

Studying the influence of climate change and variability on mid-21st century US PM_{2.5} by dynamical downscaling

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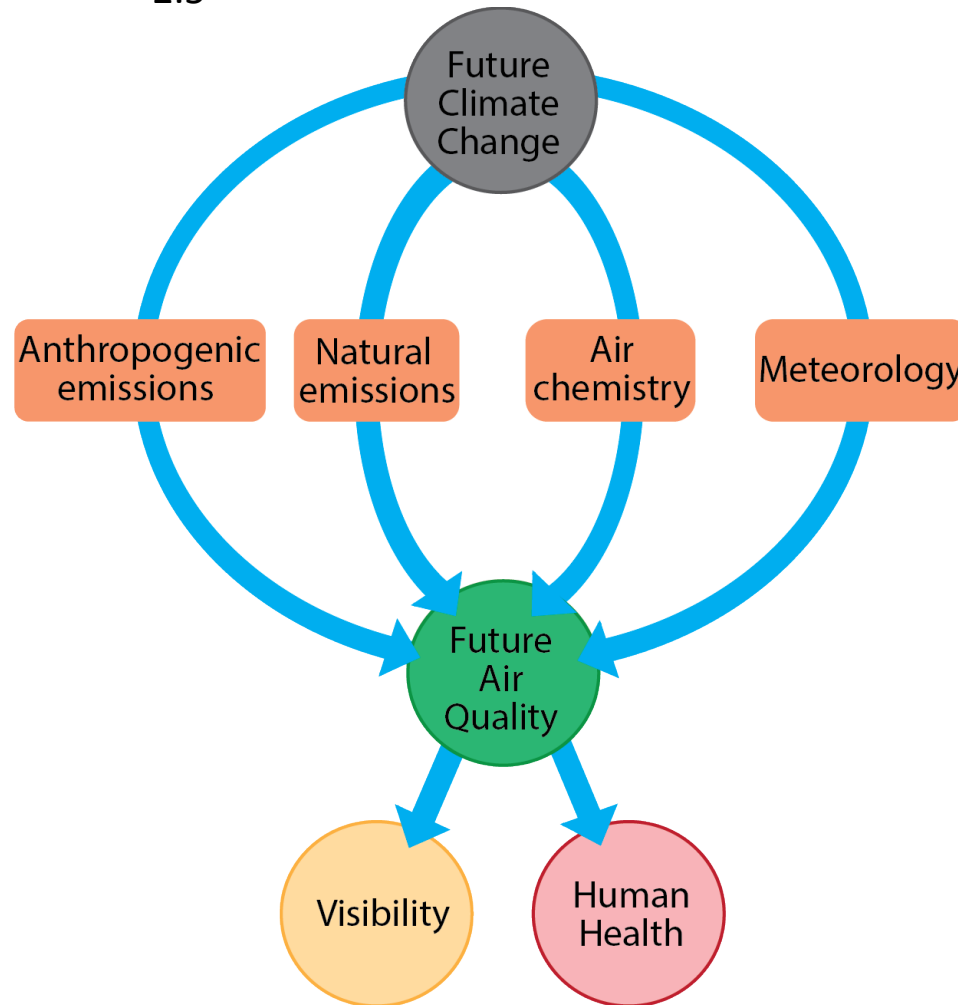
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Climate Change Impacts on Air Quality: Pathways

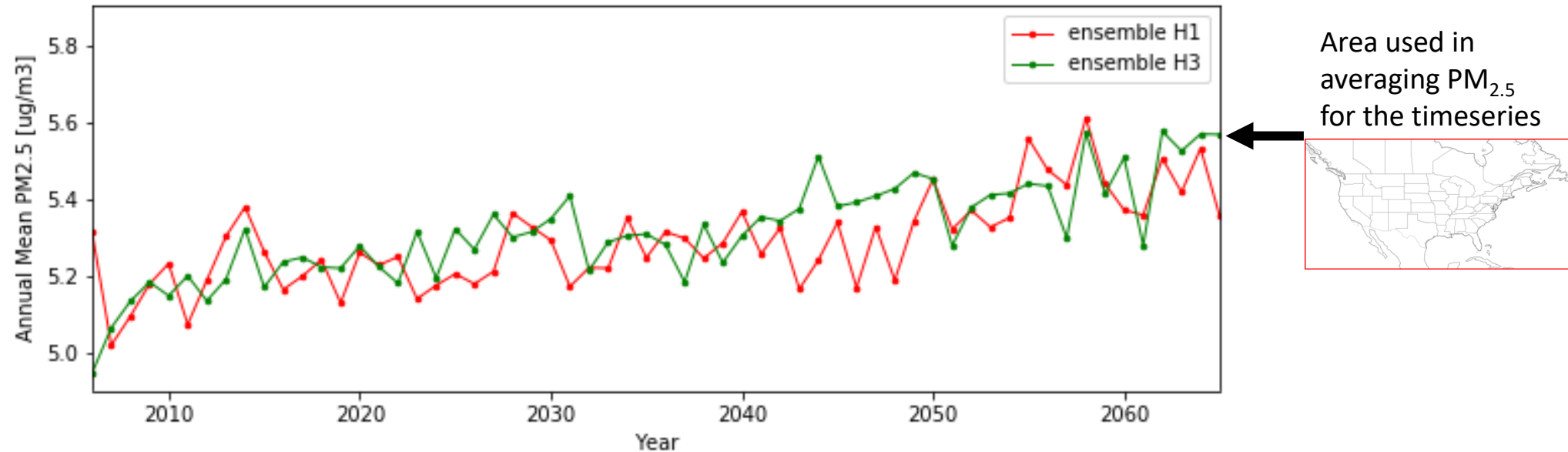
- Meteorology influences $\text{PM}_{2.5}$ air quality in many ways:



- $\text{PM}_{2.5}$, in turn, affects visibility and human health

Climate Variability vs Climate Change for PM_{2.5}

- PM_{2.5} variability+change illustrated by two GFDL ensemble members H1 and H3:



**NATURAL CLIMATE VARIABILITY =
fluctuation around a steady mean**

≠

**CLIMATE CHANGE (SIGNAL) =
long term change of mean**

NATURAL FORCING =
caused by solar activity,
volcanoes

+

INTERNAL VARIABILITY (NOISE) =
internally arising due to chaotic
nature of climate system

- Internal Variability (noise) can confound Climate Change (signal)

Past Studies of Climate Change on US PM_{2.5}

- Notable findings of past studies:
- synoptic meteorology key driver of PM_{2.5} and O₃
 - inconsistency in climate impact on air quality:

	[O ₃] results	[PM _{2.5}] results
Δ Direction	Consistently +ve	Inconsistent sign
Δ Magnitude	1-10 ppb (polluted regions)	Between -1 and +1 μgm ⁻³

Fiore et al, 2015

- Complex PM_{2.5} components with different climate response

Crustal Elements			Bulk Organic Carbon		Secondary Inorganic Ions			Anthropogenic (Industrial) Tracers		
Si	Ca	Al	OC	EC	NH ₄ ⁺	SO ₄ ²⁻	NO ₃ ⁻	Fe	Zn	Pb

from Kundu & Stone, 2015 study

- But some studies have:
- Averaged limited number of future years
 - Used single realization of one climate model

Study Objectives and Method

Objective - Characterize the role of climate variability and change on US PM_{2.5} distribution in fine scale, using a novel approach:

3-ensemble, coarse Global Chemistry-Climate Model simulations for 2006-2100



Select 8 GCM years representing high/median PM_{2.5}



Dynamical downscaling of meteorology (WRF 12km)



Air quality downscaling (CMAQ 12km) with inline biogenic, lightning, dust emissions



Construct fine scale probability distribution of mean annual PM_{2.5}



Study associated probabilistic impacts on visibility & human health

Year Selection for Downscaling based on GFDL Output EOF Analysis

We select years from GFDL chemistry-climate global model that represent upper quartile and median $\text{PM}_{2.5}$ levels in each US region

Method of Year Selection

Daily mean $\text{PM}_{2.5}$ from GFDL-CM3

EOF analysis of GFDL

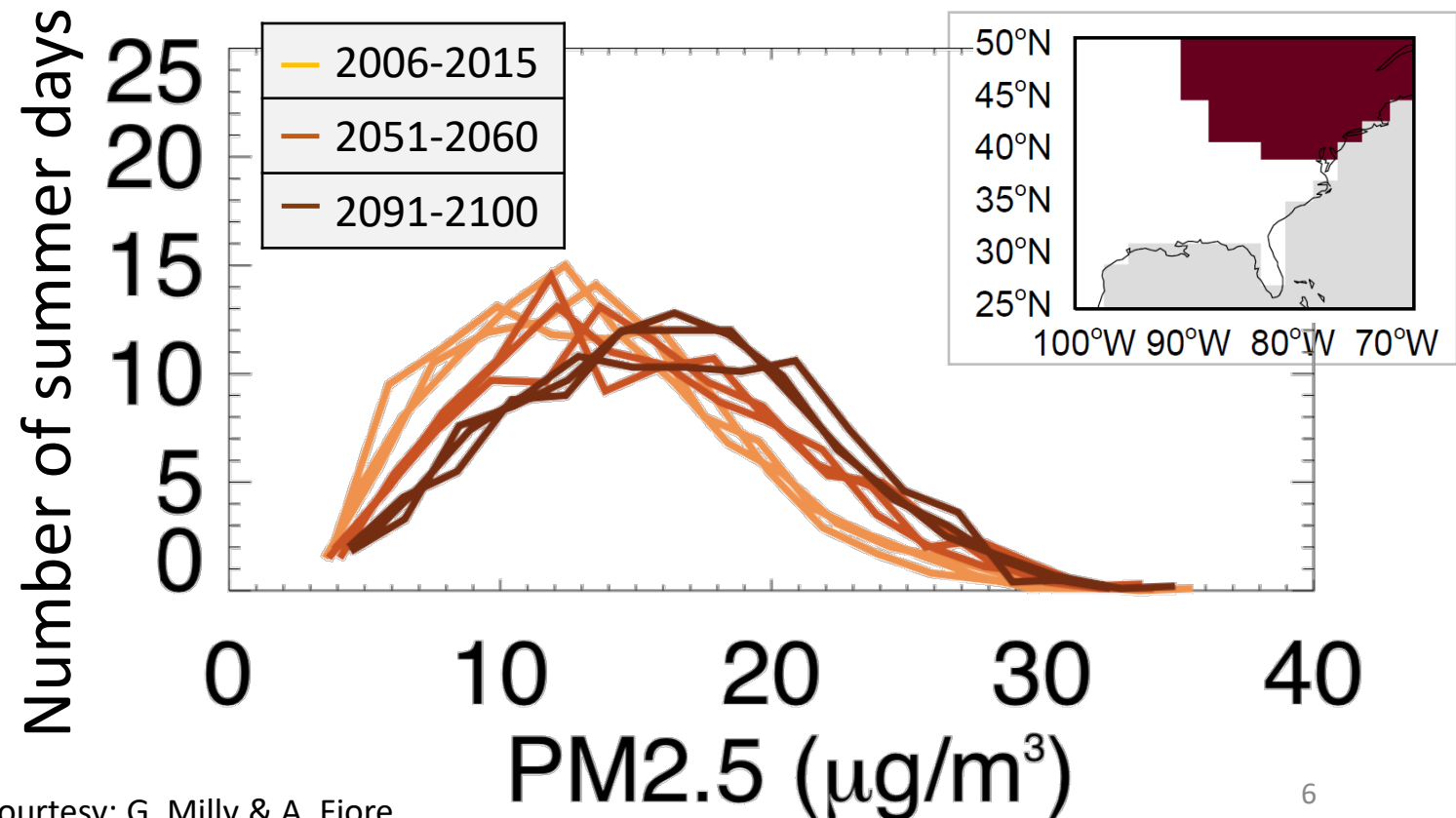
Identify US regions that vary $\text{PM}_{2.5}$ coherently

Year Selection for Downscaling

Identify upper-quartile and median annual $\text{PM}_{2.5}$ years in different CONUS regions

Present years: 2006/07 H1, 2010/11 H5,
2014/15 H1, 2018/19 H3
Future years: 2054/55 H3, 2054/55 H5,
2058/59 H1, 2058/59 H5

Histograms of summer daily mean $\text{PM}_{2.5}$ of 3 ensemble members of GFDL CM3 to (i) better characterize internal variability, and (ii) show the shift in $\text{PM}_{2.5}$ distribution due to climate change



WRF/CMAQ Simulations

Scenario	Time	Meteorology	GFDL IC/BCs	Anthrop. Emissions	# Realizations
RCP8.5m_2005e_PRES	2006-2020	2005 RCP8.5_WMGG	RCP8.5_WMGG	2016 NEI	4
RCP8.5m_2005e_FUT	2050-2065	2050 RCP8.5_WMGG	RCP8.5_WMGG	2016 NEI	4

RCP8.5m_2005e_FUT - RCP8.5m_2005e_PRES = effect of only climate change on future PM_{2.5}

- Land Use/Cover remains constant for all WRF/CMAQ simulations
- GFDL RCP8.5_WMGG fixes aerosol, ozone precursor emissions at 2005 level
- CMAQ simulations use 2016NEI emissions to reflect current emissions

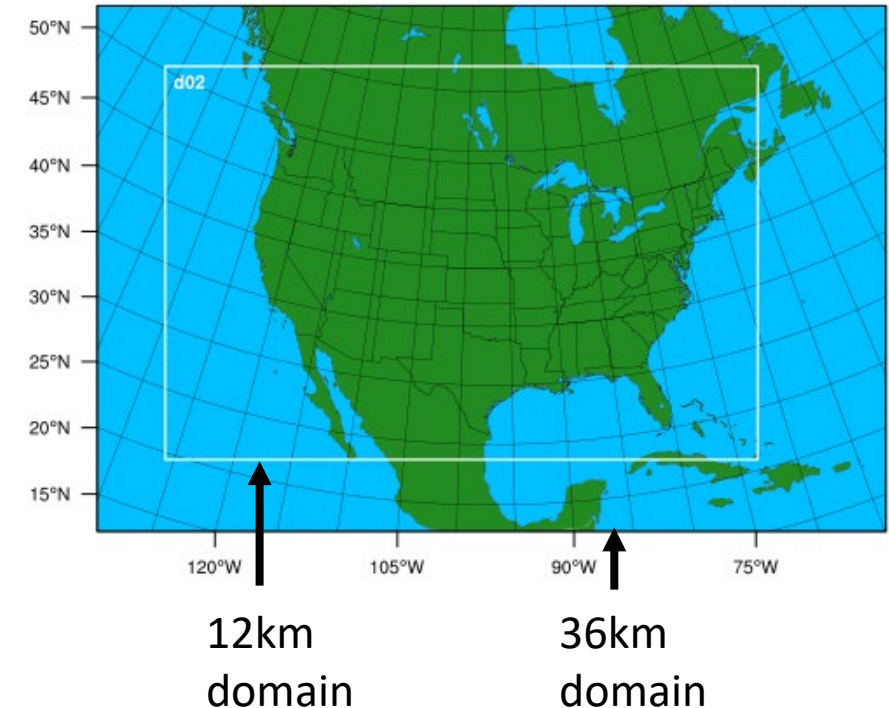
WRF Physics Options

- 8 selected GFDL years (RCP8.5 met. and 2005 emissions) downscaled in WRF:

Physics Options used in WRFv3.9.1.1 simulations

Parameter	Physics options used in WRF simulation
mp_physics = 6	WSM 6-class graupel scheme microphysics
ra_lw_physics = 4	RRTMG radiative transfer scheme for longwave radiation
ra_sw_physics = 4	RRTMG radiative transfer scheme for shortwave radiation
sf_surface_physics = 2	Unified Noah land-surface model
cu_physics = 1	Kain-Fritsch (new Eta) scheme for cumulus parameterization
num_land_cat = 40	40 land categories of NLCD2011 used
num_soil_cat = 16	16 categories of soil data

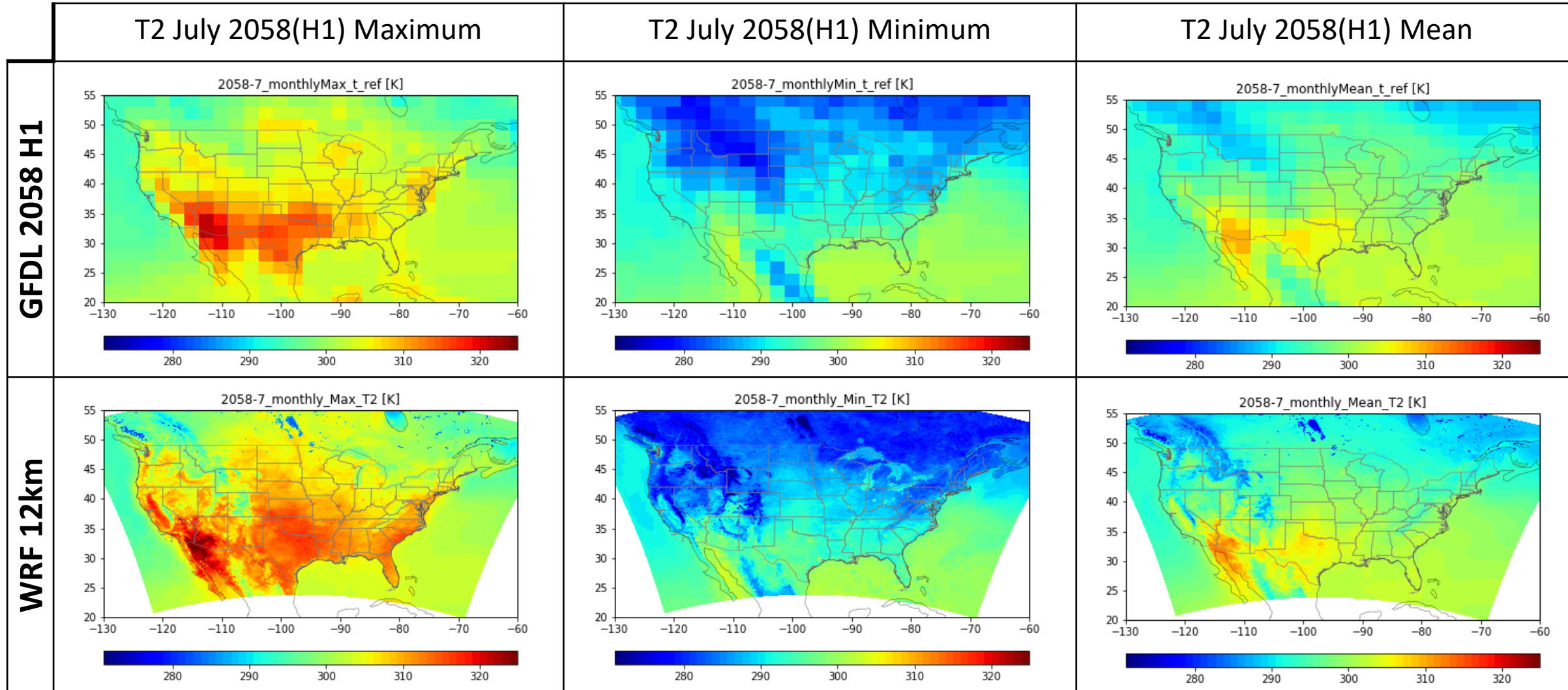
Domains used in Simulations



* Spectral nudging is applied to moisture for better precipitation results (Spero et al, 2018)

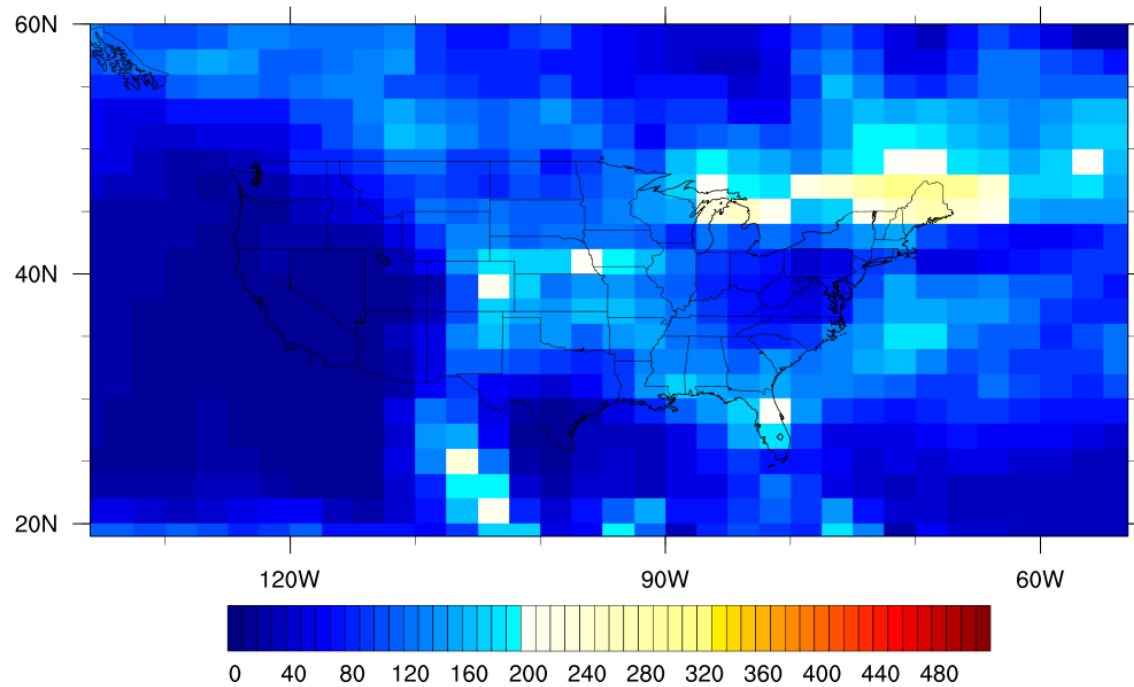
Comparing GFDL & WRF T2 [K] Statistics: July 2058 (ens. H1) Example

- General temperature patterns of GFDL simulations are represented in WRF
- WRF simulation adds fine scale details

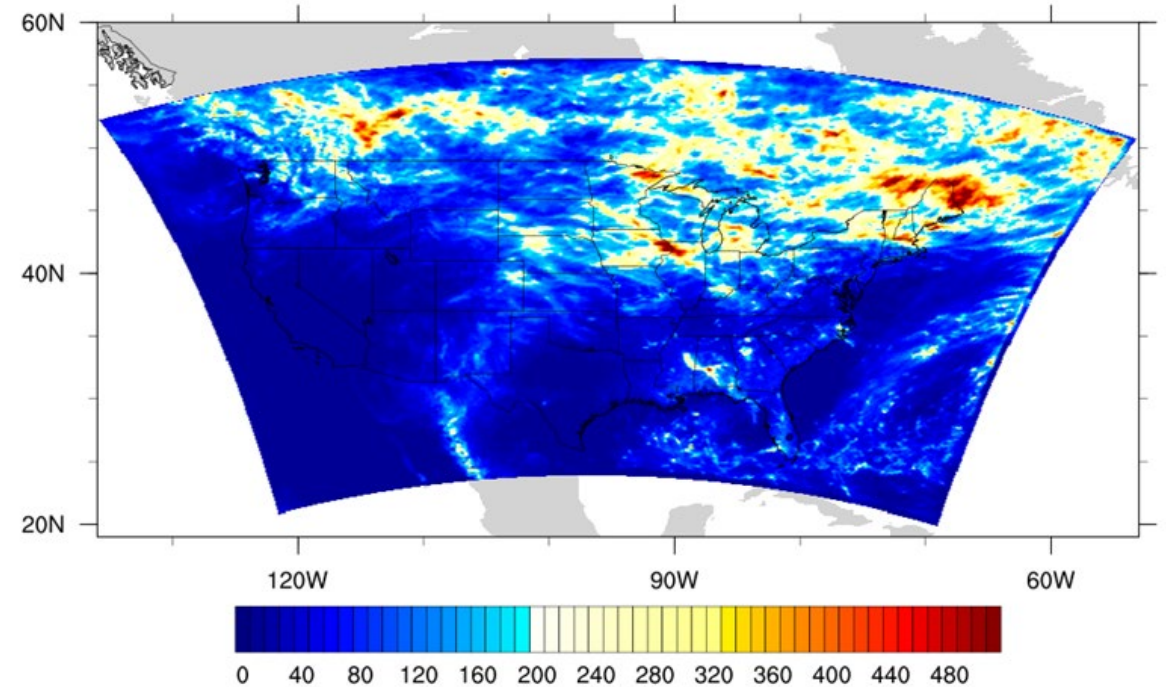


Comparing GFDL & WRF Monthly Total Precipitation [mm]: July 2058 (ens. H1) Example

- General precipitation pattern of GFDL are represented well in WRF*
- WRF simulation adds finer scale details in precipitation



GFDL 2058 H1

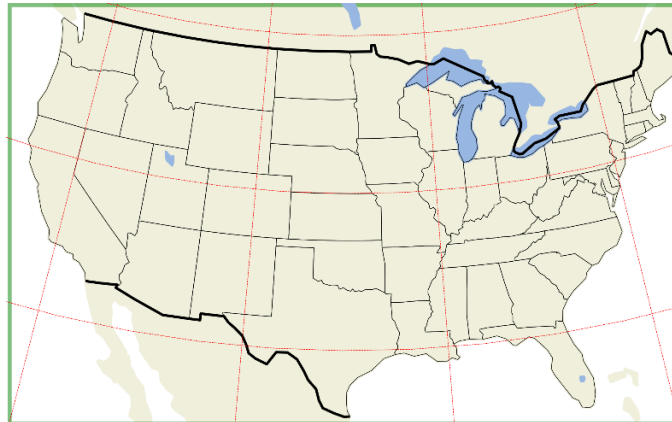


WRF 12km

- * Spectral nudging applied to moisture in WRF simulations for better precipitation results (Spero et al, 2018)
- * July-December 6-month spinup used for surface temperature IC for better Inland lake model results

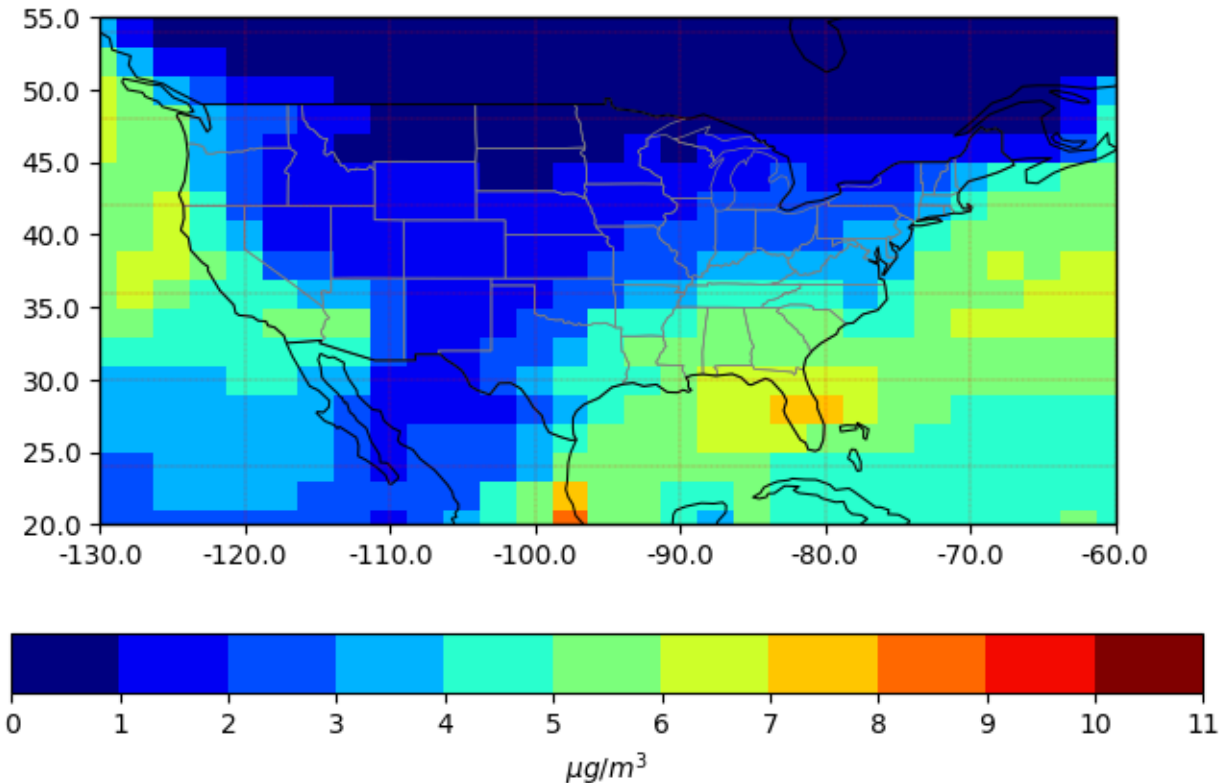
Current Progress: CMAQ test-run configuration

- CMAQ test-run of Jan-Feb of a selected GFDL year 2014/15 H1 conducted
- Meteorology-sensitive emissions used inline in CMAQ:
 - sea spray aerosol emission
 - windblown dust emissions
 - lightning NO_x emissions
 - biogenic emissions
- 12US2 domain (12km) used in CMAQ test-run:

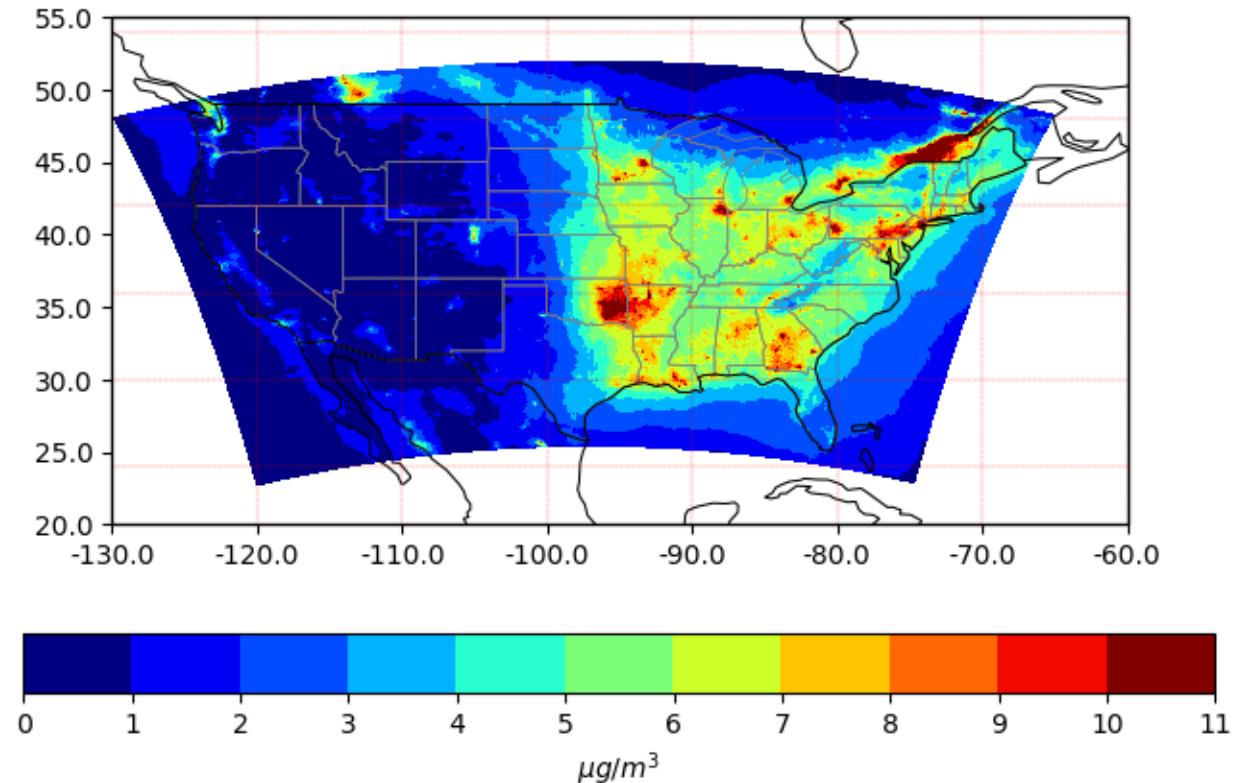


Comparing GFDL & CMAQ Feb 2014 (H1) Monthly Mean of Total PM_{2.5}

- CMAQ test-run looks different from GFDL-CM3:
 - they are different in horizontal grid size
 - they use different emissions
 - other technical issues also being investigated for the difference



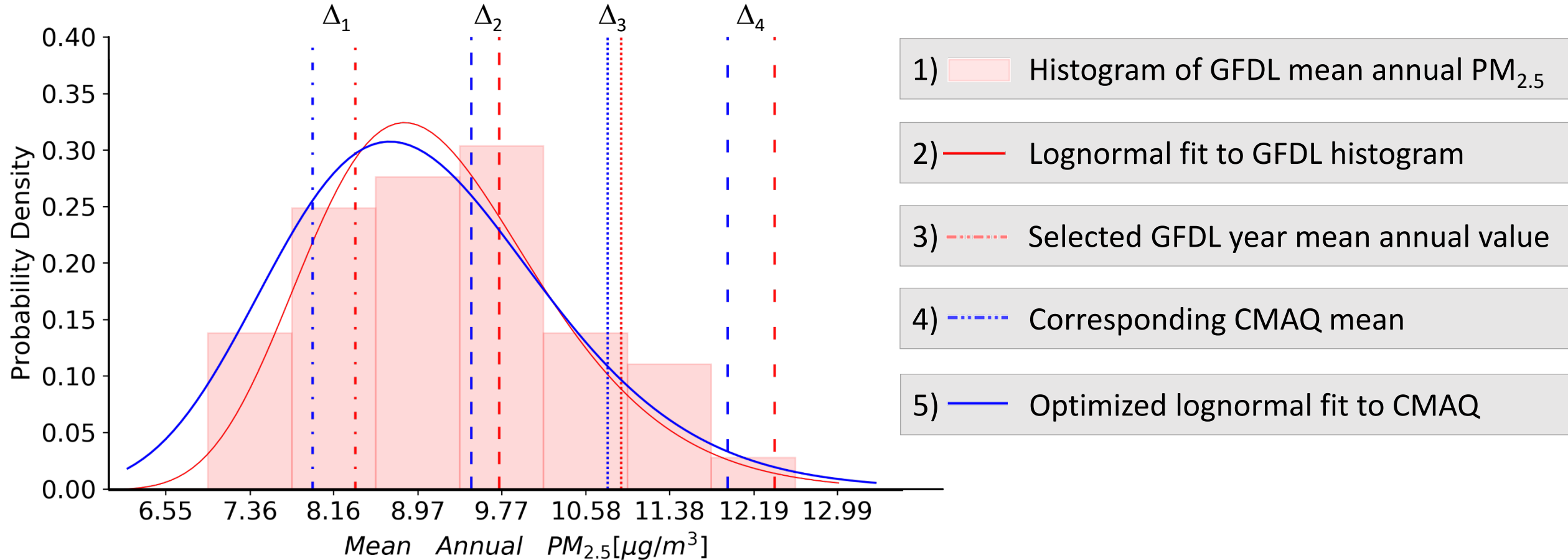
GFDL 2014 H1



CMAQ 12km

Constructing Fine Scale $PM_{2.5}$ Probability Distribution based on Global Model Ensembles

- Illustration of a single grid cell mean annual $PM_{2.5}$ for a specific period (e.g. present decade)



- Optimum distribution parameters minimize $(\Delta_1^2 + \Delta_2^2 + \Delta_3^2 + \Delta_4^2)$ which is the least sum of squares of distribution percentile differences
- Impact of climate change estimated by Monte Carlo sampling from present and future distributions

Expected Outcomes & Summary

- To quantify climate change impacts on US PM_{2.5} in the 2050s, considering variability, we:
 - use large ensemble global model simulation to characterize variability
 - downscale meteorology and air quality in selected years to fine resolution (12km)
 - set anthropogenic emissions to present day levels
 - allow dust, sea spray, lightning and biogenic emissions to evolve with meteorology
 - map fine scale probability distributions of PM_{2.5} in individual grid cells
- Our study will yield an improved air quality projection method for individual US subregions, in context of future climate change and variability.
- We will also map the associated impacts of climate change and variability on human health and visibility.

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Thank You for listening!

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Questions?