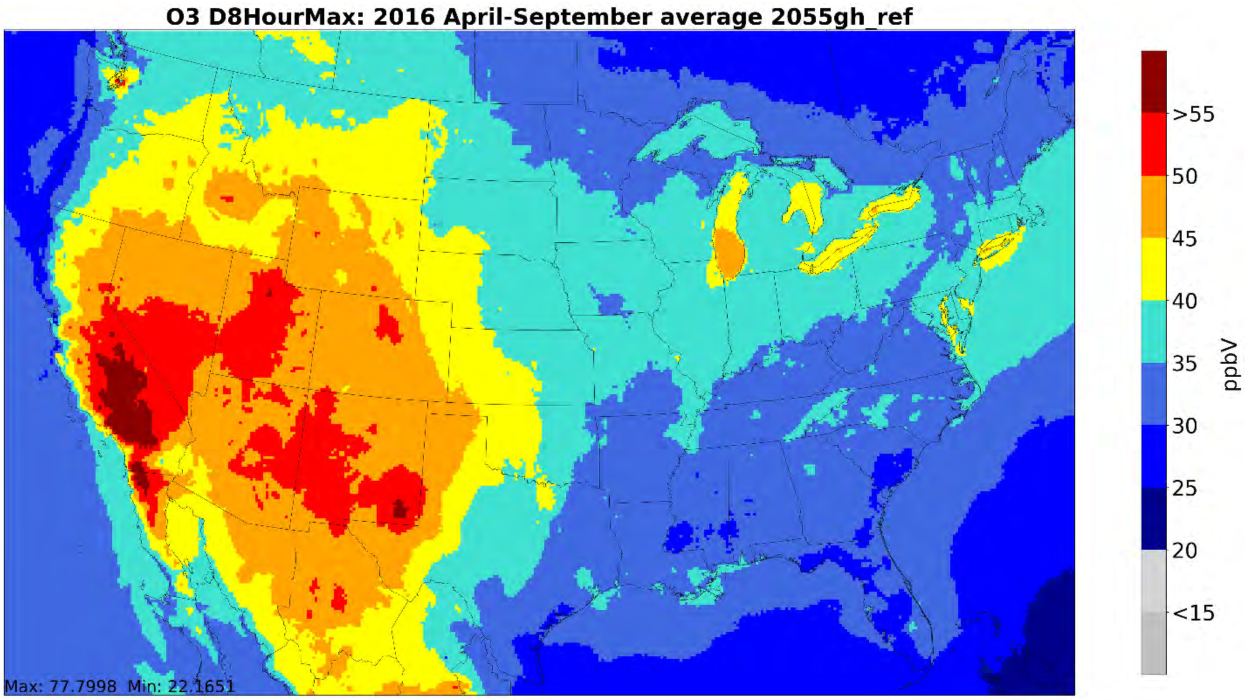

Figure 8-4 Projected Ozone Season (Apr-Sept) 8-hour Maximum Average Ozone Concentrations in 2055 Reference case (ppb)

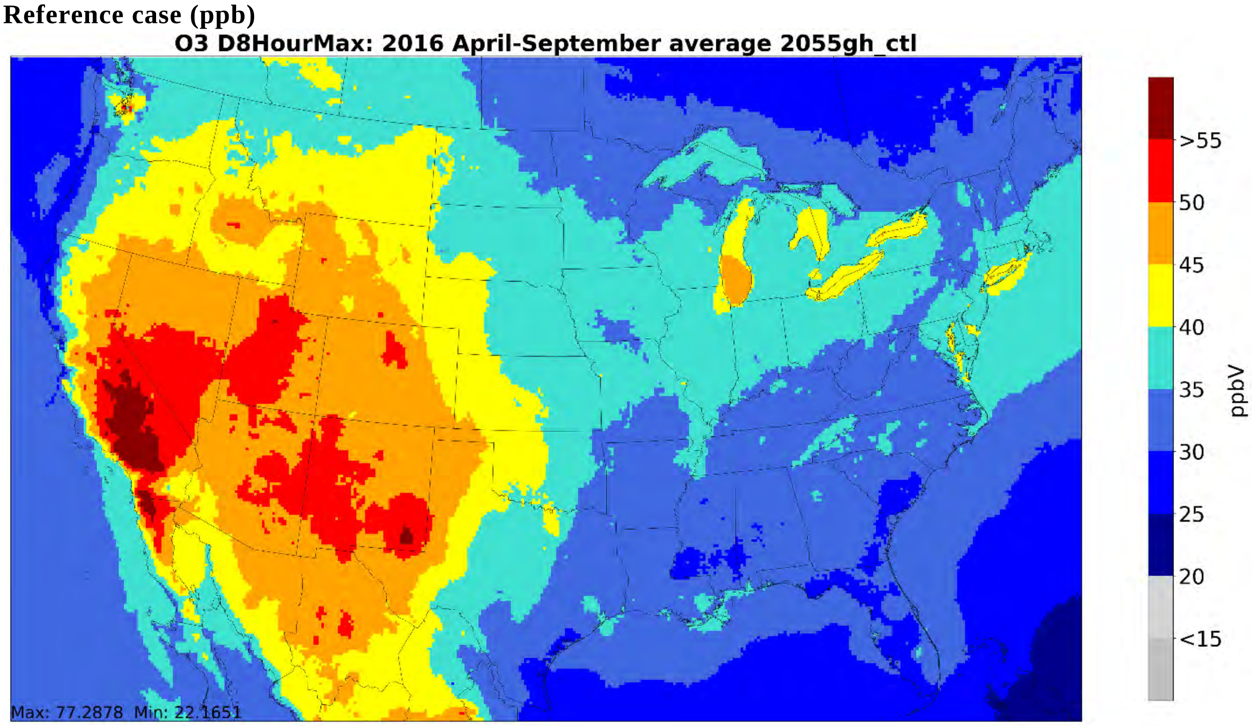

Figure 8-5 Projected Ozone Season (Apr-Sept) 8-hour Maximum Average Ozone Concentrations in 2055 LMDV Regulatory Scenario (ppb)

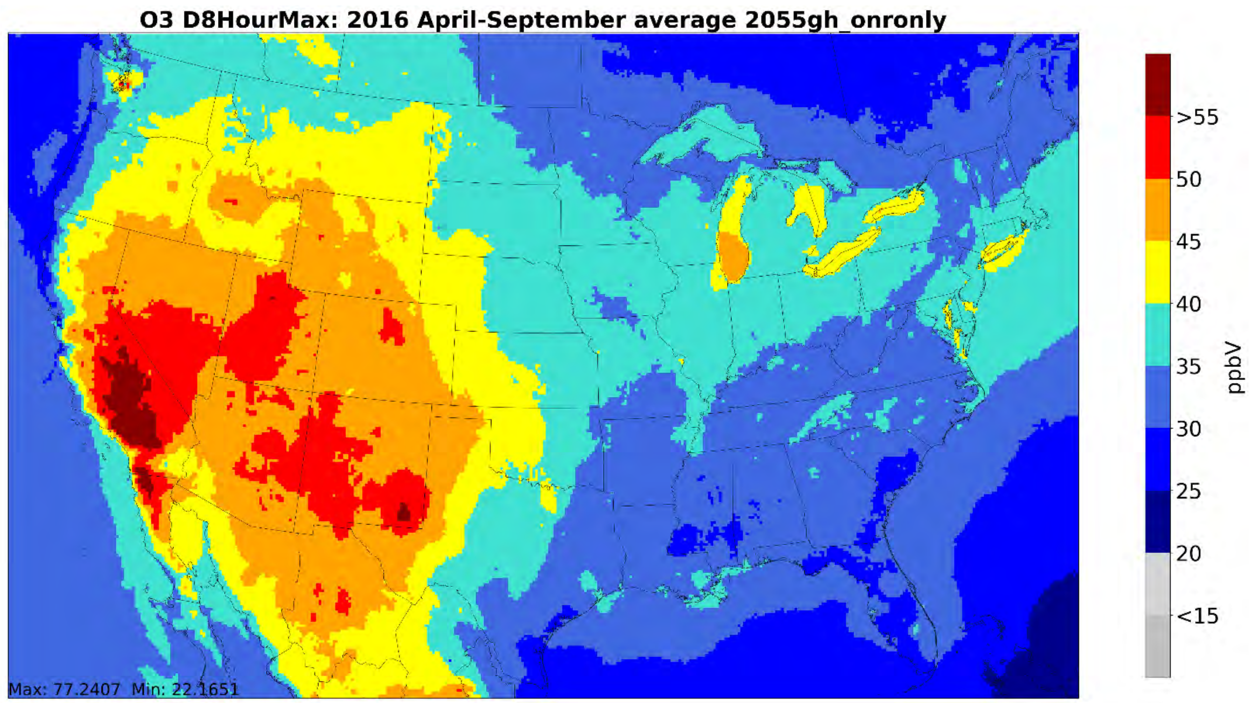

Figure 8-6 Projected Ozone Season (Apr-Sept) 8-hour Maximum Average Ozone Concentrations in 2055 Onroad-Only Scenario (ppb)

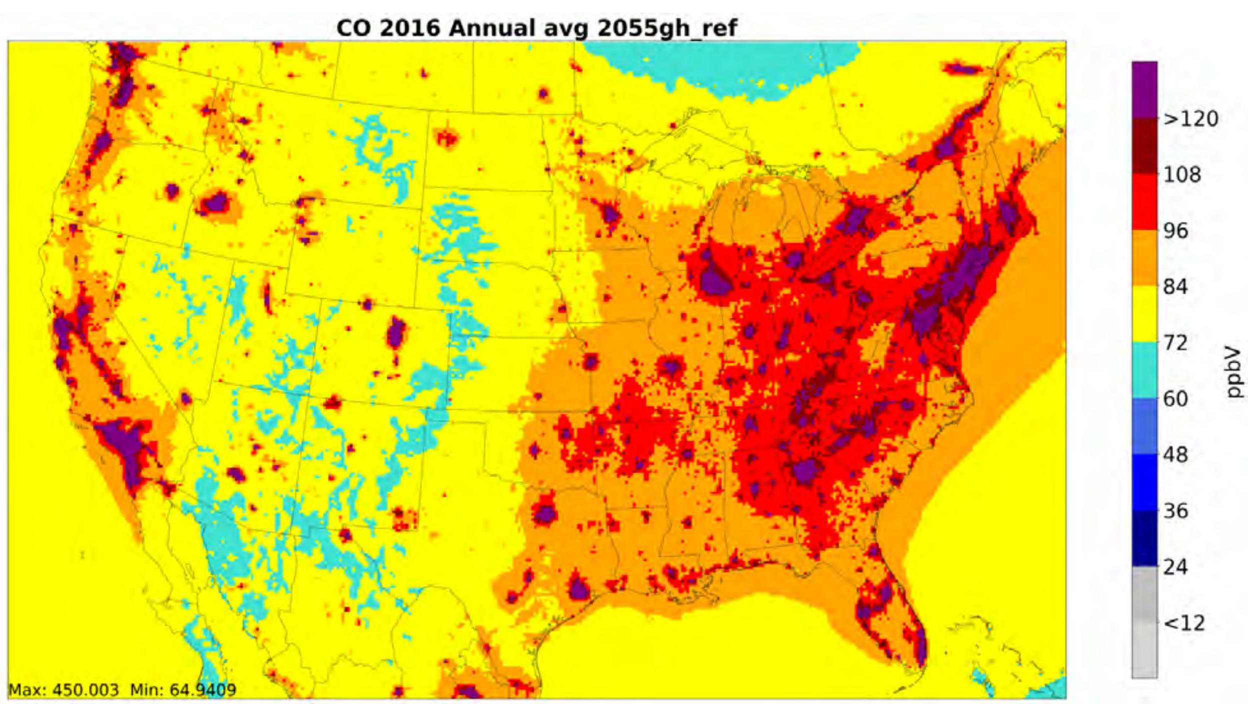

Figure 8-7 Projected Annual Average CO Concentrations in 2055 Reference Case (ppb)

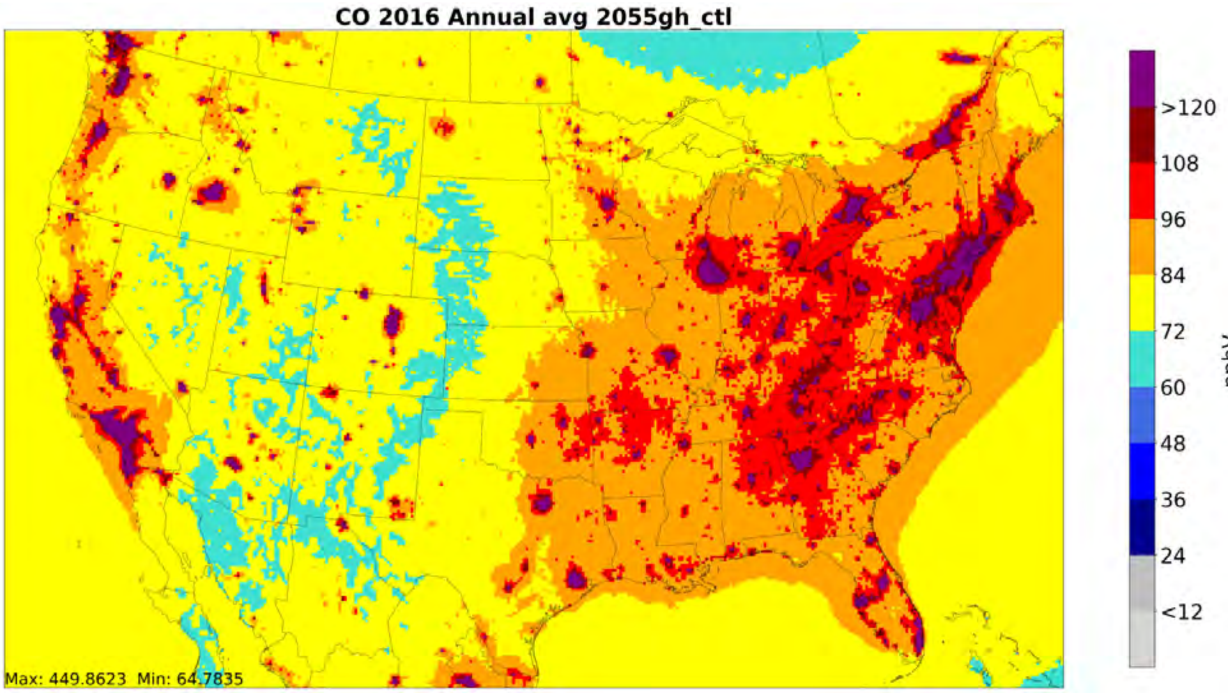

Figure 8-8 Projected Annual Average CO Concentrations in 2055 LMDV Regulatory Scenario (ppb)

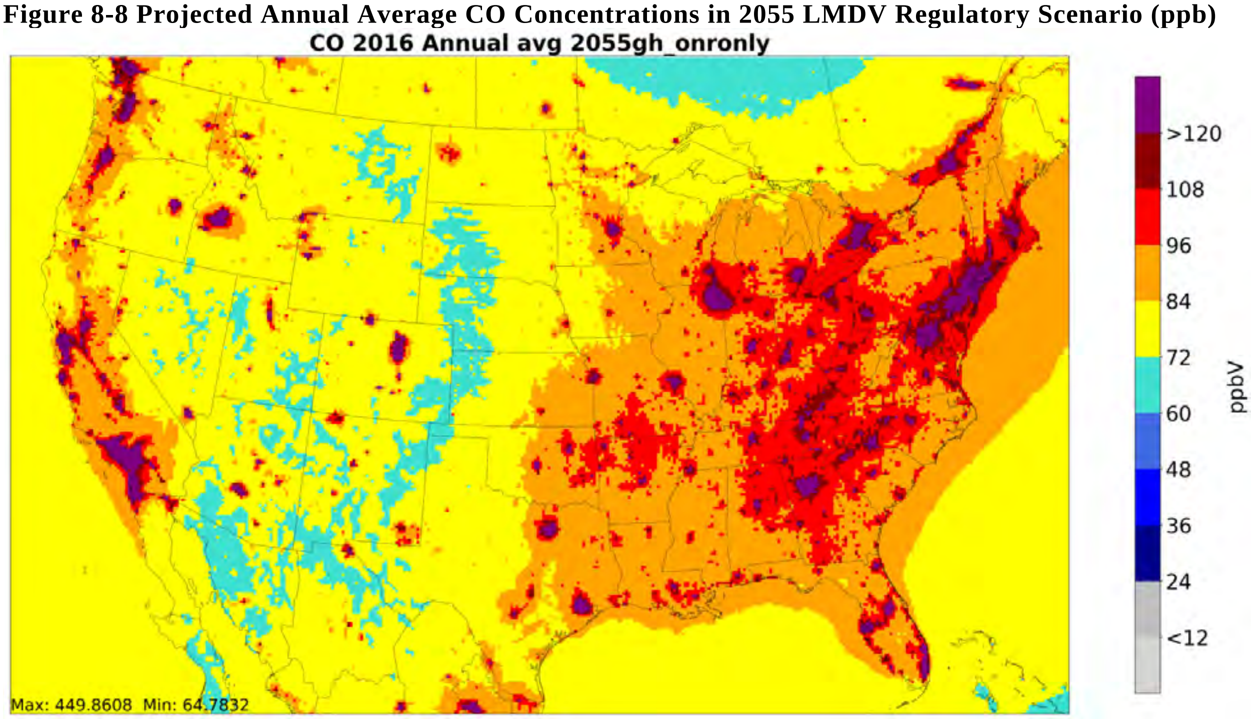

Figure 8-9 Projected Annual Average CO Concentrations in 2055 Onroad-Only Scenario (ppb)

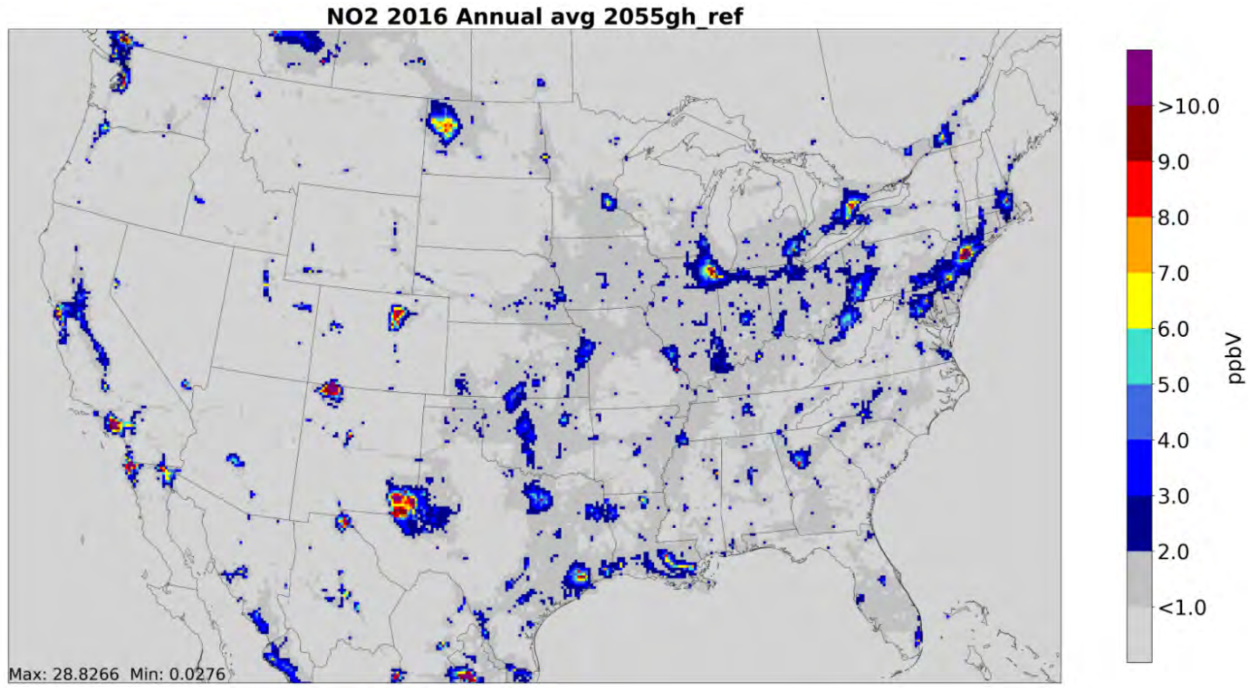

Figure 8-10 Projected Annual Average NO_2 Concentrations in 2055 Reference Case (ppb)

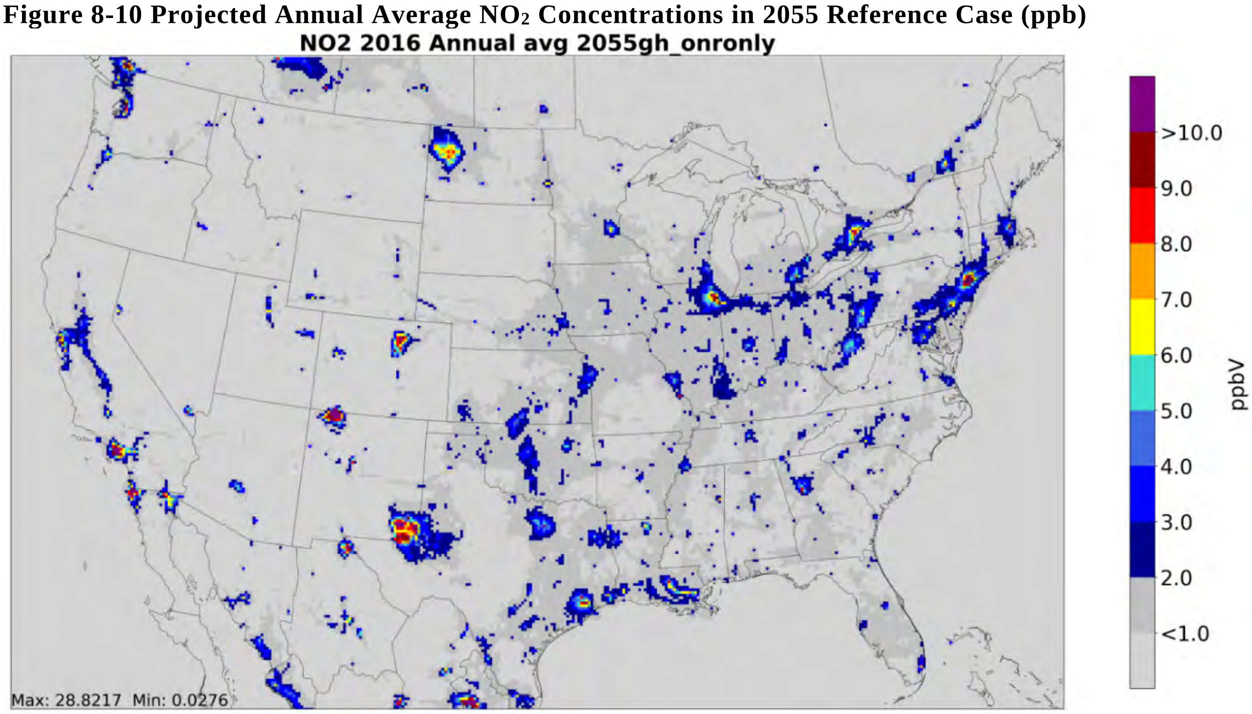

Figure 8-11 Projected Annual Average NO_2 Concentrations in 2055 LMDV Regulatory Scenario (ppb)

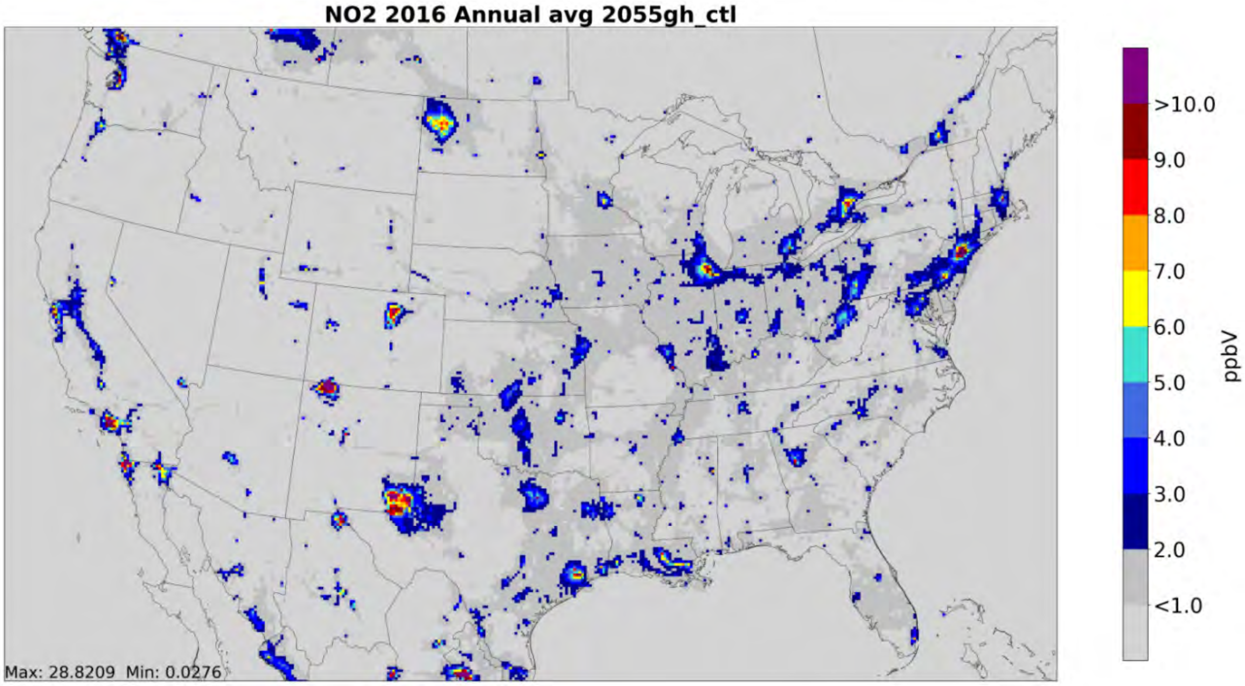

Figure 8-12 Projected Annual Average NO_2 Concentrations in 2055 Onroad-Only Scenario (ppb)

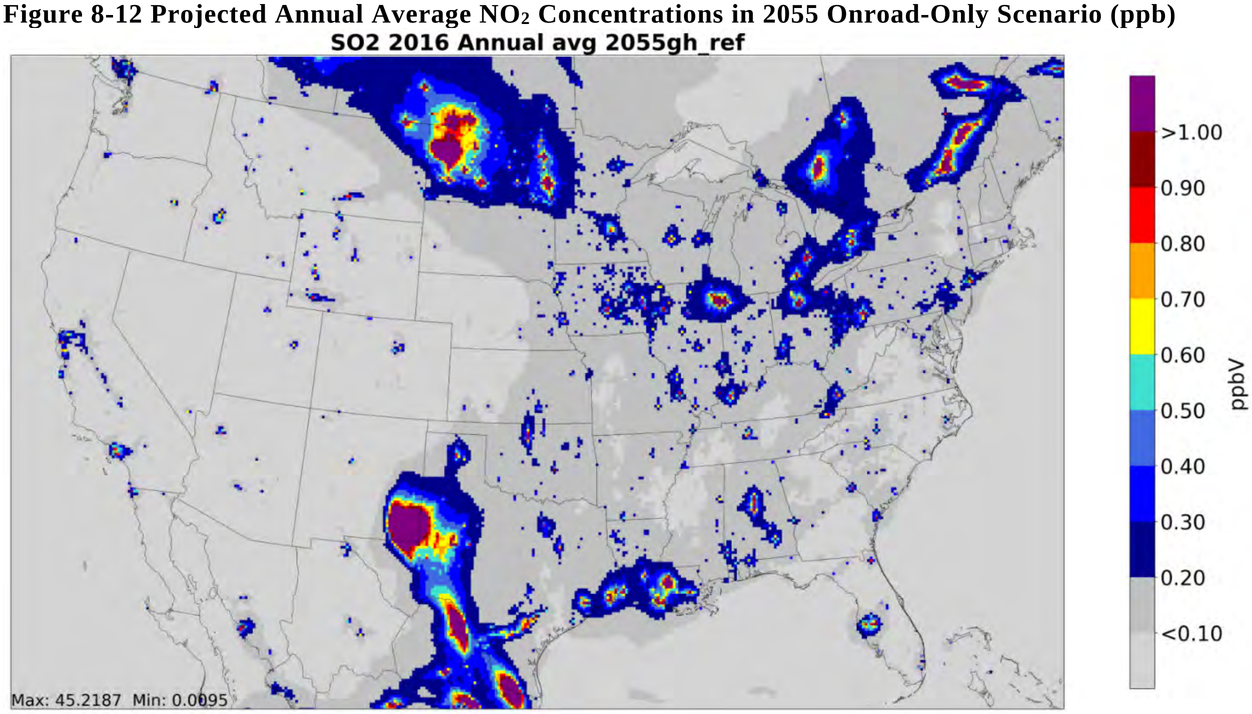

Figure 8-13 Projected Annual Average SO_2 Concentrations in 2055 Reference Case (ppb)

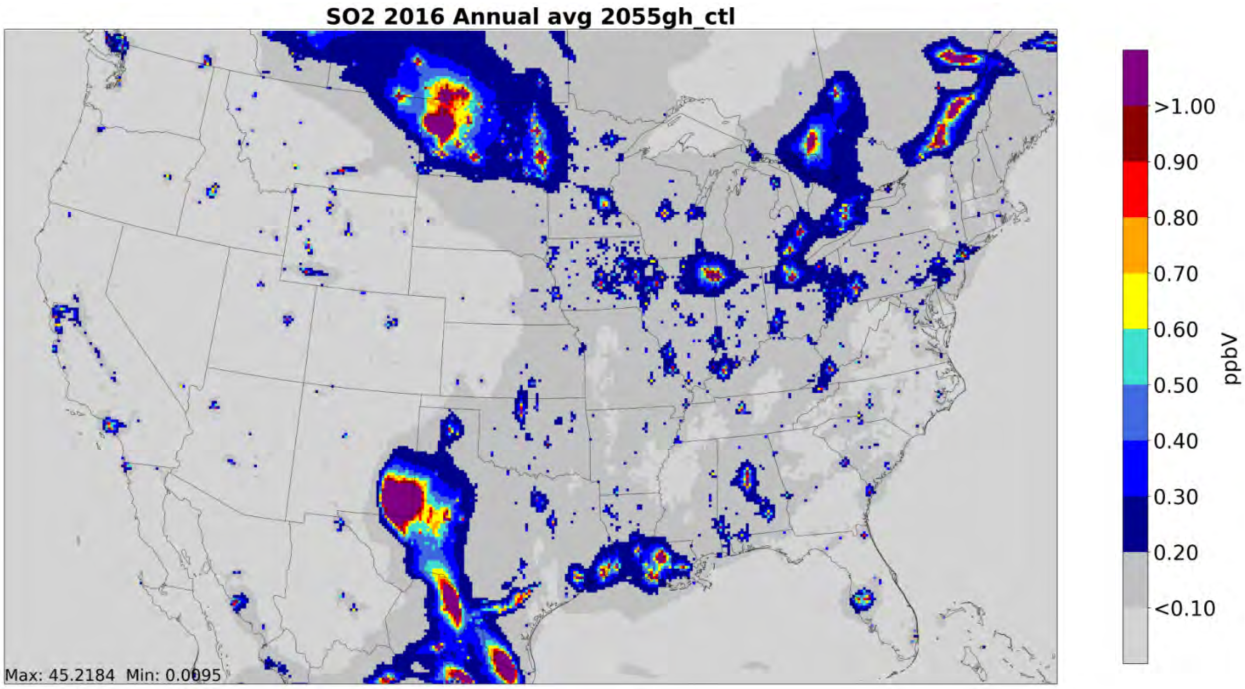

Figure 8-14 Projected Annual Average SO_2 Concentrations in 2055 LMDV Regulatory Scenario (ppb)

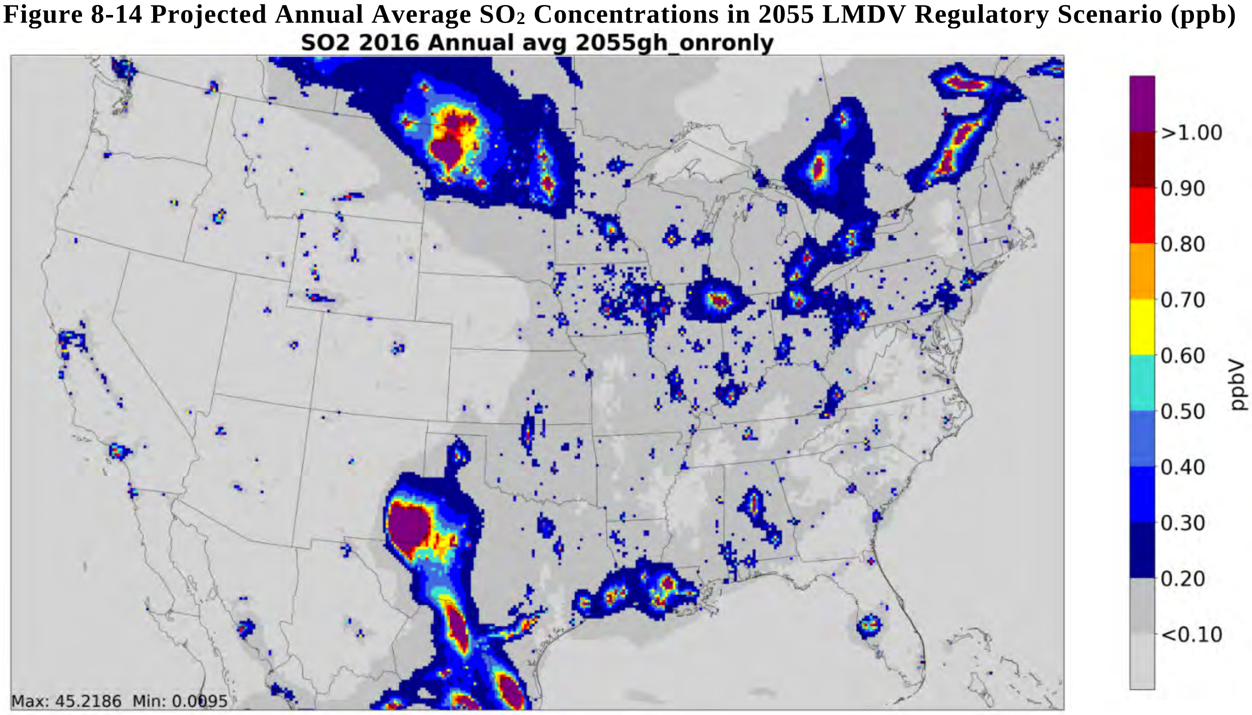

Figure 8-15 Projected Annual Average SO_2 Concentrations in 2055 Onroad-Only Scenario (ppb)

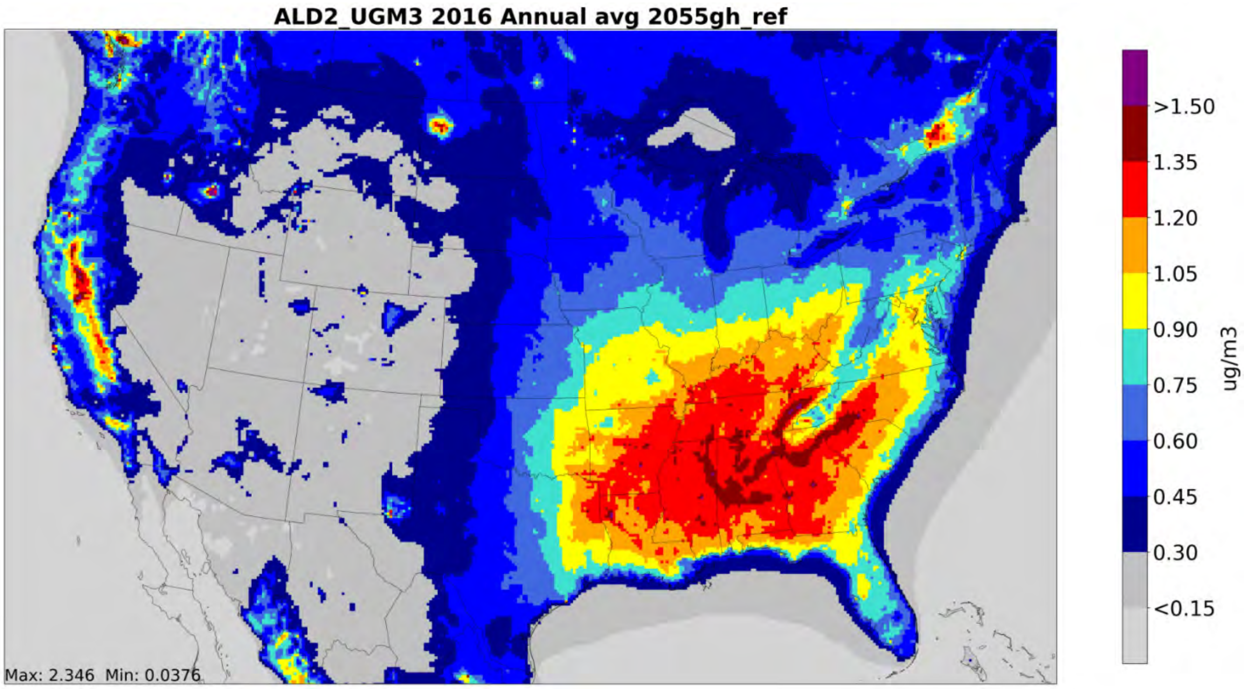

Figure 8-16 Projected Annual Average Acetaldehyde Concentrations in 2055 Reference Case (ug/m^3)

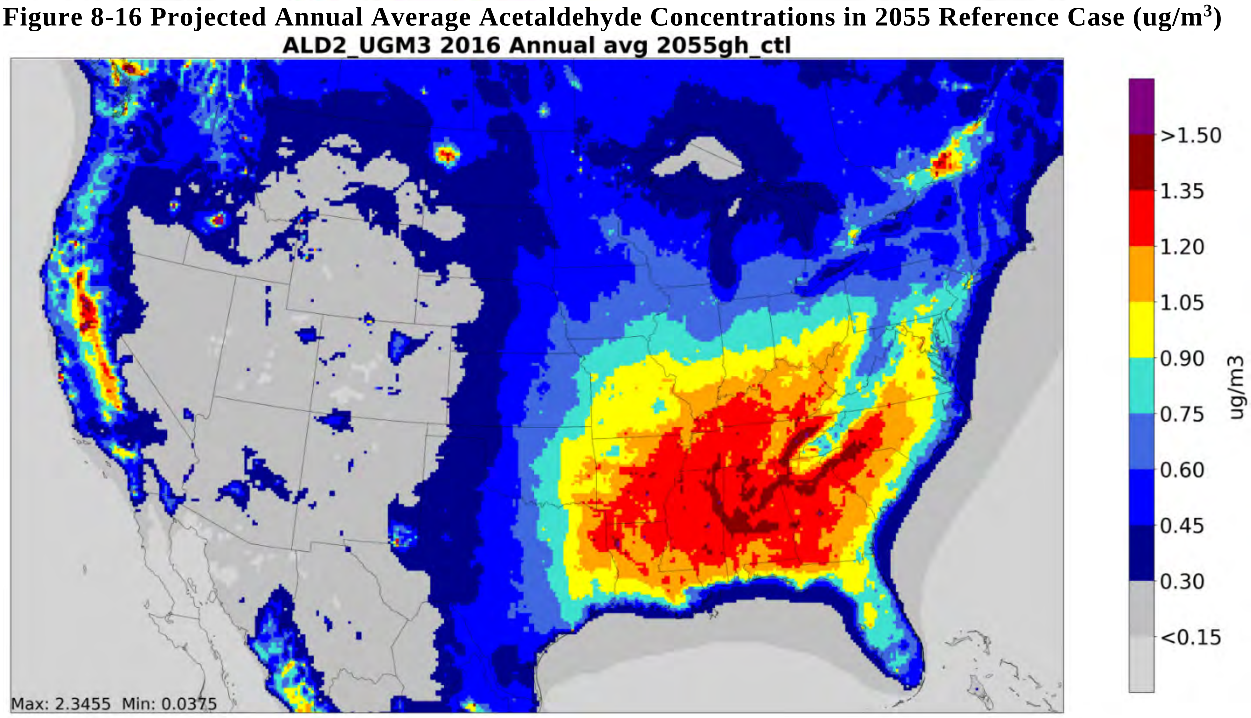

Figure 8-17 Projected Annual Average Acetaldehyde Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

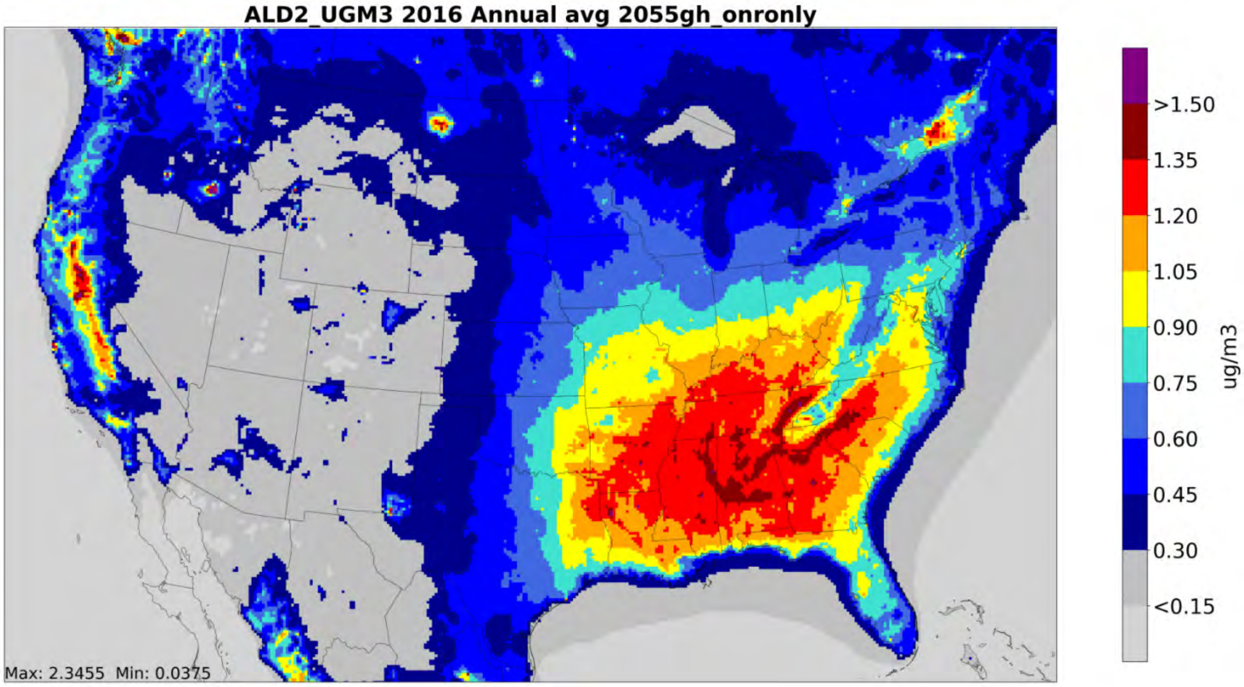

Figure 8-18 Projected Annual Average Acetaldehyde Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

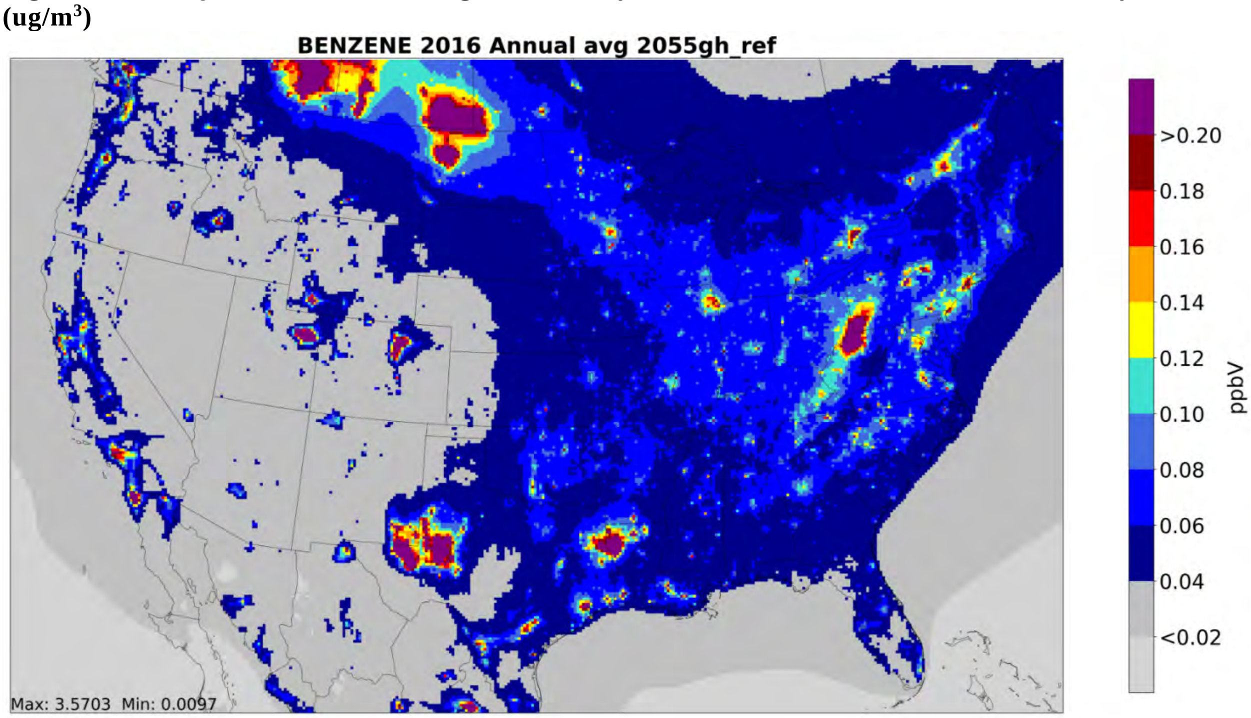

Figure 8-19 Projected Annual Average Benzene Concentrations in 2055 Reference Case (ug/m^3)

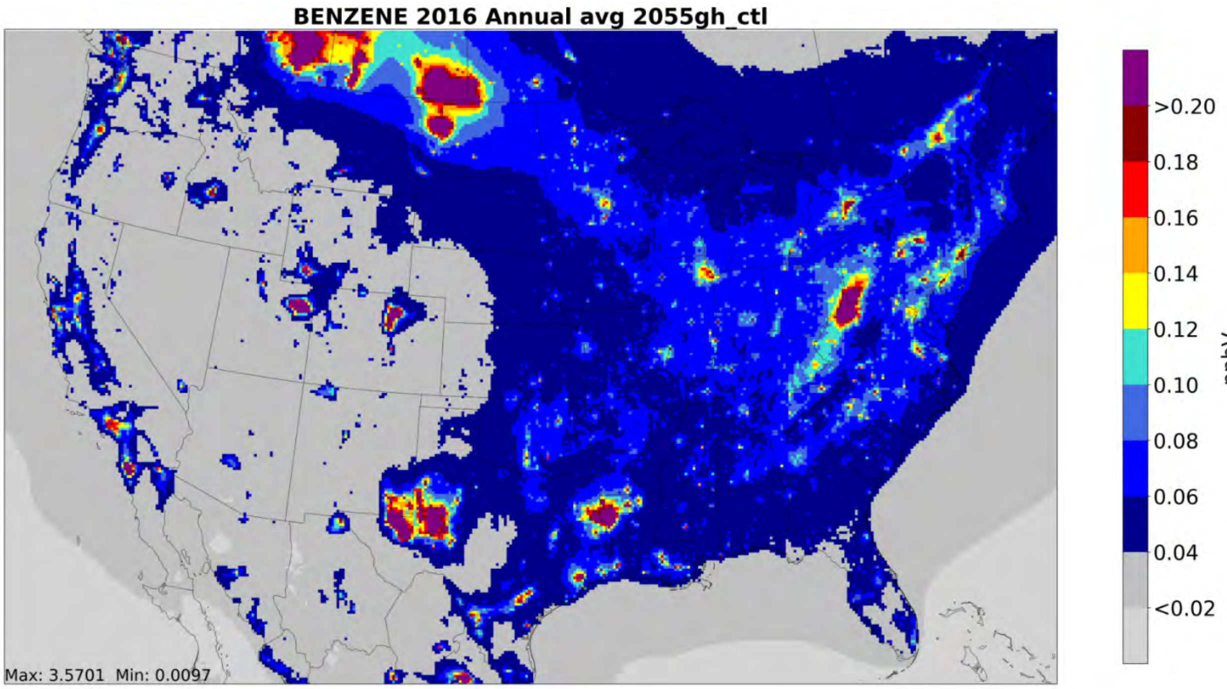

Figure 8-20 Projected Annual Average Benzene Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

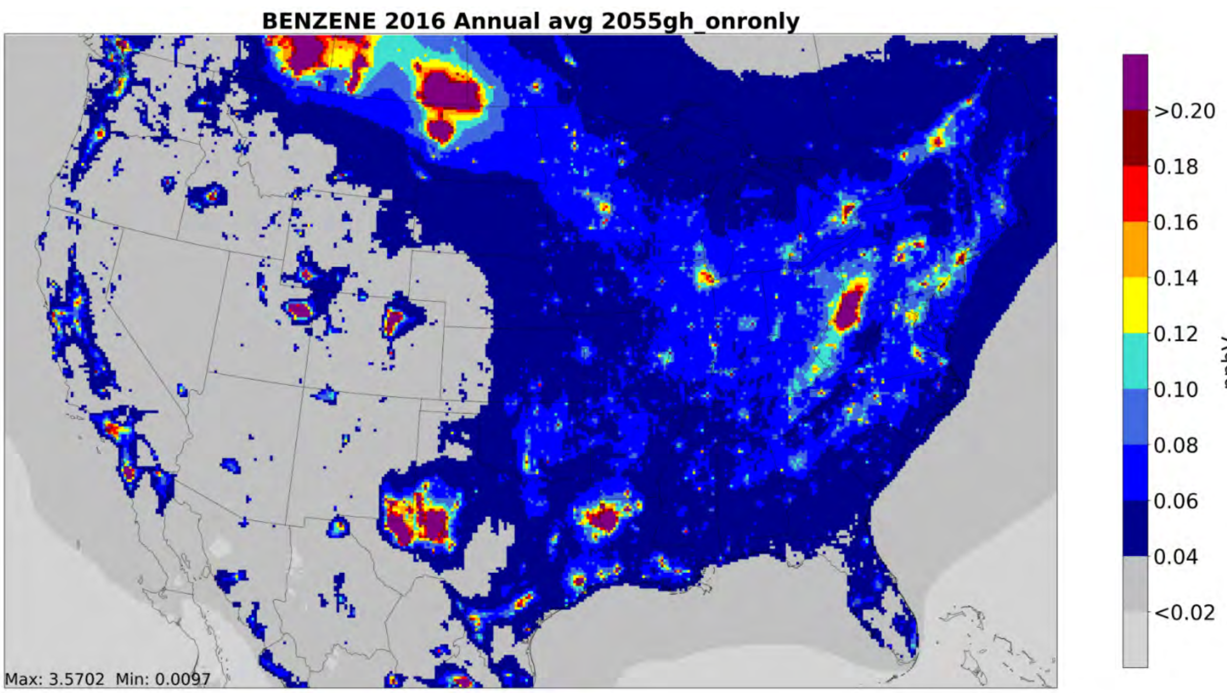

Figure 8-21 Projected Annual Average Benzene Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

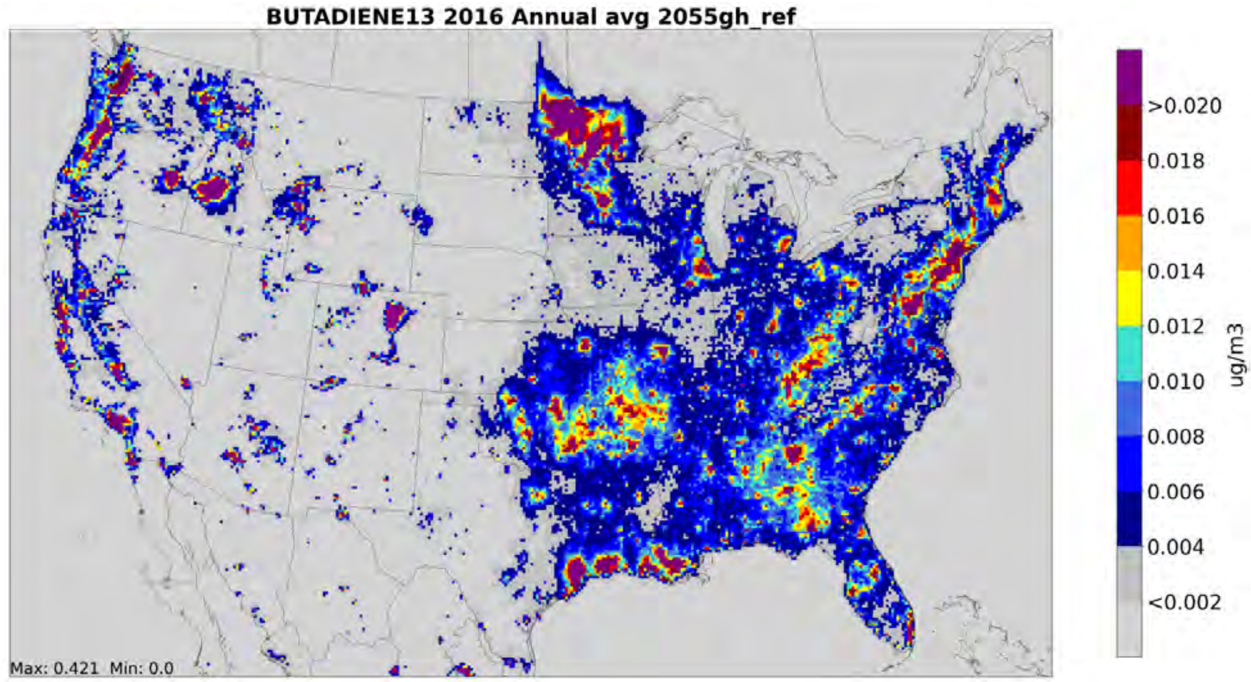

Figure 8-22 Projected Annual Average 1,3-Butadiene Concentrations in 2055 Reference Case (ppb)

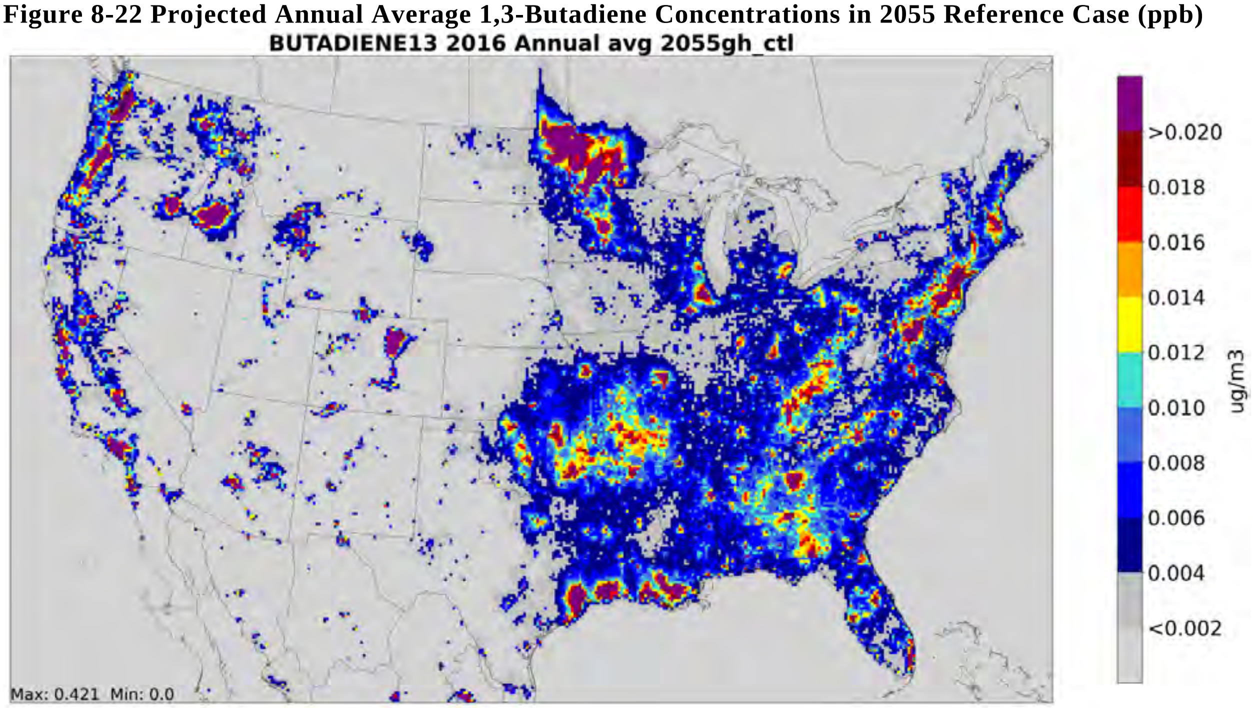

Figure 8-23 Projected Annual Average 1,3-Butadiene Concentrations in 2055 LMDV Regulatory Scenario (ppb)

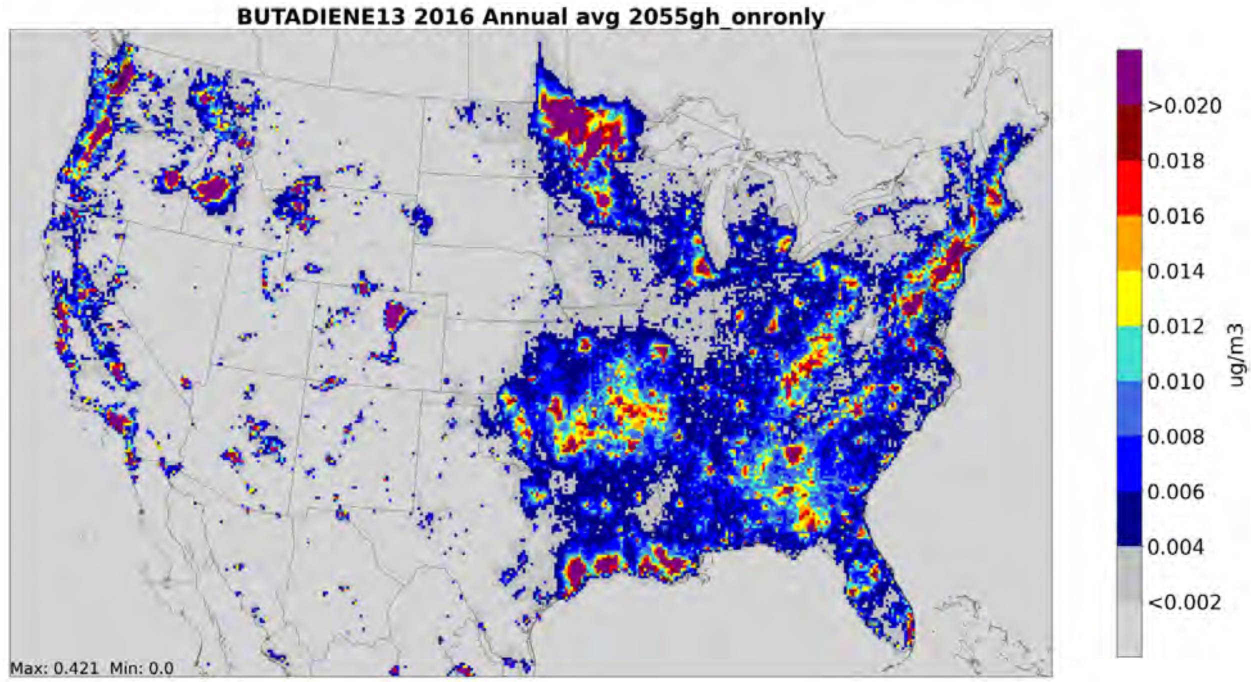

Figure 8-24 Projected Annual Average 1,3-Butadiene Concentrations in 2055 Onroad-Only Scenario (ppb)

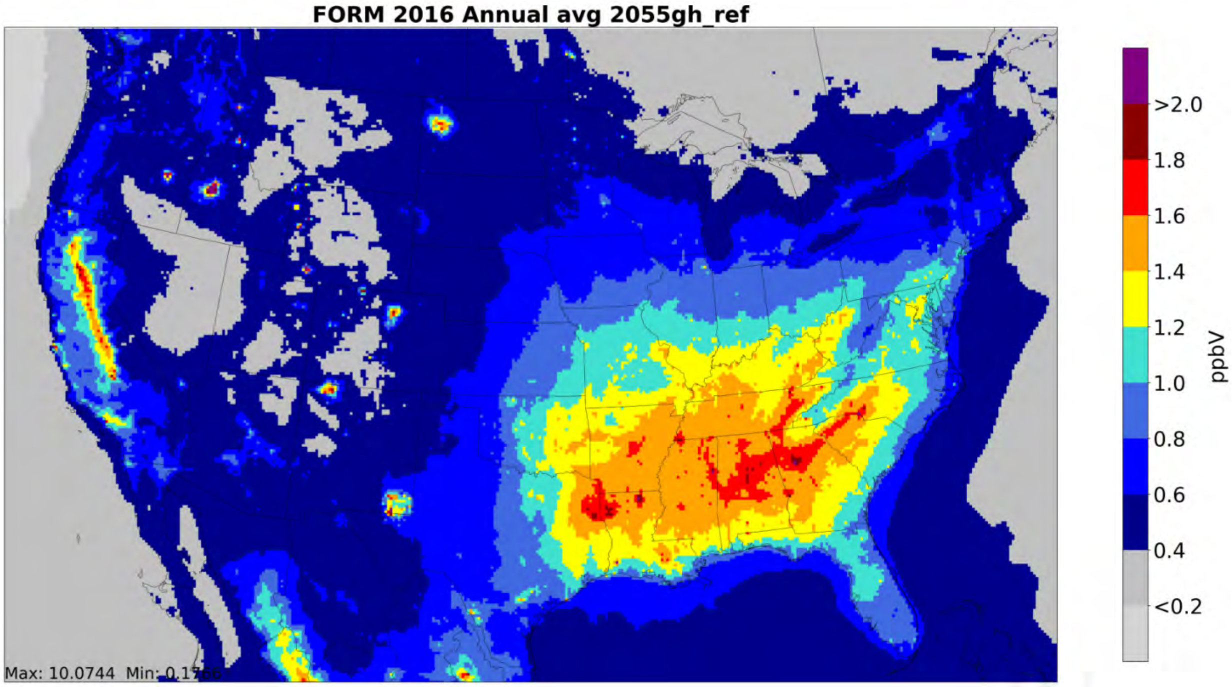

Figure 8-25 Projected Annual Average Formaldehyde Concentrations in 2055 Reference Case (ug/m^3)

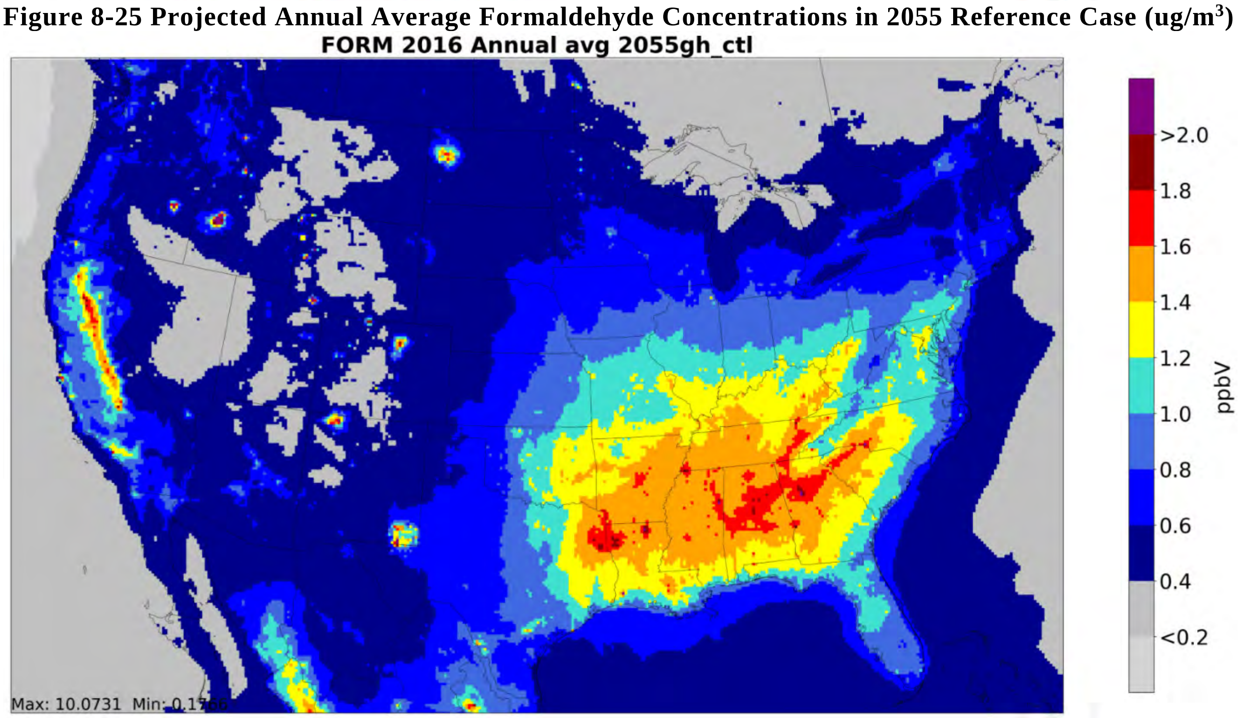

Figure 8-26 Projected Annual Average Formaldehyde Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

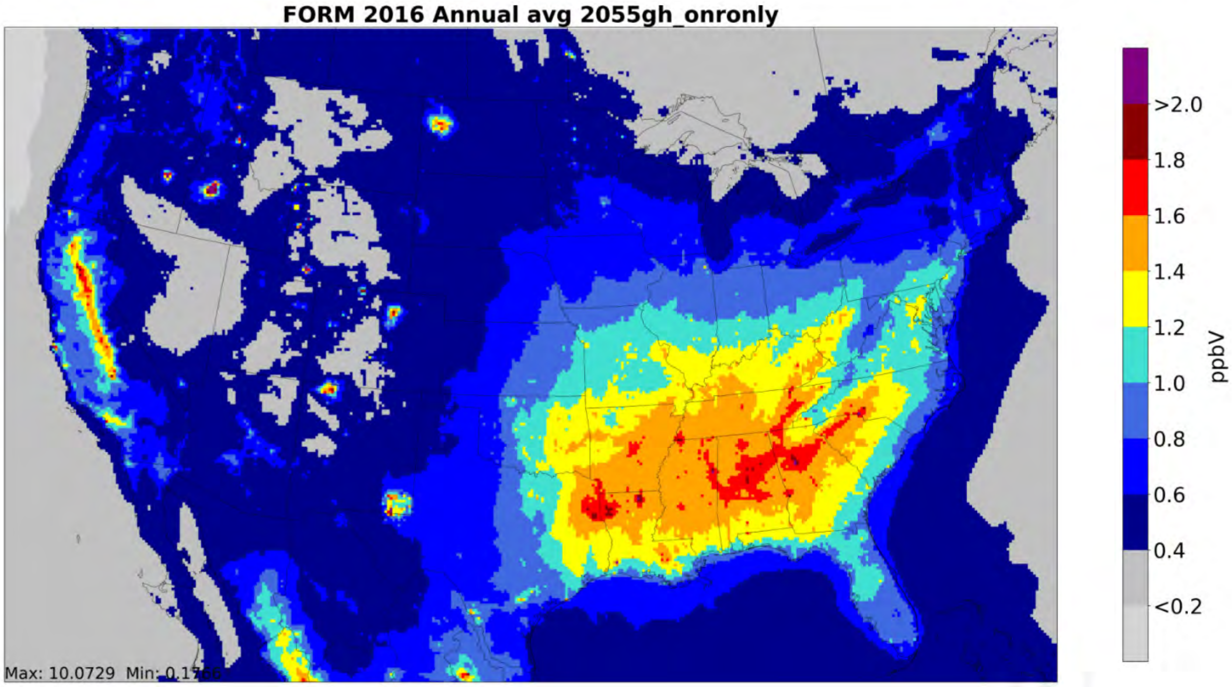

Figure 8-27 Projected Annual Average Formaldehyde Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

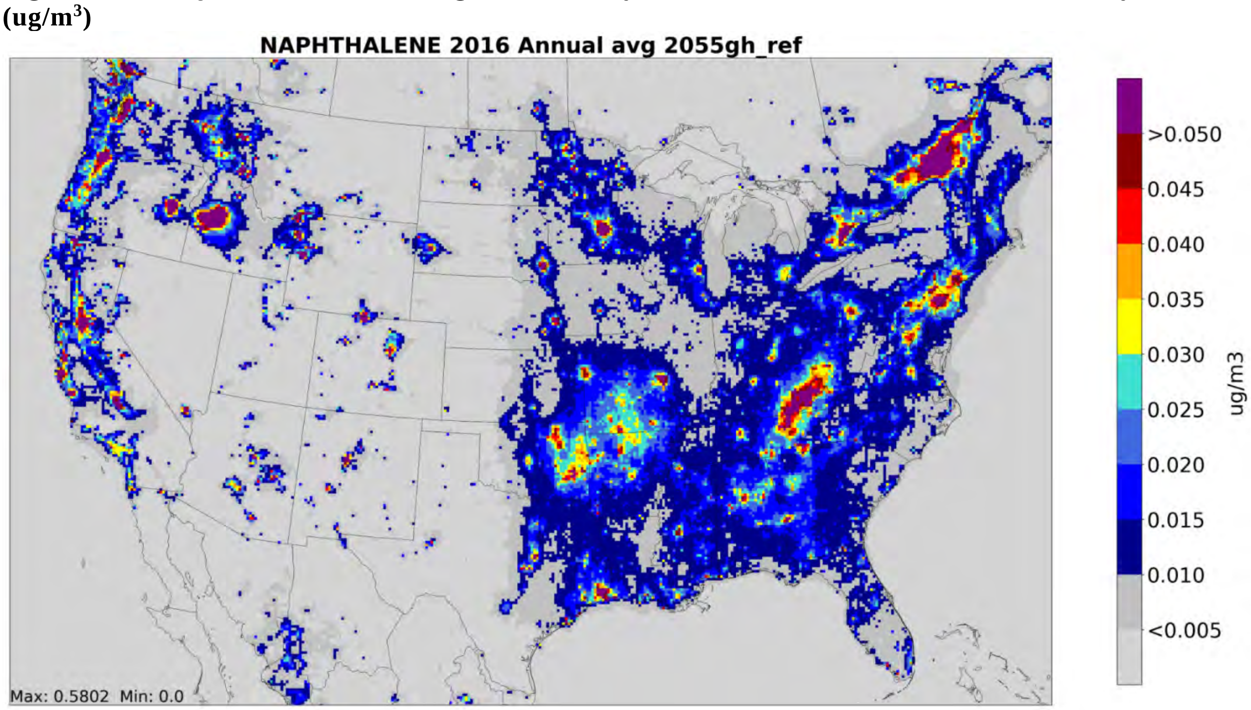

Figure 8-28 Projected Annual Average Naphthalene Concentrations in 2055 Reference Case (ug/m^3)

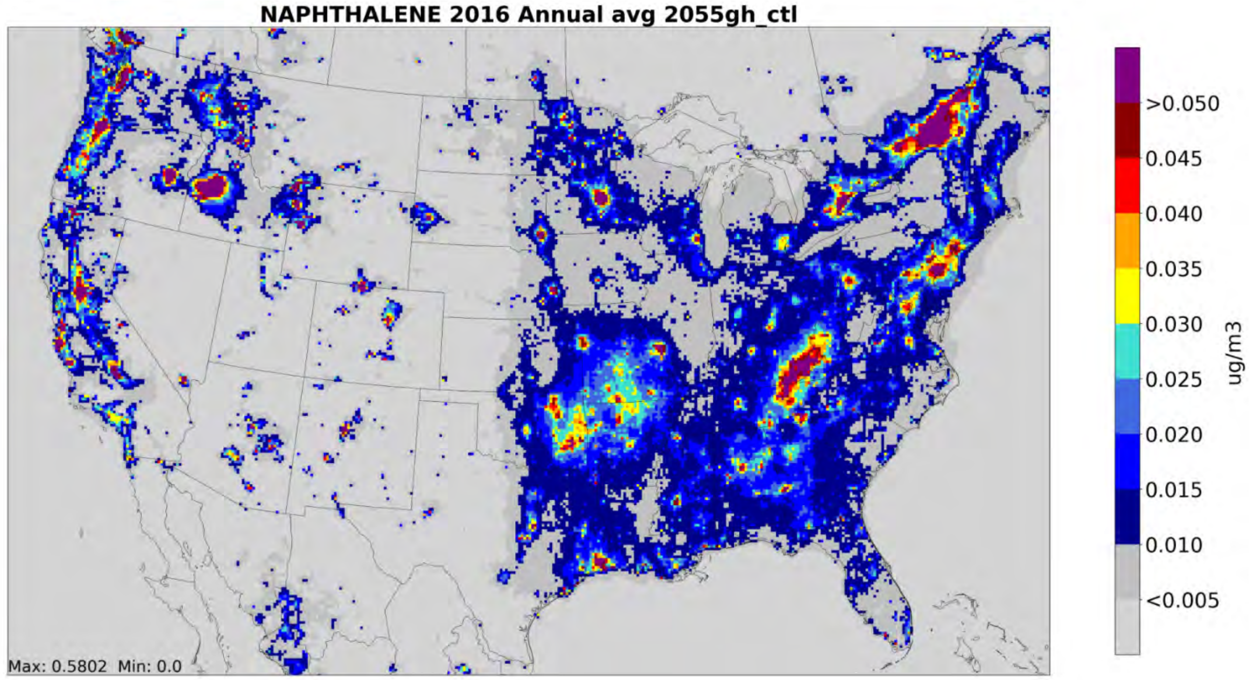

Figure 8-29 Projected Annual Average Naphthalene Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

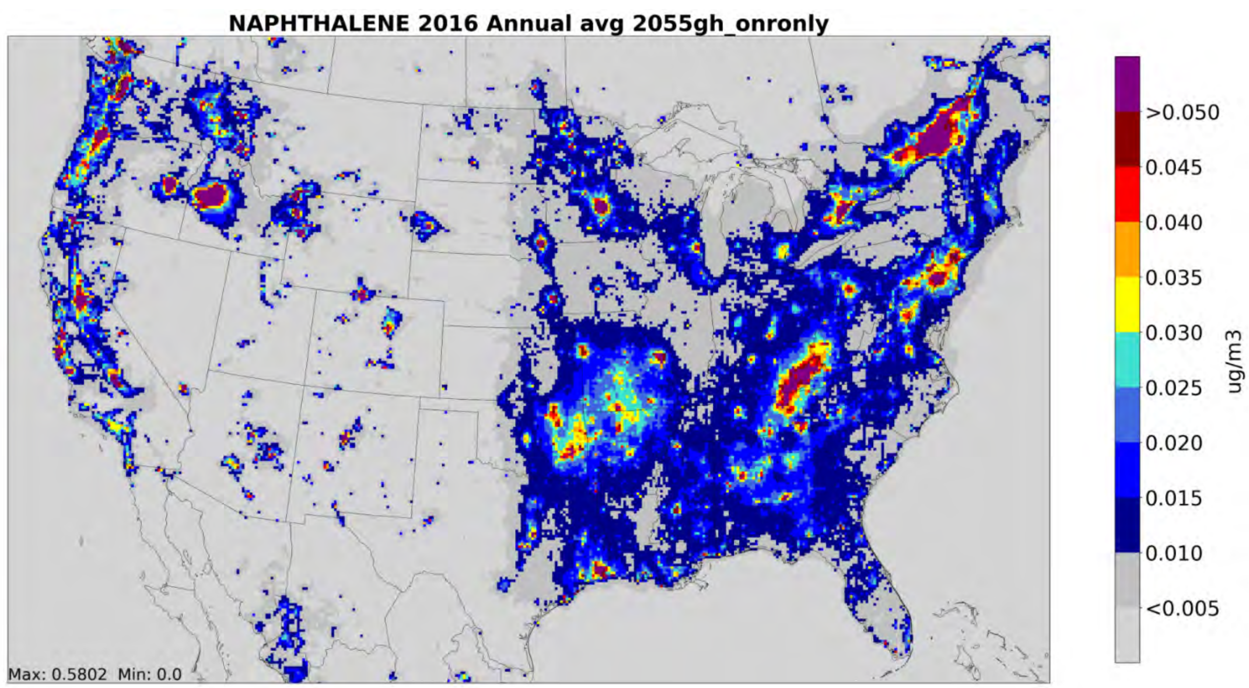

Figure 8-30 Projected Annual Average Naphthalene Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

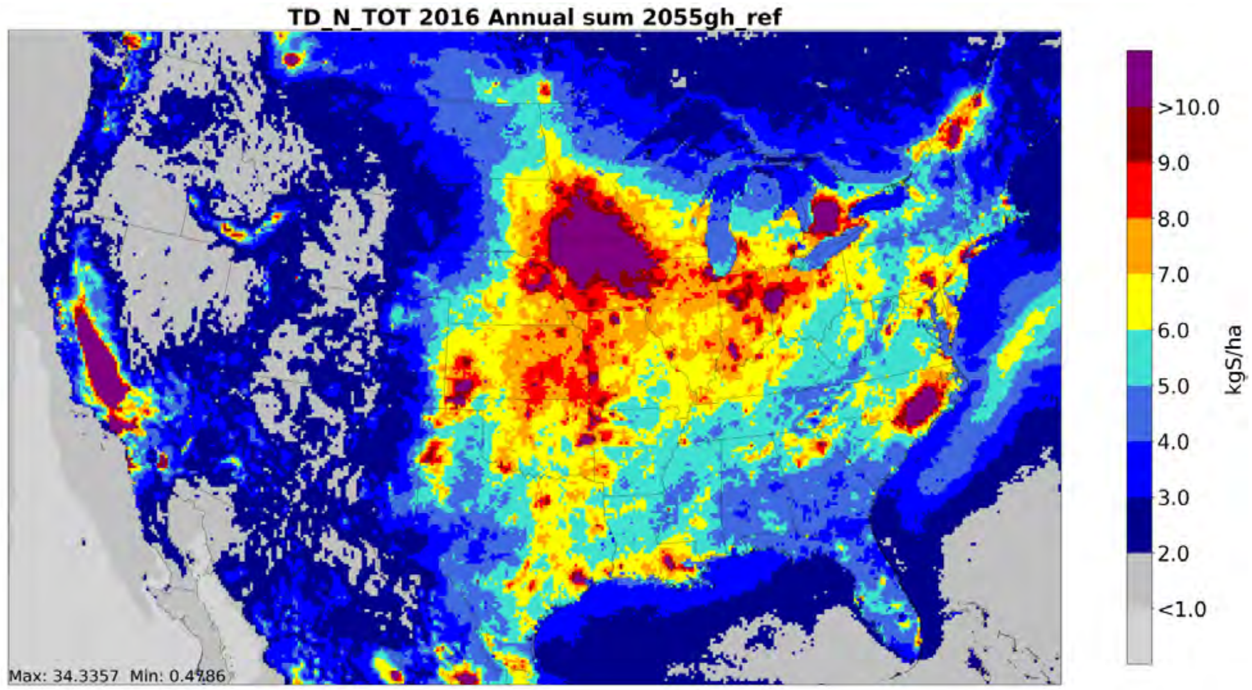

Figure 8-31 Projected Annual Nitrogen Deposition in 2055 Reference Case (kg N/ha)

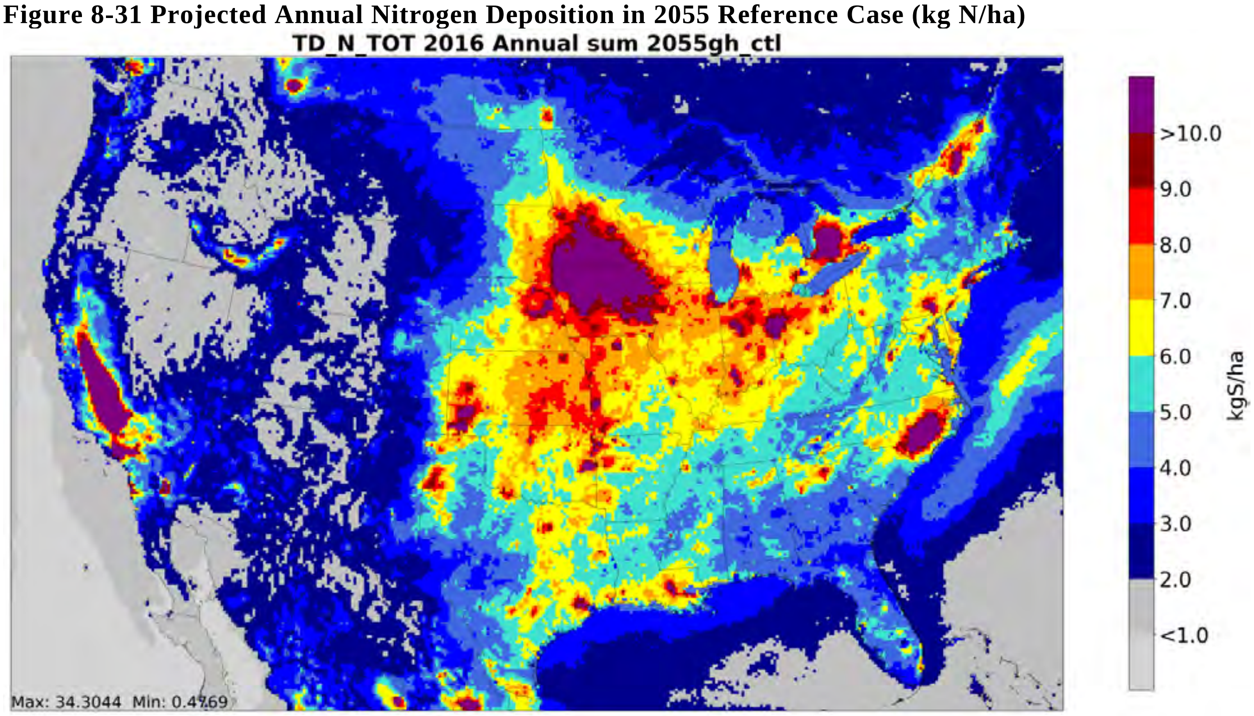

Figure 8-32 Projected Annual Nitrogen Deposition in 2055 LMDV Regulatory Scenario (kg N/ha)

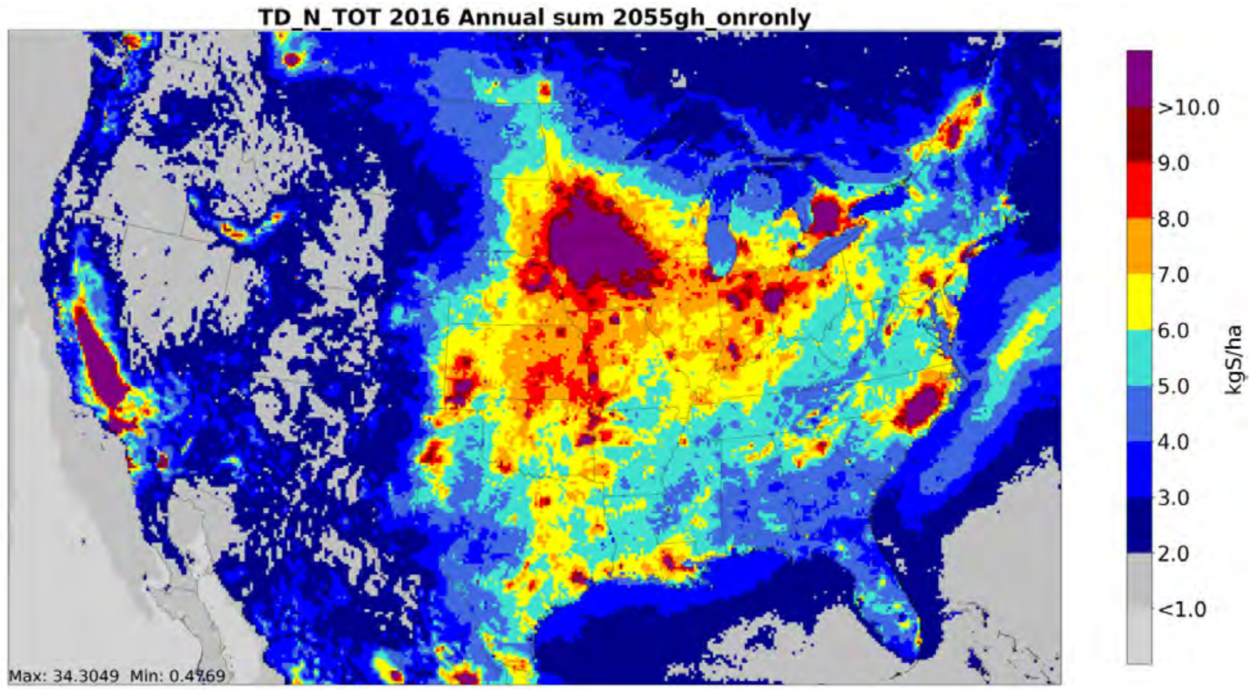

Figure 8-33 Projected Annual Nitrogen Deposition in 2055 Onroad-Only Scenario (kg N/ha)

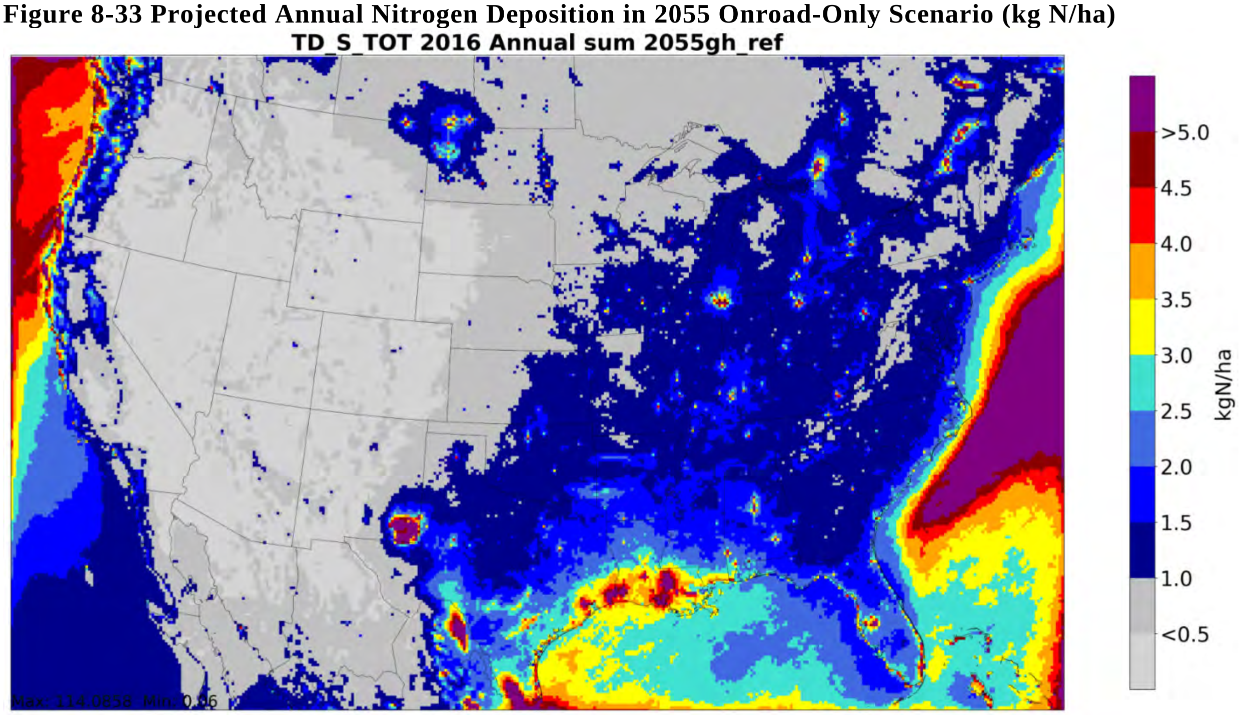

Figure 8-34 Projected Annual Sulfur Deposition in 2055 Reference Case (kg S/ha)

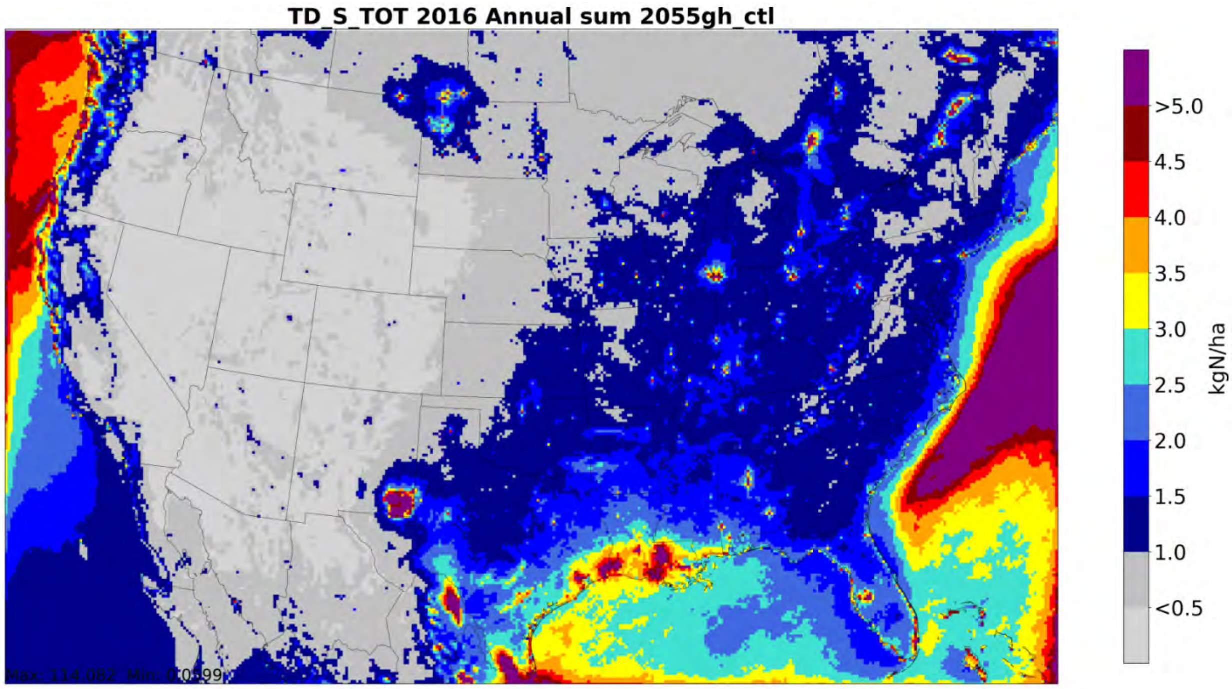

Figure 8-35 Projected Annual Sulfur Deposition in 2055 LMDV Regulatory Scenario (kg S/ha)

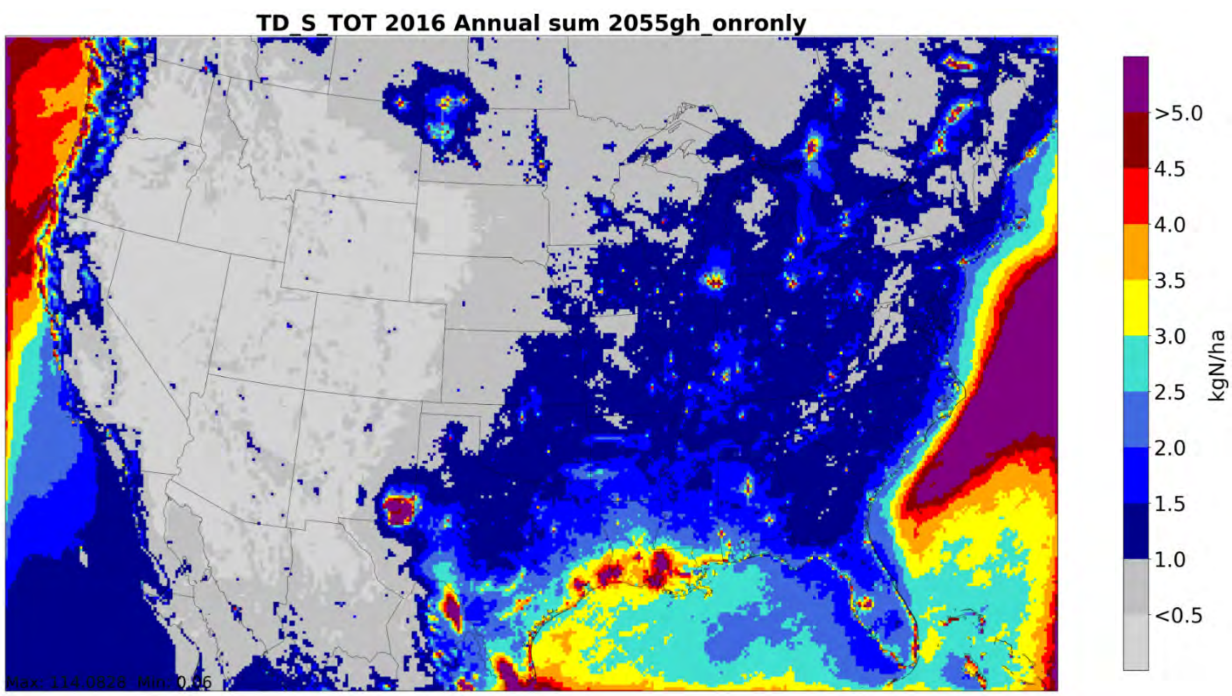

Figure 8-36 Projected Annual Sulfur Deposition in 2055 Onroad-Only Scenario (kg S/ha)

8.2 Seasonal Air Toxics Maps

The following section presents maps of projected January and July monthly ambient concentrations for acetaldehyde, benzene, 1,3-butadiene, formaldehyde, and naphthalene in the

2055 reference case and the 2055 LMDV regulatory scenario and the 2055 onroad-only scenario, as well as maps of projected January and July monthly average changes in ambient concentrations in 2055.

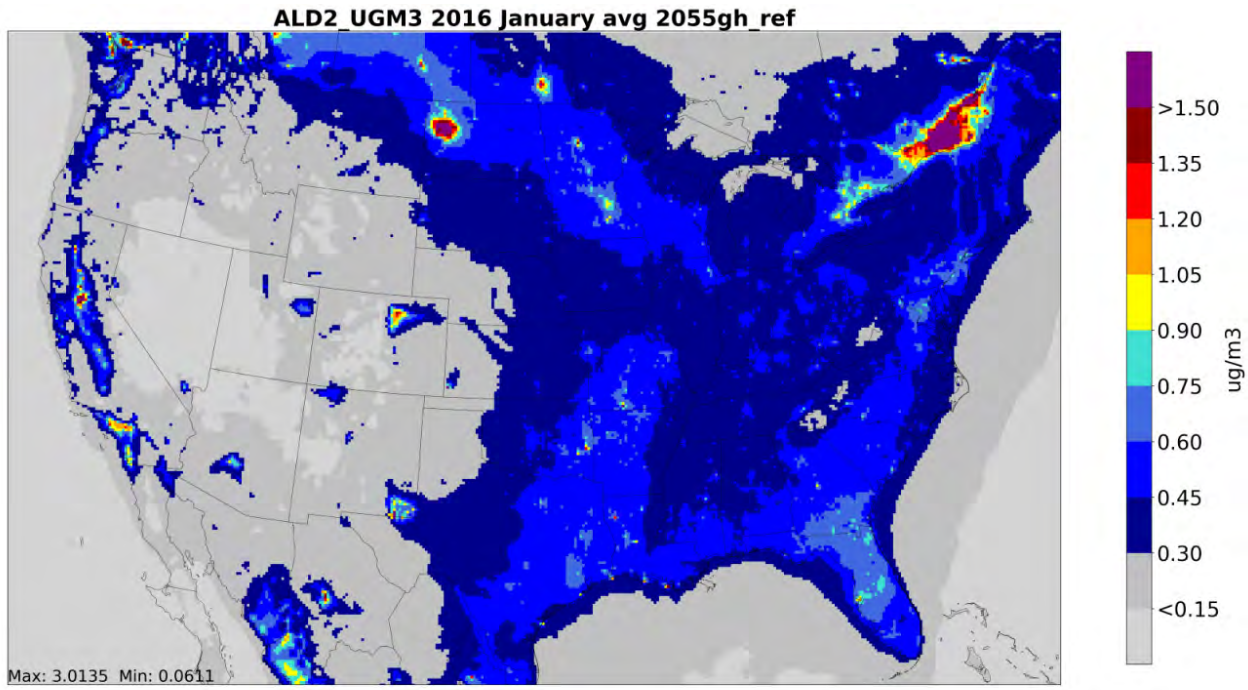

Figure 8-37 Projected January Average Acetaldehyde Concentrations in 2055 Reference Case (ug/m^3)

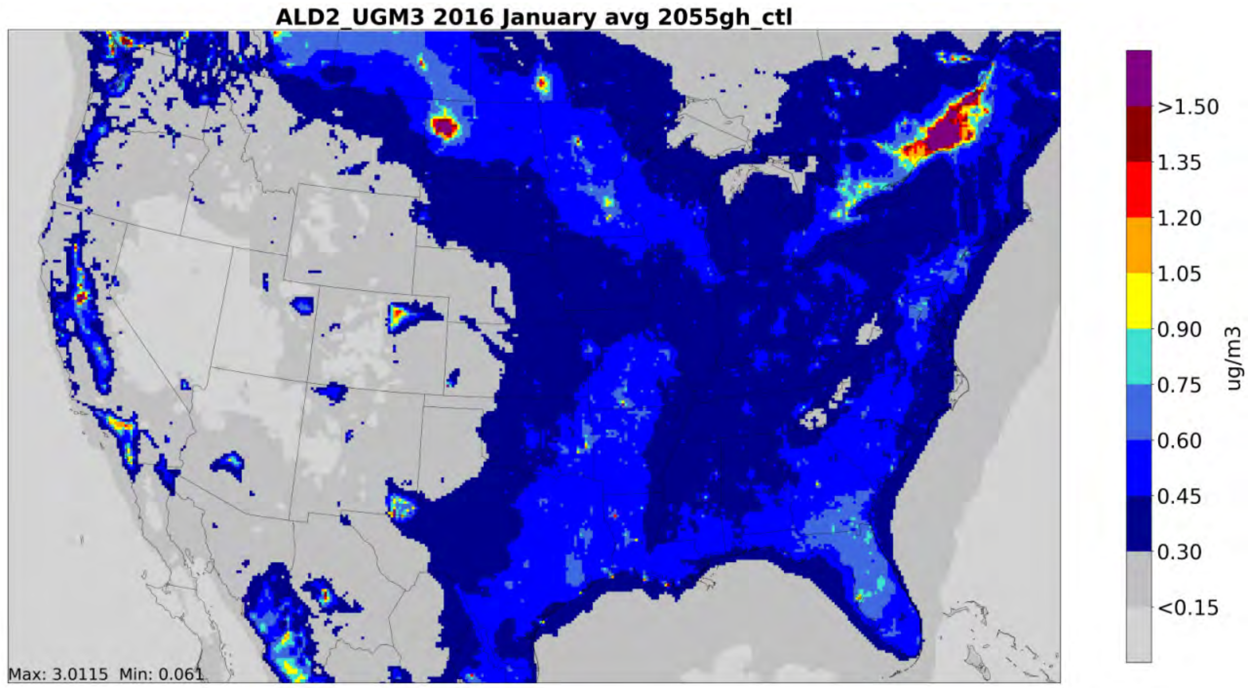

Figure 8-38 Projected January Average Acetaldehyde Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

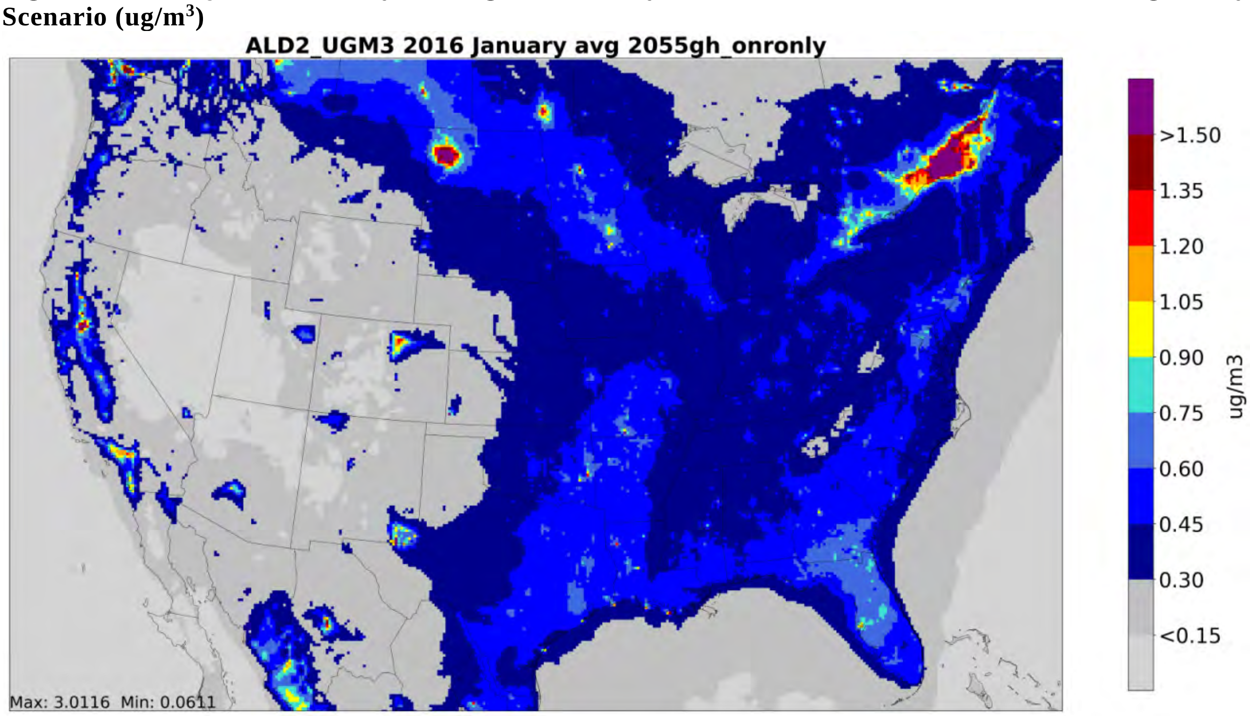

Figure 8-39 Projected January Average Acetaldehyde Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

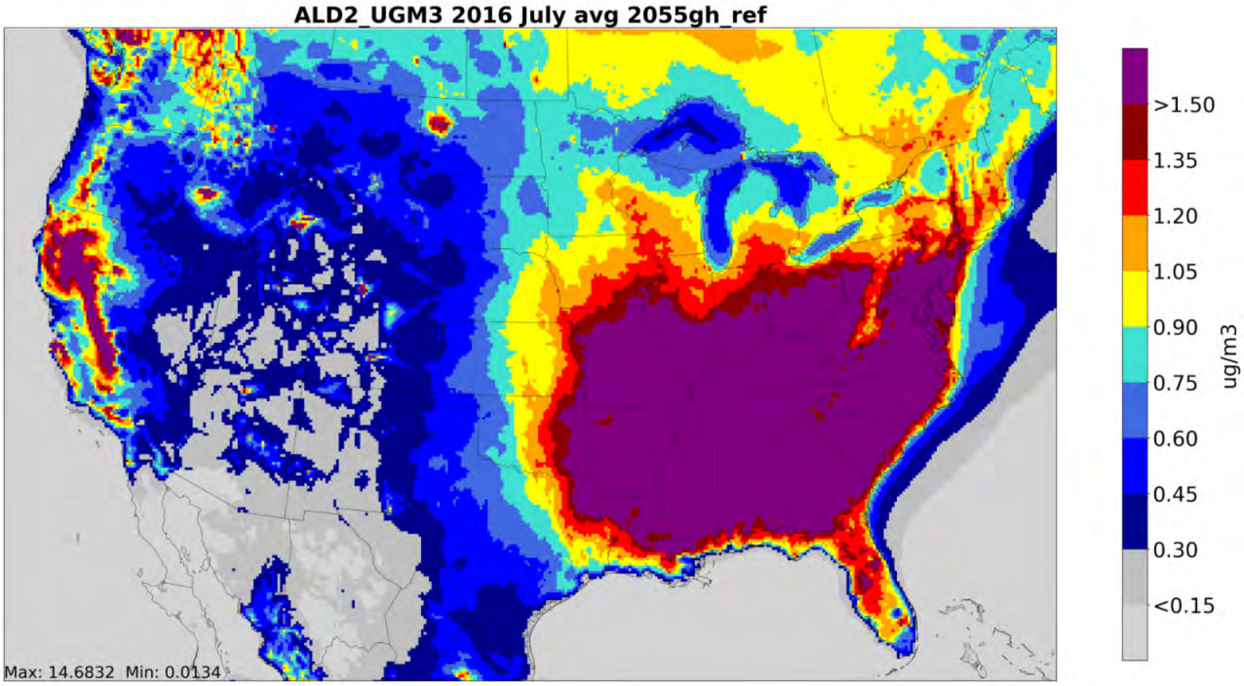

Figure 8-40 Projected July Average Acetaldehyde Concentrations in 2055 Reference Case (ug/m^3)

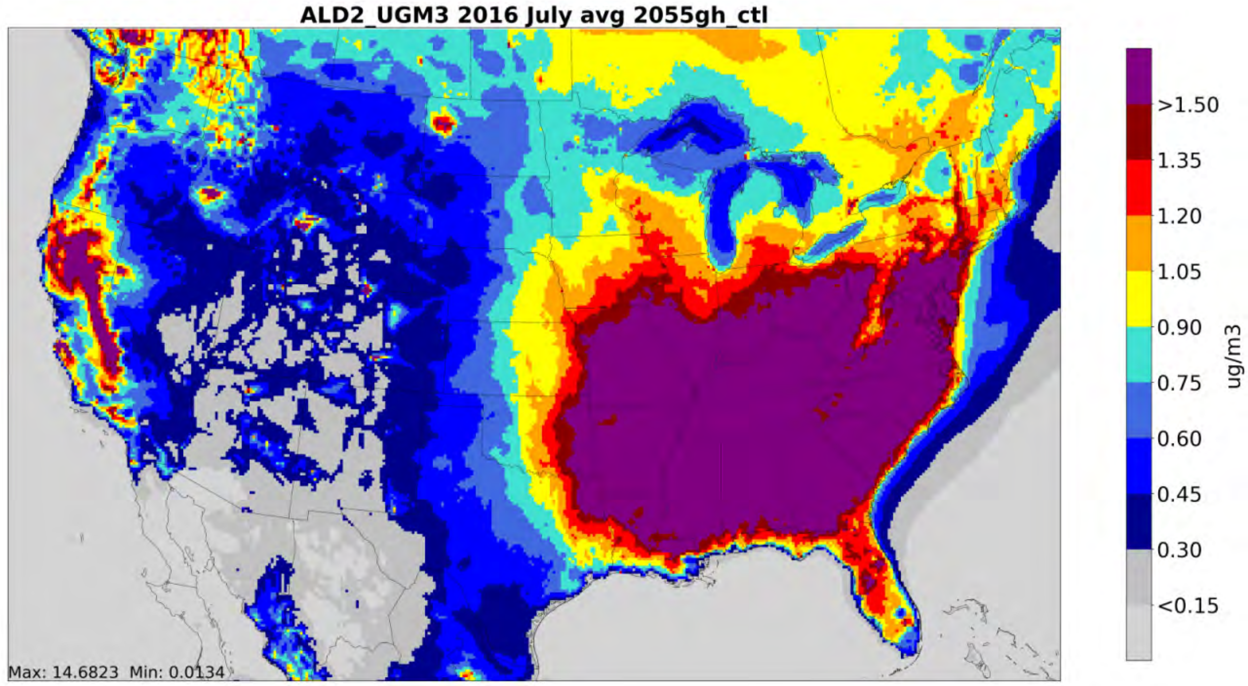

Figure 8-41 Projected July Average Acetaldehyde Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

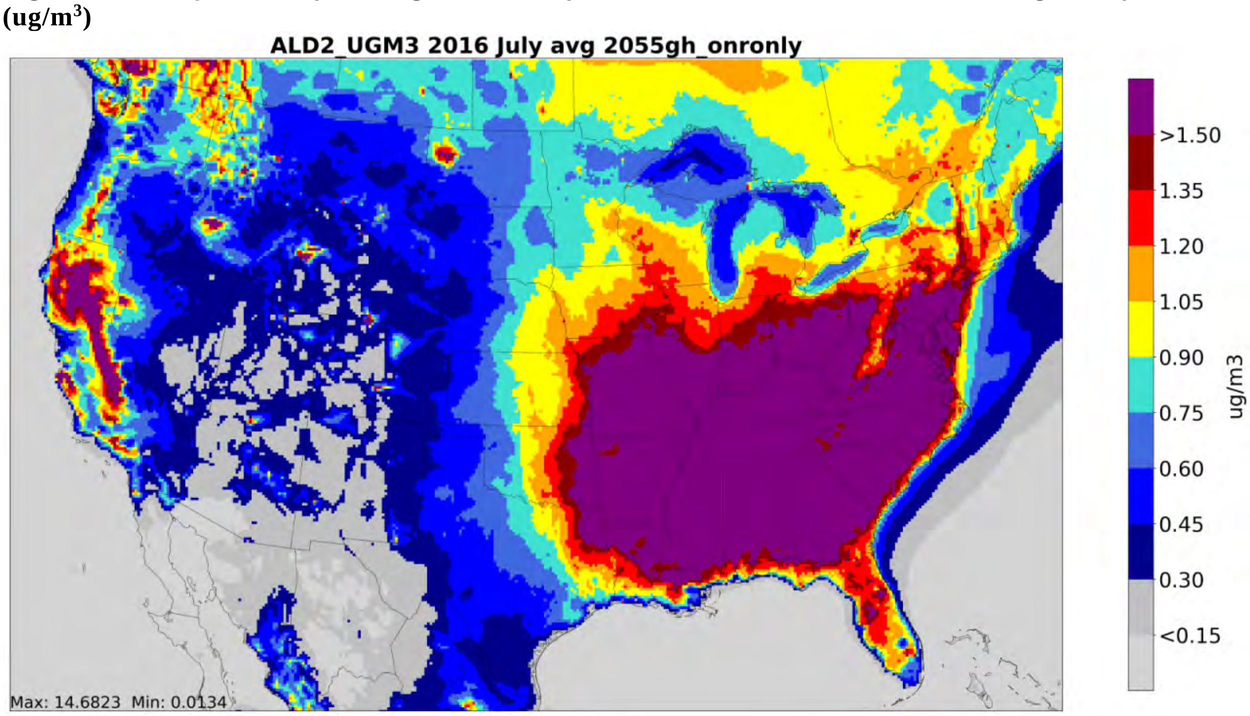

Figure 8-42 Projected July Average Acetaldehyde Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

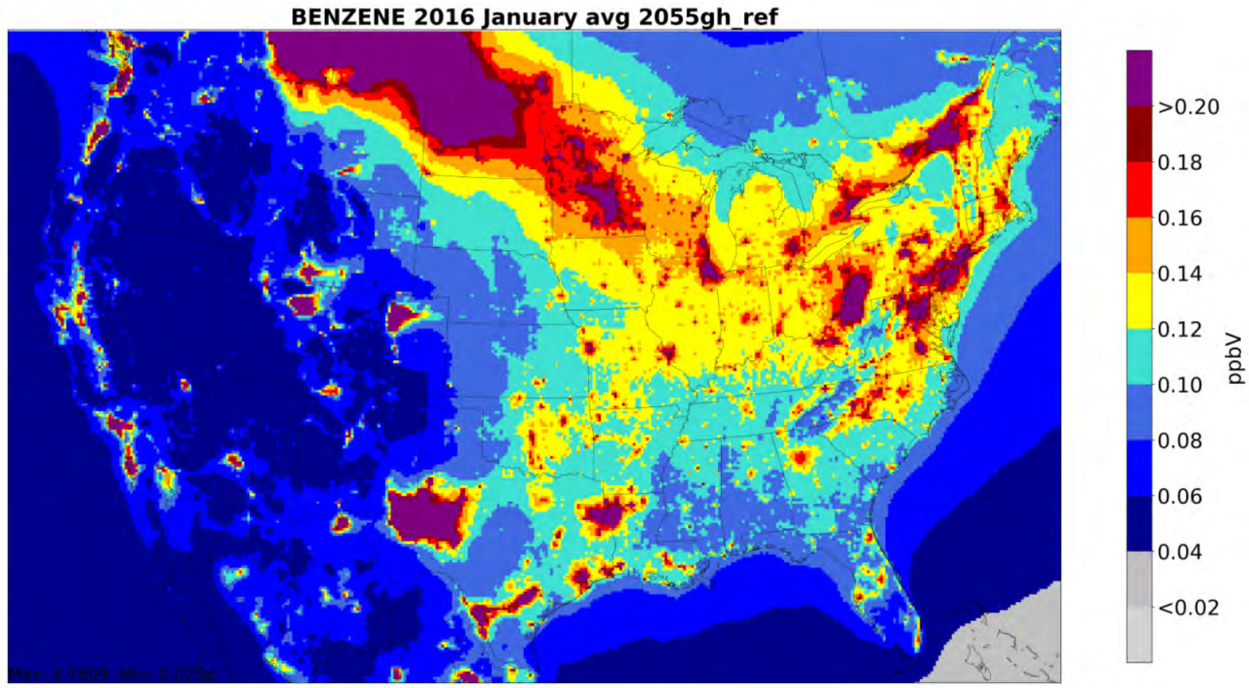

Figure 8-43 Projected January Average Benzene Concentrations in 2055 Reference Case (ppb)

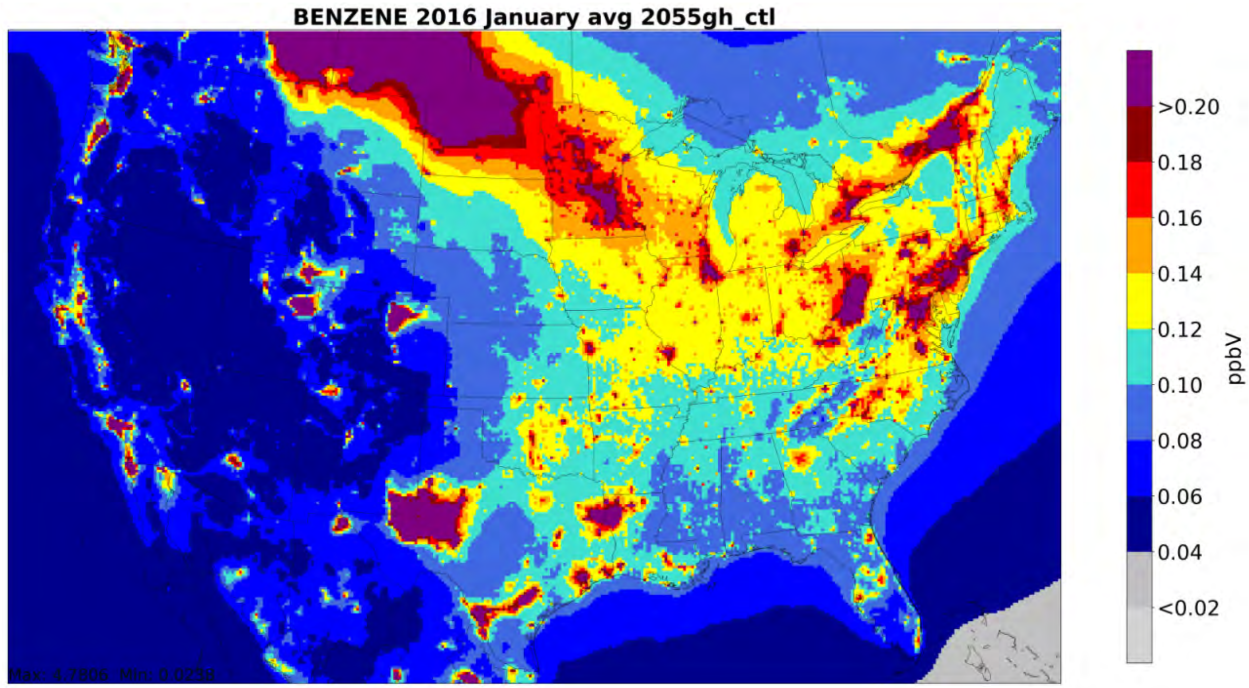

Figure 8-44 Projected January Average Benzene Concentrations in 2055 LMDV Regulatory Scenario (ppb)

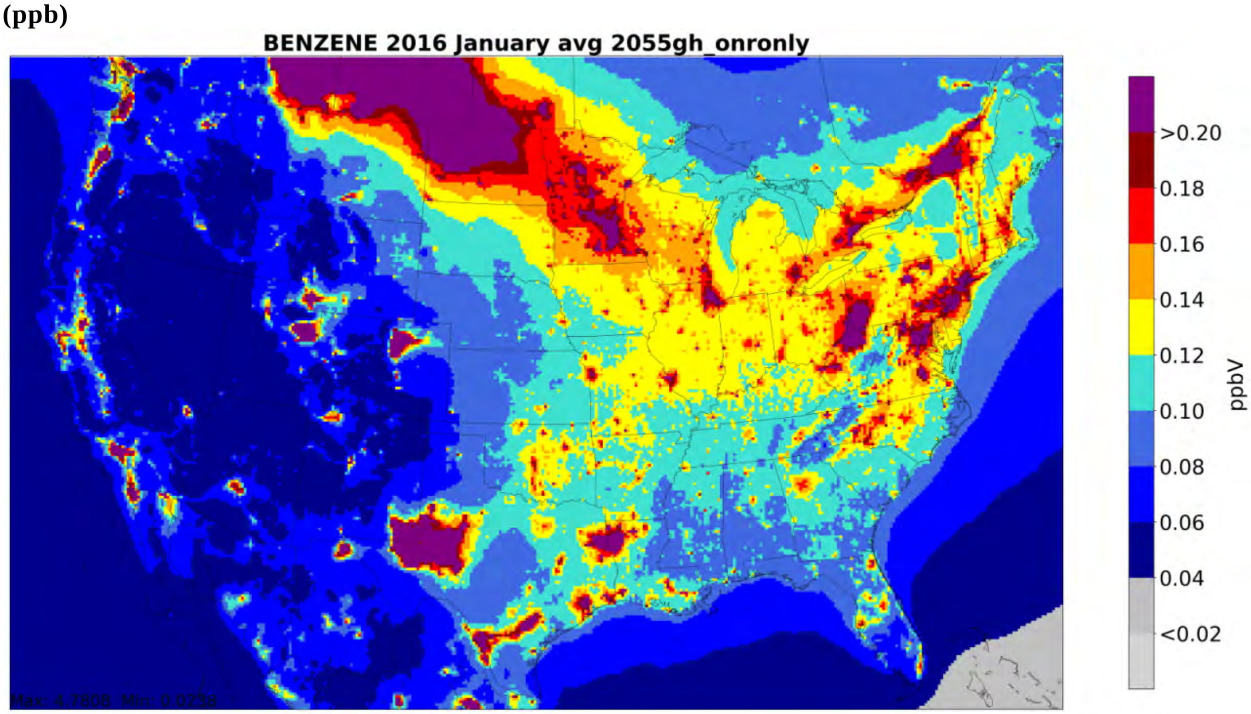

Figure 8-45 Projected January Average Benzene Concentrations in 2055 Onroad-Only Scenario (ppb)

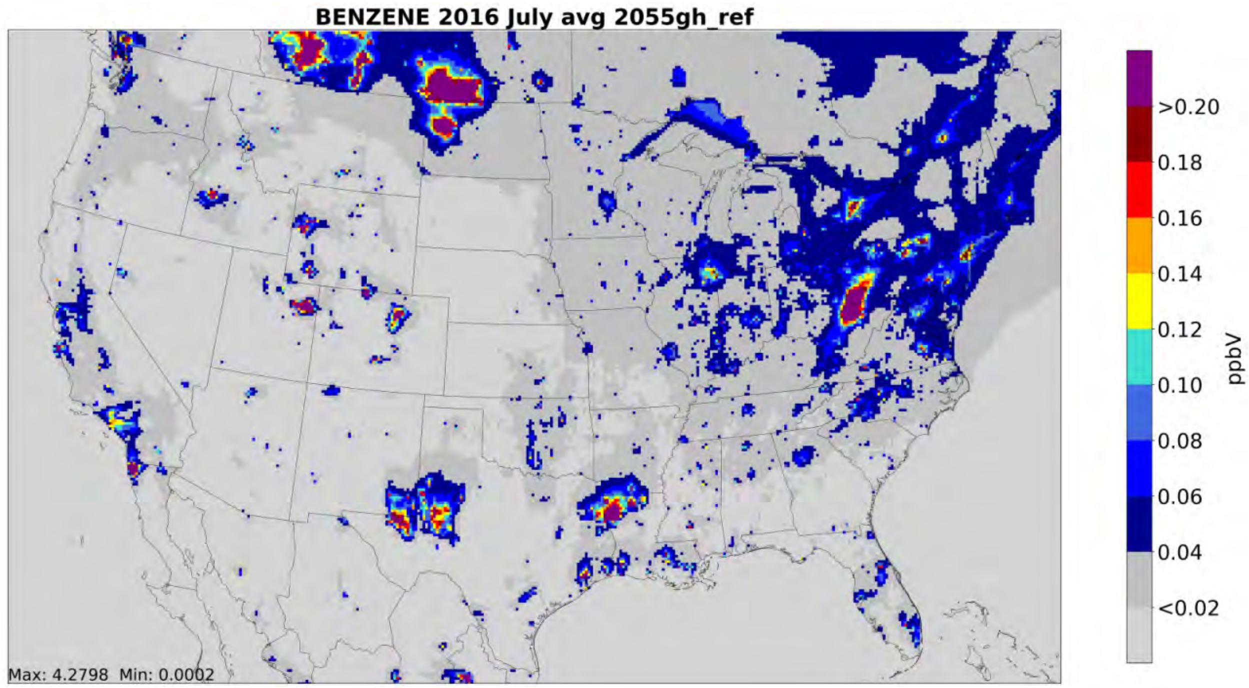

Figure 8-46 Projected July Average Benzene Concentrations in 2055 Reference Case (ppb)

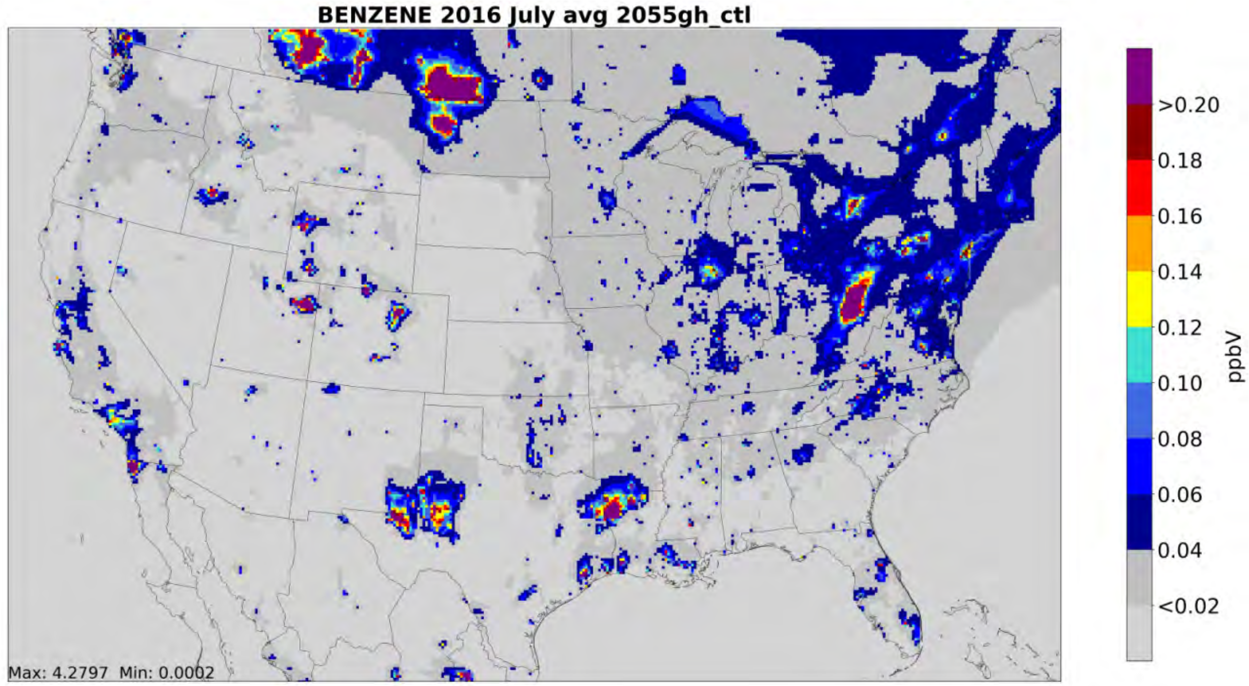

Figure 8-47 Projected July Average Benzene Concentrations in 2055 LMDV Regulatory Scenario (ppb)

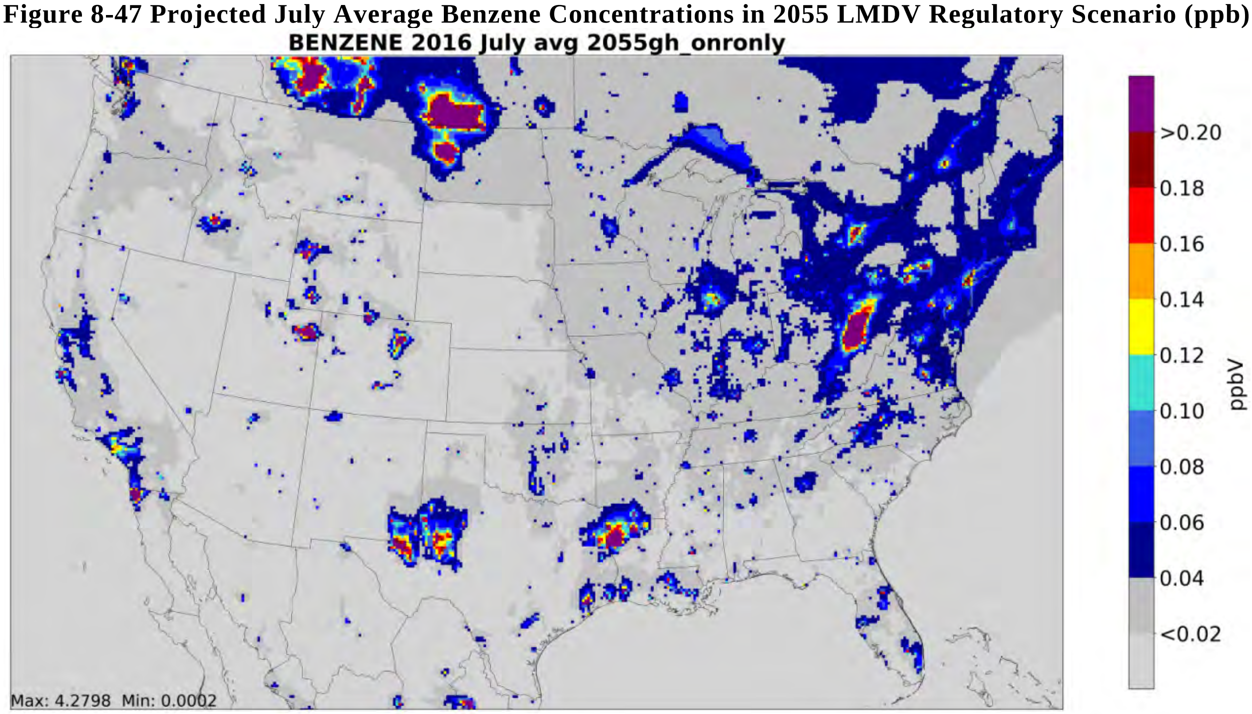

Figure 8-48 Projected July Average Benzene Concentrations in 2055 Onroad-Only Scenario (ppb)

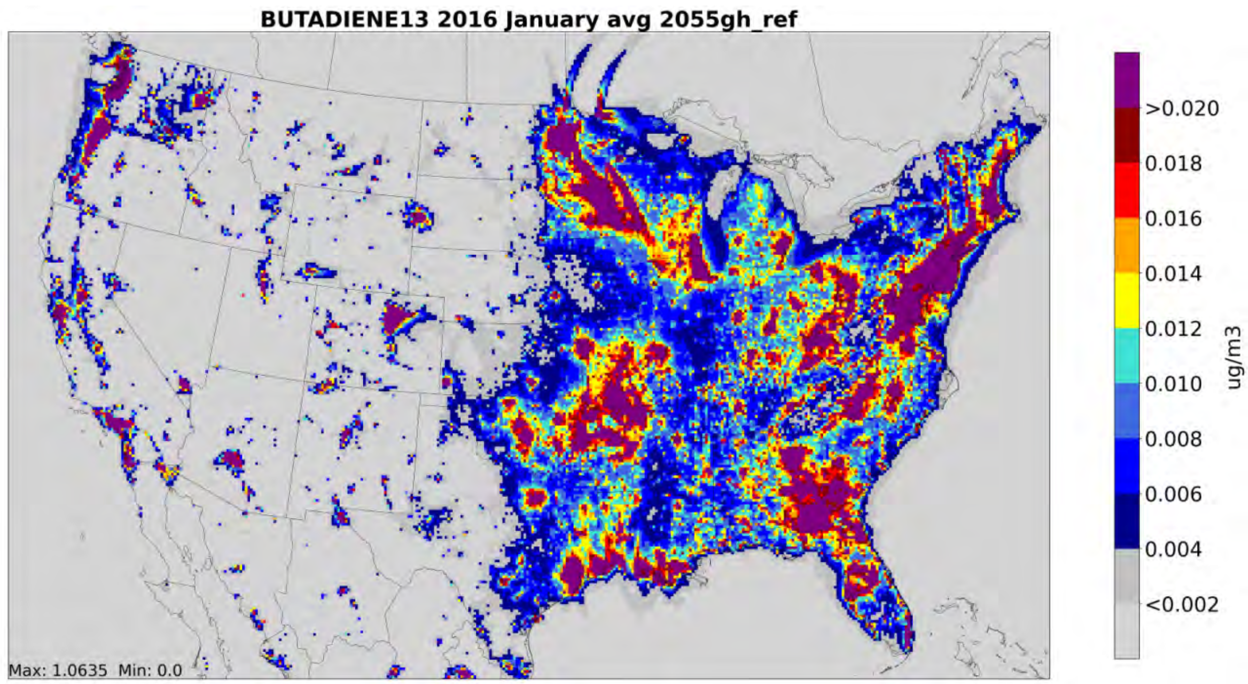

Figure 8-49 Projected January Average 1,3-butadiene Concentrations in 2055 Reference Case (ug/m^3)

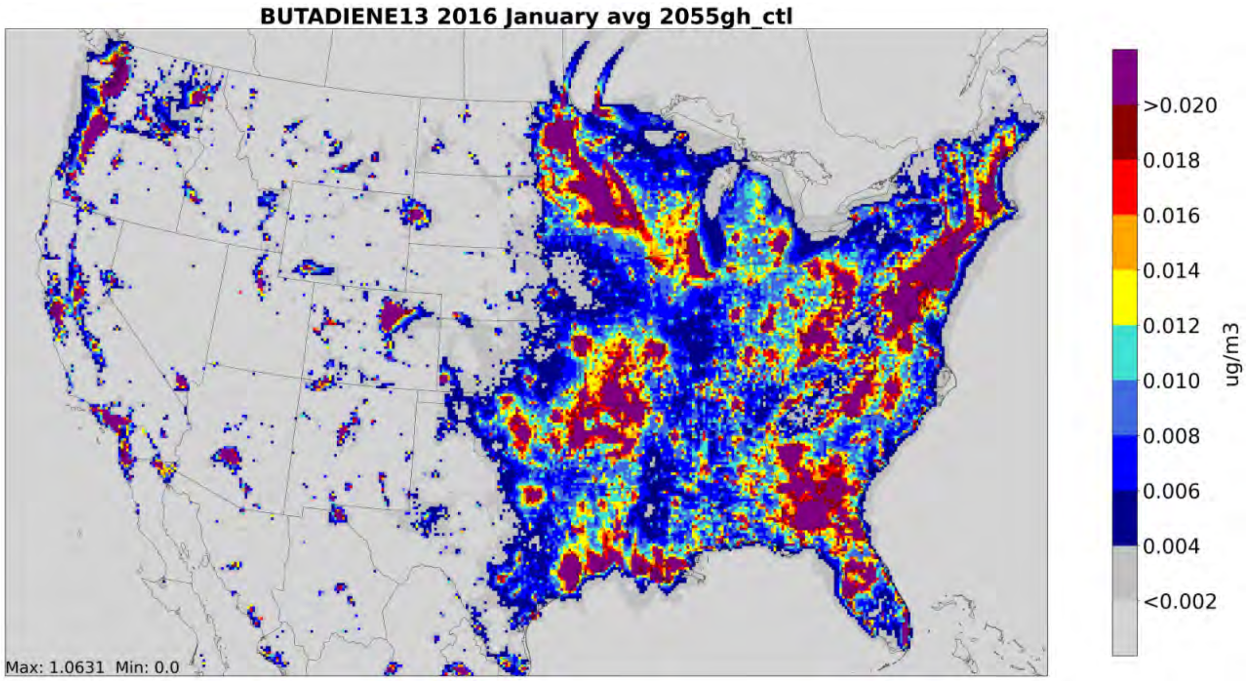

Figure 8-50 Projected January Average 1,3-butadiene Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

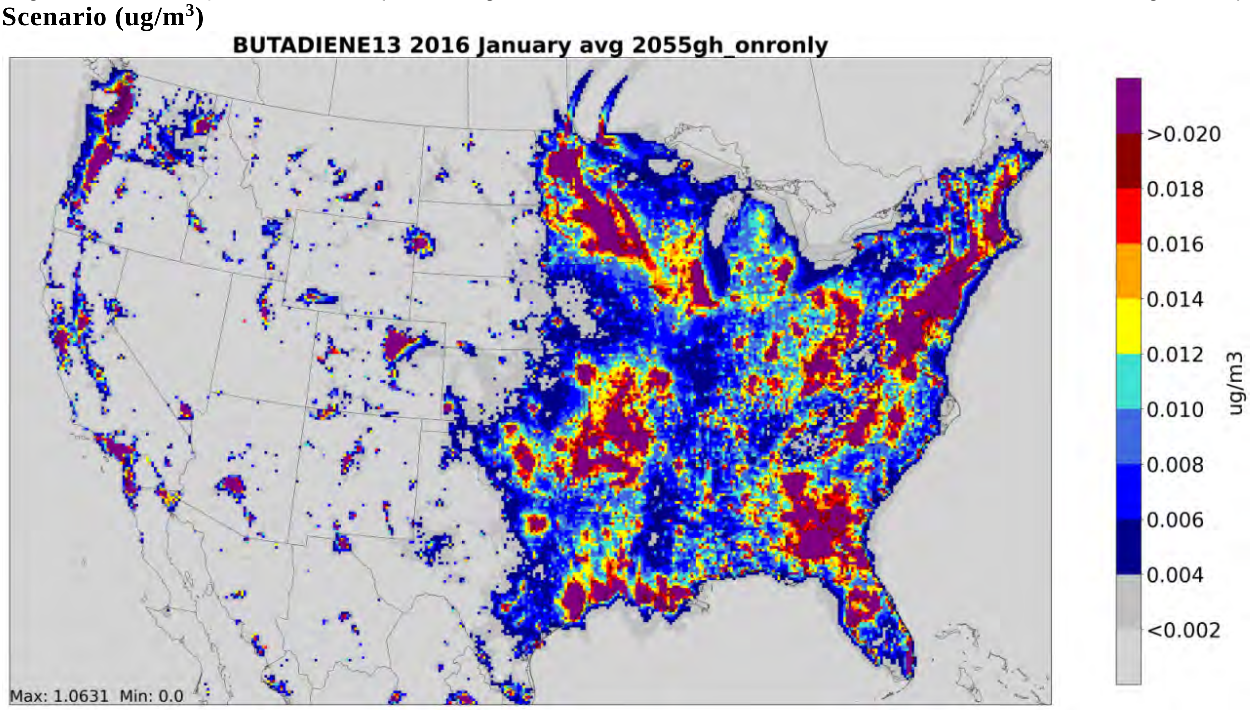

Figure 8-51 Projected January Average 1,3-butadiene Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

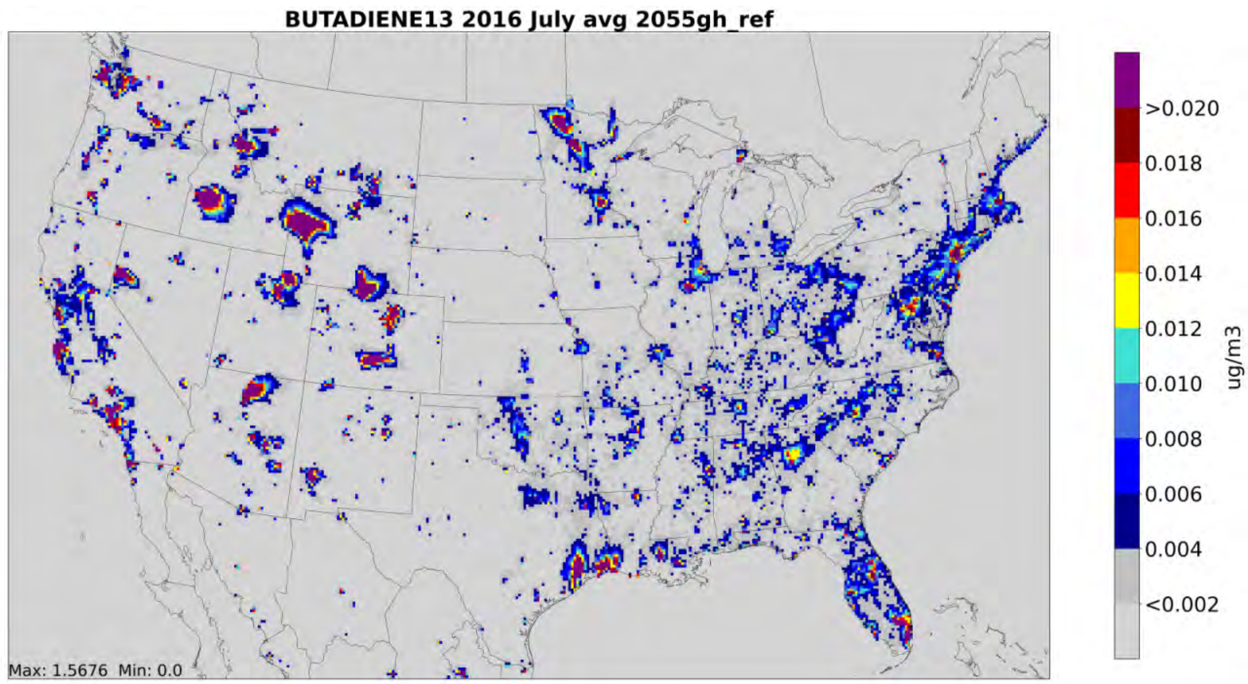

Figure 8-52 Projected July Average 1,3-butadiene Concentrations in 2055 Reference Case (ug/m³)

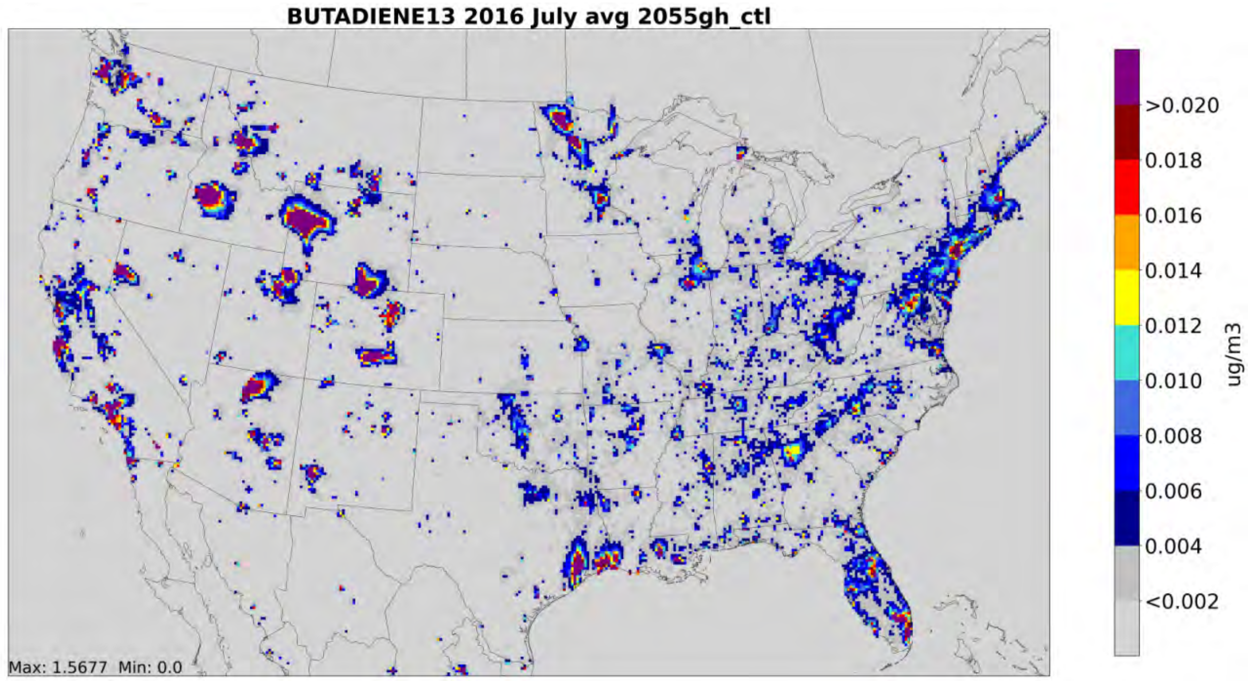

Figure 8-53 Projected July Average 1,3-butadiene Concentrations in 2055 LMDV Regulatory Scenario (ug/m³)

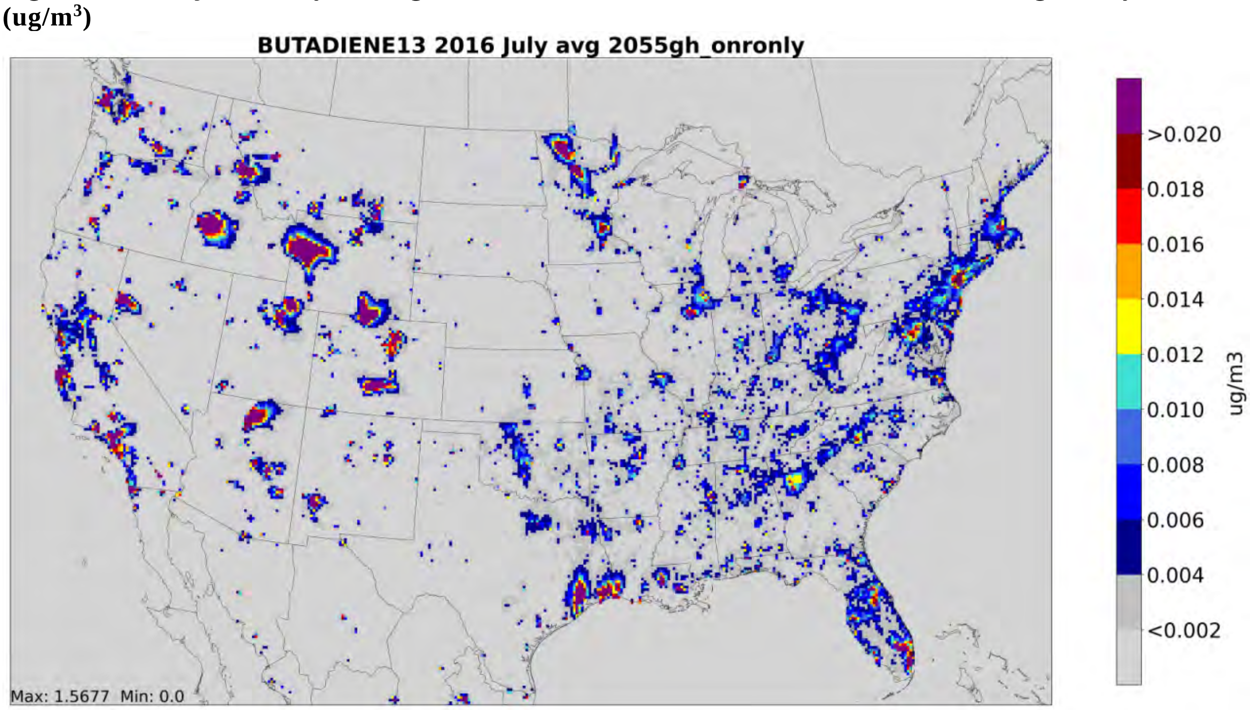

Figure 8-54 Projected July Average 1,3-butadiene Concentrations in 2055 Onroad-Only Scenario (ug/m³)

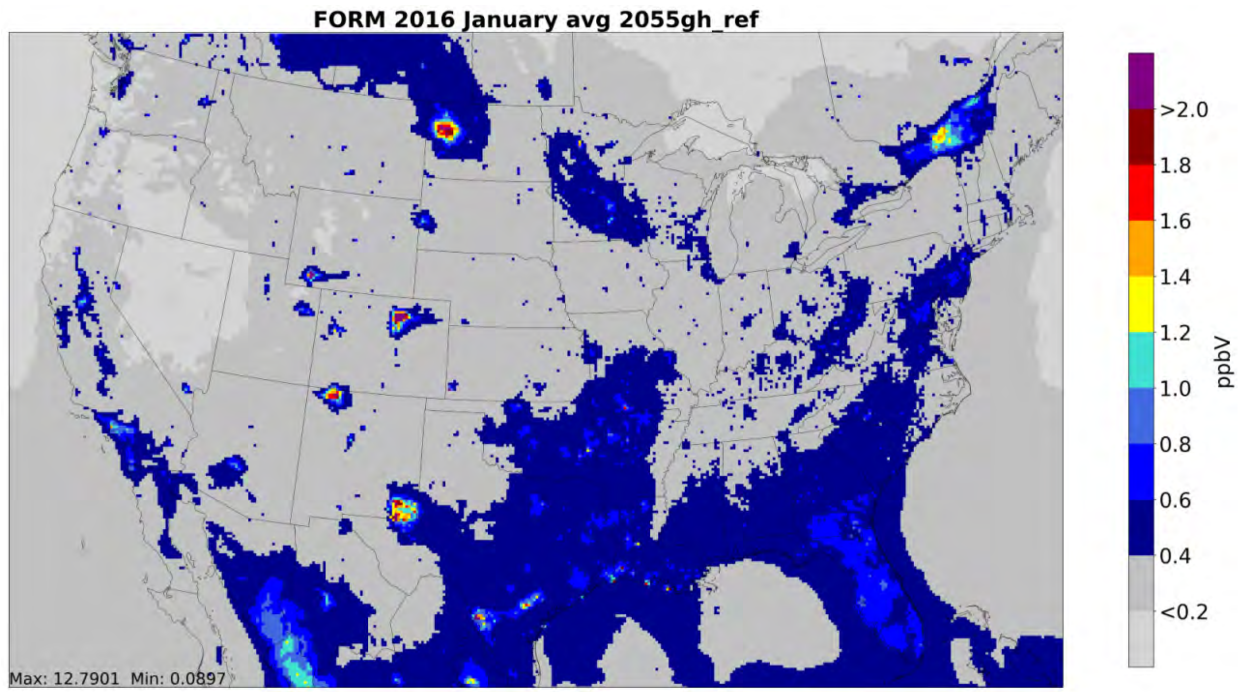

Figure 8-55 Projected January Average Formaldehyde Concentrations in 2055 Reference Case (ppb)

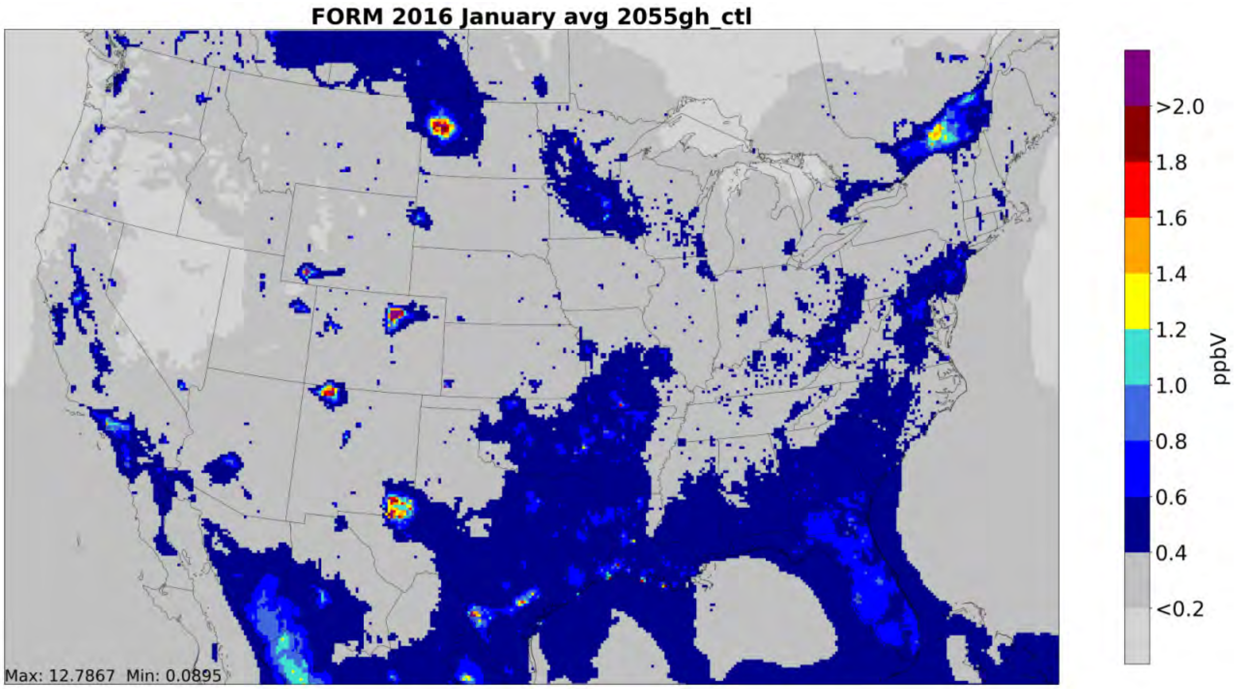

Figure 8-56 Projected January Average Formaldehyde Concentrations in 2055 LMDV Regulatory Scenario (ppb)

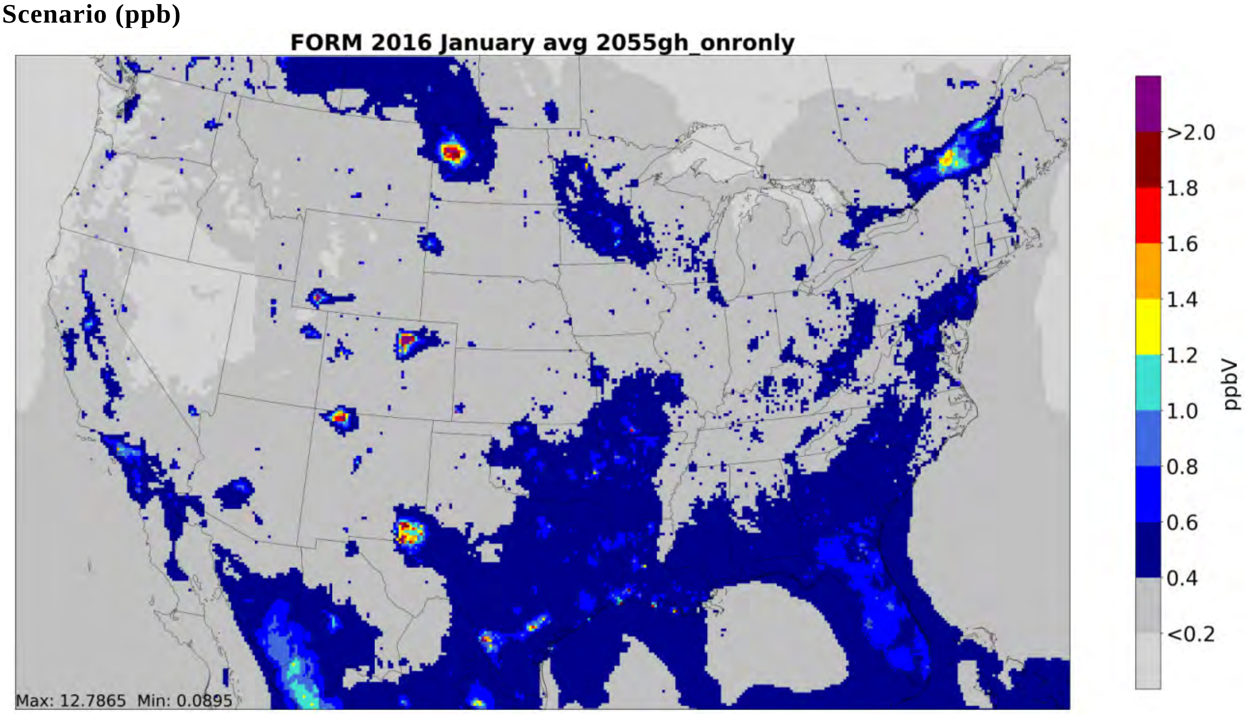

Figure 8-57 Projected January Average Formaldehyde Concentrations in 2055 Onroad-Only Scenario (ppb)

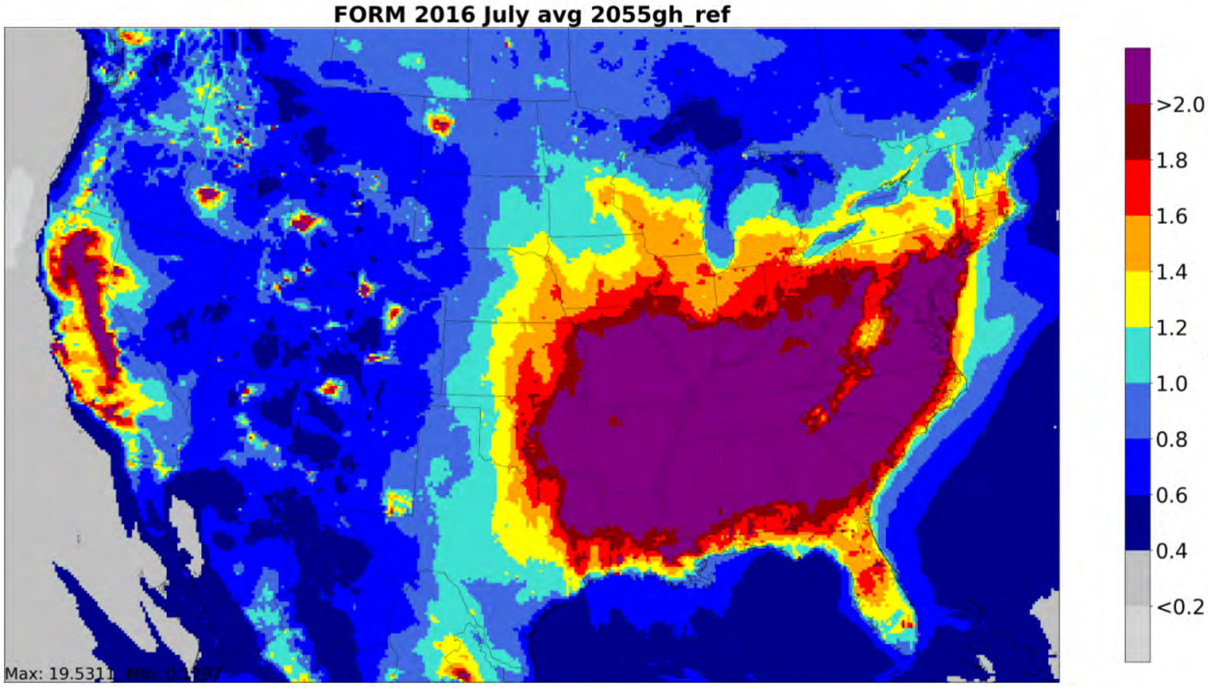

Figure 8-58 Projected July Average Formaldehyde Concentrations in 2055 Reference Case (ppb)

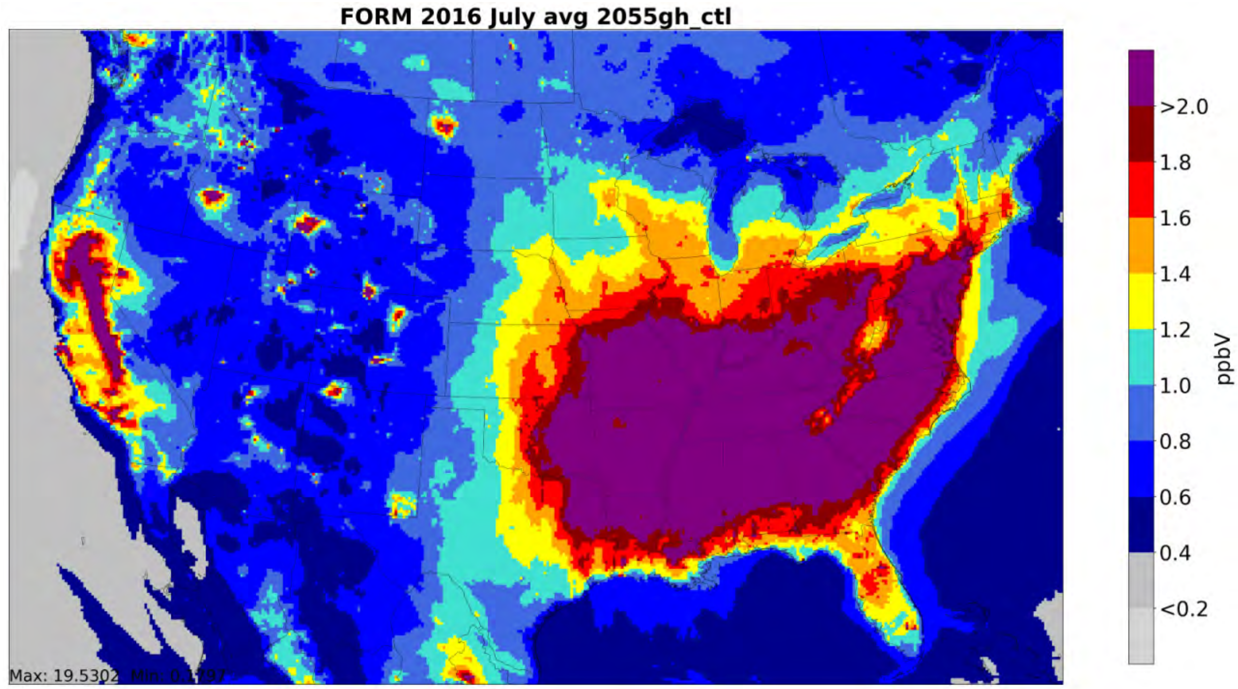

Figure 8-59 Projected July Average Formaldehyde Concentrations in 2055 LMDV Regulatory Scenario (ppb)

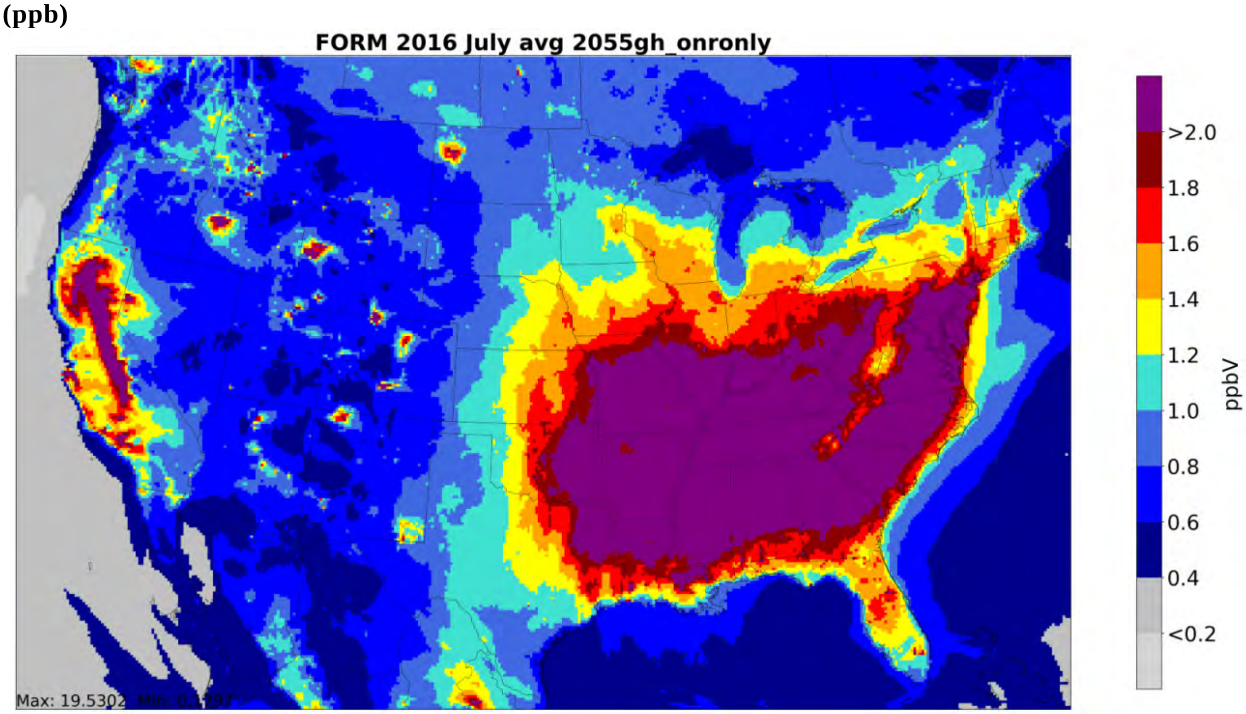

Figure 8-60 Projected July Average Formaldehyde Concentrations in 2055 Onroad-Only Scenario (ppb)

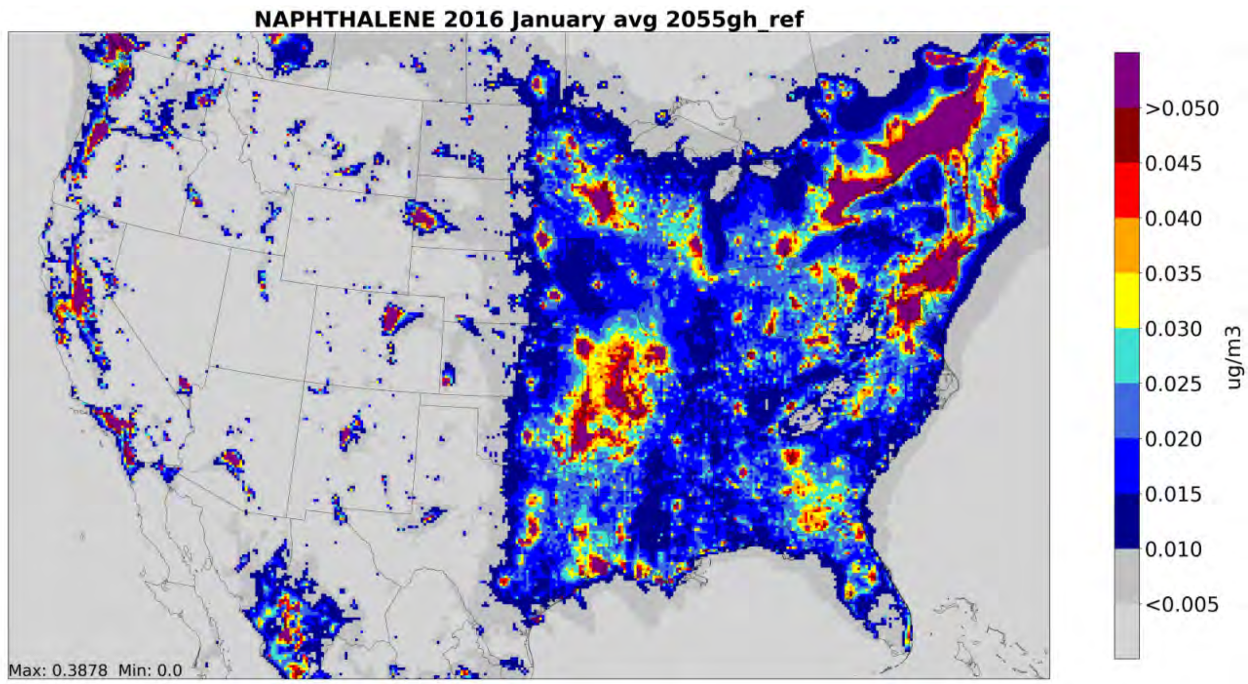

Figure 8-61 Projected January Average Naphthalene Concentrations in 2055 Reference Case (ug/m^3)

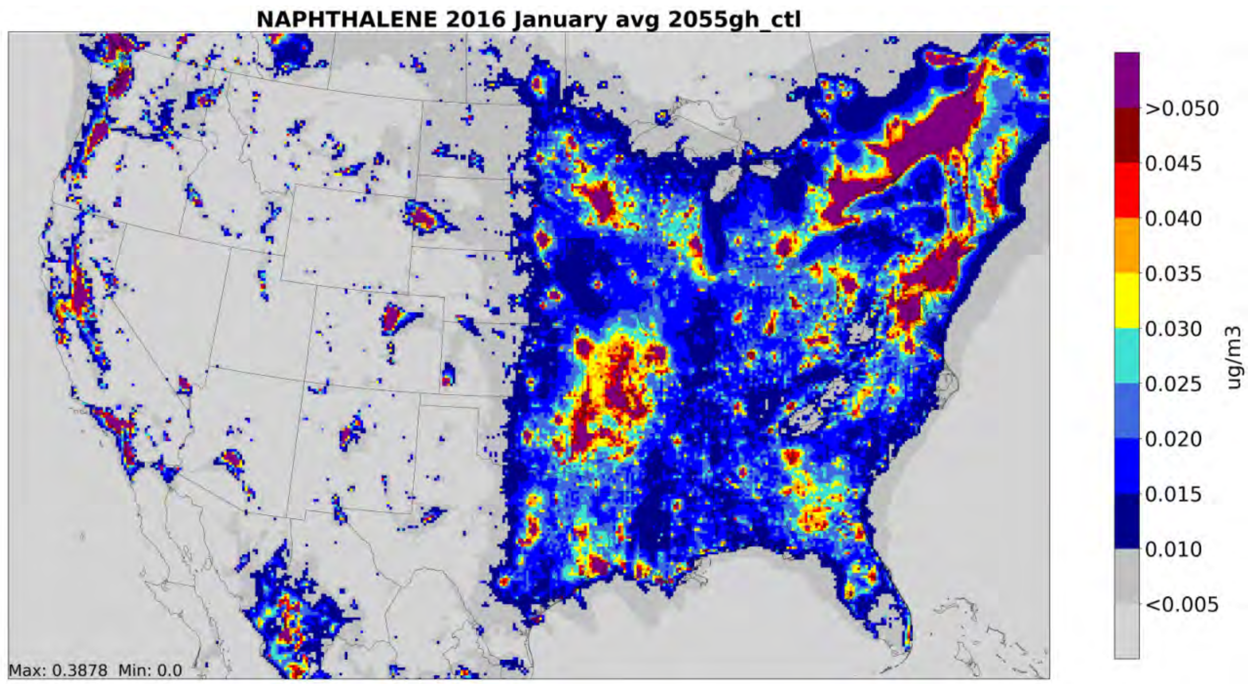

Figure 8-62 Projected January Average Naphthalene Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

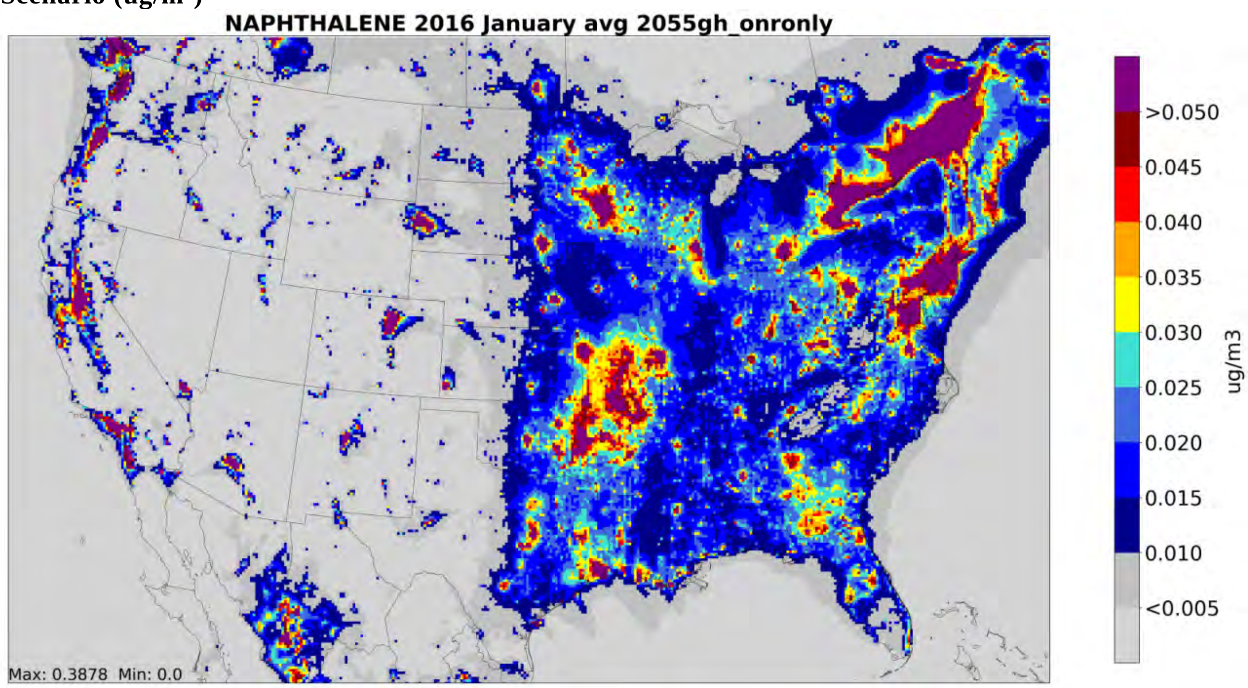

Figure 8-63 Projected January Average Naphthalene Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

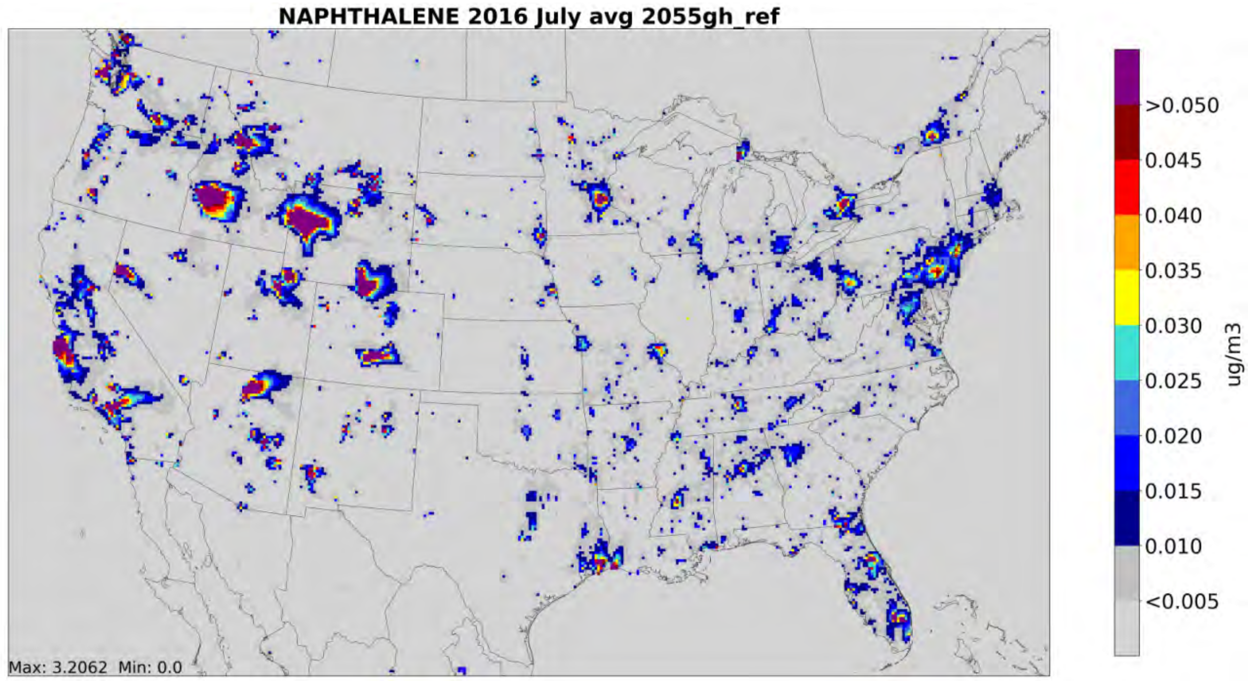

Figure 8-64 Projected July Average Naphthalene Concentrations in 2055 Reference Case (ug/m^3)

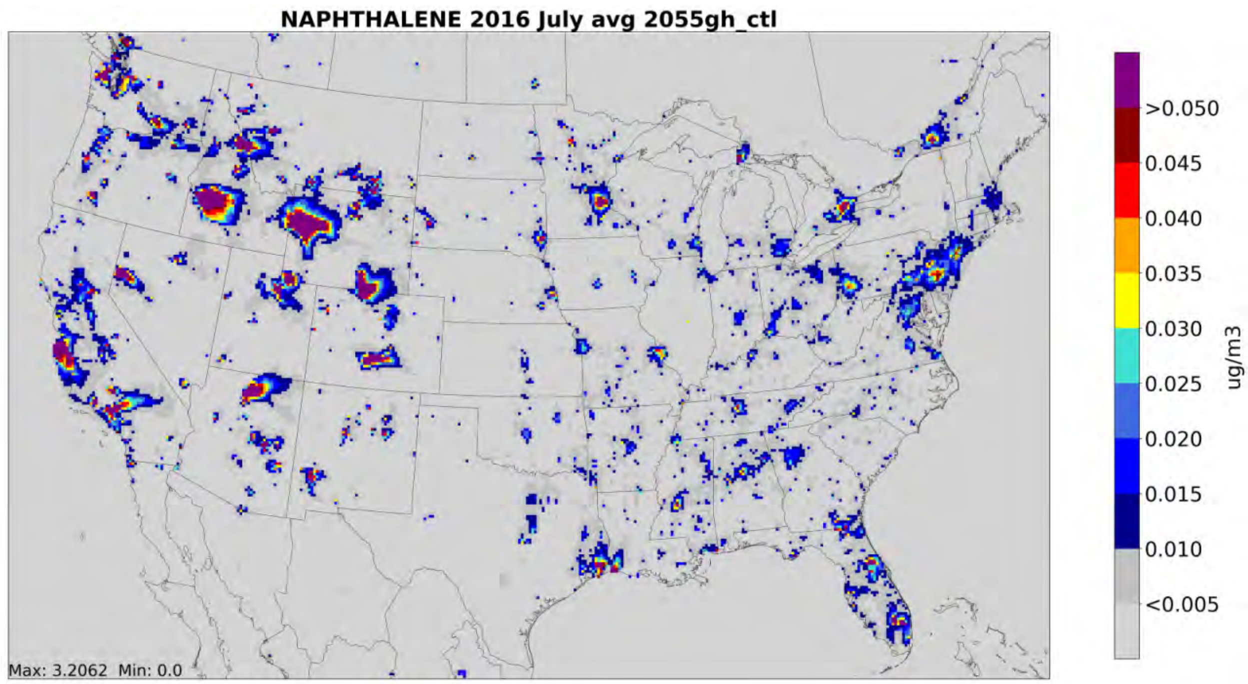

Figure 8-65 Projected July Average Naphthalene Concentrations in 2055 LMDV Regulatory Scenario (ug/m^3)

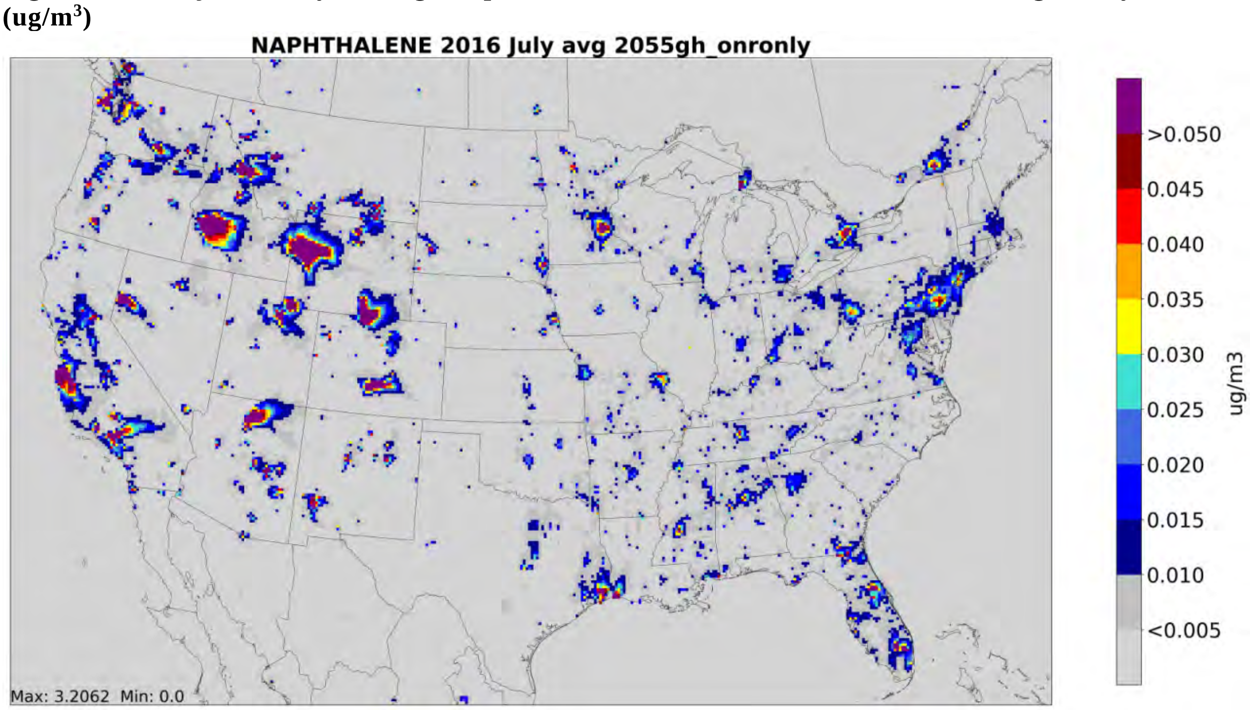

Figure 8-66 Projected July Average Naphthalene Concentrations in 2055 Onroad-Only Scenario (ug/m^3)

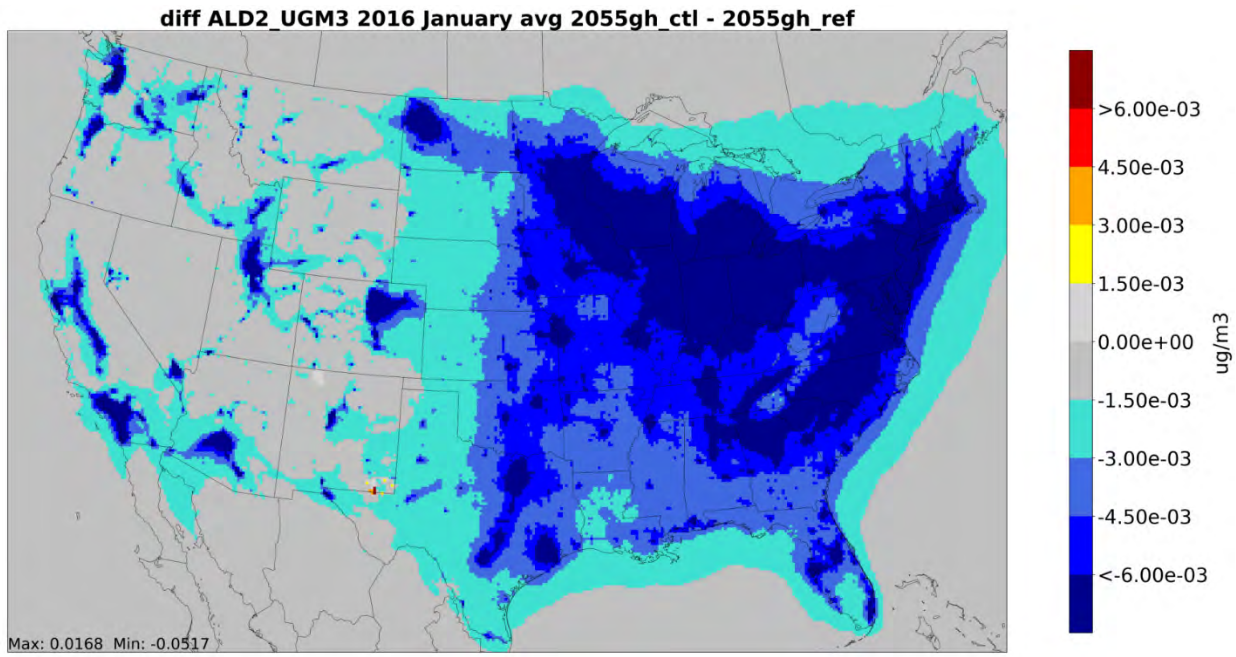

Figure 8-67 Projected Changes in Average Acetaldehyde Concentrations in January 2055 due to LMDV Regulatory Scenario

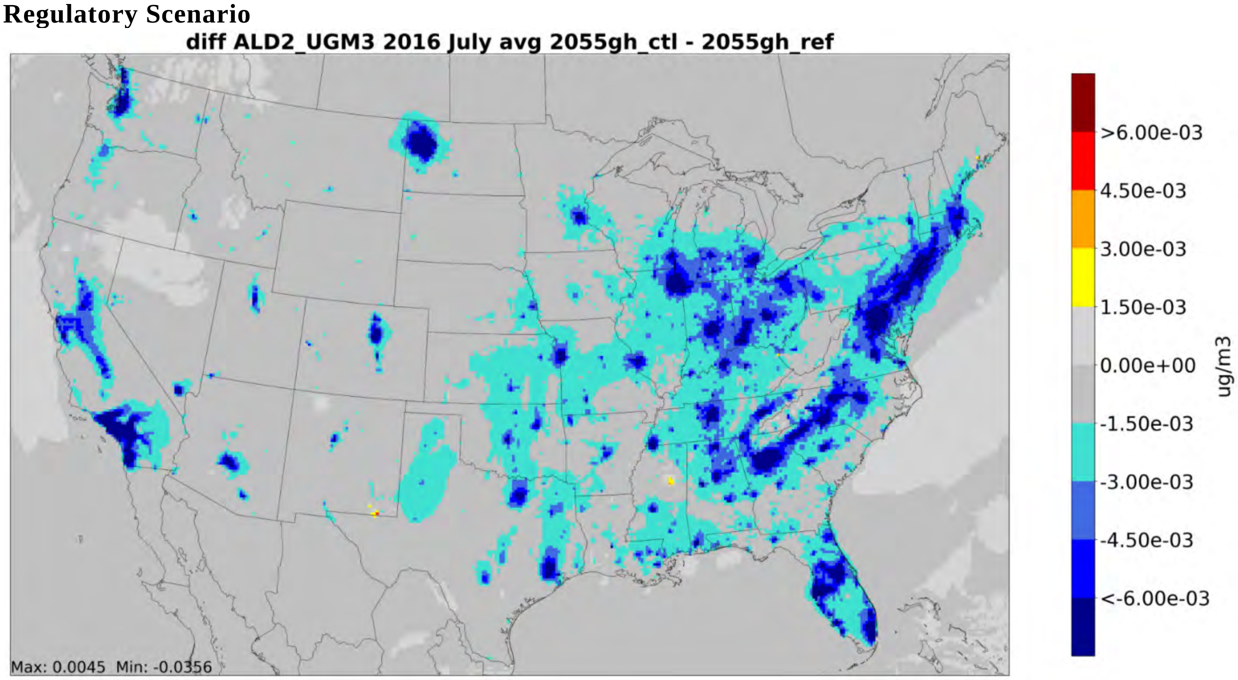

Figure 8-68 Projected Changes in Average Acetaldehyde Concentrations in July 2055 due to LMDV Regulatory Scenario

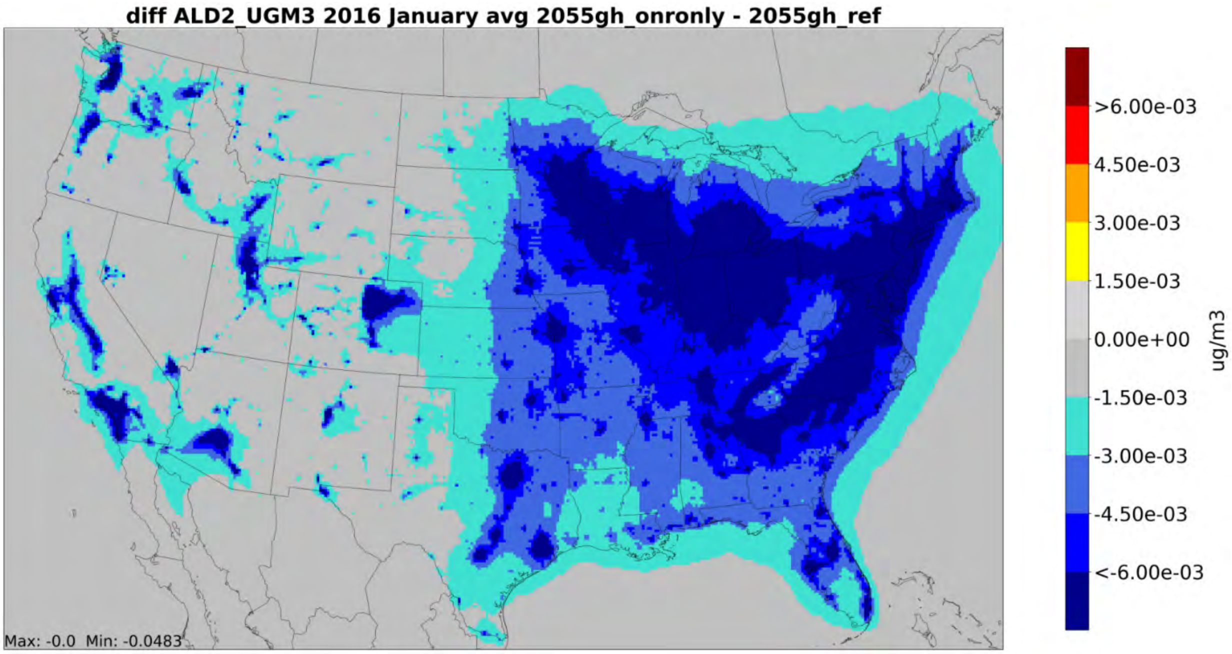

Figure 8-69 Projected Changes in Average Acetaldehyde Concentrations in January 2055 from "Onroad Only" Emissions Changes

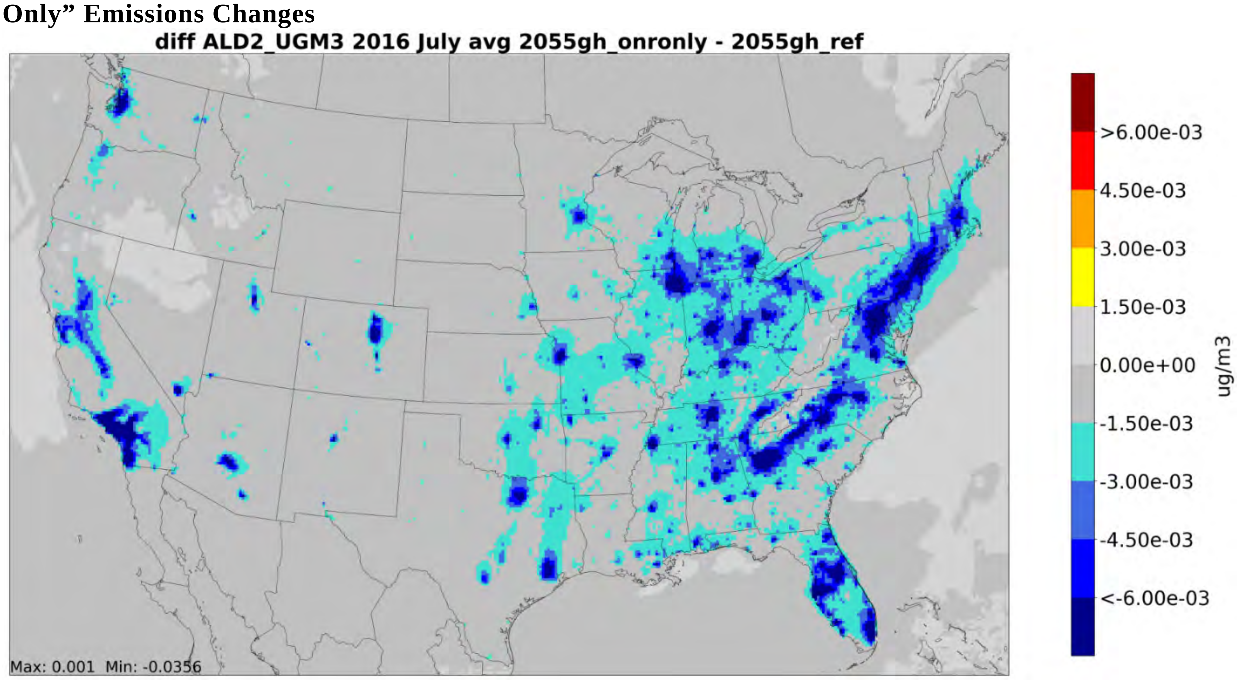

Figure 8-70 Projected Changes in Average Acetaldehyde Concentrations in July 2055 from "Onroad Only" Emissions Changes

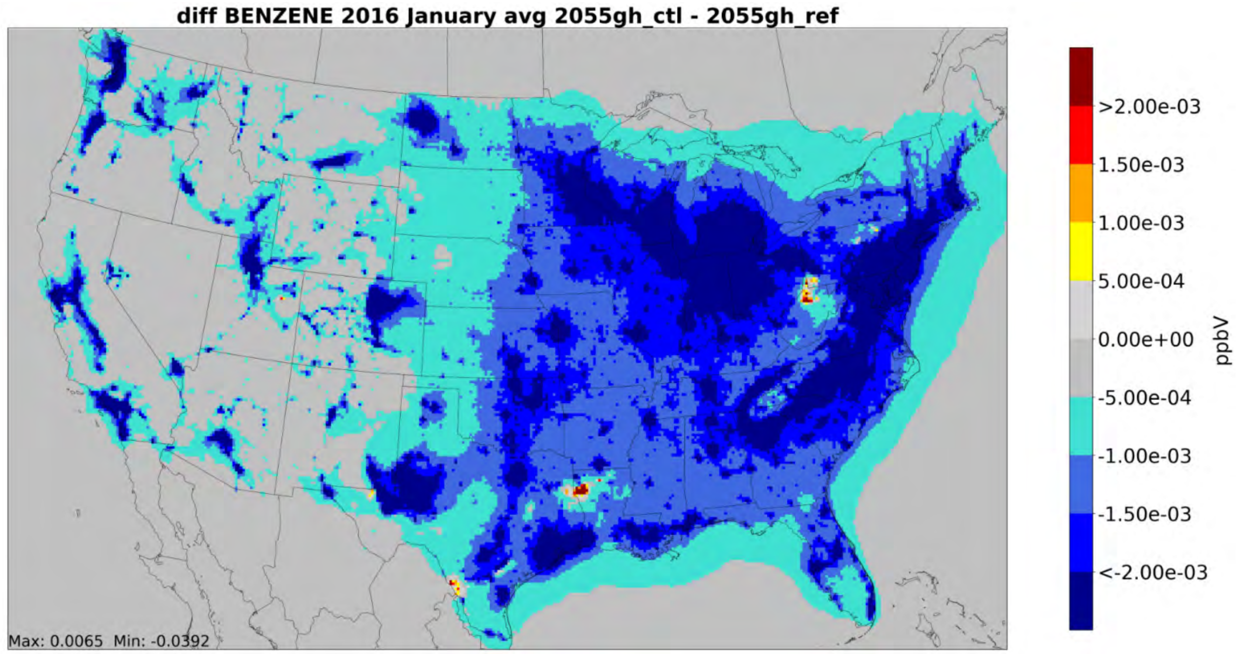

Figure 8-71 Projected Changes in Average Benzene Concentrations in January 2055 due to LMDV Regulatory Scenario

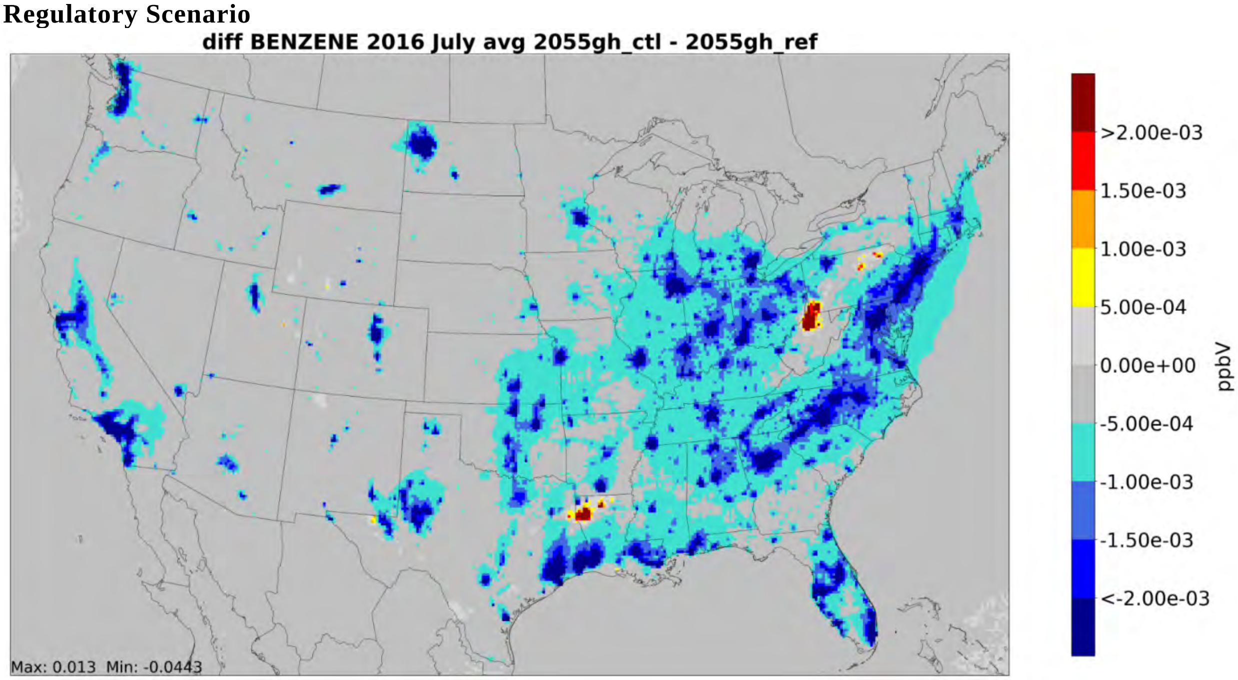

Figure 8-72 Projected Changes in Average Benzene Concentrations in July 2055 due to LMDV Regulatory Scenario

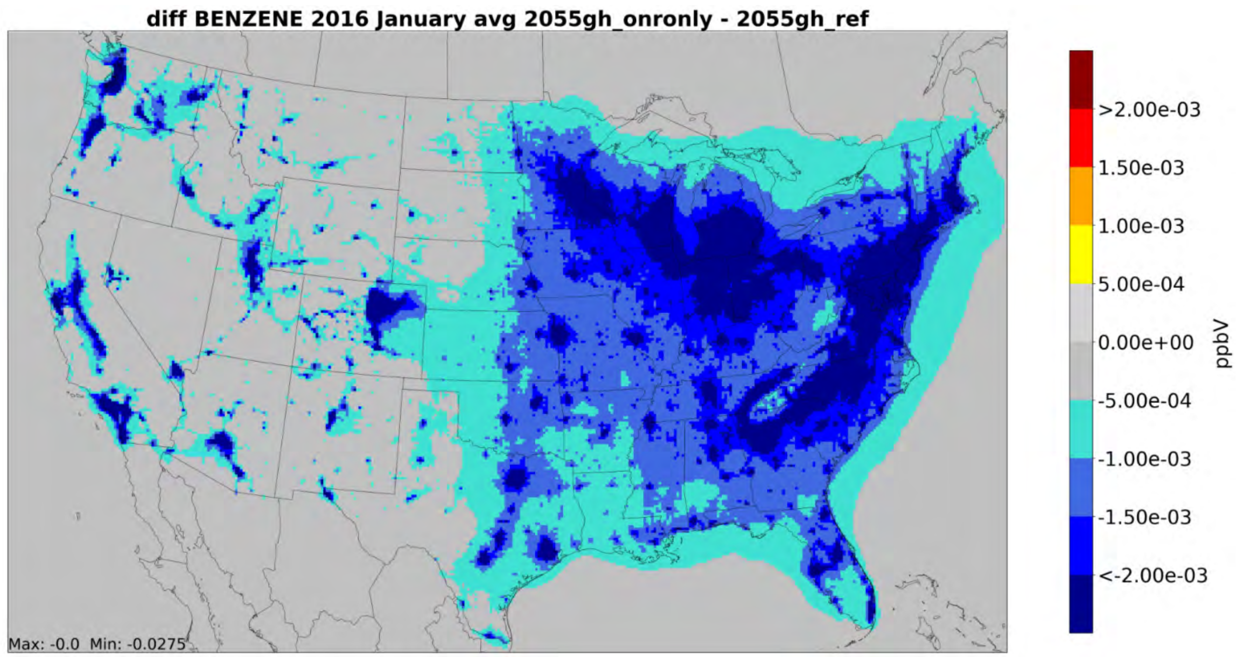

Figure 8-73 Projected Changes in Average Benzene Concentrations in January 2055 from "Onroad Only" Emissions Changes

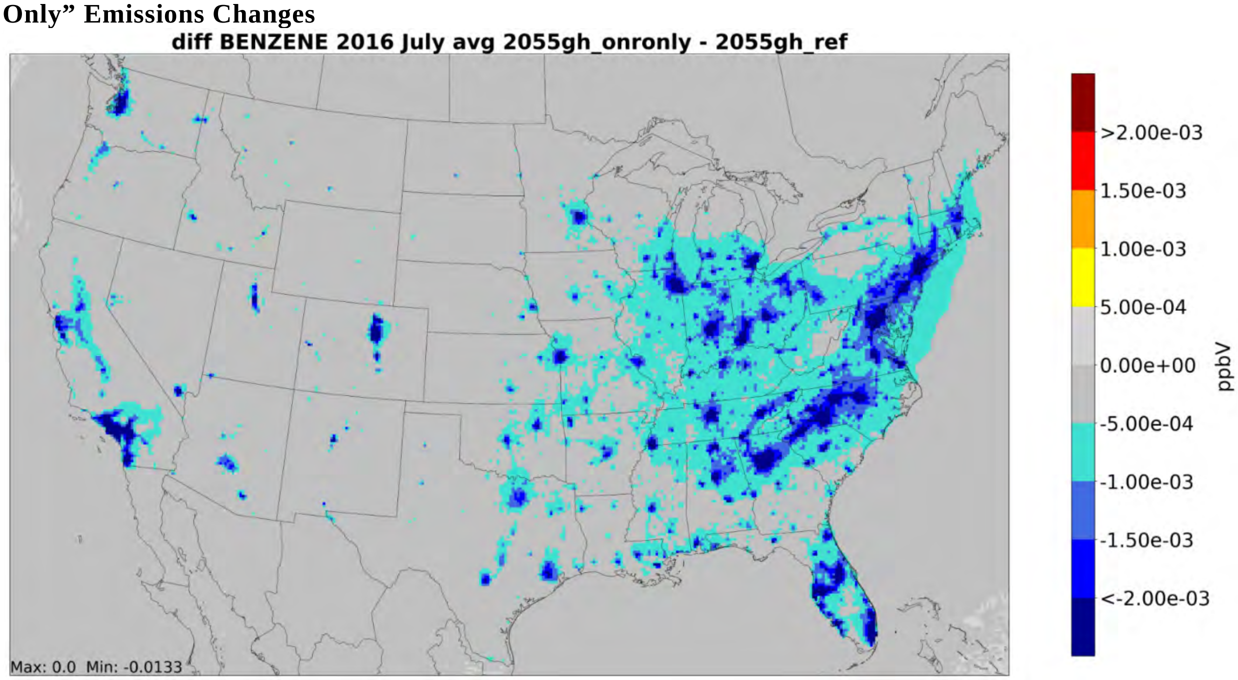

Figure 8-74 Projected Changes in Average Benzene Concentrations in July 2055 from "Onroad Only" Emissions Changes

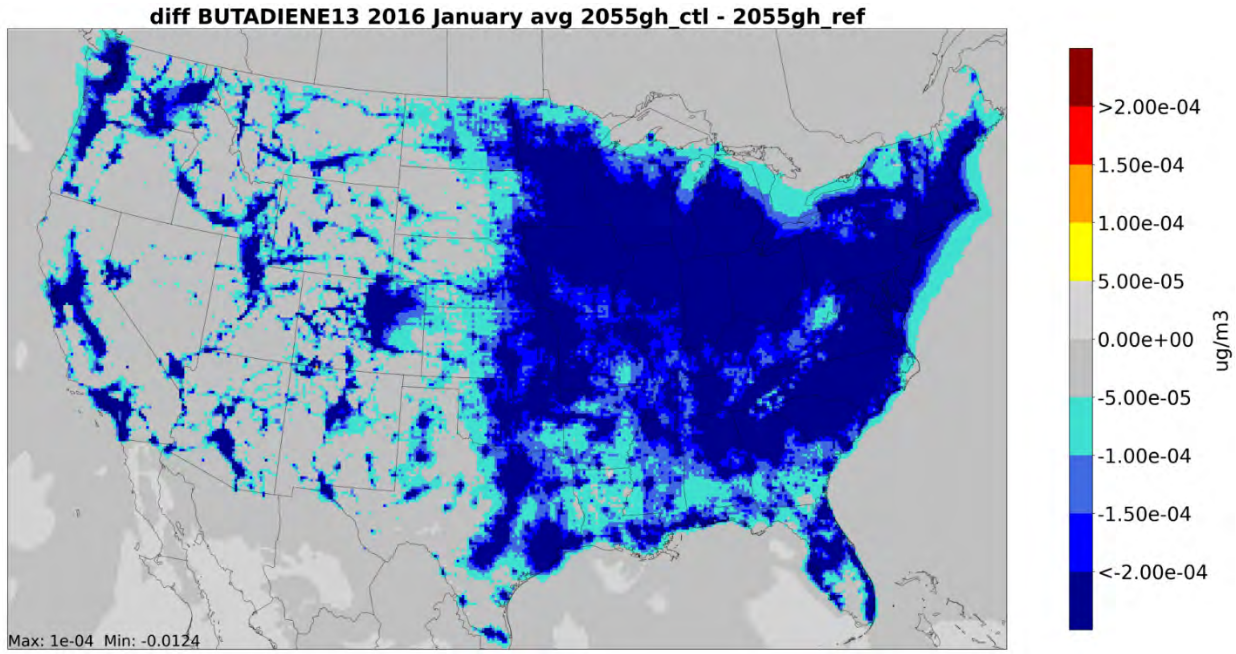

Figure 8-75 Projected Changes in Average 1,3-Butadiene Concentrations in January 2055 due to LMDV Regulatory Scenario

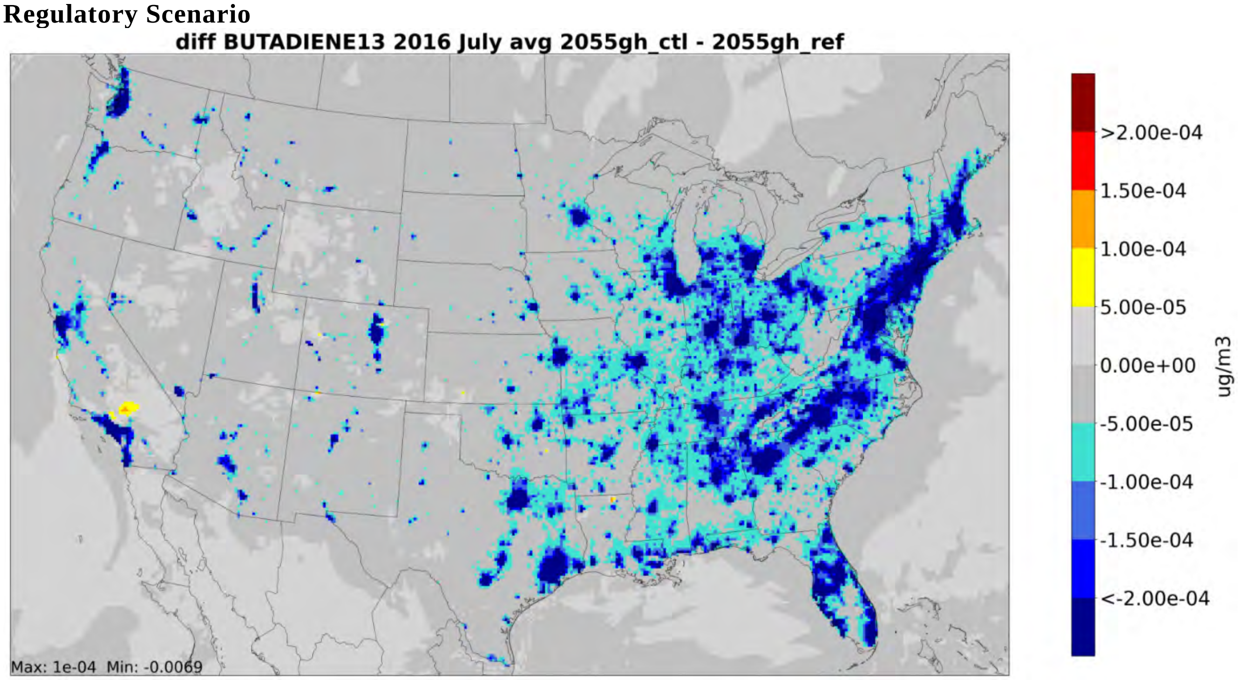

Figure 8-76 Projected Changes in Average 1,3-Butadiene Concentrations in July 2055 due to LMDV Regulatory Scenario

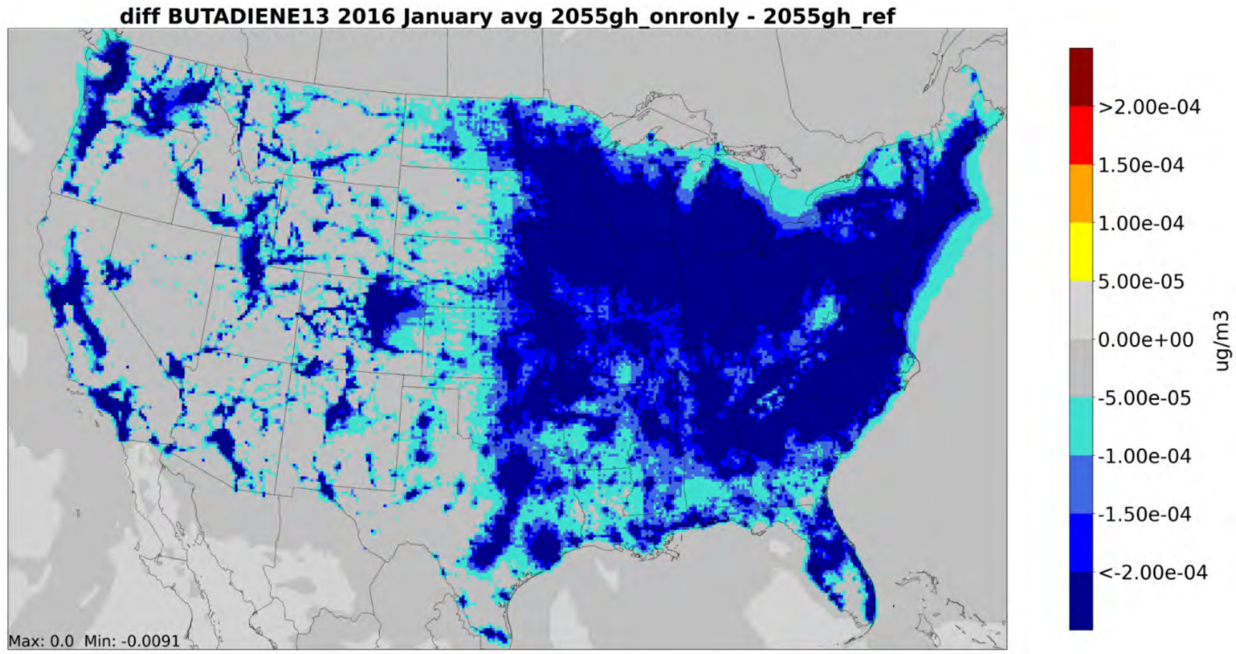

Figure 8-77 Projected Changes in Average 1,3-Butadiene Concentrations in January 2055 from "Onroad Only" Emissions Changes

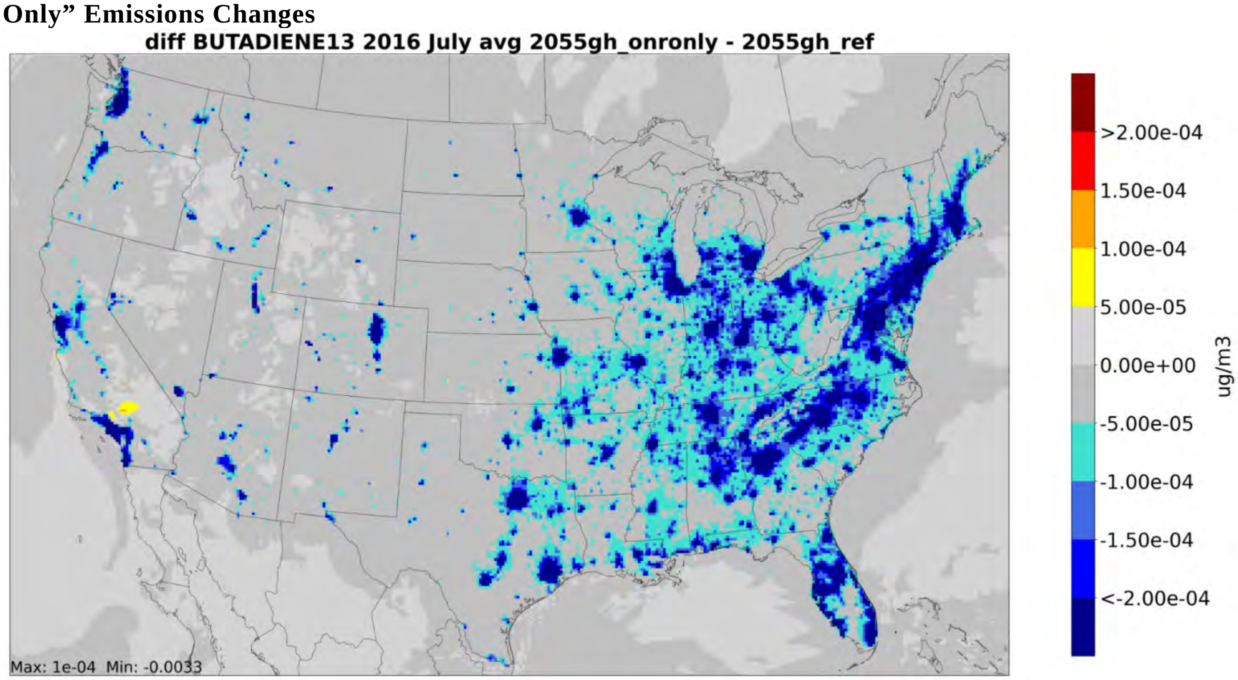

Figure 8-78 Projected Changes in Average 1,3-Butadiene Concentrations in July 2055 from "Onroad Only" Emissions Changes

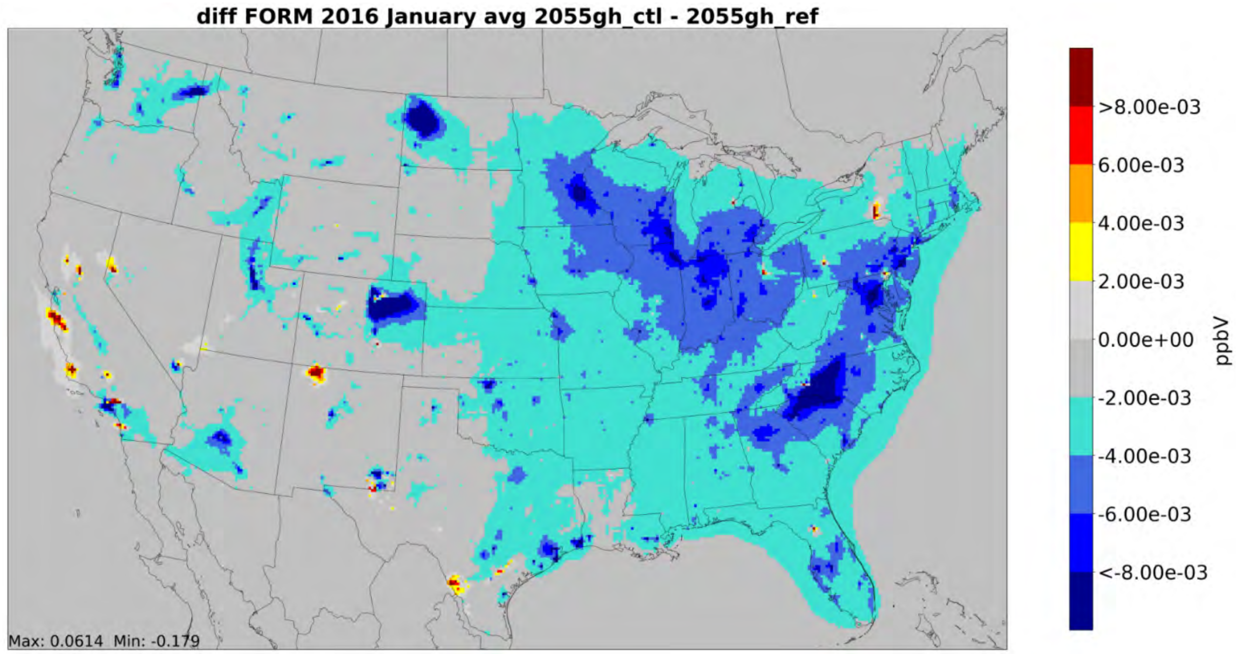

Figure 8-79 Projected Changes in Average Formaldehyde Concentrations in January 2055 due to LMDV Regulatory Scenario

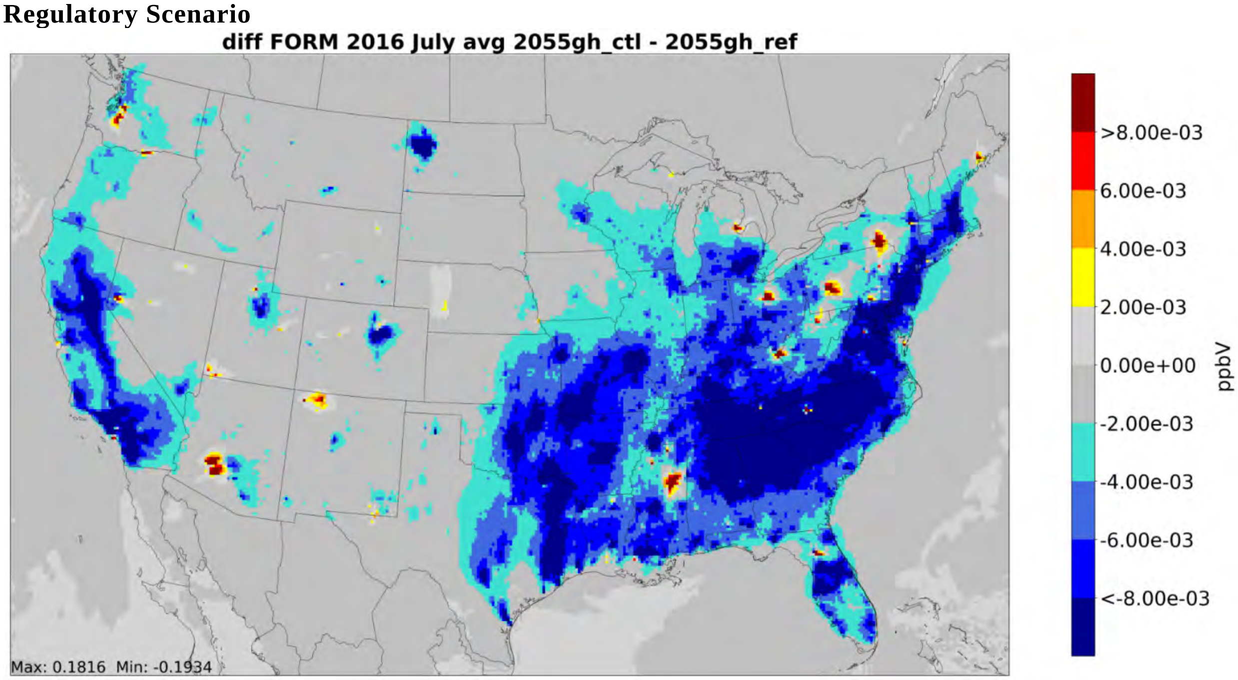

Figure 8-80 Projected Changes in Average Formaldehyde Concentrations in July 2055 due to LMDV Regulatory Scenario

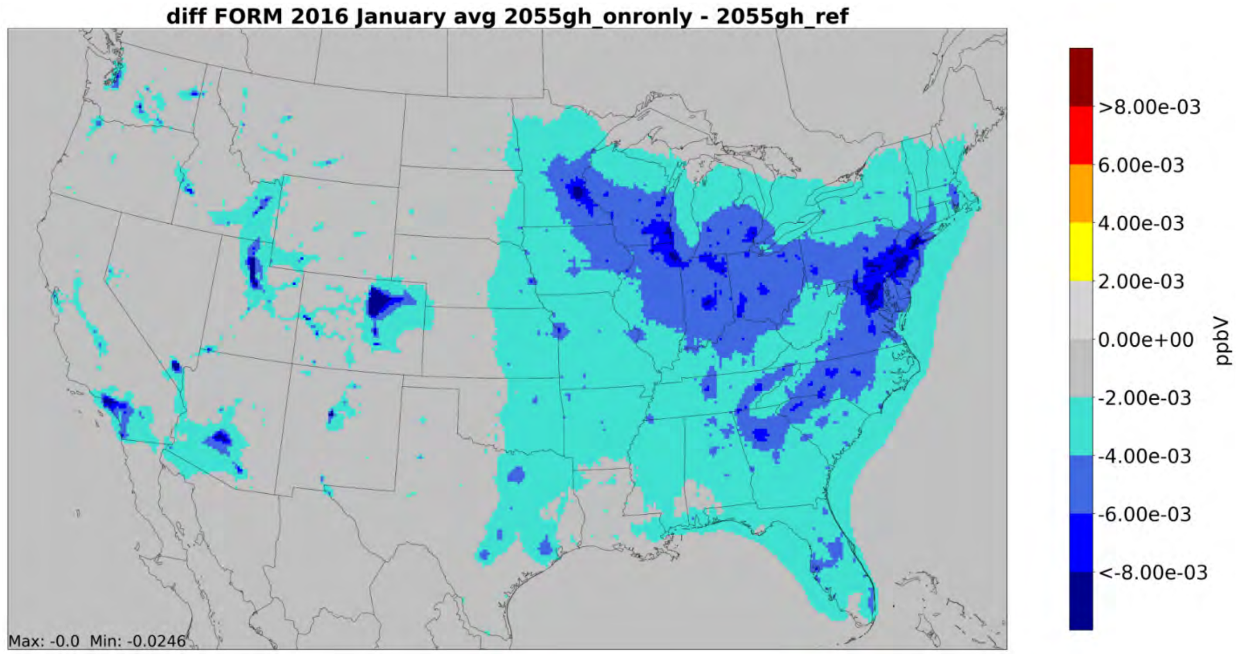

Figure 8-81 Projected Changes in Average Formaldehyde Concentrations in January 2055 from "Onroad Only" Emissions Changes

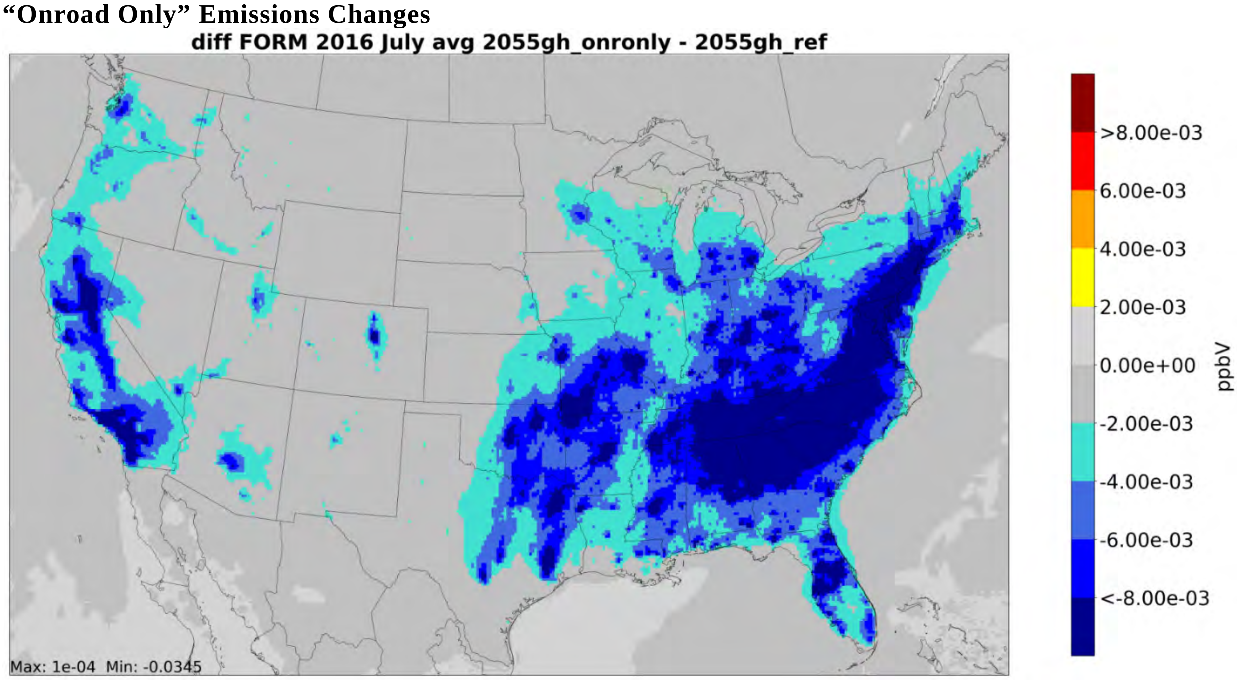

Figure 8-82 Projected Changes in Average Formaldehyde Concentrations in July 2055 from "Onroad Only" Emissions Changes

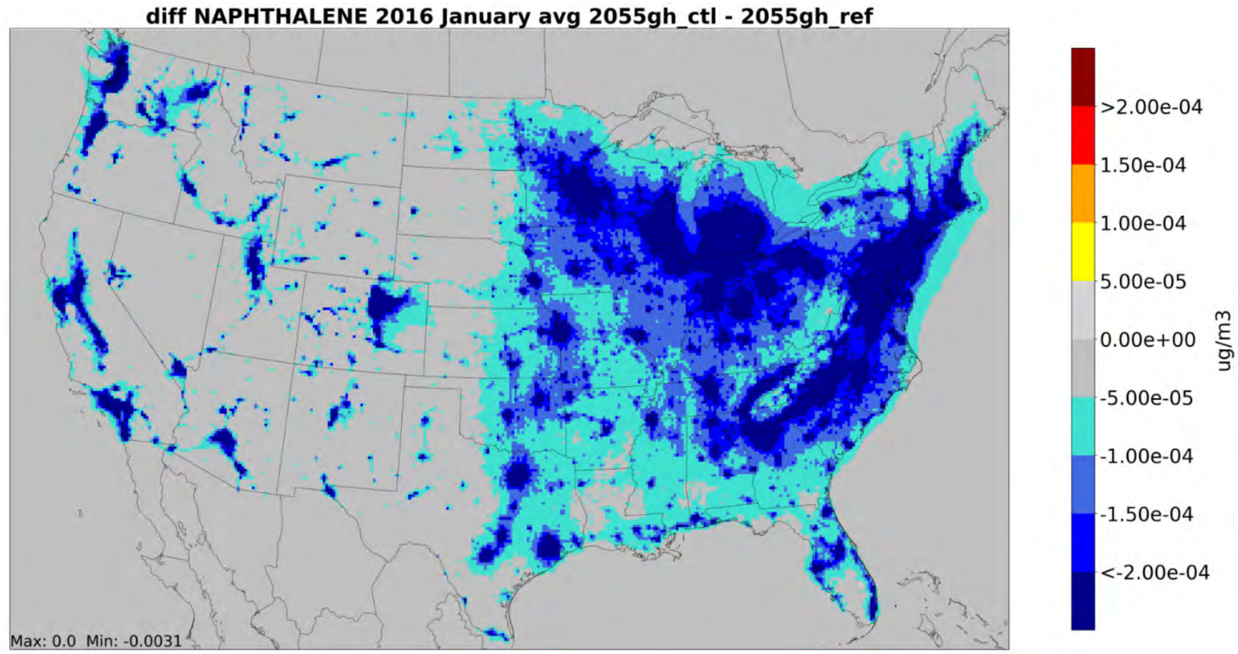

Figure 8-83 Projected Changes in Average Naphthalene Concentrations in January 2055 due to LMDV Regulatory Scenario

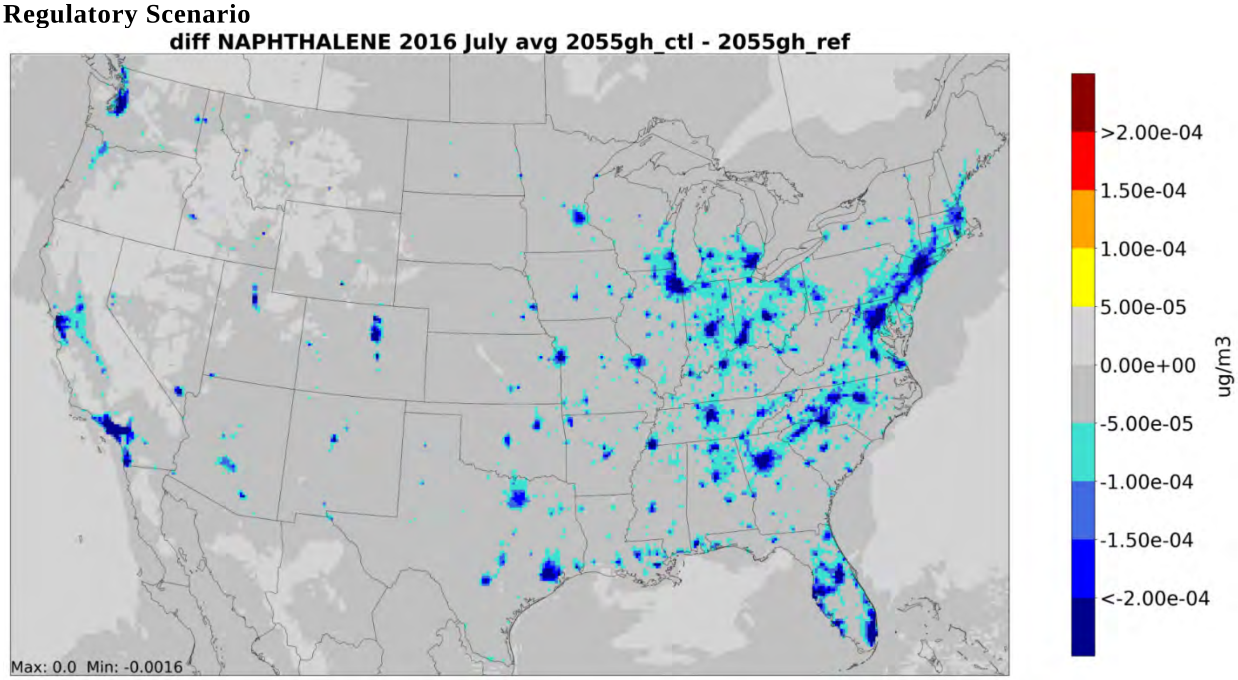

Figure 8-84 Projected Changes in Average Naphthalene Concentrations in July 2055 due to LMDV Regulatory Scenario

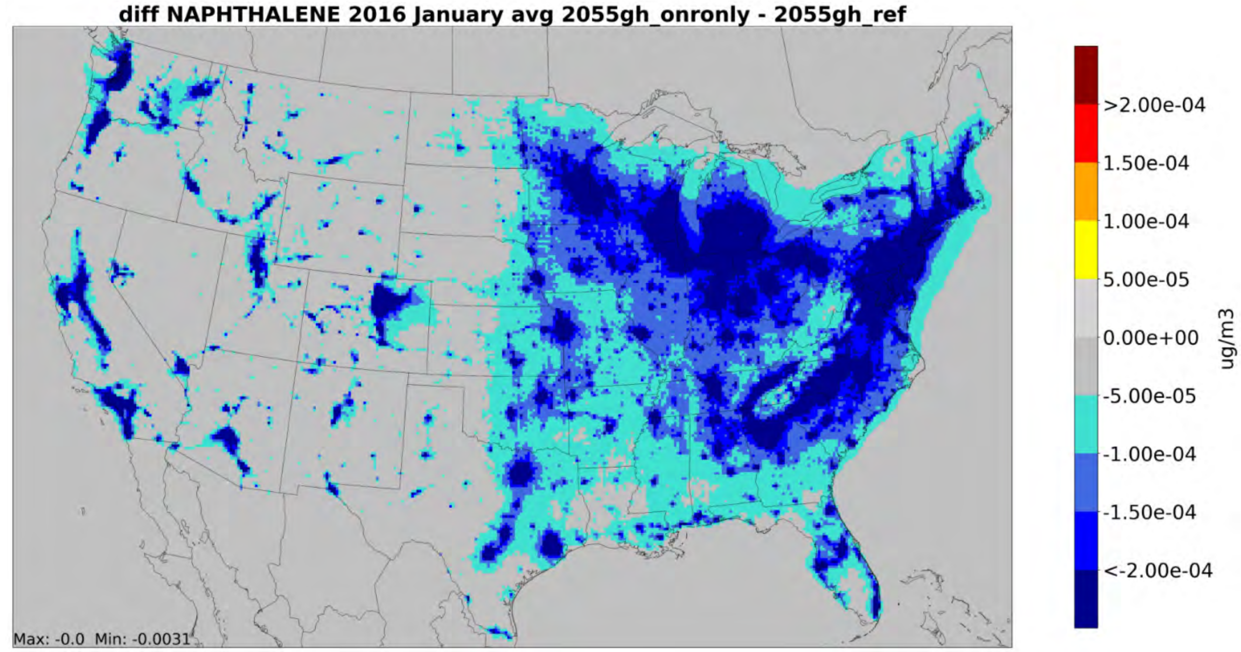

Figure 8-85 Projected Changes in Average Naphthalene Concentrations in January 2055 from "Onroad Only" Emissions Changes

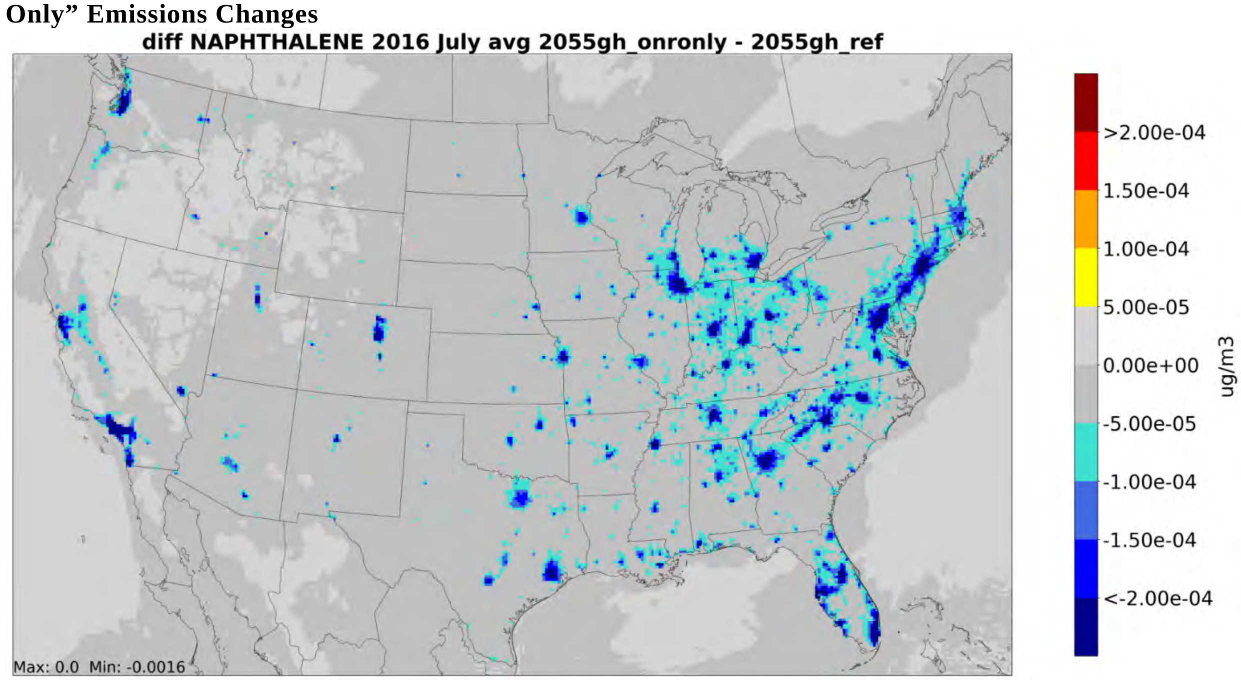

Figure 8-86 Projected Changes in Average Naphthalene Concentrations in July 2055 from "Onroad Only" Emissions Changes

8.3 Projected Visibility in Mandatory Class I Federal Areas

Air quality modeling was used to project visibility conditions in 145 Mandatory Class I Federal areas across the U.S. with and without the rule in 2055. The results show that in 2055, the rule will improve projected visibility on the 20% most impaired days in 138 of the modeled areas (95%) and will lead to no change for the other 7 modeled areas (5%). The average visibility on the 20 percent most impaired days at all modeled Mandatory Class I Federal areas is projected to improve by 0.04 deciviews, or 0.34 percent, in 2055. The greatest improvement in visibility would occur in Mammoth Cave Area in Kentucky, where visibility is projected to improve by 1.26 percent (0.20 deciviews) in 2055 due to the rule.

Table 8-1Projected Visibility in Mandatory Class I Federal areas in 2055 in AQM Reference and Regulatory cases

Class I Area Name	State	2016 Baseline Visibility (dv) on 20% Most Impaired Days	2055 Reference Visibility (dv) on 20% Most Impaired Days	2055 LMDV Regulatory Scenario Visibility (dv) on 20% Most Impaired Days	2055 Onroad-Only Scenario Visibility (dv) on 20% Most Impaired Days	Natural Background (dv) on 20% Most Impaired Days
Sipsey Wilderness	Alabama	19.03	14.72	14.59	14.59	9.62
Chiricahua NM	Arizona	7.29	6.87	6.86	6.86	4.18
Chiricahua Wilderness	Arizona	9.41	8.74	8.72	8.72	4.93
Galiuro Wilderness	Arizona	9.41	8.74	8.72	8.72	4.93
Grand Canyon NP	Arizona	9.41	8.74	8.72	8.72	4.93
Mazatzal Wilderness	Arizona	6.87	6.38	6.37	6.36	4.16
Mount Baldy Wilderness	Arizona	9.47	8.90	8.88	8.88	5.22
Petrified Forest NP	Arizona	8.16	7.50	7.48	7.48	4.21
Pine Mountain Wilderness	Arizona	9.47	8.90	8.88	8.88	5.22
Saguaro NM	Arizona	10.75	10.20	10.16	10.16	5.14
Superstition Wilderness	Arizona	10.45	9.81	9.78	9.78	5.14
Sycamore Canyon Wilderness	Arizona	11.96	11.58	11.57	11.57	4.68
Caney Creek Wilderness	Arkansas	18.29	14.04	13.96	13.98	9.54
Upper Buffalo Wilderness	Arkansas	17.95	14.18	14.08	14.09	9.41
Agua Tibia Wilderness	California	16.34	14.93	14.84	14.86	7.66
Ansel Adams Wilderness (Minarets)	California	10.98	10.28	10.26	10.26	6.06
Caribou Wilderness	California	10.23	9.66	9.64	9.64	6.10
Cucamonga Wilderness	California	13.19	11.66	11.51	11.54	6.12
Desolation Wilderness	California	9.31	8.82	8.80	8.81	4.91
Dome Land Wilderness	California	15.14	14.32	14.29	14.30	6.19
Emigrant Wilderness	California	11.57	11.08	11.06	11.06	6.29
Hoover Wilderness	California	7.65	7.31	7.30	7.30	4.90
John Muir Wilderness	California	10.98	10.28	10.26	10.26	6.06
Joshua Tree NM	California	12.87	12.16	12.12	12.12	6.09
Kaiser Wilderness	California	10.98	10.28	10.26	10.26	6.06
Kings Canyon NP	California	18.43	17.40	17.36	17.37	6.29
Lassen Volcanic NP	California	9.67	9.29	9.28	9.28	6.18

Class I Area Name	State	2016 Baseline Visibility (dv) on 20% Most Impaired Days	2055 Reference Visibility (dv) on 20% Most Impaired Days	2055 LMDV Regulatory Scenario Visibility (dv) on 20% Most Impaired Days	2055 Onroad-Only Scenario Visibility (dv) on 20% Most Impaired Days	Natural Background (dv) on 20% Most Impaired Days
Lava Beds NM	California	10.23	9.66	9.64	9.64	6.10
Mokelumne Wilderness	California	9.31	8.82	8.80	8.81	4.91
Pinnacles NM	California	14.10	13.38	13.36	13.35	6.94
Redwood NP	California	14.11	13.09	13.06	13.07	6.80
San Gabriel Wilderness	California	12.65	12.42	12.42	12.42	8.59
San Gorgonio Wilderness	California	13.19	11.66	11.51	11.54	6.12
San Jacinto Wilderness	California	14.45	12.54	12.42	12.44	6.20
San Rafael Wilderness	California	14.45	12.54	12.42	12.44	6.20
Sequoia NP	California	18.43	17.40	17.36	17.37	6.29
South Warner Wilderness	California	9.67	9.29	9.28	9.28	6.18
Thousand Lakes Wilderness	California	10.23	9.66	9.64	9.64	6.10
Ventana Wilderness	California	14.10	13.38	13.36	13.35	6.94
Yosemite NP	California	11.57	11.08	11.06	11.06	6.29
Black Canyon of the Gunnison NM	Colorado	6.55	6.16	6.15	6.15	3.97
Eagles Nest Wilderness	Colorado	4.98	4.53	4.52	4.52	3.02
Flat Tops Wilderness	Colorado	4.98	4.53	4.52	4.52	3.02
Great Sand Dunes NM	Colorado	8.02	7.52	7.50	7.50	4.45
La Garita Wilderness	Colorado	6.55	6.16	6.15	6.15	3.97
Maroon Bells-Snowmass Wilderness	Colorado	4.98	4.53	4.52	4.52	3.02
Mesa Verde NP	Colorado	6.51	5.78	5.76	5.75	4.20
Mount Zirkel Wilderness	Colorado	5.47	4.89	4.86	4.86	3.16
Rawah Wilderness	Colorado	5.47	4.89	4.86	4.86	3.16
Rocky Mountain NP	Colorado	8.41	7.39	7.35	7.35	4.94
Weminuche Wilderness	Colorado	4.98	4.53	4.52	4.52	3.02
West Elk Wilderness	Colorado	6.55	6.16	6.15	6.15	3.97
Chassahowitzka	Florida	17.41	15.43	15.38	15.38	9.03
Everglades NP	Florida	14.90	14.07	14.06	14.06	8.33
St. Marks	Florida	17.39	15.25	15.22	15.22	9.13
Cohutta Wilderness	Georgia	17.37	13.58	13.49	13.50	9.88
Okefenokee	Georgia	17.39	15.66	15.63	15.63	9.45
Wolf Island	Georgia	17.39	15.66	15.63	15.63	9.45
Craters of the Moon NM	Idaho	8.50	7.54	7.48	7.47	4.97
Sawtooth Wilderness	Idaho	8.61	8.34	8.33	8.33	4.70
Selway-Bitterroot Wilderness	Idaho	8.37	8.13	8.13	8.13	5.45

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Mammoth Cave NP	Kentucky	21.02	15.87	15.67	15.68	9.80
Breton	Louisiana	18.97	17.33	17.29	17.30	9.23
Acadia NP	Maine	14.54	13.36	13.31	13.31	10.39
Moosehorn	Maine	13.32	12.41	12.37	12.37	9.98
Roosevelt Campobello International Park	Maine	13.32	12.41	12.37	12.37	9.98
Isle Royale NP	Michigan	15.54	14.05	13.97	13.98	10.17
Seney	Michigan	17.57	15.37	15.23	15.23	11.11
Boundary Waters Canoe Area	Minnesota	13.96	12.53	12.46	12.47	9.09
Voyageurs NP	Minnesota	14.18	12.86	12.81	12.81	9.37
Hercules-Glades Wilderness	Missouri	18.72	15.02	14.91	14.92	9.30
Mingo	Missouri	20.13	16.18	16.00	16.01	9.18
Anaconda-Pintler Wilderness	Montana	8.37	8.13	8.13	8.13	5.45
Bob Marshall Wilderness	Montana	10.06	9.86	9.86	9.86	5.53
Cabinet Mountains Wilderness	Montana	9.87	9.61	9.59	9.59	5.64
Gates of the Mountains Wilderness	Montana	7.47	7.33	7.32	7.32	4.53
Glacier NP	Montana	13.77	13.39	13.34	13.34	6.90
Medicine Lake	Montana	15.30	15.25	15.18	15.20	5.95
Mission Mountains Wilderness	Montana	10.06	9.86	9.86	9.86	5.53
Red Rock Lakes	Montana	7.52	7.16	7.15	7.15	3.97
Scapegoat Wilderness	Montana	10.06	9.86	9.86	9.86	5.53
UL Bend	Montana	10.93	10.97	10.96	10.96	5.87
Jarbidge Wilderness	Nevada	7.97	7.75	7.74	7.74	5.23
Great Gulf Wilderness	New Hampshire	13.07	11.43	11.38	11.38	9.78
Presidential Range-Dry River Wilderness	New Hampshire	13.07	11.43	11.38	11.38	9.78
Brigantine	New Jersey	19.31	16.45	16.28	16.27	10.68
Bandelier NM	New Mexico	8.44	7.74	7.70	7.70	4.59
Bosque del Apache	New Mexico	10.47	9.62	9.59	9.60	5.39
Carlsbad Caverns NP	New Mexico	12.64	12.60	12.58	12.59	4.83
Gila Wilderness	New Mexico	7.58	7.10	7.08	7.08	4.20
Pecos Wilderness	New Mexico	5.95	5.35	5.33	5.33	3.50
Salt Creek	New Mexico	14.97	14.70	14.63	14.66	5.49
San Pedro Parks Wilderness	New Mexico	6.43	5.87	5.86	5.85	3.33
Wheeler Peak Wilderness	New Mexico	9.95	9.56	9.54	9.54	4.89
White Mountain Wilderness	New Mexico	5.95	5.35	5.33	5.33	3.5

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Linville Gorge Wilderness	North Carolina	16.42	12.62	12.57	12.56	9.70
Shining Rock Wilderness	North Carolina	15.49	11.68	11.63	11.64	10.25
Swanquarter	North Carolina	16.30	13.40	13.29	13.29	10.01
Lostwood	North Dakota	16.18	16.35	16.28	16.29	5.87
Theodore Roosevelt NP	North Dakota	14.06	13.29	13.20	13.21	5.94
Wichita Mountains	Oklahoma	18.12	15.40	15.31	15.32	6.92
Crater Lake NP	Oregon	7.98	7.68	7.67	7.67	5.16
Diamond Peak Wilderness	Oregon	7.98	7.68	7.67	7.67	5.16
Eagle Cap Wilderness	Oregon	11.19	10.19	10.15	10.15	6.58
Gearhart Mountain Wilderness	Oregon	7.98	7.68	7.67	7.67	5.16
Hells Canyon Wilderness	Oregon	12.33	11.37	11.31	11.31	6.57
Kalmiopsis Wilderness	Oregon	11.97	11.57	11.55	11.55	7.78
Mount Hood Wilderness	Oregon	9.27	8.78	8.76	8.76	6.59
Mount Jefferson Wilderness	Oregon	11.28	10.85	10.84	10.84	7.30
Mount Washington Wilderness	Oregon	7.98	7.68	7.67	7.67	5.16
Mountain Lakes Wilderness	Oregon	11.28	10.85	10.84	10.84	7.30
Strawberry Mountain Wilderness	Oregon	11.19	10.19	10.15	10.15	6.58
Three Sisters Wilderness	Oregon	11.28	10.85	10.84	10.84	7.30
Cape Romain	South Carolina	17.67	15.32	15.28	15.28	9.78
Badlands NP	South Dakota	12.33	11.45	11.40	11.40	6.09
Wind Cave NP	South Dakota	10.53	9.44	9.43	9.41	5.64
Great Smoky Mountains NP	Tennessee	17.21	13.54	13.45	13.45	10.05
Joyce-Kilmer-Slickrock Wilderness	Tennessee	17.21	13.54	13.45	13.45	10.05
Big Bend NP	Texas	14.06	13.31	13.30	13.31	5.33
Guadalupe Mountains NP	Texas	12.64	12.60	12.58	12.59	4.83
Arches NP	Utah	6.76	5.80	5.77	5.76	4.13
Bryce Canyon NP	Utah	6.60	6.03	6.01	6.01	4.08
Canyonlands NP	Utah	6.76	5.80	5.77	5.76	4.13
Capitol Reef NP	Utah	7.18	6.56	6.54	6.54	4.00
Zion NP	Utah	8.76	8.31	8.31	8.30	5.18
Lye Brook Wilderness	Vermont	14.75	12.55	12.44	12.44	10.24
James River Face Wilderness	Virginia	17.89	13.83	13.71	13.71	9.47
Shenandoah NP	Virginia	17.07	12.06	11.96	11.95	9.52
Alpine Lake Wilderness	Washington	12.74	11.71	11.63	11.64	7.27

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Glacier Peak Wilderness	Washington	9.98	9.57	9.54	9.55	6.89
Goat Rocks Wilderness	Washington	7.98	7.63	7.62	7.62	6.14
Mount Adams Wilderness	Washington	12.66	12.11	12.08	12.08	7.66
Mount Rainier NP	Washington	9.98	9.57	9.54	9.55	6.89
North Cascades NP	Washington	11.90	11.72	11.71	11.71	6.90
Olympic NP	Washington	9.46	9.05	9.04	9.04	5.96
Pasayten Wilderness	Washington	7.98	7.63	7.62	7.62	6.14
Dolly Sods Wilderness	West Virginia	17.65	12.26	12.17	12.17	8.92
Otter Creek Wilderness	West Virginia	17.65	12.26	12.17	12.17	8.92
Bridger Wilderness	Wyoming	6.77	6.34	6.33	6.33	3.92
Fitzpatrick Wilderness	Wyoming	6.77	6.34	6.33	6.33	3.92
Grand Teton NP	Wyoming	7.52	7.16	7.15	7.15	3.97
North Absaroka Wilderness	Wyoming	7.17	6.80	6.79	6.79	4.55
Teton Wilderness	Wyoming	7.52	7.16	7.15	7.15	3.97
Washakie Wilderness	Wyoming	7.17	6.80	6.79	6.79	4.55
Yellowstone NP	Wyoming	7.52	7.16	7.15	7.15	3.97

[a] The level of visibility impairment in an area is based on the light-extinction coefficient and a unitless visibility index, called a “deciview”, which is used in the valuation of visibility. The deciview metric provides a scale for perceived visual changes over the entire range of conditions, from clear to hazy. Under many scenic conditions, the average person can generally perceive a change of one deciview. The higher the deciview value, the worse the visibility. Thus, an improvement in visibility is a decrease in deciview value.