

Integrated Multiscale Modeling of Drought and Air Quality under Climate Change: Health and Environmental Implications

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

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December 2025

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DEDICATION

I dedicate this dissertation to my family for their endless love and support.

ACKNOWLEDGEMENTS

With heartfelt gratitude, I would like to thank my advisor Dr. Joshua S. Fu, for his continuous support, valuable guidance, and confidence in my potential throughout of my Ph.D. journey since 2021. His mentorship not only nurtured my academic and professional growth but also taught me to persevere, to question deeply, and to lead with integrity.

I am truly grateful to my committee members, Dr. Forrest Hoffman, Dr. Jia Xing, and Dr. Russell Zaretski, for their thoughtful feedback, generous time, and constant encouragement that helped me refine my research and expand my thinking. My sincere thanks also go to my lab mates and friends in the research group, especially Hannah Rubin, Rong-You Chien, Zhixu Sun, Xinxin Zhang, Cheng-En Yang, Tao Wang, Cheng-pin Kuo, Matthew Tipton, G. Andrew Ferrada and Valeria Campos, whose kindness and support have made both the challenges and achievements of this journey more meaningful.

Above all, I owe my deepest gratitude to my family and friends for their unconditional love and constant support. Their quiet strength carried me through long nights, moments of uncertainty, and every small success along the way. This dissertation is not only a reflection of my work, but a tribute to the people who believed in me even when I struggled to believe in myself.

ABSTRACT

Extreme climate variability and limited air quality monitoring coverage continue to challenge environmental planning and public health protection. This dissertation investigates two major aspects of environmental risk in the contiguous United States: the evolution of drought under future climate conditions and the improvement of ground level $\text{PM}_{2.5}$ estimation using an integrated modeling framework. The first part evaluates drought projections under the SSP5-8.5 scenario using a six member CMIP6 ensemble dynamically downscaled with a Regional Climate Model version 4 (RegCM4). Three drought indices, the Self Calibrating Palmer Drought Severity Index (ScPDSI), the 12 month Standardized Precipitation Index (SPI-12), and the 12 month Standardized Precipitation Evapotranspiration Index (SPEI-12), are applied to assess projected drought patterns across the contiguous United States for the near future and mid century periods. Results show that mild droughts become more frequent, while severe and extreme droughts generally decline. Persistent drying is projected in the western and southwestern regions due to long term soil moisture deficits. Although total drought exposure decreases after 2040, urban populations remain more affected than rural populations, indicating unequal vulnerability across regions. The second part develops a CMAQ machine learning framework to improve satellite based $\text{PM}_{2.5}$ estimation. The approach integrates outputs from a chemical transport model with aerosol optical depth retrievals and extended surface monitoring networks. Including spatial and temporal features improves accuracy in rural and downwind regions where monitoring coverage is limited. The final part links drought and $\text{PM}_{2.5}$ exposure to health and economic outcomes. Health impact assessments show that respiratory and cardiovascular diseases dominate the total burden, with urban populations experiencing three to five times higher risks than rural areas. National drought related health costs exceed 40 billion USD in the early decades, while $\text{PM}_{2.5}$

related impacts surpass 100 billion USD each year. These findings highlight that climate driven environmental stressors impose substantial and unequal burdens on human health and economic wellbeing across the United States.

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CHAPTER 1 INTRODUCTION

1.1 Research Motivation

Climate change has profoundly altered the characteristics of extreme environmental stressors, introducing substantial uncertainties for both natural and human systems. Among these stressors, drought and fine particulate matter (PM_{2.5}) are two of the most consequential, with wide-ranging implications for water resources, ecosystems, agriculture, and public health. Globally, drought has emerged as one of the costliest natural hazards, responsible for more than USD 124 billion in economic losses and affecting over 1.5 billion people between 1998 and 2017 (FAO 2018). The most recent assessment by the Intergovernmental Panel on Climate Change (IPCC) highlights that anthropogenic warming has already increased the likelihood and intensity of agricultural and ecological droughts in many regions (IPCC 2021).

At the same time, air pollution remains a leading global environmental risk factor. Ambient PM_{2.5} exposure is estimated to contribute to approximately 4.2 million premature deaths annually, primarily through cardiovascular and respiratory diseases (World Health Organization 2021, Murray *et al* 2020). In the contiguous United States (CONUS) alone, recent studies have suggested that nearly 100,000 annual deaths can be attributed to long-term PM_{2.5} exposure, with significant economic costs exceeding USD 800 billion per year (Burnett *et al* 2018, Tessum *et al* 2021).

The concurrent risks posed by drought and PM_{2.5} pollution present unique challenges. Drought threatens water and food security by disrupting hydrological cycles and agricultural production, while PM_{2.5} pollution disproportionately burdens vulnerable populations such as children, the elderly, and those with pre-existing conditions. Importantly, both hazards are strongly modulated by climate variability. Projected increases in temperature extremes and

precipitation variability under future warming scenarios may exacerbate drought conditions, while climate-driven meteorological changes, including enhanced atmospheric stagnation and increased wildfire activity, are expected to worsen PM_{2.5} episodes (Dai 2013, Mickley *et al* 2004).

This dissertation is motivated by the urgent need to quantify the evolving risks of drought and air pollution under climate change using an integrated, multiscale modeling framework. By bridging climate dynamics, atmospheric chemistry, and human exposure assessment, this research seeks to provide actionable insights for environmental management and policy adaptation.

1.2 Climate Change, Drought and Air Pollution

Drought is a multifaceted climatic phenomenon driven by interactions among precipitation, evapotranspiration, soil moisture, and atmospheric circulation. Unlike unidirectional intensification, projections suggest that drought patterns will become more erratic, with some regions experiencing longer, more persistent dry periods, while others face alternating episodes of drought and extreme rainfall (Trenberth *et al* 2014, Zhao and Dai 2022). This variability challenges traditional water management strategies that rely on historical stationarity, underscoring the need for flexible, adaptive frameworks (Milly *et al* 2008).

To capture the complexity of drought, several indices have been developed. The Standardized Precipitation Index (SPI) (McKee *et al* 1993) focuses solely on precipitation anomalies, while the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano *et al* 2010) incorporates atmospheric evaporative demand, making it more responsive to warming-driven changes. The Palmer Drought Severity Index (PDSI) and its self-calibrating variant (ScPDSI) (Wells *et al* 2004) integrate soil moisture accounting and have been widely

applied in long-term drought assessments. Each metric highlights different aspects of drought risk, and discrepancies among them complicate regional projections (Ault 2020). This dissertation leverages multiple indices to evaluate drought variability across spatial and temporal scales.

Air pollution, particularly $PM_{2.5}$, arises from diverse anthropogenic and natural sources, including fossil fuel combustion, industrial processes, agriculture, biomass burning, wildfires, and dust storms (Pope and Dockery 2006, Lelieveld *et al* 2015). Climate change affects both the sources and atmospheric processing of $PM_{2.5}$. For instance, higher temperatures can accelerate secondary aerosol formation, while drought-induced wildfires and dust storms increase episodic $PM_{2.5}$ emissions (Ford *et al* 2018, Stowell *et al* 2022). Conversely, increased precipitation may temporarily improve air quality via wet deposition, but this benefit is offset by the rising frequency of stagnation events and persistent high-pressure systems that inhibit pollutant dispersion (Jacob and Winner 2009).

The interaction between drought and air pollution is particularly concerning. During drought, reduced soil moisture and vegetation stress enhance wildfire probability and dust mobilization, both of which inject substantial amounts of particulate matter into the atmosphere. Moreover, drought conditions often coincide with synoptic-scale high-pressure systems that suppress vertical mixing, prolonging pollutant residence times near the surface (He *et al* 2024). Recent studies in western North America have shown that compound hot and dry conditions amplify $PM_{2.5}$ extremes by increasing both fire risk and atmospheric stagnation, posing severe challenges for air quality management (Zhong *et al* 2025, Wang *et al* 2017).

In sum, climate change simultaneously modifies drought characteristics and air pollution dynamics, with overlapping consequences for ecosystems and human health. Despite extensive

independent research on each hazard, there remains a pressing need to understand their coupled evolution under warming conditions, particularly at high spatial resolution and across multiple timescales. Given these changing environmental dynamics, it is critical to evaluate their health and environmental consequences.

1.3 Impacts on Human Health and the Environment

The instability of drought conditions and the persistence of degraded air quality have far-reaching implications for human health, ecosystems, and socio-economic systems. These hazards interact with and reinforce one another, producing overlapping stressors that affect multiple aspects of human and environmental well-being. A growing body of research underscores the urgency of understanding these interactions to improve resilience strategies.

1.3.1 Human Health Impacts of Drought

Drought exerts direct and indirect health effects through pathways that include water scarcity, food insecurity, and heightened exposure to extreme heat and wildfires. Reduced water availability compromises hygiene and sanitation, increasing the risk of diarrheal and vector-borne diseases (Ebi and Bowen 2016). Agricultural drought reduces crop yields, contributing to undernutrition and micronutrient deficiencies, particularly in low-income communities dependent on subsistence farming (Belesova *et al* 2019). Prolonged drought conditions also intensify heat stress, elevating risks of dehydration, heatstroke, and mortality, especially among elderly populations (Horton *et al* 2010).

In regions prone to wildfire, drought-induced vegetation dryness substantially increases fire frequency and severity, resulting in hazardous smoke exposure (Ford *et al* 2018). Wildfire smoke is a major source of PM_{2.5}, containing a complex mixture of organic carbon, black carbon, and toxic trace elements, which contribute to respiratory infections, asthma exacerbation, and

cardiovascular morbidity (Reid *et al* 2016). Recent epidemiological evidence from California indicates that wildfire PM_{2.5} is associated with disproportionately higher respiratory hospital admissions compared to PM_{2.5} from urban sources (O'Dell *et al* 2019).

1.3.2 Human Health Impacts of PM_{2.5} Pollution

Air pollution, particularly fine particulate matter (PM_{2.5}, aerodynamic diameter ≤ 2.5 μm), is one of the most pervasive environmental risk factors worldwide. Long-term exposure to PM_{2.5} has been linked to increased incidence of ischemic heart disease, stroke, chronic obstructive pulmonary disease, lung cancer, and diabetes (Pope and Dockery 2006, Lelieveld *et al* 2015). In the CONUS, fine particles are implicated in more than 90,000 deaths annually, disproportionately affecting disadvantaged and minority communities (Tessum *et al* 2021).

The biological mechanisms underlying PM_{2.5} health impacts include systemic inflammation, oxidative stress, endothelial dysfunction, and altered autonomic nervous system regulation (Brook *et al* 2010). Emerging evidence also suggests associations with neurodevelopmental disorders and cognitive decline, indicating that the health burden of PM_{2.5} may be broader than previously recognized (Liu *et al* 2023a). Short-term exposure during pollution episodes has been associated with acute respiratory infections and increased hospital admissions, while chronic exposure reduces life expectancy (Shah *et al* 2015).

1.3.3 Environmental Impacts of Drought and Air Pollution

Beyond human health, drought and air pollution destabilize ecological systems. Drought-induced reductions in soil moisture impair plant productivity and alter species composition, accelerating desertification and biodiversity loss (Hassan *et al* 2024). Soil degradation reduces carbon sequestration capacity, feeding back into climate change by releasing stored carbon (Lal 2004). Persistent drought also undermines aquatic ecosystems, leading to declining freshwater

availability, reduced habitat quality, and increased fish mortality (Mosley 2015).

Air pollution similarly affects ecosystems. Elevated concentrations of PM_{2.5} reduce solar radiation reaching the surface, impairing photosynthesis and crop yields (Richard *et al* 2024). Deposition of pollutants such as nitrogen and sulfur compounds alters soil chemistry, leading to acidification and nutrient imbalances that stress vegetation (Biswas *et al* 2018). When drought and pollution co-occur, the combined stress often accelerates ecosystem collapse. For example, ozone and particulate pollution exacerbate drought-induced crop losses, with cascading consequences for food prices and livelihoods (Tian *et al* 2016).

1.3.4 Socioeconomic Dimensions

The socio-economic impacts of drought and air pollution are profound. Drought-driven agricultural losses increase food insecurity, disrupt rural economies, and may trigger migration (Moghaddam *et al* 2024). Air pollution imposes substantial economic costs through healthcare expenditures, reduced labor productivity, and crop damage. In the CONUS, the annual economic burden of air pollution-related mortality and morbidity is estimated at hundreds of billions of dollars (Ahmed *et al* 2025). These burdens are not equally distributed: socially disadvantaged groups often experience higher exposures and lower adaptive capacity, underscoring the environmental justice dimension of the problem (Smith *et al* 2022).

1.3.5 Compound and Cascading Risks

Crucially, drought and air pollution are not independent. Drought intensifies air pollution through wildfire emissions, dust storms, and atmospheric stagnation, while pollution can exacerbate drought impacts by reducing precipitation via aerosol-cloud interactions (He *et al* 2024). Such compound events create cascading risks that extend across sectors, amplifying threats to food, water, health, and energy systems (Alcántara-Ayala 2025). Understanding these

compound interactions is vital for developing integrated adaptation strategies.

1.4 Knowledge Gaps

Although many studies have examined climate change, drought, and air pollution, most of them focus on each process separately. As a result, there is still limited understanding of how these systems co-evolve under future climate conditions. Existing climate models often have simplified representations of land–atmosphere processes, which constrain their ability to reproduce regional hydrological variability and drought persistence. Current projections also differ widely across models and regions, partly because of inconsistent approaches to bias correction, downscaling, and model validation. Another important gap lies in the integration of physical and social dimensions of drought risk. Many studies quantify meteorological or hydrological droughts without connecting them to population exposure or potential health and economic impacts. This disconnect restricts our ability to evaluate who is most affected and where the risks are concentrated. In addition, few studies use a multiscale perspective that links global climate drivers to local exposure assessments. Without such integration, it remains difficult to assess how large-scale climate forcing translating into local vulnerability.

1.4.1 Gaps in Drought Projections

Most projections of future drought rely on global climate models (GCMs) that operate at coarse spatial resolutions (100–250 km). While GCMs provide valuable insights into global hydroclimatic trends, their limited spatial resolution restricts the accurate simulation of regional drought processes such as soil moisture dynamics, topography-driven precipitation patterns, and land–atmosphere feedbacks (Dai 2013, Cook *et al* 2015). Biases in GCM precipitation and temperature fields further complicate regional drought assessment, leading to uncertainty in the frequency and severity of projected droughts (Zhou *et al* 2023). Dynamical downscaling via

regional climate models (RCMs) has been applied to address these challenges, but relatively few studies have combined RCMs with multiple drought indices to provide a systematic assessment of drought characteristics at high spatial resolution (Raju and Kumar 2020, Zhou *et al* 2023). Furthermore, the implications of downscaling biases for population-level exposure remain poorly quantified.

1.4.2 Gaps in Air Pollution Estimation under Climate Change

Air pollution research has advanced rapidly with the integration of satellite observations, chemical transport models (CTMs), and machine learning (ML) techniques (van Donkelaar *et al* 2019). However, several gaps persist: First, sample imbalance and monitoring bias: Most ML models are trained on monitoring networks that are denser in urban areas, leading to systematic underperformance in rural and underserved regions (Li *et al* 2024b, Zhen *et al* 2025). This imbalance skews exposure estimates, with important implications for environmental equity. Second, the climate sensitivity of PM_{2.5}: While previous studies have examined how meteorological conditions influence PM_{2.5} formation and dispersion (Jacob and Winner 2009, Stowell *et al* 2019), few have evaluated how future changes in temperature, humidity, and atmospheric circulation may modify PM_{2.5} concentrations and the associated health risks. Third, the integration of multiyear and multisource data: Many ML studies focus on single-year or single-network datasets, which limit generalizability. There is a need for frameworks that integrate multiyear observations and multiple monitoring networks to reduce bias and enhance spatial coverage.

1.4.3 Gaps in Health and Socioeconomic Impact Assessments

Although the adverse health effects of both drought and PM_{2.5} exposure are well documented, their joint impacts remain poorly understood. Most epidemiological studies isolate

individual hazards rather than considering compound or cascading risks (Reid *et al* 2016, Zscheischler *et al* 2018). Moreover, relatively few studies have incorporated population projections into climate and air quality impact assessments, limiting our ability to anticipate future burdens under different socioeconomic pathways (Huang *et al* 2020). The lack of integrated frameworks linking climate projections, air quality modeling, and population vulnerability hinders comprehensive evaluations of environmental justice and public health equity.

1.4.4 Need for Integrated Multiscale Approaches

Current research is often fragmented, focusing either on climate-driven drought projections, air pollution modeling, or health impact assessment in isolation. What is missing is an integrated, multiscale approach that: 1. Dynamically downscales GCMs to resolve regional drought processes. 2. Incorporates multiple drought indices to capture different hydroclimatic dimensions. 3. Couples CTM outputs with ML algorithms to address monitoring gaps and improve the predictions of PM_{2.5}. 4. Links climate and air quality projections with population and health exposure assessments.

Bridging these gaps is critical for developing actionable knowledge. Without integrated frameworks, policymakers risk underestimating the compound hazards posed by drought and air pollution, particularly for vulnerable populations. This dissertation addresses these gaps by combining regional climate downscaling, multivariate drought characterization, machine learning-based PM_{2.5} estimation, and population exposure assessments into a unified framework.

1.5 Research Contributions

This dissertation makes several contributions to the fields of climate change impacts, drought and air quality modeling, and environmental health assessment. By integrating high-

resolution climate modeling, machine learning approaches, and exposure analysis, the study advances scientific understanding of how compound hazards evolve under warming conditions and what their implications are for vulnerable populations. The major contributions can be summarized as follows:

1.5.1 Advancing High-Resolution Drought Projections

Most prior studies of future drought rely on coarse-resolution global climate models (GCMs), which fail to adequately represent regional hydrological processes. This dissertation uses a six-member CMIP6 ensemble dynamically downscaled to 4 km resolution with a regional climate model to provide a comprehensive assessment of drought characteristics across the contiguous United States for 1980–2059. Multiple drought indices, including SPI, SPEI, and ScPDSI, are applied to ensure a multi-perspective evaluation of regional variability.

This is one of the first systematic efforts to assess how different drought metrics project regional variability at such fine spatial resolution, enabling improved representation of local hydrological processes and better alignment with decision-making needs. The study also explicitly quantifies biases introduced by downscaling and their implications for drought frequency and intensity, addressing a key gap in climate impact assessments.

1.5.2 Developing a CMAQ–Machine Learning (CMAQ–ML) Testbed for PM_{2.5} Estimation

Traditional PM_{2.5} estimation approaches using satellite remote sensing or empirical models are often biased toward well-monitored urban regions, leaving large uncertainties in rural areas. This dissertation develops a hybrid testbed that integrates outputs from the Community Multiscale Air Quality (CMAQ) model with machine learning algorithms (Random Forest, XGBoost, LightGBM, ResNet). This framework addresses sample imbalance, evaluates the role of multiyear training data, and examines the influence of spatially distributed monitoring

networks.

The testbed provides a reproducible, scalable framework for assessing PM_{2.5} estimation biases and correcting them under different observational constraints. It demonstrates that integrating physical model simulations with ML significantly reduces prediction errors in monitor-sparse regions, enhancing the accuracy of air quality assessments. This represents a methodological innovation that bridges atmospheric science and data-driven modeling.

1.5.3 Linking Drought and Air Pollution to Human Health and Equity

A critical but underexplored research area is the joint impact of drought and air pollution on human exposure and health. This dissertation integrates drought classifications with gridded population projections under SSP5-8.5 to evaluate future drought exposure. It further combines improved PM_{2.5} estimates with population data to assess health impacts and economic costs, with particular attention to environmental equity between urban and rural populations.

This is one of the first studies to jointly quantify population exposure to both drought and PM_{2.5} under climate change using an integrated modeling framework. By linking hazard projections to socioeconomic and health outcomes, the research bridges a longstanding gap between climate science and public health. The findings provide actionable insights for adaptation planning, especially for agencies such as the U.S. Environmental Protection Agency (EPA), Centers for Disease Control and Prevention (CDC), and Department of Energy (DOE).

1.5.4 Overarching Framework and Novelty

The dissertation is unified by a multiscale, interdisciplinary framework (Figure 1.1) that connects global climate drivers, regional hazard projections, machine learning-based air quality estimation, and population exposure assessment. The novelty lies not only in advancing individual methodological components but also in their integration, which allows for a holistic

understanding of climate-driven compound risks.

Overall Contribution: 1. Scientific: Provides high-resolution projections of drought and PM_{2.5} evolution under climate change, addressing key methodological and knowledge gaps. 2. Methodological: Introduces a novel CMAQ–ML testbed that reduces bias in PM_{2.5} exposure estimates, particularly in under-monitored regions. 3. Societal: Quantifies health and economic impacts of drought and air pollution, highlighting implications for environmental justice and informing adaptation strategies.

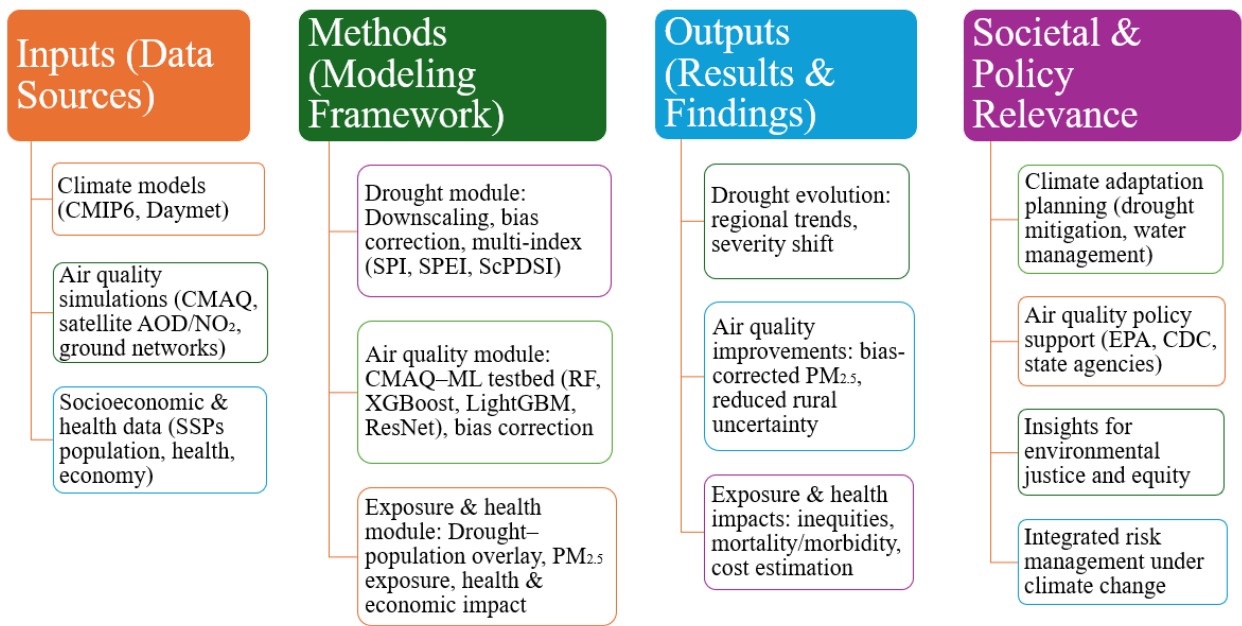


Figure 1.1 Research Flowchart: Drought, Air Quality, and Health Impacts under Climate Change.

CHAPTER 2 DROUGHT EVOLUTION AND BIAS IN CLIMATE DOWNSCALING

A version of this chapter has been published as: Zhang, L., Rubin, H.J., Chien, R.Y., Fu, J.S., Rastogi, D., Kao, S.C. and Ashfaq, M., 2025. Projected evolution of droughts and human exposure in the contiguous United States under SSP5-8.5: a regional downscaling perspective. *Environmental Research Letters*, 20(9), p.094021, <https://doi.org/10.1088/1748-9326/adf4f9>.

2.1 Research Question

Evaluating the Evolution of Droughts and Human Exposure in the Contiguous United States (CONUS) under SSP5-8.5: Insights from Regional Dynamical Downscaling of CMIP6.

2.2 Introduction

Drought is a complex and persistent climatic hazard that significantly impacts water resources, agriculture, public health, and economic stability across the CONUS (Heim 2002, Leeper *et al* 2022, Sugg *et al* 2020, Wilhite 2000, Zhang *et al* 2020). Recent extreme droughts, such as those in 2000, 2002, 2006, and 2011–2013, have highlighted the increasing severity and spatial variability of drought conditions (Rippey 2015). These events have exacerbated wildfire risks, crop losses, and water shortages, while also impacting human health through increased respiratory diseases, vector-borne infections, and reduced water quality (Chang *et al* 2016, Littell *et al* 2016, Falloon *et al* 2018, Covich *et al* 2009, Chiang *et al* 2018). Economically, drought disasters in the U.S. have accounted for over \$31 billion in losses between 1980 and 2023 (Smith 2020), underscoring the need for improved drought prediction and management strategies. The 2012 Midwest drought, for instance, caused severe agricultural losses and disrupted global food markets (Hoerling *et al* 2014, Otkin *et al* 2018), while the 2020–2021 Western U.S. megadrought

has been described as the most severe in at least 1200 years (Williams *et al* 2020). These events emphasize the urgency of understanding both historical variability and future projections of drought under climate change. Beyond the U.S., major droughts in Australia, Europe, and China further demonstrate the global nature of this risk (Spinoni *et al* 2019), highlighting the value of CONUS as a testbed for regional drought assessment.

Drought monitoring relies on quantitative indices that assess precipitation deficits, evapotranspiration, and soil moisture conditions, each with unique strengths and limitations (Mishra and Singh 2010). The Standardized Precipitation Index (SPI-12) is widely used for meteorological drought monitoring, as it is based solely on precipitation variability, making it useful for comparisons across different climate zones and time scales (McKee *et al* 1993, Vicente-Serrano *et al* 2010, Agnew 2000). However, SPI does not account for evapotranspiration, making it less reliable in regions where temperature-driven water loss is significant, such as the Western U.S. under a warming climate (Hoffmann *et al* 2020). To address these limitations, the Standardized Precipitation-Evapotranspiration Index (SPEI-12) extends SPI by incorporating potential evapotranspiration (PET), enabling a more comprehensive assessment of temperature-driven drought risks (Vicente-Serrano *et al* 2012, Beguería *et al* 2014). However, the accuracy of SPEI depends on the PET estimation method, with the Thornthwaite PET method being highly sensitive to temperature changes but lacking explicit energy balance considerations, which can lead to overestimation of drought severity in warming scenarios (Vicente-Serrano *et al* 2020). To mitigate these uncertainties, studies increasingly adopt the Penman-Monteith PET method, which accounts for radiative and aerodynamic influences and provides a more physically realistic estimation (Li *et al* 2024c). Beyond precipitation and temperature, soil moisture dynamics play a crucial role in determining

drought severity. The Self-Calibrating Palmer Drought Severity Index (ScPDSI) explicitly accounts for soil moisture balance and water-holding capacity, making it particularly useful for evaluating hydrological and agricultural droughts (Dai and Zhao 2017). Additional indices such as the Evaporative Demand Drought Index (EDDI) have been developed to emphasize atmospheric drivers of drought (Hobbins *et al* 2016), while satellite-based products from SMOS and SMAP missions provide novel opportunities for soil-moisture-driven drought monitoring (Entekhabi *et al* 2010). Moreover, short-term indices (e.g., SPEI-3) have been shown to better capture agricultural droughts, whereas long-term indices (e.g., SPEI-12) are more relevant for water resource planning (Vicente-Serrano *et al* 2012).

Unlike SPI and SPEI, ScPDSI integrates regional soil moisture conditions, providing a long-term perspective on drought persistence. However, its reliance on predefined calibration coefficients may limit its responsiveness to short-term precipitation variability (Karl 1986). Studies have shown that soil moisture-based drought indices, such as ScPDSI, align more closely with hydrological and agricultural drought risks than precipitation-based indices alone (Vicente-Serrano *et al* 2020, Wang *et al* 2017). While these indices differ in methodology and scope, their combined use provides a comprehensive assessment of drought evolution, capturing distinct precipitation-driven, temperature-driven, and soil moisture-based drought dynamics. In the U.S., the U.S. Drought Monitor (USDM) integrates multiple indices, including SPI and PDSI, to provide a comprehensive national drought classification system, ensuring that no single index dominates drought assessments and enhancing the robustness of decision-making for water resource management, agriculture, and emergency planning (Svoboda *et al* 2002). Thus, employing a multi-index approach is critical to capturing diverse drought processes and reduce uncertainty in future projections.

While historical precipitation and temperature trends are well-documented (McEnery *et al* 2005), predicting future drought conditions requires high-resolution climate models that can capture fine-scale atmospheric and land-surface interactions. The Coupled Model Intercomparison Project Phase 6 (CMIP6) provides standardized future projections from global climate models (GCMs), incorporating Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) to assess climate impacts under various emissions scenarios (Eyring *et al* 2016, O'Neill *et al* 2016). Among these, the SSP5-8.5 scenario, which represents a high-emissions trajectory with an 8.5 W/m² radiative forcing, is commonly used to assess worst-case climate impacts. However, the coarse resolution (~110 km) of CMIP6 models limits their ability to resolve regional drought characteristics, necessitating dynamical downscaling for improved accuracy (Ashfaq *et al* 2016a, Maurer *et al* 2013). Compared to CMIP5, CMIP6 models offer enhanced representation of land-atmosphere feedbacks and improved simulation of hydroclimatic extremes (Eyring *et al* 2016, Zhao and Dai 2022). Yet significant inter-model spread persists, underscoring the importance of multi-model ensembles to capture uncertainty (Niu *et al* 2025). Furthermore, while SSP2-4.5 represents a stabilization pathway, focusing on SSP5-8.5 allows this study to explore the upper bound of potential risks, consistent with other high-end risk assessments (Zhou *et al* 2023).

While statistical downscaling relies on empirical relationships between historical observations and GCM outputs, dynamical downscaling explicitly resolves regional climate processes, including orographic precipitation and land-atmosphere feedbacks (Coppola *et al* 2021, Rastogi *et al* 2022). This study employs RegCM4-based downscaling to refine CMIP6 projections to 4-km resolution, coupled with bias correction using Daymet V4 to enhance the accuracy of precipitation and temperature estimates. Bias correction methods such as quantile

mapping and distribution mapping have been widely applied (Cannon *et al* 2015), but trend-preserving methods are increasingly recognized as essential for maintaining long-term climate signals. The Daymet V4 dataset offers high-resolution gridded daily meteorological fields and has been widely adopted for ecological and hydrological studies, making it a robust basis for correcting biases in regional projections.

In summary, while prior studies have examined drought trends using global or coarse-resolution datasets, important gaps remain in linking fine-scale projections with multi-index drought assessments and human exposure. This chapter addresses these gaps by applying RegCM4-based dynamical downscaling to a six-member CMIP6 ensemble under SSP5-8.5, bias-corrected with Daymet V4, and integrating SPI-12, SPEI-12, and ScPDSI to provide a comprehensive assessment of drought evolution across CONUS.

2.3 Objective

This study provides a comprehensive assessment of projected drought trends across CONUS using three widely recognized drought indices: SPI-12, SPEI-12, and ScPDSI. By integrating high-resolution dynamical downscaling with bias correction, we improve the spatial resolution and reliability of drought projections compared to traditional methods. Furthermore, our regional climate-zone-based analysis and multi-model ensemble approach allow for a detailed evaluation of localized drought variations.

Beyond these overarching aims, the specific objectives of this chapter are threefold. First, we seek to quantify the evolution of drought characteristics under the SSP5-8.5 scenario using a six-member CMIP6 ensemble dynamically downscaled to a spatial resolution of 4 kilometers. Second, we evaluate the strengths and limitations of multiple drought indices (SPI-12, SPEI-12, and ScPDSI) in capturing distinct hydroclimatic processes, thereby providing a multi-perspective

view of future drought risk. Third, we analyze regional variations in drought projections by applying the NOAA climate region classification, which facilitates the identification of geographically heterogeneous trends across the eastern, central, and western United States.

2.4 Methods and Data

2.4.1 Drought Indices and Classification

To assess projected drought conditions, we employ three widely used drought indices: SPI-12, SPEI-12, and ScPDSI. SPI-12 is calculated solely based on precipitation variability, making it particularly useful for assessing meteorological droughts, whereas SPEI-12 extends SPI by incorporating PET to account for temperature-driven drought conditions. ScPDSI, in contrast, explicitly considers soil moisture balance, making it more suitable for assessing long-term hydrological and agricultural droughts.

For SPI-12 and SPEI-12, we use a 12-month accumulation period, allowing for the detection of prolonged precipitation deficits relevant to water availability, reservoir storage, and agricultural droughts. Shorter accumulation periods (e.g., 3- or 6-month SPEI) are often applied in agricultural drought studies to reflect rapid soil moisture changes (Vicente-Serrano *et al* 2012), whereas longer accumulation periods (12 months or more) better capture hydrological drought signals and water resource planning concerns (Svoboda *et al* 2002). Thus, we focus on 12-month indices to assess basin-scale and long-term water security.

The standardization of SPI-12 and SPEI-12 is performed using the 1980–2019 period as the historical reference baseline, ensuring consistency in drought characterization and enabling meaningful comparisons with future projections. SPEI-12 is computed using the Penman-Monteith PET method, which accounts for radiative and aerodynamic influences, providing a more physically robust estimation than the commonly used Thornthwaite approach (Zhao *et al*

2023b). ScPDSI calculations follow the methodology outlined in (Dai and Zhao 2017), integrating precipitation, temperature, and soil moisture conditions to assess long-term drought severity.

SPI (Standardized Precipitation Index) (McKee *et al* 1993):

$$SPI = \frac{P - \bar{P}}{\sigma_P} \quad (2.1)$$

where P is the observed precipitation, $\bar{P}$ is the long-term mean precipitation, and σ_P is the standard deviation of precipitation over a selected period. By standardizing precipitation deviations, SPI allows for drought classification based on how much a given month or year deviates from the norm. SPI does not account for temperature or evapotranspiration and is therefore primarily a measure of meteorological drought. In this study, SPI was calculated on a 12-month timescale (SPI-12) to assess long-term precipitation anomalies.

SPEI (Standardized Precipitation-Evapotranspiration Index) (Vicente-Serrano *et al* 2010):

$$SPEI = \frac{D - \bar{D}}{\sigma_D}, D = P - PET \quad (2.2)$$

where D represents the water balance, $\bar{D}$ and σ_D represent the mean and standard deviation of the D series over the selected period. Like SPI, SPEI is standardized, allowing for direct comparisons across different climatic regions. The inclusion of PET makes SPEI more sensitive to temperature-driven droughts, particularly in a warming climate. In this study, PET was estimated using the Variable Infiltration Capacity (VIC) hydrological model, with bias-corrected downscaled General Circulation Model (GCM) data (Zhao *et al* 2023a). By considering both precipitation deficits and increased evaporative demand, SPEI provides a more comprehensive assessment of drought severity.

ScPDSI (Self-Calibrating Palmer Drought Severity Index) (Palmer 1965). The ScPDSI is

based on a soil moisture accounting model and involves a more complex recursive calculation. It adjusts the original PDSI by dynamically calibrating climate and soil coefficients based on local conditions:

$$PDSI = Z_k + \left(\frac{P - PET - \text{Runoff} - \text{Recharge}}{\text{Water Demand}} \right) \quad (2.3)$$

where Z_k is the moisture anomaly index, and Runoff and Recharge represent soil moisture dynamics. ScPDSI dynamically adjusts its parameters based on local climate conditions, making it applicable across different regions.

The Penman-Monteith equation is shown below (Allen *et al* 1998):

$$PET = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)} \quad (2.4)$$

where R_n is net radiation at the crop surface ($\text{MJ m}^{-2} \text{ day}^{-1}$), G is soil heat flux density ($\text{MJ m}^{-2} \text{ day}^{-1}$), T is mean daily air temperature ($^{\circ}\text{C}$), u_2 is wind speed at 2 m height (m s^{-1}), e_s is saturation vapor pressure (kPa), e_a is actual vapor pressure (kPa), Δ is the slope of the vapor pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$), and γ is the psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$).

To estimate potential evapotranspiration (PET), this study employs the Variable Infiltration Capacity (VIC) hydrological model with the Penman-Monteith algorithm, using bias-corrected downscaled GCM data as input (Zhao *et al* 2023b). While the Penman-Monteith method is widely regarded as a physically realistic approach, it does not explicitly account for CO₂-induced stomatal resistance changes, which can affect plant water use efficiency and transpiration rates (Yang *et al* 2019). Given the growing body of research suggesting that CO₂-sensitive PET formulations may refine projections of future drought severity, future studies could incorporate dynamic vegetation models to better account for plant physiological responses under elevated CO₂ conditions (Swann *et al* 2016, Lemordant *et al* 2018).

Drought classification follows the U.S. Drought Monitor (USDM) and National Oceanic and Atmospheric Administration (NOAA) standardized thresholds, as shown in Table 2.1 (Svoboda *et al* 2002, Nam *et al* 2015). The D0–D4 categories represent increasing severity levels, ensuring consistency with historical drought assessments. While alternative indices such as the Evaporative Demand Drought Index (Hobbins *et al* 2016) or satellite-derived soil moisture drought indicators (Entekhabi *et al* 2010) offer additional perspectives, we focus on SPI, SPEI, and ScPDSI to ensure comparability with existing national monitoring frameworks and long-term hydroclimatic assessments.

Table 2.1 Drought Classification for SPI, SPEI, and ScPDSI. (*refer from USDM and NOAA).

Label	Category	SPI/SPEI (USDM)	ScPDSI (NOAA)
W4	Exceptional wet	2.0 or greater	5.0 or greater
W3	Extreme wet	1.6 to 2	4.0 to 5.0
W2	Severe wet	1.3 to 1.6	3.0 to 4.0
W1	Moderate wet	0.8 to 1.3	2.0 to 3.0
W0	Abnormally wet	0.5 to 0.8	1.0 to 2.0
N	Near Normal	-0.5 to 0.5	-1.0 to 1.0
D0	Abnormally drought	-0.8 to -0.5	-2.0 to -1.0
D1	Moderate drought	-1.3 to -0.8	-3.0 to -2.0
D2	Severe drought	-1.6 to -1.3	-4.0 to -3.0
D3	Extreme drought	-2.0 to -1.6	-5.0 to -4.0
D4	Exceptional drought	-2.0 or less	-5.0 or less

Given that drought severity and frequency are influenced by local precipitation patterns, evapotranspiration rates, and soil moisture conditions, our classification approach reflects regional hydroclimatic variability, particularly for ScPDSI-based drought analysis. Spatial

analyses primarily focus on ScPDSI, given its ability to capture long-term drought persistence and hydrological drought risks. However, comparisons with SPI-12 and SPEI-12 are conducted to evaluate the relative influence of precipitation variability and temperature-driven evapotranspiration in shaping future drought conditions across CONUS. Taken together, the multi-index approach provides complementary insights into different dimensions of drought, reducing the likelihood of over-reliance on any single metric.

2.4.2 Dynamical Downscaling and Bias Correction

To improve the spatial resolution of drought projections, this study employs dynamical downscaling using the Regional Climate Model version 4 (RegCM4). This approach refines the coarse-resolution CMIP6 global climate models (GCMs) (~110 km) to a high-resolution 4 km grid, improving the representation of regional climate variability, particularly in topographically complex regions such as the Western U.S. (Giorgi *et al* 2012, Coppola *et al* 2021). The primary advantage of dynamical downscaling lies in its ability to explicitly resolve land-atmosphere interactions and convective precipitation, factors that are often underestimated in raw GCM outputs (Rastogi *et al* 2022).

However, while downscaling enhances regional detail, it may inherit biases from the driving GCMs (Ashfaq *et al* 2016b). To correct these biases, we applied quantile mapping (QM) bias correction using the Daymet V4 observational dataset, a high-resolution (1 km) daily gridded meteorological dataset (Thornton *et al* 2022). Daymet was selected instead of alternatives such as PRISM or ERA5 due to its fine spatial resolution and long-term temporal consistency, which aligns with the needs of bias correction at local scales.

Previous studies have demonstrated that bias correction significantly improves the accuracy of precipitation and temperature projections, particularly in semi-arid and mountainous

regions where climate models struggle to capture local precipitation extremes (Rastogi *et al* 2022). This ensures that the temperature and precipitation inputs used for calculating SPI, SPEI, and ScPDSI are physically meaningful and statistically consistent with historical observations. Nonetheless, statistical corrections may alter the distribution of extreme values or dampen climate-change signals (Cannon *et al* 2015). To mitigate these risks, we apply trend-preserving approaches where feasible, ensuring that long-term climate trajectories remain intact.

The dataset covers a historical baseline (1980–2019) and two future periods: near-term (2020–2039) and mid-term (2040–2059), with additional details provided in (Rastogi *et al* 2022). The historical baseline extends to 2019 to incorporate the most recent high-resolution observations for bias correction, ensuring consistency with observational datasets and capturing recent climate conditions critical for drought assessment. The future periods are selected to assess both short-term climate variability and longer-term trends, aligning with policy-relevant timeframes used in previous hydroclimate assessments (Rastogi *et al* 2022) and facilitating comparisons across different research efforts. This design allows comparison of near-future adaptation challenges with mid-century policy-relevant horizons, consistent with IPCC WGII practices.

The reliability of the dynamically downscaled dataset used in this study is supported by prior evaluations presented in Rastogi *et al.* (Rastogi *et al* 2022). Their study assessed the performance of the RegCM4-downscaled CMIP6 models by comparing temperature and precipitation outputs against observational datasets, including Daymet and Livneh. The results demonstrated significant improvements in the representation of hydroclimatic variables after dynamical downscaling and bias correction. Temperature biases were notably reduced, particularly in regions where GCMs exhibited historical cold biases. The mean absolute error for

maximum temperature (Tmax) decreased by approximately 30% across CONUS, indicating that the downscaling process effectively corrects systematic errors in temperature simulations. In terms of precipitation, the downscaled dataset better captured precipitation variability compared to raw GCM outputs, particularly in the Southwest and Western U.S., where coarse-resolution models tend to underestimate extreme precipitation events. This enhancement is crucial for accurately assessing drought characteristics, as precipitation variability plays a key role in drought onset and persistence. Moreover, the finer grid resolution of $1/24^\circ$ (~4 km) significantly improved the representation of regional drought characteristics. This was especially evident in mountainous and semi-arid regions, where coarse-resolution GCMs struggle to accurately simulate localized climate patterns. This combination of dynamical downscaling and statistical bias correction ensures physically consistent and spatially detailed projections suitable for regional drought analysis.

2.4.3 Model Selection and Experimental Design

The multi-model ensemble consists of six CMIP6 GCMs (Table 2.2), selected based on (1) availability of high-frequency (6-hourly) atmospheric data required for downscaling, (2) demonstrated skill in reproducing historical precipitation and temperature variability over CONUS (Ashfaq *et al* 2022), (3) diversity in climate sensitivity to capture a broad range of hydroclimatic responses (Meehl et al., 2020), and (4) consistency with previous hydroclimate studies to ensure inter-comparability (Rastogi *et al* 2022). The selected models include high-sensitivity GCMs (e.g., ACCESS-CM2, CNRM-ESM2-1), which simulate stronger warming trends, and low-sensitivity models (e.g., MRI-ESM2-0, NorESM2-MM), which exhibit more moderate temperature increases. This diversity ensures that the ensemble captures both upper and lower bounds of projected warming and its associated impacts on drought patterns (Rastogi

et al 2022). The inclusion of models from different modeling centers also reduces the dependence on any single structural assumption and allows cross-validation of results, consistent with best practices in multi-model intercomparison projects (Eyring *et al* 2016). The study examines three time periods: a historical baseline (1980–2019), a near-term future (2020–2039), and a mid-term future (2040–2059), aligning with IPCC-relevant climate impact assessment timeframes (IPCC 2021). This experimental design ensures that the ensemble captures not only mean drought responses but also inter-model spread, enhancing the robustness of uncertainty quantification.

Table 2.2 The CMIP6 models were downscaled and combined into a multi model ensemble.

Model Name	Institution	Historical Performance	6-Hourly Data	Climate Sensitivity Class
ACCESS-CM2	CSIRO	High skill	Yes	High
CNRM-ESM2-1	CNRM-CERFACS	Moderate-high	Yes	High
GFDL-ESM4	NOAA-GFDL	High	Yes	Medium
IPSL-CM6A-LR	IPSL	Moderate	Yes	High
MRI-ESM2-0	MRI-JMA	Good	Yes	Low
NorESM2-MM	NCC	Good	Yes	Low

2.5 Results

Before examining temporal drought variability, this study adopts the National Centers for Environmental Information (NCEI) classification of the contiguous United States (CONUS) to ensure spatial consistency in regional analysis (Karl and Koss 1984). The NCEI divides CONUS into nine climate regions based on similarities in long-term temperature, precipitation, and circulation patterns. This framework provides a coherent spatial basis for comparing climatic

conditions and evaluating regional variability across the United States (Figure 2.1).

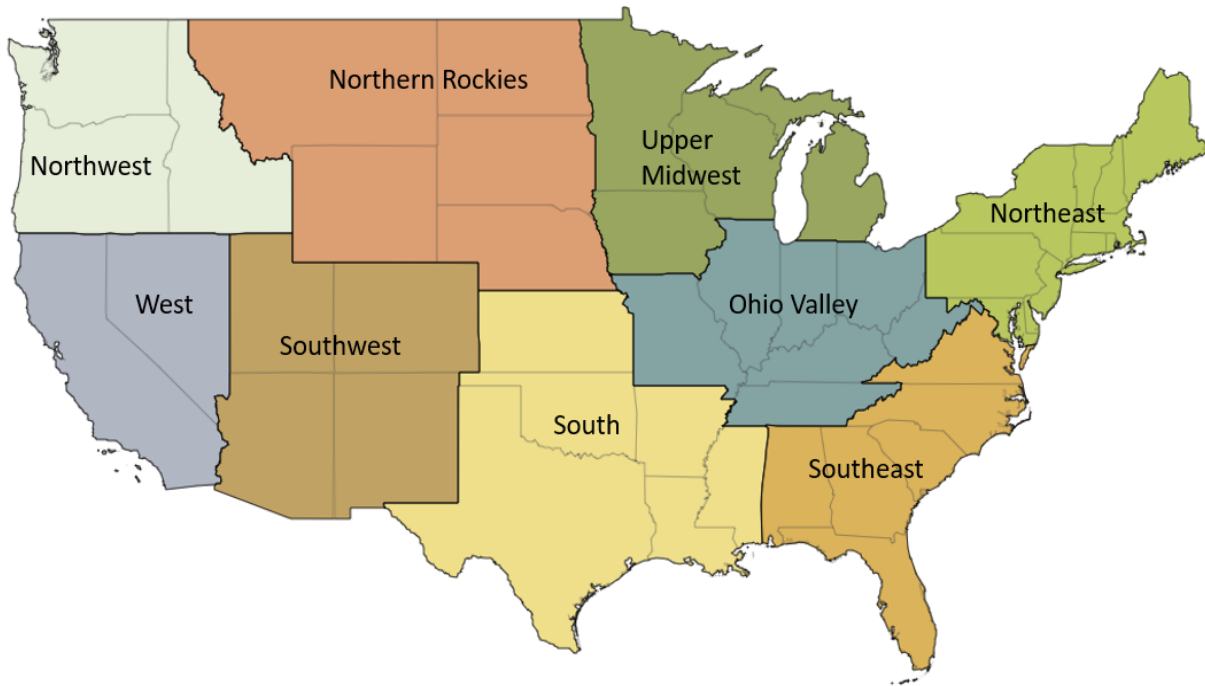


Figure 2.1 CONUS climate regions, as shown on the NCEI website (Karl and Koss 1984).

To better capture fine-scale climate processes, this study employs a six-member CMIP6 ensemble dynamically downscaled using RegCM4 and bias-corrected via a trend-preserving quantile-mapping method with the 1-km Daymet V4 dataset (Thornton *et al* 2022, Rastogi *et al* 2022). This approach improves the spatial representation of precipitation and temperature and provides a physically consistent basis for drought analysis. To examine temporal drought variability, the Standardized Precipitation–Evapotranspiration Index (SPEI) was first evaluated across multiple accumulation timescales (1-, 3-, 6-, 9-, and 12-month) to characterize short-term and long-term hydroclimatic fluctuations (Figure 2.2). Shorter timescales (e.g., SPEI-1 and SPEI-3) capture rapid moisture changes related to meteorological and agricultural droughts, while longer timescales (SPEI-9 and SPEI-12) highlight persistent hydrological drought conditions. The figure illustrates that short-term droughts exhibit higher variability and quicker

recovery, whereas long-term droughts display stronger persistence and deeper deficits, particularly during the early 2000s and after 2040 under continued warming.

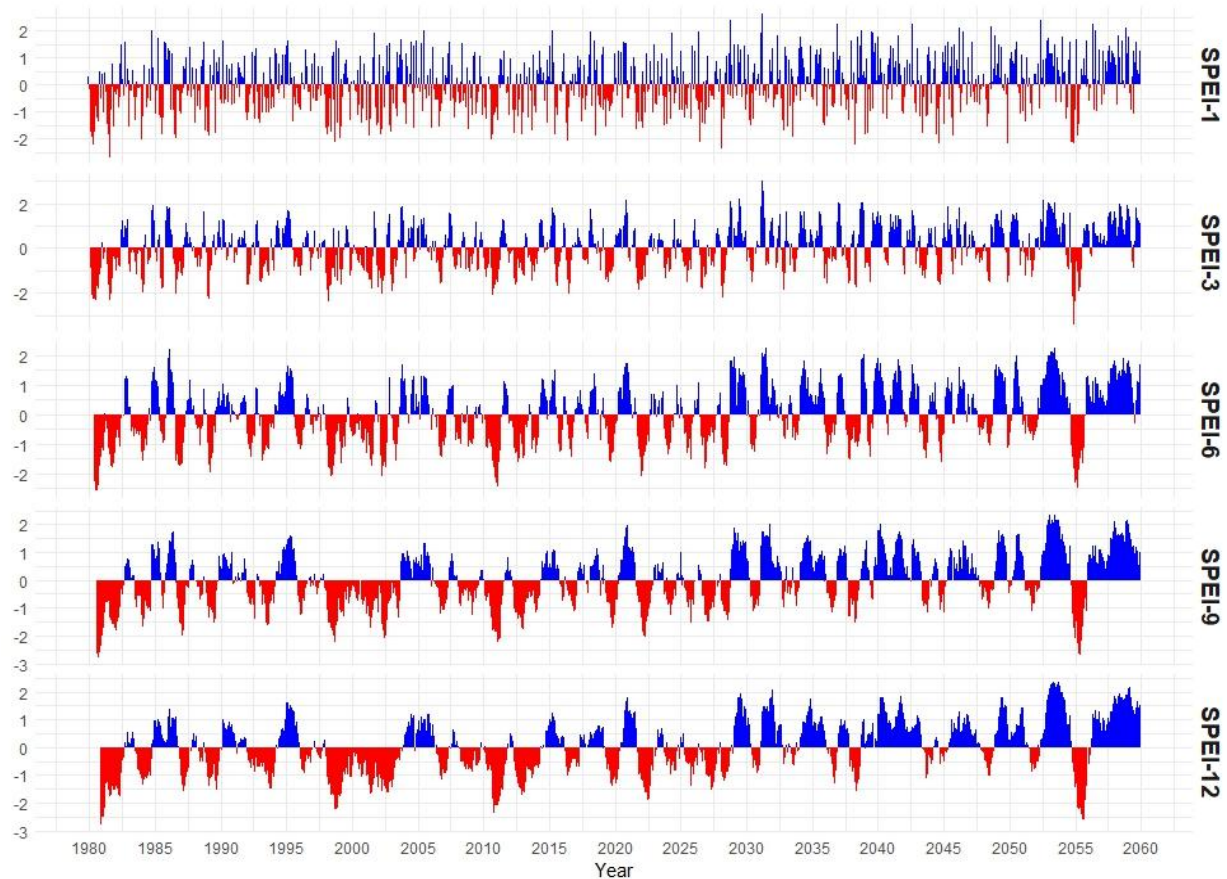


Figure 2.2 Temporal evolution of drought conditions across CONUS based on SPEI.

To assess regional drought characteristics, we analyzed SPI-12, SPEI-12, and ScPDSI across the CONUS from 1980 to 2059 (Figure 2.3). During the historical period, all three indices captured major drought events, indicating general consistency. For example, the indices collectively reproduce the 1988 Midwest drought, the early 2000s western drought, and the 2011–2013 Southern Plains drought, demonstrating their ability to reflect observed large-scale hydroclimatic anomalies. However, SPI-12 indicates a prolonged dry period between 1980 and the early 2000s, with frequent drops below -1, reflecting persistent precipitation deficits. In contrast, SPEI-12 captures shorter drought episodes, as increased evapotranspiration offsets

some precipitation deficits. ScPDSI drops below -5 during major droughts in the late 1990s and early 2000s, indicating deep and prolonged soil moisture depletion. Between 2020 and 2059, the indices reveal greater interannual variability, with differing directional trends. SPI-12 indicates a trend toward wetter conditions after 2040, marked by more frequent positive anomalies. While SPEI-12 continues to exhibit strong variability, with droughts intensifying during warmer years due to increased evapotranspiration. ScPDSI shows that the gradual soil moisture recovery in parts of the region reaches values above +5 in some cases after 2030. Taken together, these results highlight two key points. First, the general agreement across indices in identifying major drought events supports the robustness of the downscaled dataset. Second, systematic differences among precipitation-based, temperature-sensitive, and soil-moisture-driven indices demonstrate the necessity of a multi-index framework for credible drought assessment.

Dynamical downscaling enhances the utility of global climate model outputs by incorporating localized atmospheric processes and land–surface interactions, thereby improving the resolution and realism of regional hydroclimate projections. This approach is particularly valuable for assessing drought risk, which is influenced by complex interactions between precipitation, temperature, and soil moisture. To capture these diverse dimensions, Figure 2 illustrates projected regional shifts in drought frequency across the contiguous United States (CONUS) for the near-term (2020 to 2039) and mid-term (2040 to 2059), relative to the historical baseline (1980 to 2019), based on SPI-12, SPEI-12, and ScPDSI. The heatmaps illustrate percentage changes in drought classifications, with warm colors (red) representing an increase and cool colors (blue) indicating a decrease in drought probability relative to historical conditions. This finding is consistent with previous global and regional assessments (Zhao and Dai 2022, Zhou *et al* 2023), which also reported a reduction in near-normal states and an

increase in hydroclimatic volatility under high-emission scenarios.

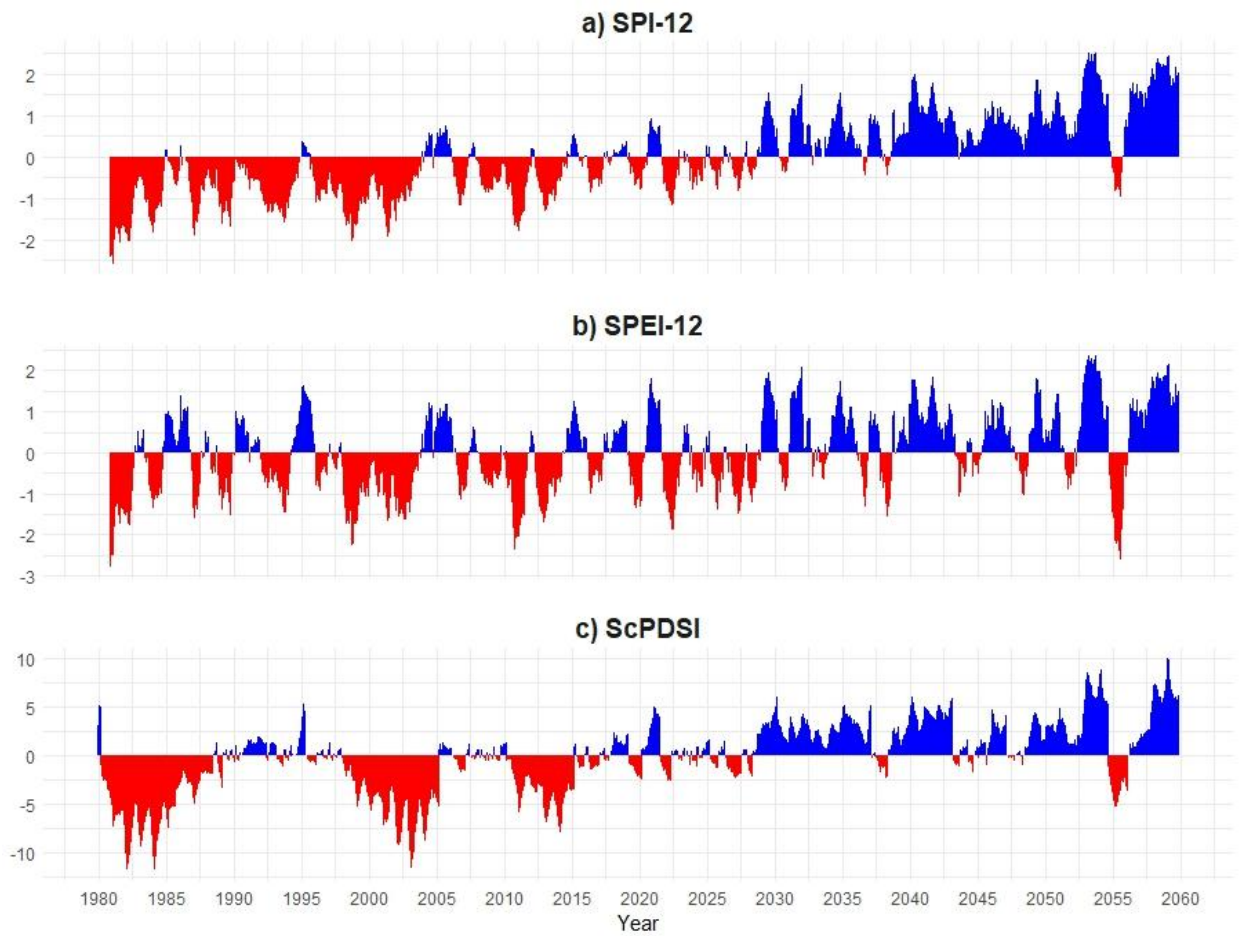


Figure 2.3 A comparison of drought conditions across CONUS. a) Standard Precipitation Index (SPI-12) calculated on a 12-month timescale, b) Standard Precipitation Evapotranspiration Index (SPEI) calculated on a 12-month timescale, and c) Self-calibrated Palmer Drought Severity Index (ScPDSI). *Note the ScPDSI uses a different Y-axis scale due to its distinct classification standards.

The three drought indices show regionally divergent yet complementary patterns across the contiguous United States, reflecting their sensitivities to precipitation variability, temperature-driven evaporative demand, and cumulative soil moisture deficits, respectively. To facilitate regional comparisons, we average the combined D1 and D2 proportions across each time period. In the Southwest, including California, Nevada, Arizona, and New Mexico, SPI-12

shows a decline of 5.70 percentage points in D1–D2 drought prevalence from the historical to near-term period and a further 7.40 points decline in the mid-term, indicating a reduction in short-term precipitation deficits. ScPDSI, by contrast, projects increase of 15.45 and 12.10 points across the same two periods, suggesting intensifying long-term drying. SPEI-12 results fall between these two, with respective increases of 1.35 and 2.40 points, likely due to enhanced evaporative demand under rising temperatures despite stable precipitation patterns. In the Northeast, both SPI-12 and SPEI-12 project substantial drought relief, with SPI-12 showing reductions of 14.45 and 15.95 points, and SPEI-12 showing declines of 9.65 and 12.95 points

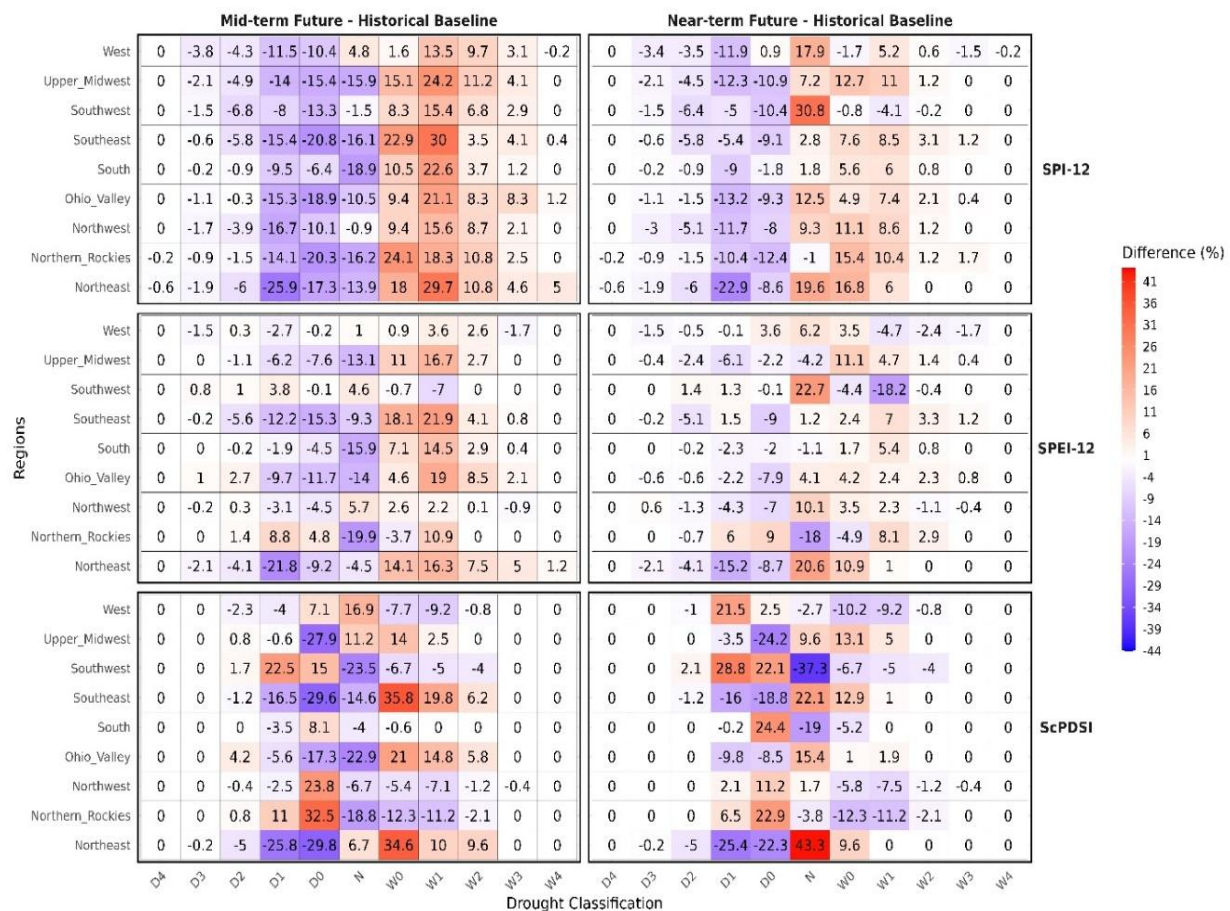


Figure 2.4 Projected regional changes in drought probability across the CONUS based on SPI-12, SPEI-12, and ScPDSI for the near-term (2020–2039) and mid-term (2040–2059) relative to the historical baseline (1980–2019).

across the two future periods. Meanwhile, ScPDSI indicates relatively stable long-term moisture conditions, with an increase in near-normal conditions and a decline in both dry and wet extremes. In the Northern Rockies, SPI-12 projects moderate declines of 5.95 and 7.80 points, while SPEI-12 shows increases of 2.65 and 5.10 points, and ScPDSI indicates 5.40 points increase in combined D1 and D2 frequencies by the mid-term. In Ohio Valley, SPI-12 suggests decreases of 7.35 and 7.80 points, SPEI-12 shows smaller reductions of 1.40 and 3.50 points, and ScPDSI indicates a shift from a 9.80-point reduction in D1 in the near-term to a 4.17-point increase in D2 in the mid-term, reflecting a transition toward long-term drying. Overall, SPI-12 frequently indicates decreasing drought severity due to its reliance on precipitation inputs alone, while ScPDSI captures persistent soil moisture deficits that develop over time. SPEI-12 reflects the compounding effects of both temperature and precipitation, often yielding intermediate outcomes. These divergent projections reinforce the value of using multiple indices to provide a more complete understanding of future drought risk across different regions and timescales.

Figure 2.5 illustrates the evolution of drought and wetness conditions across the CONUS from the 1980s to the 2050s, highlighting a clear divergence in regional climate trajectories, with increasing drought severity in the West and progressively wetter conditions in the East. The 10th percentile ScPDSI maps, which capture the most extreme dry conditions, indicate that drought was historically confined to the Southwest and southern Great Plains in the 1980s but gradually expanded over time. By the 2000s, severe drought (D3 to D4) became widespread across the Southwest, Great Plains, and portions of the Midwest, with California, Nevada, Arizona, and New Mexico showing persistent drying trends. From the 2020s through the 2050s, this pattern intensifies, placing the Southwest and Great Plains into prolonged drought cycles and heightening risks to agriculture, water availability, and wildfire occurrence. In contrast, the

Northeast and Great Lakes remain relatively resilient to prolonged drought, while the Southeast begins to exhibit growing drought risks, particularly in Texas, Alabama, Georgia, and Florida.

The median ScPDSI maps, representing typical moisture conditions each decade, further illustrate a shift toward drier baseline conditions across the West and Great Plains, where even average climate states are increasingly dominated by moderate to severe drought (D1-D2), suggesting that what was once considered an extreme dry period is becoming the new normal (Figure 2.5). This baseline drying trend has critical implications for groundwater recharge, agricultural productivity, and reservoir management, as systems historically designed around 20th-century norms may no longer be adequate under shifting baselines (Famiglietti 2014). The Northeast and Great Lakes, however, show a gradual shift in the opposite direction, with baseline conditions becoming wetter by the mid-century. The Southeast and Midwest exhibit greater variability, with alternating dry and wet periods, making long-term projections more uncertain. Such variability highlights the challenge of distinguishing anthropogenic signals from natural decadal variability (Hoerling *et al* 2014), emphasizing the need for ensemble-based assessments.

Meanwhile, the 90th percentile ScPDSI maps, which represent extreme wet periods, indicate that the Northeast, Great Lakes, and Ohio Valley are experiencing a sharp increase in extreme wetness events (W3-W4), with intense precipitation and flooding risks becoming more prominent from the 2020s onward. The Southeast, particularly along the Gulf Coast, also sees an increase in extreme wet conditions, likely linked to intensifying tropical storms and hurricanes. This finding is consistent with observed trends of increasing heavy rainfall events in the eastern U.S. (Easterling *et al* 2017, Kunkel *et al* 2020), suggesting that future flood risks will intensify alongside drought risks in different regions. In contrast, the Southwest and Great Plains experience a notable decline in extreme wet periods, reinforcing concerns that these regions are

not only drying out but also losing their ability to recover from drought through periodic wet spells. This growing climate divergence between the arid West and the increasingly wet East underscores the need for region-specific adaptation strategies. The Southwest and Great Plains must prioritize large-scale water conservation, drought-resistant infrastructure, and wildfire mitigation, while the Northeast and Ohio Valley must focus on flood management, stormwater resilience, and infrastructure upgrades to cope with more frequent heavy precipitation events. The Midwest and Southeast, facing both heightened drought and flood risks, will require flexible, dual-response strategies to manage increasing climate variability. From a national policy perspective, these findings suggest that a “one-size-fits-all” adaptation strategy is insufficient; instead, tailored regional approaches will be essential to address diverging hydroclimatic futures across the United States.

Figure 2.6 presents a detailed analysis of historical and projected percentage area affected by different drought categories (D0–D4) in the contiguous United States (CONUS) from 1980 to 2059, based on SPI-12, SPEI-12, and ScPDSI. The stacked bar plots (Figures 2.6a, 2.6c, 2.6e) illustrate the temporal evolution of the land area affected by each drought category over time, while the box plots (Figures 2.6b, 2.6d, 2.6f) summarize the distribution of the percentage area affected across three time periods: 1981–2019 (historical baseline), 2020–2039 (near-term future), and 2040–2059 (mid-term future). These visualizations highlight how projected changes in precipitation variability, temperature-driven evapotranspiration, and long-term soil moisture trends influence the extent of drought-affected areas under the SSP5-8.5 climate scenario. By combining both stacked time series and boxplot summaries, this framework captures not only long-term mean shifts but also variability and extremes, which are critical for understanding risks to agriculture, water supply, and ecosystems.

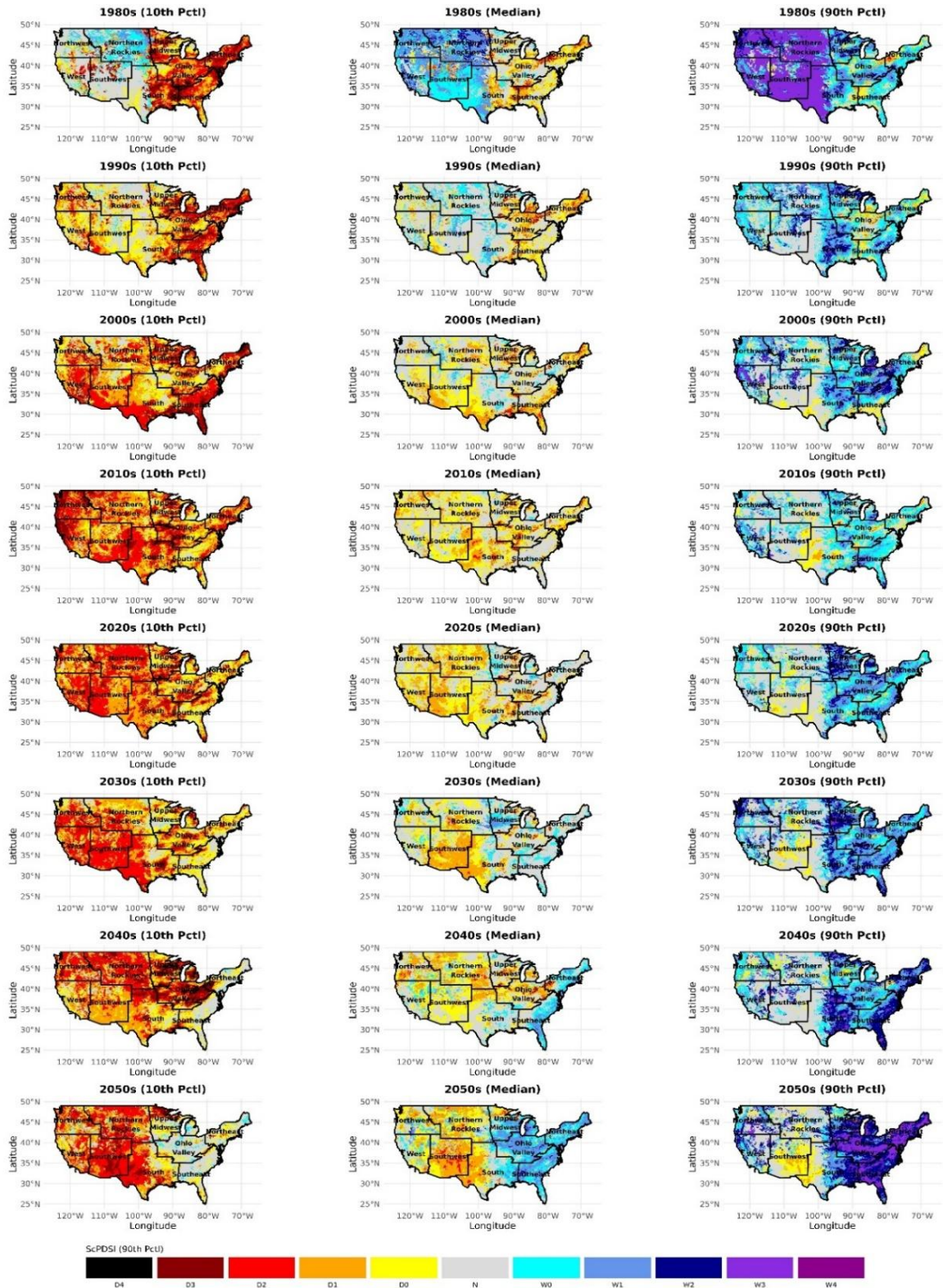


Figure 2.5 Comparison of 10th, Median, and 90th Percentile ScPDSI (1980s–2050s) by decade across CONUS.

The stacked bar plots (Figures 2.6a, 2.6c, 2.6e) reveal distinct trends in the percentage of land area affected by different drought categories over time. In SPI-12 (Figure 2.6a), the total area affected by D1 (moderate drought) and D2 (severe drought) shows a general decline from the 1980s onward, with notable peaks during well-documented drought events such as those in the late 1980s, early 2000s, and mid-2010s. The fraction of CONUS experiencing D3 (extreme drought) and D4 (exceptional drought) remains relatively low, and projections suggest that these categories will continue to affect smaller areas in the future. The area affected by D0 (abnormally dry conditions) remains relatively stable, reflecting continued short-term precipitation fluctuations. In contrast, SPEI-12 (Figure 2.6c), which accounts for temperature-driven moisture loss, exhibits greater year-to-year variability, particularly in D1 and D2 categories, suggesting that evapotranspiration will contribute to drying in certain years, even when precipitation patterns do not indicate a widespread reduction. The total area affected by D3 and D4 under SPEI-12 remains low but sporadic, with occasional peaks that indicate years of more widespread drying driven by temperature extremes. ScPDSI (Figure 2.6e) presents a distinct trend, showing a gradual increase in the area affected by D0 and D1, particularly after 2020, while D2–D4 categories remain more stable compared to SPI-12 and SPEI-12. This suggests a shift toward prolonged dry conditions affecting large portions of CONUS, rather than episodic severe drought events. Such divergence among indices highlights that while precipitation-based indices suggest a potential decline in widespread severe drought, soil moisture-based metrics reveal growing risks of chronic dryness, which are especially relevant for agriculture and water management (Vicente-Serrano *et al* 2020).

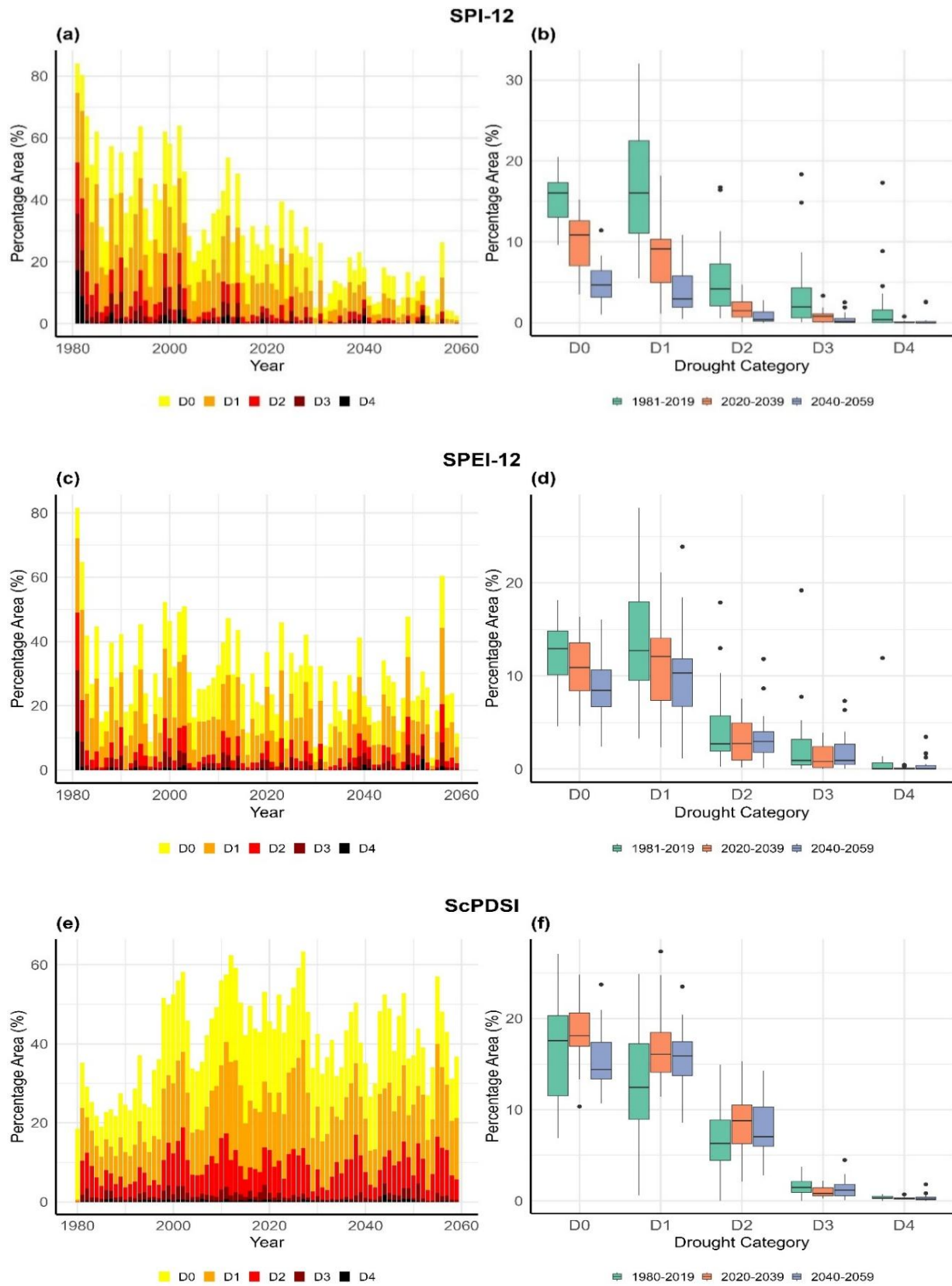
The box plots (Figures 2.6b, 2.6d, 2.6f) provide additional insight into these trends by summarizing how the percentage of land area affected by each drought category changes across

different time periods. In SPI-12 (Figure 2.6b), the median area affected by D1 and D2 decreases in future periods, with a noticeable reduction in interquartile range (IQR), indicating a more consistent trend toward lower coverage of these drought categories. However, the whiskers (5th–95th percentiles) and outliers highlight that individual years with high drought coverage may still occur, emphasizing the potential for occasional years with larger areas affected despite the median decline. The area affected by D3 and D4 remains low across all time periods, with limited variability, reinforcing that SPI-12-based projections do not indicate a widespread expansion of the most severe drought categories. In SPEI-12 (Figure 2.6d), the median area affected by D1 and D2 remains relatively stable compared to SPI-12, but the IQR expands, indicating greater uncertainty in future projections. The presence of more outliers in D2–D4 categories suggests that despite a general stabilization, some models still project years where a larger portion of CONUS experiences widespread drying, particularly due to higher temperatures increasing moisture loss. Unlike SPI-12, SPEI-12 suggests that the total area affected by moderate to severe drought may not decrease significantly but will vary more from year to year. ScPDSI (Figure 2.6f) shows a clear increase in the median percentage of land affected by D0 and D1 in both future periods, with a larger IQR, suggesting that more of CONUS will experience abnormally dry or moderate drought conditions on a regular basis. This aligns with long-term soil moisture deficits projected under a warming climate, where reduced precipitation effectiveness leads to widespread but less extreme drying. The area affected by D2 remains relatively stable, while D3 and D4 continue to affect only a small percentage of land, with sporadic extreme years as shown by the outliers. From a management perspective, this implies that adaptation strategies may need to shift away from planning for rare catastrophic droughts alone, and increasingly focus on mitigating the impacts of more frequent, persistent moderate

droughts that strain water and food systems over time.

The comparison across indices highlights key differences in how drought-affected areas are projected to change. SPI-12 shows a decreasing trend in the total area affected by moderate (D1) and severe (D2) droughts, likely due to projected increases in precipitation. In contrast, SPEI-12 reflects a more uncertain future, where temperature-driven drying leads to greater year-to-year variability in the total area affected by moderate to extreme droughts. ScPDSI, on the other hand, suggests a shift toward persistent dry conditions, with more land consistently experiencing D0 and D1 drought categories rather than short-term fluctuations in D2–D4. This divergence underscores the importance of using multiple drought indices to assess future drought risks, as precipitation-based, temperature-sensitive, and soil moisture-driven metrics capture different aspects of the changing hydroclimate. These results also emphasize the importance of ensemble-based drought assessments: while some indices suggest declining severe drought risk, others reveal heightened exposure to persistent mild-to-moderate droughts that may be equally disruptive when compounded with population growth and increasing water demand (Spinoni *et al* 2019).

Figure 2.6 Projected trends and historical patterns of drought in the CONUS (1980–2059) based on SPI-12, SPEI-12, and ScPDSI. (a, c, e) Stacked bar plots showing the percentage of land area affected by different drought categories (D0–D4) over time for SPI-12, SPEI-12, and ScPDSI, respectively. (b, d, f) Box plots representing the distribution of drought-affected areas across three time periods (1981–2019, 2020–2039, and 2040–2059) based on multi-model ensembles.



2.6 Discussion

This study investigates projected drought characteristics across the CONUS under the SSP5-8.5 scenario, focusing on regional trends and potential population impacts. By using a multi-model ensemble of bias-corrected and dynamically downscaled data from six CMIP6 GCMs, we analyzed drought events through ScPDSI, with additional insights provided by SPI-12 and SPEI-12. Unlike previous studies that rely solely on global climate models (GCMs) or statistical downscaling methods, this study employs high-resolution dynamical downscaling, which improves the representation of regional climate variability. Such fine-scale modeling is particularly valuable in complex terrains (e.g., the Rocky Mountains and the Southwest), where coarse-resolution GCMs often underestimate localized drought risks (Coppola *et al* 2021). Additionally, we incorporate a climate-zone-based regional analysis and inter-model spread evaluation to better capture localized drought characteristics, providing more actionable insights for decision-making.

Each index captures distinct aspects of drought dynamics, with SPI-12 reflecting precipitation-driven variability, SPEI-12 incorporating temperature-driven evapotranspiration, and ScPDSI representing long-term soil moisture balance. The comparison across indices reveals that while SPI-12 and SPEI-12 indicate more substantial interannual fluctuations and a decline in the affected drought area by 2050, ScPDSI suggests that soil moisture deficits will persist for longer periods, particularly in the Southwest. This divergence among indices has also been noted in global studies (Zhao and Dai 2022, Niu *et al* 2025), which emphasize that precipitation-based indices may underestimate risks when warming-driven evapotranspiration dominates.

This highlights the importance of incorporating multiple drought metrics into assessments, as reliance on a single index could overlook key aspects of drought persistence and

recovery. It is important to recognize that the study is based on a relatively small ensemble of six models under a single climate scenario (SSP5-8.5), with drought trends analyzed over 20-year time slices. This limitation affects the statistical robustness of results, particularly for rare extreme drought categories (D3 and D4), which by definition have lower occurrences and greater variability. Consequently, while median trends provide useful guidance, policymakers should also prepare for “tail risks” represented by outliers in the model ensemble (Wehner *et al* 2017).

Although our results suggest an overall decrease in the median extent of extreme droughts (D3-D4), particularly in SPI-12 and SPEI-12, individual events of severe drought still emerge, as seen in the ScPDSI projections where some regions continue to experience long-lasting droughts beyond 2050. This indicates that while the frequency of extreme droughts may decline, the persistence of soil moisture deficits could still pose significant risks to water resources and agriculture. These findings echo concerns raised in IPCC AR6 (IPCC 2021), which emphasizes that compound events, such as persistent moderate droughts combined with heat extremes, can cause more damage than isolated and infrequent severe droughts.

Future research incorporating a larger ensemble of GCMs, multiple scenarios, and longer time periods would help refine projections and improve confidence in assessing the frequency and severity of extreme droughts. Such extensions would also facilitate probabilistic risk assessments, moving beyond deterministic projections to provide likelihood estimates that are more relevant for adaptation planning (Seneviratne *et al* 2012).

To further ensure the reliability of our projections, we assessed the impact of dynamical downscaling on drought assessments. Unlike statistical downscaling methods that rely on empirical relationships, dynamical downscaling explicitly resolves fine-scale climate processes, improving the representation of regional precipitation and temperature variability. For example,

RegCM4 has been shown to better capture orographic precipitation gradients in the Sierra Nevada and the Rockies, which are often smoothed out in coarse-resolution GCMs (Giorgi *et al* 2012, Giorgi and Gao 2018). This is particularly important in regions with complex topography, such as the Western U.S., where GCMs tend to underestimate precipitation variability and local convective activity.

By applying bias correction with Daymet V4, our downscaling approach significantly reduces systematic errors in precipitation and temperature, leading to improved drought index calculations. The refined spatial resolution ensures a more accurate representation of temperature-driven drought trends, particularly for indices such as SPEI and ScPDSI, where small temperature changes can strongly influence projected drought severity. Bias correction also improves intercomparability across indices, as demonstrated in recent hydroclimate assessments where uncorrected GCM outputs systematically underestimated the frequency of extreme drought events in the Southwest (Rastogi *et al* 2022).

Additionally, the ability of dynamical downscaling to capture localized drought conditions allows for a more nuanced assessment of regional drought variability. While raw GCM-based projections smooth out fine-scale drought patterns, our downscaled dataset provides a more detailed spatial representation of drought persistence and intensity across different climate zones. This higher spatial fidelity is especially critical for stakeholder applications, such as water utilities and agricultural planning, which require localized information rather than national averages (Maraun and Widmann 2018).

Despite these improvements, some biases remain. While precipitation biases in the Southwest were reduced compared to raw GCM outputs, there is still a slight underestimation of extreme precipitation events, indicating the need for further refinement in hydrological

applications. Similarly, temperature biases in RegCM4-based datasets were lower than those in raw GCMs, improving the reliability of temperature-sensitive drought indices. These residual errors are consistent with other regional downscaling studies (Bukovsky and Mearns 2020), which show that while downscaling reduces mean biases, extremes remain difficult to capture accurately due to limitations in convective parameterizations. These results highlight the added value of dynamical downscaling in climate impact studies, particularly for refining regional drought projections and supporting local adaptation strategies. However, they also underscore the need for multi-method ensembles that integrate both dynamical and statistical downscaling, in order to better quantify uncertainties across modeling frameworks (Shakeel *et al* 2025).

Our findings align with previous research indicating a general trend toward fewer droughts across CONUS, driven by projected increases in average precipitation (Xue and Ullrich 2022, Chen and Ford 2023). However, this overall trend masks significant regional variability. Persistent and intensifying drought conditions are projected in the Southwest and parts of the West, including New Mexico, Arizona, and California, where rising temperatures and increased evapotranspiration rates exacerbate soil moisture deficits (Heim 2017, Leeper *et al* 2022, Rastogi *et al* 2023). This regional contrast mirrors findings in (Zhao and Dai 2022), who showed that while global precipitation is expected to rise, subtropical and arid regions may experience “dry-get-drier” dynamics due to enhanced evaporative demand.

The influence of rising temperatures on drought indices varies depending on how PET is calculated. SPEI explicitly incorporates temperature effects through PET estimation, often using the Thornthwaite method, which is highly sensitive to warming trends but does not account for physiological changes in vegetation under elevated CO₂. ScPDSI, in contrast, integrates temperature effects indirectly through its soil moisture balance framework but may not fully

capture PET variations in response to increasing CO₂ concentrations. This methodological divergence has been widely discussed in drought literature (Beguería *et al* 2014, Vicente-Serrano *et al* 2020), with evidence that Thornthwaite-based SPEI may overestimate drying under strong warming.

The Penman-Monteith method, which accounts for radiative and aerodynamic controls on PET, remains widely used but does not explicitly consider CO₂-induced stomatal closure, potentially leading to overestimation of future drying trends. Recent studies (Lemordant *et al* 2018, Swann *et al* 2016) highlight that vegetation physiological responses, such as reduced stomatal conductance under elevated CO₂, can significantly decrease transpiration and partially offset increased evaporative demand. Given the increasing importance of plant physiological responses under climate change, future studies should explore CO₂-sensitive PET models, which could refine projections of drought severity and duration by better accounting for plant water use efficiency under rising CO₂ levels. Incorporating dynamic vegetation models into drought assessments could therefore bridge the gap between atmospheric drivers and biospheric feedbacks, reducing uncertainty in long-term drought projections (Seneviratne *et al* 2010).

From an agricultural perspective, the indices reveal significant risks associated with shifting drought patterns. SPI-12 predicts a decrease in prolonged droughts, which could reduce water stress in some agricultural regions but pose challenges for rainfed farming that depends on consistent precipitation (Harp and Horton 2022). However, ScPDSI indicates persistent soil moisture deficits, particularly in the Southwest, where soil moisture-driven drought exposure remains high even in 2050. This persistence of baseline drying is consistent with long-term observations of declining soil moisture and groundwater depletion across the western United States (Famiglietti 2014, Scanlon *et al* 2012). This suggests that despite projected increases in

precipitation, long-term soil moisture deficits may continue to impact crop resilience and yields (Ficklin *et al* 2015).

The irregular distribution of precipitation, characterized by more intense but less frequent events, could disrupt irrigation management and crop planning, even in regions expected to experience wetter conditions (Leeper *et al* 2022, Rastogi *et al* 2023). This phenomenon, often described as “precipitation whiplash” (Swain *et al* 2018), increases the difficulty of agricultural adaptation because farmers must cope with both water shortages and flood risks within short timeframes. These changes suggest that agricultural systems will need to adapt not only to more frequent mild droughts but also to the increased baseline water stress they create (Wahl *et al* 2022). Potential adaptation measures include shifting crop calendars, adopting drought-resistant cultivars, and expanding sustainable irrigation techniques such as deficit irrigation and micro-drip systems (Howell *et al* 2015, Elliott *et al* 2018).

To calculate PET, this study used the Penman-Monteith method with the VIC hydrological model and bias-corrected GCM outputs, a widely recognized standard for hydrological studies (Goh *et al* 2021, Lang *et al* 2017). However, limitations such as temporal uncertainties and energy balance closure issues may propagate errors in drought index calculations (Hao *et al* 2018). For instance, small biases in net radiation or wind speed can translate into significant differences in PET, which then amplify uncertainties in indices like SPEI and ScPDSI that directly incorporate evapotranspiration (Sheffield *et al* 2013).

Additionally, the modifiable areal unit problem (MAUP) complicates results, as spatial scale and aggregation choices may affect conclusions, even when dividing the CONUS into NCEI climate regions to align with previous studies (Jelinski and Wu 1996, Ashfaq *et al* 2016b). This scaling sensitivity has been highlighted in other hydroclimate studies, where results differed

when shifting from watershed-based to grid-based drought aggregation (Keyantash and Dracup 2002), suggesting that multi-scale analyses are necessary for robust conclusions.

In addition, different drought classification thresholds, such as -0.5 for SPI/SPEI and -1 for PDSI, influence the areas and populations identified as drought-affected (Chivangulula *et al* 2023, Nam *et al* 2015, Maule *et al* 2013). While our study follows established classification methods, non-parametric approaches, such as those proposed by Farahmand and AghaKouchak (2015), provide an alternative for generating statistically consistent drought indices across different variables, enhancing inter-comparability in multi-index drought assessments (Farahmand and AghaKouchak 2015). Adopting such unified statistical frameworks would be particularly valuable for cross-regional comparisons and for integrating multiple datasets (e.g., climate models, remote sensing, reanalysis), where differing assumptions can otherwise hinder synthesis (Dai 2011).

These methodological challenges emphasize the need for standardized approaches to improve consistency and reliability in drought assessments. Future research should also integrate uncertainty quantification, for example through ensemble-based probabilistic methods, to provide stakeholders with ranges of risk rather than single deterministic outcomes (Hao *et al* 2018).

Overall, the updated results highlight the complexity of future drought projections and the necessity of using multiple indices to fully capture regional drought variability. While SPI-12 and SPEI-12 indicate a decline in overall drought-affected areas by mid-century, ScPDSI suggests persistent soil moisture deficits in key regions, particularly the Southwest. This reinforces the broader understanding that precipitation-based metrics alone are insufficient to characterize drought risk under climate change, since warming-driven evapotranspiration and

soil water dynamics play increasingly dominant roles (Vicente-Serrano *et al* 2020, Dai and Zhao 2017).

The projected urban and agricultural impacts further emphasize the importance of adaptive water management strategies that account for both short-term precipitation variability and long-term soil moisture trends. For urban systems, this means planning beyond short drought relief cycles and investing in resilient infrastructure such as aquifer recharge projects, distributed storage, and advanced wastewater reuse (Gleick 2018). For agriculture, adaptive strategies must balance water conservation with food security, requiring not only technological interventions (e.g., precision irrigation) but also institutional changes such as drought insurance and regional water-sharing agreements (Wheeler *et al* 2020).

From a policy perspective, the study highlights the need for integrated adaptation frameworks that connect climate science with socioeconomic planning. Drought is not only a hydrological hazard but also a cross-sectoral stressor that influences energy production, food prices, and public health (AghaKouchak *et al* 2021). Therefore, effective adaptation must be multi-scalar, combining federal-level investments in infrastructure with local initiatives tailored to community-specific vulnerabilities.

2.7 Conclusion

This study examines the projected characteristics of drought across CONUS and its population impacts under the SSP5-8.5 scenario. By utilizing a multi-model ensemble with high-resolution dynamical downscaling, we provide a detailed assessment of future drought conditions across various climate regions. Unlike previous studies that rely solely on global climate models or statistical downscaling, our approach enhances the spatial resolution and reliability of drought projections, enabling a more localized evaluation of drought risks. Given the high variability in

projected precipitation across models, particularly under the SSP5-8.5 scenario, our analysis incorporates the 10th–90th percentile range alongside the ensemble median, providing a more comprehensive understanding of inter-model uncertainty. While most models indicate a drying trend in the Southwest, the magnitude of change varies considerably, highlighting the need for further examination of precipitation variability. In contrast, regions such as the Upper Midwest and Northeast exhibit higher model agreement, suggesting greater confidence in projected trends. The comparison of SPI-12, SPEI-12, and ScPDSI reveals distinct drought responses, with SPI-12 and SPEI-12 showing an overall decline in drought-affected areas by mid-century, while ScPDSI suggests persistent soil moisture deficits, particularly in the Southwest, emphasizing the importance of incorporating multiple drought indices in climate risk assessments. Taken together, this study demonstrates the necessity of multi-index approaches for capturing the full spectrum of hydroclimatic risks, since reliance on a single metric can obscure critical drivers of drought persistence and recovery (Vicente-Serrano *et al* 2020).

Our findings highlight substantial regional disparities in future drought trends. While some regions, such as the Upper Midwest and Southeast, may experience a reduction in the overall area affected by drought due to increased precipitation, these gains could be offset by temperature-driven increases in evapotranspiration. In contrast, the Western and Southwestern U.S. are projected to experience persistent and intensifying drought conditions, driven by rising temperatures and prolonged soil moisture depletion. New Mexico, Arizona, and California are expected to face severe and recurrent water stress, with ScPDSI indicating prolonged drought conditions well into 2050, affecting up to 1.1 million people under D0 and D1 categories. Unlike other regions where precipitation increases may alleviate some drought conditions, these areas are projected to experience longer-lasting soil moisture deficits due to increasing

evapotranspiration. This Southwest drying trend is consistent with recent reconstructions of megadroughts in North America, which suggest that 21st-century warming could lock the region into drought regimes comparable to or worse than the Medieval Climate Anomaly (Williams *et al* 2020). The shift toward a drier climate in the Southwest, as indicated by both ScPDSI and SPEI-12, underscores the need for proactive adaptation measures, such as improved water resource management, enhanced irrigation strategies, and long-term drought mitigation policies tailored to vulnerable regions. Failure to act may increase the risks of agricultural decline, water allocation conflicts, and wildfire-driven damages across already vulnerable landscapes.

While our study provides valuable insights into future drought projections, it does not explicitly account for CO₂-induced reductions in transpiration, which could influence PET estimates and, consequently, drought severity assessments. Given the growing body of research suggesting that CO₂-sensitive PET formulations can modify drought severity projections (Yang *et al* 2019, Swann *et al* 2016, Lemordant *et al* 2018), future research should integrate dynamic vegetation models and CO₂-responsive PET methods to improve the accuracy of drought impact assessments. Additionally, expanding the analysis to include multiple SSP scenarios and a broader ensemble of CMIP6 models would further enhance confidence in regional drought projections, supporting long-term water resource planning and climate adaptation strategies under a changing climate. Given the uncertainties associated with extreme drought projections, particularly for rare categories like D3 and D4, future studies should also explore alternative drought classification methods to refine the detection of high-impact drought events. Future research should also explicitly examine compound extremes, such as concurrent drought and heatwaves, or drought and wildfire events, which can amplify risks far beyond what single-hazard assessments suggest (Zscheischler *et al* 2018).

In summary, this chapter provides a comprehensive assessment of future drought evolution and associated human exposure across the contiguous United States under the SSP5-8.5 scenario. By integrating high-resolution dynamical downscaling, bias correction, and multi-index drought metrics, we identified strong regional contrasts: while the Upper Midwest and Northeast are projected to experience modest wetting trends, the Southwest and parts of the Western U.S. are likely to face persistent soil moisture deficits and heightened drought risk. Population exposure analyses further revealed that urban residents, due to their concentration in drought-prone regions and dependence on centralized infrastructure, will remain disproportionately vulnerable even as the total drought-affected population declines by mid-century. These findings underscore both the physical complexity and the socioeconomic significance of drought under climate change, highlighting the necessity of tailored regional adaptation strategies.

Building on these results, the next chapter shifts focus from drought to air quality, specifically the estimation and bias analysis of PM_{2.5}. While drought primarily represents a hydroclimatic stressor, PM_{2.5} embodies an atmospheric pollutant with equally profound health implications. Importantly, the two issues are interconnected: drought-induced wildfires and dust storms contribute directly to PM_{2.5} emissions, while atmospheric stagnation during drought episodes can exacerbate pollutant accumulation. By addressing PM_{2.5} estimation challenges through machine learning and the integration of models and observations, Chapter 3 advances the dissertation's broader goal of improving multiscale assessments of climate-related environmental risks.

CHAPTER 3 MACHINE LEARNING-BASED PM_{2.5} ESTIMATION AND BIAS ANALYSIS

3.1 Research Question

This chapter focuses on the challenges associated with estimating ground-level PM_{2.5} concentrations using machine learning methods, particularly in the context of sample imbalance and limited observational data. The key research question is: How can machine learning techniques be optimized to improve PM_{2.5} estimation accuracy, particularly in regions with limited ground monitoring? This question reflects a broader challenge in atmospheric science, namely how to bridge the gap between sparse observational networks, heterogeneous emission sources, and complex meteorological processes that shape PM_{2.5} distribution (Di *et al* 2019). Addressing this challenge is not only a technical problem but also a public health priority, as PM_{2.5} remains one of the leading global environmental risk factors for mortality (Cohen *et al* 2017).

3.2 Introduction

Air pollution has significantly altered the Earth's radiation balance, disrupted ecosystems, and increased human morbidity and mortality (Geng *et al* 2021). Ambient PM_{2.5} (airborne particles <2.5 μm in diameter) has profound effects on human health, ecosystems, and climate change, necessitating accurate estimates of its concentration in the atmosphere. PM_{2.5} can penetrate the bronchi and lungs, causing damage to the respiratory and cardiovascular systems, and is associated with an increased risk of premature death (Dockery *et al* 1993, Lelieveld *et al* 2015). Given these severe health and environmental impacts, the U.S. Environmental Protection Agency (EPA) recently revised the primary annual PM_{2.5} standard from 12.0 $\mu\text{g}/\text{m}^3$ to 9.0 $\mu\text{g}/\text{m}^3$ on February 7, 2024, while maintaining the primary 24-hour PM_{2.5} standard at 35 $\mu\text{g}/\text{m}^3$. This

regulatory tightening underscores the urgency of improving PM_{2.5} exposure assessments, since even small underestimations in modeled concentrations could have direct implications for compliance, health burden estimates, and environmental justice analyses (Johnson *et al* 2024, Henneman *et al* 2017).

Despite the notable decline in PM_{2.5} concentrations achieved across the United States over the past decade, the monitoring network remains spatially sparse and is unable to capture the full extent of population exposure, particularly in rural and underserved communities. This limitation not only hampers the protection of public health but also exacerbates environmental inequity by failing to monitor air quality in vulnerable areas (Yu *et al* 2023). The use of traditional methods has been shown to introduce biases in PM_{2.5} concentration estimates due to the limited spatial and temporal coverage of surface monitoring (Cheng *et al* 2024). High-resolution spatiotemporal data are essential for addressing these limitations, as they facilitate more accurate assessments of exposure, particularly when integrated with advanced machine learning models to that incorporate satellite and ground-based data (He *et al* 2024, Ma *et al* 2023). These approaches not only enhance the precision of exposure assessments but also support studies addressing environmental justice by highlighting disparities in pollution distribution and its health impacts (Jain *et al* 2023). Such integrative approaches are increasingly recognized as the frontier of exposure science, providing datasets that are both policy-relevant and capable of supporting epidemiological studies with unprecedented granularity (Van Donkelaar *et al* 2021).

The limited availability of ground stations and issues of sample imbalance have significantly impacted the accuracy of machine learning models used for PM_{2.5} estimation in the U.S. Studies have shown that the concentration of monitoring stations in urban areas leads to a

training sample bias toward high-pollution regions, resulting in overestimation of $\text{PM}_{2.5}$ in downwind areas (Li *et al* 2024b). Even though the AQS monitors pollution levels across the country, the lack of sufficient monitoring stations in rural and remote areas introduces considerable uncertainty in $\text{PM}_{2.5}$ estimates for these regions. This study integrates data from U.S. networks like CASTNET and IMPROVE to assess the impact of sample imbalance on machine learning models and evaluate the efficacy of applying such models in low-pollution regions. By explicitly addressing spatial imbalance, this work contributes to filling a major gap in the U.S. air quality literature, where rural and suburban exposures have historically been underrepresented in both modeling and monitoring (Jerrett *et al* 2017).

Reliable $\text{PM}_{2.5}$ retrievals from satellites can fill gaps in surface measurements and improve air quality models, especially in regions with limited monitoring networks. Aerosol optical depth (AOD) has been widely used for these retrievals, and studies have demonstrated that MAIAC AOD outperforms MODIS AOD in several contexts (Lyapustin *et al* 2018, Zhang *et al* 2019). In addition to AOD, meteorological conditions are a significant factor in determining $\text{PM}_{2.5}$ concentrations. The incorporation of datasets such as ERA5 has been demonstrated to enhance the precision of $\text{PM}_{2.5}$ estimates when integrated into machine learning models (Zuo *et al* 2023). Nevertheless, previous studies employing techniques such as Multivariate Adaptive Regression Splines (Sorek-Hamer *et al* 2013) have identified constraints in addressing intricate atmospheric dynamics and regional transport, which can result in imprecise $\text{PM}_{2.5}$ estimations. These challenges underscore the necessity of addressing the inherent spatial and temporal imbalances in current monitoring networks and highlight the importance of developing novel methods for improving $\text{PM}_{2.5}$ retrievals. In this context, hybrid approaches that integrate chemical transport models (e.g., CMAQ, GEOS-Chem) with machine learning offer promising

pathways to combine physical constraints with data-driven flexibility (Xiao *et al* 2020).

Several machine learning (ML) techniques have emerged to address the challenges associated with PM_{2.5} estimation, particularly in handling spatial and temporal data gaps. Decision tree-based methods, including Random Forests (RF), XGBoost, and LightGBM, are widely used due to their efficiency and high predictive accuracy. Random Forests employ an ensemble of decision trees to improve prediction performance and reduce overfitting (Belgiu and Drăguț 2016, Breiman 2001). XGBoost, an optimized gradient-boosting framework, has been extensively applied in PM_{2.5} prediction studies, providing high efficiency and superior performance in handling structured data (Chen and Guestrin 2016, Wang *et al* 2023, Li *et al* 2024b). Similarly, LightGBM, a highly efficient gradient-boosting decision tree model, is popular for large-scale datasets due to its fast training speed and computational efficiency (Ke *et al* 2017). It has been widely used in satellite-based PM_{2.5} estimation, where large amounts of data must be processed quickly and accurately (Ma *et al* 2023, Wei *et al* 2021). However, ensemble-based methods may still struggle to extrapolate under novel climate or emission conditions, highlighting the importance of continuous retraining with updated datasets (Shan *et al* 2022).

More advanced models like Deep-RF combine the deep learning feature extraction capability with the ensemble learning power of random forests, offering superior performance in PM_{2.5} estimation (Wei *et al* 2023, Zheng *et al* 2021). Residual Neural Networks (ResNet) have also been adapted to air quality estimation tasks due to their ability to handle nonlinear relationships in atmospheric processes (He *et al* 2016, Li *et al* 2024a). ResNet's architecture, which consists of residual blocks and convolutional layers, allows it to capture both spatial and temporal patterns in PM_{2.5} concentrations, significantly improving prediction accuracy (Song *et*

al 2020). Recent advances in spatiotemporal deep learning, such as graph neural networks and transformers, may provide additional gains by explicitly modeling spatial adjacency and long-range temporal dependencies (Li *et al* 2023, Yu *et al* 2025).

To evaluate the performance of these machine learning models, cross-validation metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Relative Error (MRE) are essential (Jolliff *et al* 2009, Willmott and Matsuura 2005). These metrics provide insights into the overall accuracy of the models, the size and direction of errors, and their ability to generalize across different geographic regions. Comprehensive evaluation using these metrics helps ensure that the models are robust and reliable for PM_{2.5} estimation across diverse conditions. For policy-relevant applications, model evaluation should also consider bias against regulatory thresholds (e.g., EPA 24-hour and annual PM_{2.5} standards), since small systematic deviations can translate into major differences in compliance assessments (Apte *et al* 2015).

However, a major limitation of existing studies is the concentration of ground measurements in urban and heavily polluted areas, especially in regions such as China. This focus on high-pollution regions, aimed at protecting human health, has led to uneven spatial distribution of data, creating significant gaps in PM_{2.5} monitoring, particularly in suburban and rural areas. In the U.S., these gaps are even more pronounced due to the lower pollution levels and the dispersed nature of ground stations in rural areas. This challenge is compounded by the lack of ground truth data to evaluate ML model predictions in less populated areas, especially along pollutant transport pathways. As a result, significant uncertainties remain in PM_{2.5} estimation in these regions, and existing approaches have not adequately addressed these challenges. This limitation directly affects environmental justice assessments, since rural and

Indigenous communities may face disproportionate exposure without being properly represented in monitoring networks (Grineski *et al* 2020). These challenges motivate the need for integrated modeling frameworks that leverage both physical and data-driven insights.

To overcome these limitations, this study presents a novel approach that integrates machine learning techniques with numerical simulations within a CMAQ-based testbed framework, specifically tailored for the U.S. domain. This integration is particularly innovative in its ability to reduce uncertainties in suburban and rural areas where ground measurements are sparse. Unlike previous studies that focus heavily on urban regions with dense monitoring, this work emphasizes the estimation of PM_{2.5} across diverse spatial regions in the U.S., providing more robust and generalizable results. By focusing on the unique landscape of the U.S. monitoring networks, including CASTNET and IMPROVE, this study addresses the underrepresentation of low-pollution and rural regions in machine learning models. This approach not only advances methodological rigor but also enhances policy relevance by providing improved datasets for exposure and health impact studies, particularly in under-monitored regions.

3.3 Objective

This chapter aims to develop a novel testbed that integrates numerical simulations with machine learning approaches to enhance the accuracy of PM_{2.5} estimation. By optimizing model structures and training samples, this study seeks to improve predictive performance, particularly in regions with limited monitoring data. Such a testbed provides a systematic framework for evaluating how different modeling strategies, including Random Forests, gradient boosting methods, and convolutional neural networks, perform under heterogeneous monitoring conditions, thereby offering a transparent and reproducible way to benchmark progress in air

quality modeling (Di *et al* 2019, Xiao *et al* 2020).

A key objective is to assess the benefits of multi-year training datasets in capturing variable atmospheric conditions and improving model robustness. Multi-year data integration has been shown to reduce overfitting to anomalous events and enhance model generalizability across years with distinct meteorological regimes, such as El Niño/La Niña cycles (Liu *et al* 2023b). By explicitly testing the contribution of temporal diversity in training data, this study advances understanding of how models can be adapted for long-term air quality forecasting. Additionally, this study explores the incorporation of additional monitoring networks, such as CASTNET and IMPROVE, to evaluate their impact on PM_{2.5} prediction accuracy and coverage. These supplemental networks provide critical rural and background site data, which are often missing in regulatory AQS networks, and their inclusion is expected to reduce urban-centric bias in ML training datasets (Malings *et al* 2020, Hand *et al* 2019).

Another focus of this research is to investigate the influence of sample imbalance on interannual variability, health risk assessments, and environmental equity in PM_{2.5} exposure. Addressing sample imbalance is essential, as models trained predominantly on urban data may systematically overestimate pollution in rural downwind areas, inflating population-weighted exposures and potentially skewing health burden estimates (Wei *et al* 2023). By quantifying these biases, the testbed contributes to both methodological refinement and environmental justice assessments. By leveraging CNN-based deep learning models, particularly ResNet, this study aims to reduce PM_{2.5} overestimation and enhance exposure assessments in downwind areas. ResNet's ability to capture nonlinear spatiotemporal dependencies makes it particularly suited for this task, as it can extract hierarchical features that traditional regression or tree-based models might overlook (Song *et al* 2020).

The ultimate goal is to provide a more reliable alternative to traditional PM_{2.5} estimation methods, with significant implications for regulatory policies and public health protection. Improved accuracy in spatially resolved PM_{2.5} estimates directly supports compliance monitoring with updated EPA standards, strengthens epidemiological research on exposure–response relationships, and informs equitable mitigation strategies at regional and national scales (Gladson *et al* 2022, Apte *et al* 2015).

3.4 Methods and Data

3.4.1 Methods

In this study, we used a novel testbed with a numerical model (Figure 3.1), specifically the Community Multiscale Air Quality (CMAQ) modeling system developed by the U.S. EPA (Appel *et al* 2021), to create ground-truth data beyond traditional monitoring points. This approach allows us to simulate PM_{2.5} concentrations and evaluate interpolation performance using a variety of machine learning models, providing a solution to mitigate uncertainties stemming from the sample imbalance problem. CMAQ-based testbeds have been increasingly adopted in atmospheric research because they allow for controlled experiments where the “true” pollutant fields are known, making it possible to evaluate the structural biases of retrieval algorithms in ways that are not feasible with sparse observations alone (Xing *et al* 2020). To address the unique challenges in the U.S., where monitoring stations are sparse in rural and suburban areas, we conducted experiments that increased the density of monitoring points virtually, testing how this impacts model accuracy in under-monitored regions.

One key experiment was the addition of virtual stations in rural areas using simulated CMAQ data to improve coverage. We compared the results of machine learning models trained with both traditional station data and the expanded virtual data set, allowing us to assess the

benefits of increasing ground station density. This experimental design simulates hypothetical scenarios of monitoring network expansion and quantifies how additional observational data could improve prediction skill in rural and downwind regions, an important policy-relevant consideration for allocating future monitoring resources (Malings *et al* 2020). We also incorporated multi-year comparisons, analyzing how the models performed over three different years (2009, 2014, 2019) to evaluate their robustness in handling temporal variations in pollutant levels and emissions. Using multiple years also ensures that models are tested under different emission regulations (e.g., implementation of Tier 2/3 vehicle standards) and meteorological conditions (e.g., ENSO events), thereby improving their generalizability (Henneman *et al* 2017).

Three decision tree-based machine learning algorithms, including Random Forest, XGBoost, and LightGBM, were used as benchmark cases because they are widely applied in PM_{2.5} estimation. Additionally, we included Deep-RF and ResNet, which combines deep learning and ensemble learning, known for its superior performance in complex environmental datasets. All models were trained using observed meteorological variables from WRF output and land use information. To further enhance accuracy, NO₂ column density from satellite observations was used instead of historical emissions data, as this variable is highly correlated with emission sources and can provide a more accurate real-time representation of pollution sources. The substitution of NO₂ satellite products for emissions inventories reflects a growing recognition that near-real-time remote sensing can better capture emission dynamics, particularly for mobile sources and biomass burning, which are often underestimated or misrepresented in inventories (Goldberg *et al* 2019).

In another key experiment, we conducted temporal validation by training the models on the first 20 days of each month and reserving the remaining days for testing. This validation

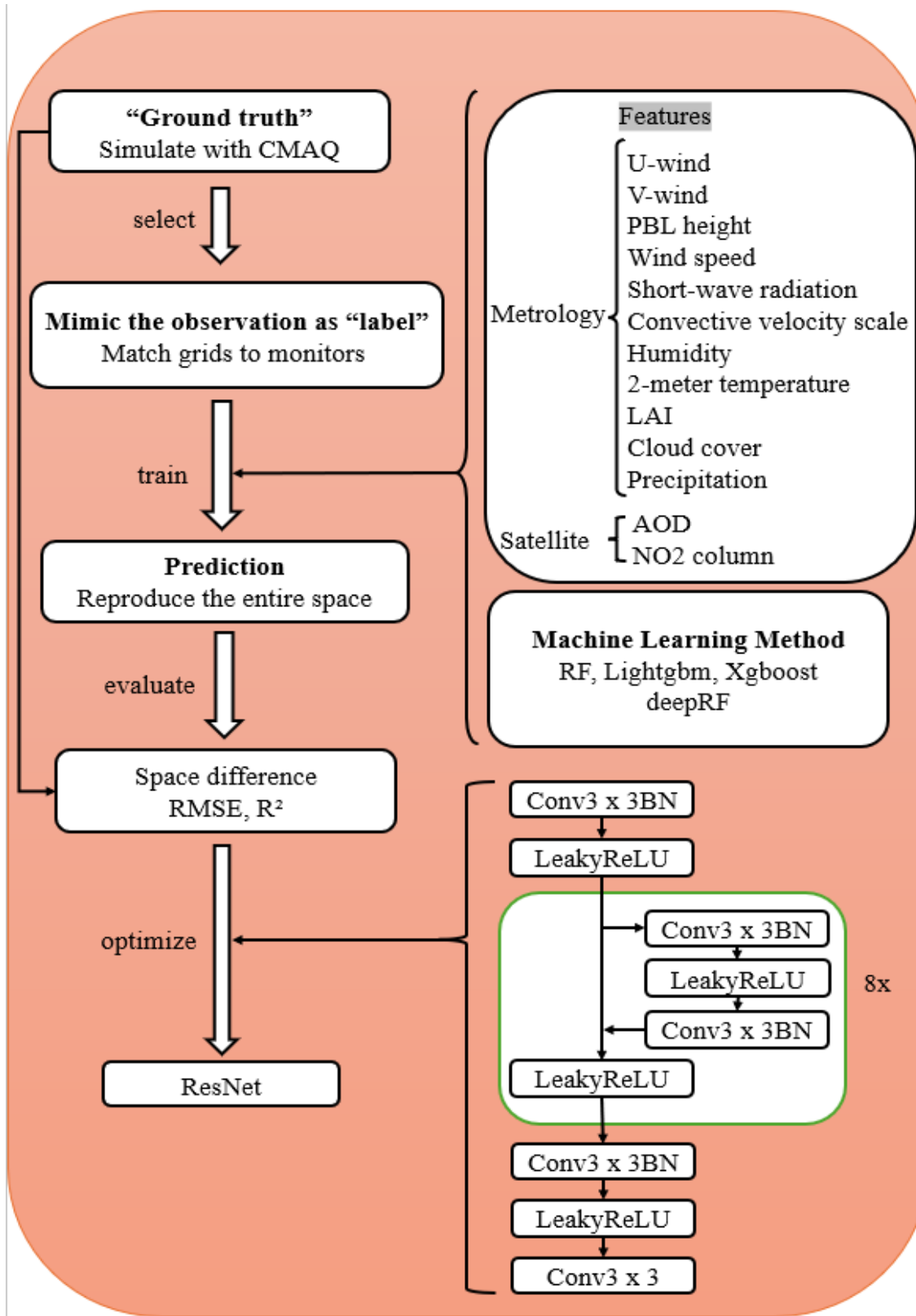


Figure 3.1 Testbed framework.

approach enabled us to measure the model's ability to generalize across different temporal conditions and assess its robustness in predicting PM_{2.5} levels in both urban and rural areas. This design simulates operational forecasting settings, where models must predict beyond the training window, and also accounts for seasonal variability within a given month (Jiang *et al* 2021). The CMAQ-simulated data served as a testbed to explore the performance of satellite retrieval models and test the limits of various machine learning techniques, providing a scalable method for reducing uncertainty in PM_{2.5} estimates, especially in areas with sparse monitoring. By systematically testing across both spatial and temporal dimensions, the framework advances beyond one-off case studies and provides a more rigorous basis for evaluating model robustness under real-world data scarcity.

3.4.2 Data

3.4.2.1 Air quality simulations (WRF/CMAQ model)

The CMAQ simulations cover the period from 2002 to 2019 with a spatial resolution of 12 km × 12 km. To maintain consistency throughout the training process, both the input features and output labels are extracted directly from the Community Multiscale Air Quality (CMAQ) model system. CMAQ, a well-established chemical transport model (CTM), provides realistic representations of air pollutant levels such as PM_{2.5} through detailed treatment of emissions, chemical reactions, transport, and deposition (Byun and Schere 2006). These capabilities make it a suitable tool for creating reliable synthetic datasets that support machine learning research (Appel *et al* 2012).

The model domain encompasses the contiguous United States and consists of 299 × 459 horizontal grid cells at 12 km resolution. The vertical structure of the atmosphere extends from the surface up to 100 mb and is resolved into 15 sigma layers. Meteorological fields are

simulated using the Weather Research and Forecasting (WRF) model (Skamarock *et al* 2008). Anthropogenic emissions are based on the high-resolution inventory developed by the U.S. Environmental Protection Agency (Marmur *et al* 2007), while biogenic emissions are generated with the Model of Emissions of Gases and Aerosols from Nature (MEGAN) (Guenther *et al* 2012). Integrating both anthropogenic and natural sources allows the model to capture urban emission hotspots as well as rural background chemistry, which is essential for studying sample imbalance among regions with different monitoring densities (Foley 2010).

The performance of WRF–CMAQ in simulating meteorological conditions and pollutant concentrations has been validated through extensive comparison with observations (Appel *et al* 2012). Simulated PM_{2.5} concentrations are spatially matched with monitoring sites and used as the training “labels” for machine learning models. The remaining grid cells represent surrounding areas where PM_{2.5} values are not directly evaluated in previous studies. This work focuses on assessing the model’s predictive ability for these unsampled locations, which make up more than 90% of the total domain. The CMAQ-simulated data serve as a reference, or “ground truth,” for model evaluation. Using such CTM outputs as pseudo-observations is common in recent model assessment studies (Xing *et al* 2020, Gilliam *et al* 2015), as it enables evaluation in regions where in-situ data are sparse or unavailable.

Meteorological predictors include U- and V-wind components, humidity, 2-m temperature, convective velocity scale, shortwave radiation, 10-m wind speed, planetary boundary layer height, leaf area index (LAI), cloud fraction, and precipitation—all generated by the WRF model (Skamarock *et al* 2008). Model training uses observational datasets from 2009, 2014, and 2019 to evaluate potential biases under real-world conditions. Bias is quantified by comparing PM_{2.5} estimates from the conventional retrieval approach with those generated by the

improved method within the proposed testbed. The selected years represent distinct regulatory and emission contexts: 2009 precedes major fleet turnover under Tier 2 standards; 2014 captures ongoing SO₂ and NO_x reductions under the Cross-State Air Pollution Rule; and 2019 reflects a relatively cleaner baseline following widespread emission control implementation (Xing *et al* 2020). Choosing these years ensures that the analysis captures both policy-driven and meteorological variability.

3.4.2.2 Satellite data: Aerosol optical depth and NO₂ column products

Moderate Resolution Imaging Spectroradiometer (MODIS) aerosol optical depth (AOD) products at 1 km × 1 km spatial resolution, based on the Multi-Angle Atmospheric Correction (MAIAC) algorithm, are provided by the Level 1 and Atmosphere Archive & Distribution System Distributed Active Archive Center (<https://ladsweb.modaps.eosdis.nasa.gov>). MODIS is a sensor on the Aqua and Terra satellites and has provided a wealth of AOD data products since 2000. The MAIAC AOD products are of higher quality compared to other MODIS AOD products, with high spatial coverage, an effective cloud masking algorithm, and almost daily global coverage (Lyapustin *et al* 2011). For this study, we used 2009, 2014, and 2019 MAIAC AOD data derived from combined Terra and Aqua satellite products. The MAIAC algorithm represents a significant advancement over traditional MODIS AOD retrievals because it applies time series analysis and surface bidirectional reflectance distribution function (BRDF) correction, which improves retrieval accuracy over bright surfaces such as urban areas and arid regions (Lyapustin *et al* 2018, Sayer *et al* 2019). This is particularly critical for U.S. regions like the arid Southwest, where conventional AOD products often fail due to high surface reflectance.

In addition to AOD, we used tropospheric nitrogen dioxide (NO₂) column products that are derived from the same MODIS MAIAC retrieval framework. These MAIAC based NO₂

products retain the advantages of the AOD retrievals, including consistent spatial coverage, improved cloud screening, and reduced surface reflectance contamination. Satellite derived NO₂ columns are strongly linked to combustion related emissions from transportation, industrial activities, and biomass burning, and therefore provide important constraints on anthropogenic pollution patterns and trends.

By combining AOD and NO₂ products from MODIS MAIAC, satellite observations provide complementary information. AOD is more sensitive to the total particle column burden, including natural aerosols such as dust and sea salt, whereas NO₂ is tightly connected to anthropogenic combustion sources. Their joint use in machine learning models has been shown to improve PM_{2.5} estimation by constraining both primary emissions and secondary aerosol formation processes (Tao *et al* 2024, Xue *et al* 2019). Moreover, using co located MAIAC AOD and NO₂ products on the same spatial grid facilitates internal consistency checks and improves model robustness in regions where ground-based data are sparse.

3.4.2.3 *Ground-based monitor measurements*

Surface PM_{2.5} measurements for the years 2009, 2014, and 2019 were obtained from the U.S. Environmental Protection Agency (EPA) Air Quality System (AQS) database (https://aq5.epa.gov/aqsweb/airdata/download_files.html). This database includes data from both the Chemical Speciation Network (CSN) and the Interagency Monitoring of Protected Visual Environments (IMPROVE) networks (Solomon *et al* 2014). Daily PM_{2.5} concentrations were mapped to their corresponding forecast grid cells and days, providing high-resolution temporal and spatial data critical for training and validating the machine learning models used in this study. The CSN sites, primarily located in urban and suburban regions, provide detailed chemical composition of particulate matter, including sulfates, nitrates, elemental carbon, and organic

carbon, which are valuable for understanding source contributions and for validating model predictions of secondary aerosols (Solomon *et al* 2014).

To complement the PM_{2.5} data and provide additional insight into pollutant trends and regional air quality, we also used data from the Clean Air Status and Trends Network (CASTNET). CASTNET provides long-term atmospheric measurements of sulfur and nitrogen species, ozone, and other parameters essential for evaluating the effectiveness of national and regional air pollution control programs (Schwede and Lear 2014). Weekly integrated filter samples of PM_{2.5} and gaseous pollutants are collected at more than 90 rural, suburban, and urban sites throughout the United States. Data are available on the CASTNET data download page (<https://www.epa.gov/castnet/download-data>). CASTNET sites are especially important because they are more evenly distributed in rural and background regions, which helps mitigate the strong urban bias inherent in the AQS network. Their long-term consistency also makes them suitable for detecting multi-decadal air quality trends (Simon and Amos 2011).

In addition, the Interagency Monitoring of Protected Visual Environments (IMPROVE) program provides detailed PM_{2.5} data focused on visibility in national parks and wilderness areas. IMPROVE includes chemical speciation of particulate matter, providing insight into the sources and composition of PM_{2.5}. The network includes more than 110 monitoring sites, primarily in rural and remote areas, increasing the spatial and chemical coverage of PM_{2.5} measurements (Hand *et al* 2019). IMPROVE data are available through the IMPROVE Data Portal (<http://views.cira.colostate.edu/fed/>). Because IMPROVE sites are often located in protected natural areas, they play a critical role in linking air pollution with ecosystem and visibility impacts, offering complementary data that strengthen exposure and environmental justice assessments (Malm *et al* 2017).

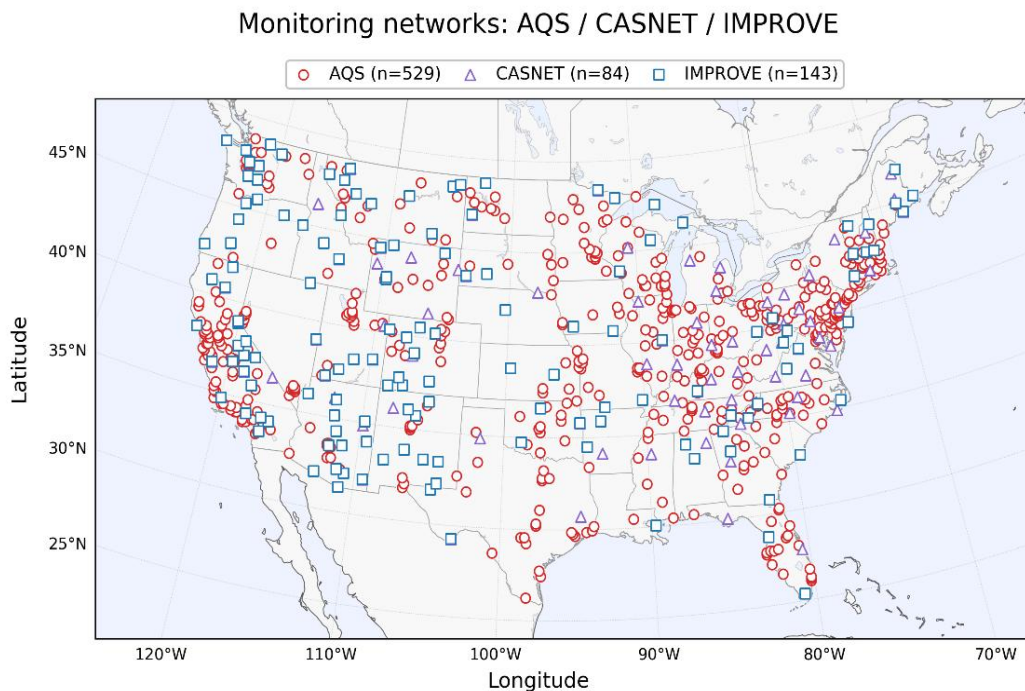


Figure 3.2 The spatial location of the AQS, CASTNET, and IMPROVE sites.

Figure 3.2 shows the spatial distribution of the AQS, CASTNET, and IMPROVE monitoring sites used in this study, illustrating the dense clustering of AQS stations in major metropolitan regions and the more dispersed coverage of CASTNET and IMPROVE stations across rural and remote areas. AQS sites (red circles) are concentrated along the Northeast Corridor, California’s Central Valley, and major urban centers in the Midwest and Southeast. In contrast, CASTNET sites (blue squares) are more evenly distributed across the central and southeastern United States, while IMPROVE sites (purple triangles) are largely located in western high-elevation and protected regions, such as the Sierra Nevada, the Colorado Plateau, and the Rocky Mountains. This spatial pattern underscores a pronounced urban–rural monitoring imbalance in the national network. While AQS provides dense coverage for regulatory compliance in populated areas, rural and background regions remain comparatively underrepresented. Incorporating CASTNET and IMPROVE sites in this study helps alleviate this

bias and provides critical observations for evaluating model performance in under-monitored regions, thereby improving the representativeness and robustness of PM_{2.5} exposure assessments.

3.5 Results

3.5.1 Evaluation of Benchmark Machine Learning Models for PM_{2.5} Prediction.

Figure 3.3 illustrates the performance of a Random Forest (RF) model in predicting 2019 surface PM_{2.5} concentrations using data only from the same locations as the target grid cells. The RF model effectively captures the spatial distribution of PM_{2.5}, identifying higher concentrations in the eastern United States and lower levels in the western regions (Figure 3.3a). The model shows good validation performance for the "label" grid cells, achieving an R² of 1 and an RMSE of 0.29 µg/m³ on the training dataset, and an R² of 0.85 with an RMSE of 1.0 µg/m³ on the test dataset (Figure 3.3b). However, significant errors are observed, particularly in regions with high baseline PM_{2.5} concentrations (Figure 3.3c, d). These errors are more pronounced in areas far from monitoring sites, where predictions tend to overestimate PM_{2.5} levels, especially in downwind areas (Figure 3.3e). This overestimation is likely due to the inability of the model to accurately account for vertical profile differences between urban and suburban areas, as training is predominantly based on urban data where pollution is concentrated near the surface. Interestingly, the largest errors are found in the central United States rather than in the West, which is contrary to traditional expectations. In the eastern US, despite a higher density of monitoring sites, significant biases occur due to the concentration of these sites in urban areas and the much higher PM_{2.5} levels. This finding echoes earlier studies showing that machine learning models trained on spatially imbalanced networks often propagate urban emission characteristics into rural predictions, thereby inflating background concentrations in downwind areas (Di *et al* 2019, Li *et al* 2024b). Addressing this “urban training bias” remains one of the

most pressing challenges for satellite–ML hybrid frameworks, especially when evaluating health impacts in underserved communities.

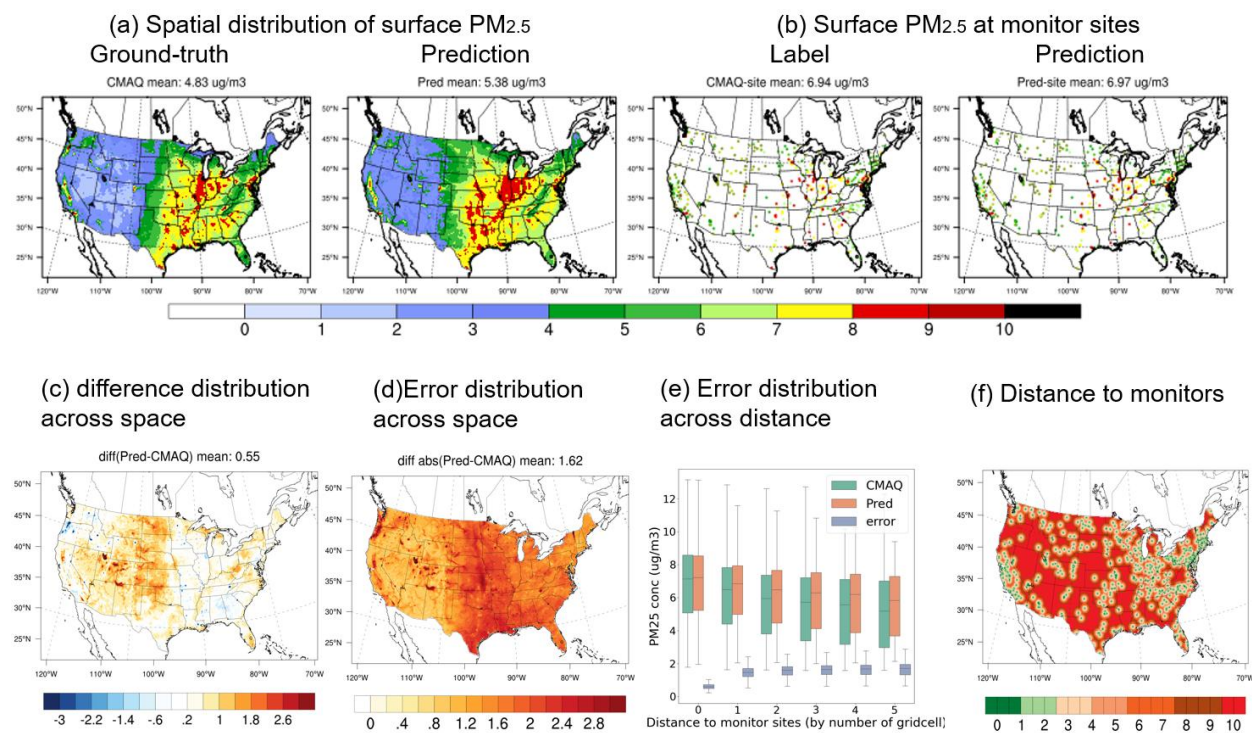


Figure 3.3 Spatial Distribution and Error Analysis of 2019 Surface PM_{2.5} Predictions Using a Random Forest Model.

Table 3.1 evaluates the performance of three machine learning models-Random Forest, LightGBM, and XGBoost-in predicting PM_{2.5} concentrations for the years 2019, 2014, and 2009. The models are evaluated at three stages: training, testing, and using all data combined, with key metrics being RMSE, R², and NMB. For 2019, Random Forest performs consistently well across all stages. In the training stage, it achieves a low RMSE and a high R², indicating that the model fits the training data well. During testing, the RMSE increases slightly to 1.5 $\mu\text{g}/\text{m}^3$ and the R² drops to 0.85, reflecting a slight decrease in accuracy when applied to unseen data, but the model still generalizes effectively. Moreover, the combined data results further reinforce its robustness, with a balanced RMSE and high R², along with a near-zero NMB, suggesting minimal prediction

bias. Similarly, LightGBM shows consistent trends, but with slightly higher errors. It also fits the data well in the training phase, but in the test phase the RMSE increases to $1.6 \mu\text{g}/\text{m}^3$ and the R^2 drops to 0.83. In addition, the combined dataset metrics confirm its reliable performance, albeit with slightly less accuracy than Random Forest. However, the NMB remains low, indicating that LightGBM, while having a slightly higher error rate, still produces unbiased predictions. This consistency across both RF and LightGBM suggests that ensemble tree-based methods are particularly well-suited for heterogeneous atmospheric datasets where nonlinearities dominate, consistent with findings from (Wang *et al* 2023).

In contrast, XGBoost shows notable differences between the training and testing phases in 2019. While it performs strongly during training, with a high R^2 and low RMSE, these metrics deteriorate significantly during testing, where the RMSE rises to $1.8 \mu\text{g}/\text{m}^3$ and R^2 falls to 0.80. This suggests that XGBoost may be overfitting the training data, resulting in less reliable predictions on new data. In addition, the combined data metrics show similar discrepancies, and the NMB is slightly higher, indicating a tendency for XGBoost to overestimate $\text{PM}_{2.5}$ levels, particularly in areas not represented in the training data. Overfitting in XGBoost has been reported in other environmental prediction studies when hyperparameter tuning is insufficient or when the training data are spatially clustered (Chen and Guestrin 2016, Wei *et al* 2021). This highlights the necessity of incorporating spatial cross-validation strategies rather than relying solely on random splits, especially when station density is uneven.

For 2014, the performance patterns are consistent with 2019. Random Forest continues to provide stable results across all stages, with a test RMSE of $1.7 \mu\text{g}/\text{m}^3$ and an R^2 of 0.82. The slight increase in error from training to testing is minimal, showing that the model generalizes well. Similarly, LightGBM follows a similar pattern, with slightly higher RMSE and lower R^2 in

Table 3.1 Performance comparison of the base line machine learning methods (Random Forest, LightGBM, and XGBoost) in predicting PM_{2.5} concentrations across 2019, 2014, and 2009 using RMSE, R², and NMB Metrics.

Year	Data	Parameter	Random Forest	Lightgbm	Xgboost
2019	train	RMSE	0.86	0.93	0.93
		R ²	0.91	0.89	0.87
		NMB	0.12	0.11	0.1
	test	RMSE	1.06	1.05	1.11
		R ²	0.85	0.83	0.81
		NMB	0.14	0.12	0.12
	all	RMSE	0.87	0.93	0.93
		R ²	0.91	0.89	0.87
		NMB	0.12	0.11	0.1
2014	train	RMSE	0.92	1.01	1.12
		R ²	0.9	0.88	0.82
		NMB	0.08	0.07	0.08
	test	RMSE	1.22	1.31	1.37
		R ²	0.85	0.83	0.78
		NMB	0.06	0.05	0.06
	all	RMSE	0.93	1.02	1.13
		R ²	0.9	0.88	0.82
		NMB	0.08	0.07	0.08
2009	train	RMSE	1.05	1.06	1.35
		R ²	0.91	0.91	0.86
		NMB	0.07	0.05	0.1
	test	RMSE	1.3	1.25	1.55
		R ²	0.86	0.87	0.81
		NMB	0.09	0.07	0.12
	all	RMSE	1.04	1.05	1.34
		R ²	0.91	0.91	0.86
		NMB	0.08	0.05	0.11

the test stage, but still maintaining low bias and reasonable accuracy in the combined stage. On the other hand, XGBoost again shows signs of overfitting, with a significant drop in test performance (RMSE of 2.1 $\mu\text{g}/\text{m}^3$ and R² of 0.75), reflecting its reduced ability to generalize beyond the training data. The persistence of this overfitting pattern across multiple years

indicates a structural limitation in the XGBoost framework when applied to spatially imbalanced datasets, suggesting that advanced regularization or hybrid ensemble-deep learning strategies may be required (Zheng *et al* 2021).

Finally, in 2009, the trends continue. Random Forest maintains its leading position, with only a slight decrease in performance from training to testing, confirming its ability to generalize well across different data sets. Furthermore, the combined data metrics (RMSE of $1.6 \mu\text{g}/\text{m}^3$ and R^2 of 0.84) indicate that it consistently captures the underlying patterns in the PM_{2.5} data. LightGBM also performs well, albeit with slightly higher errors in the test phase, but remains a reliable predictor with low bias. In contrast, XGBoost continues to struggle with overfitting and shows the largest discrepancies between the training and test phases, with the RMSE increasing to $2.3 \mu\text{g}/\text{m}^3$ and R^2 decreasing to 0.70 in the test phase, indicating significant challenges in generalizing the model. This comparison across three years highlights that Random Forest not only achieves higher accuracy but also demonstrates greater temporal robustness, a critical feature for long-term PM_{2.5} exposure assessments that inform regulatory policy and epidemiological studies.

In conclusion, Random Forest shows consistently strong performance at all stages- training, testing, and combined-and is the most reliable model for predicting PM_{2.5} concentrations. LightGBM also performs well, but with slightly higher errors and less precision in generalization. XGBoost, however, struggles with overfitting, particularly in the testing phase, resulting in higher prediction errors and reduced accuracy when applied to unseen data, underscoring the importance of evaluating model performance across all phases to ensure reliable and unbiased predictions. These findings suggest that while gradient boosting frameworks remain powerful tools, careful attention must be given to training sample imbalance,

hyperparameter tuning, and spatial cross-validation strategies in order to achieve robust predictions across diverse regions.

3.5.2 Temporal and Spatial Consistency between CMAQ and Machine Learning Predictions

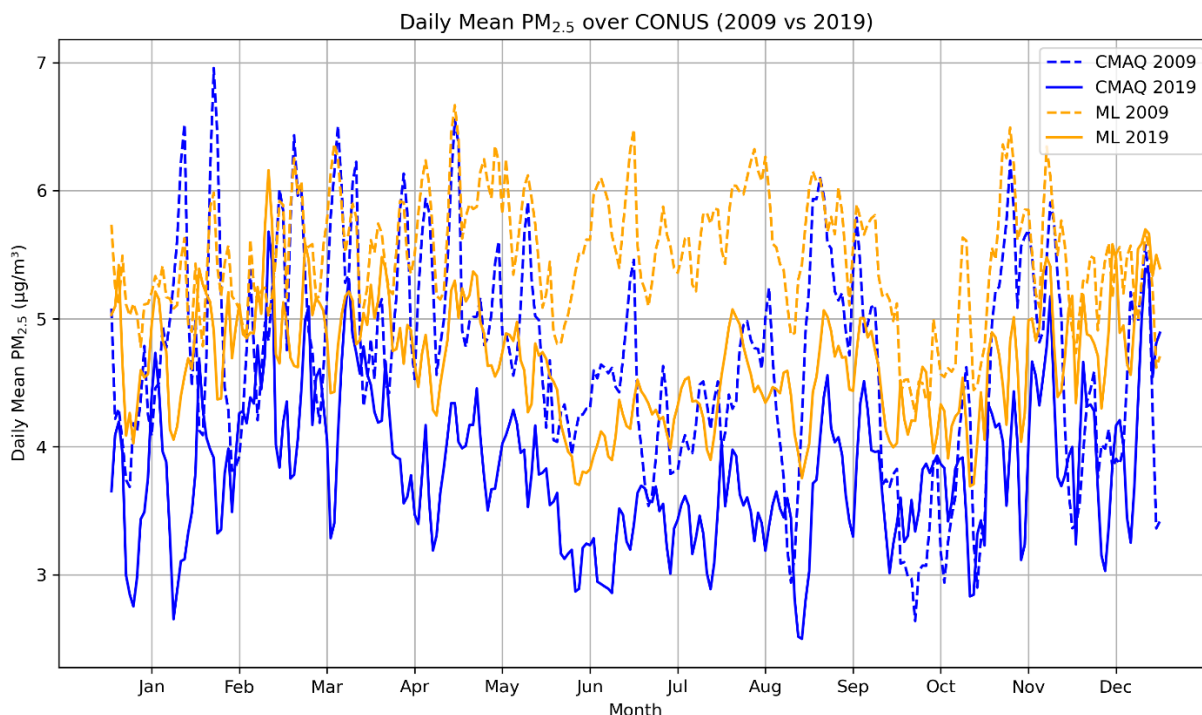


Figure 3.4 Daily mean $PM_{2.5}$ concentrations over the CONUS from CMAQ simulations and machine learning predictions for 2009 and 2019.

To further assess whether machine learning models trained on multi-year data can effectively capture long-term emission-driven trends and reduce spatial generalization errors, Figure 3.4 -3.7 presents the comparison of $PM_{2.5}$ concentrations derived from CMAQ simulations and Random Forest (RF) predictions across the contiguous United States (CONUS) from 2009 to 2019. Figure 3.4 shows the daily variation of national mean $PM_{2.5}$ concentrations over this period. Both CMAQ and RF capture consistent seasonal patterns, with elevated concentrations during winter and early spring and lower values in summer and fall, corresponding to known seasonal emission and atmospheric conditions. Between 2009 and 2019,

CMAQ indicates a clear downward shift in annual averages from approximately $6.2 \mu\text{g}/\text{m}^3$ in 2009 to $4.8 \mu\text{g}/\text{m}^3$ in 2019. The RF predictions reproduce this overall decline, though with slightly higher summertime values and a smoother curve, which may reflect the influence of urban-dominated training data that fails to fully capture regional differences in meteorology and source activity. This smoothing effect is consistent with previous findings that ML models trained on dense urban monitoring data often underestimate the amplitude of seasonal cycles, particularly in rural or emission-limited regions (Lin *et al* 2024, Liu *et al* 2025).

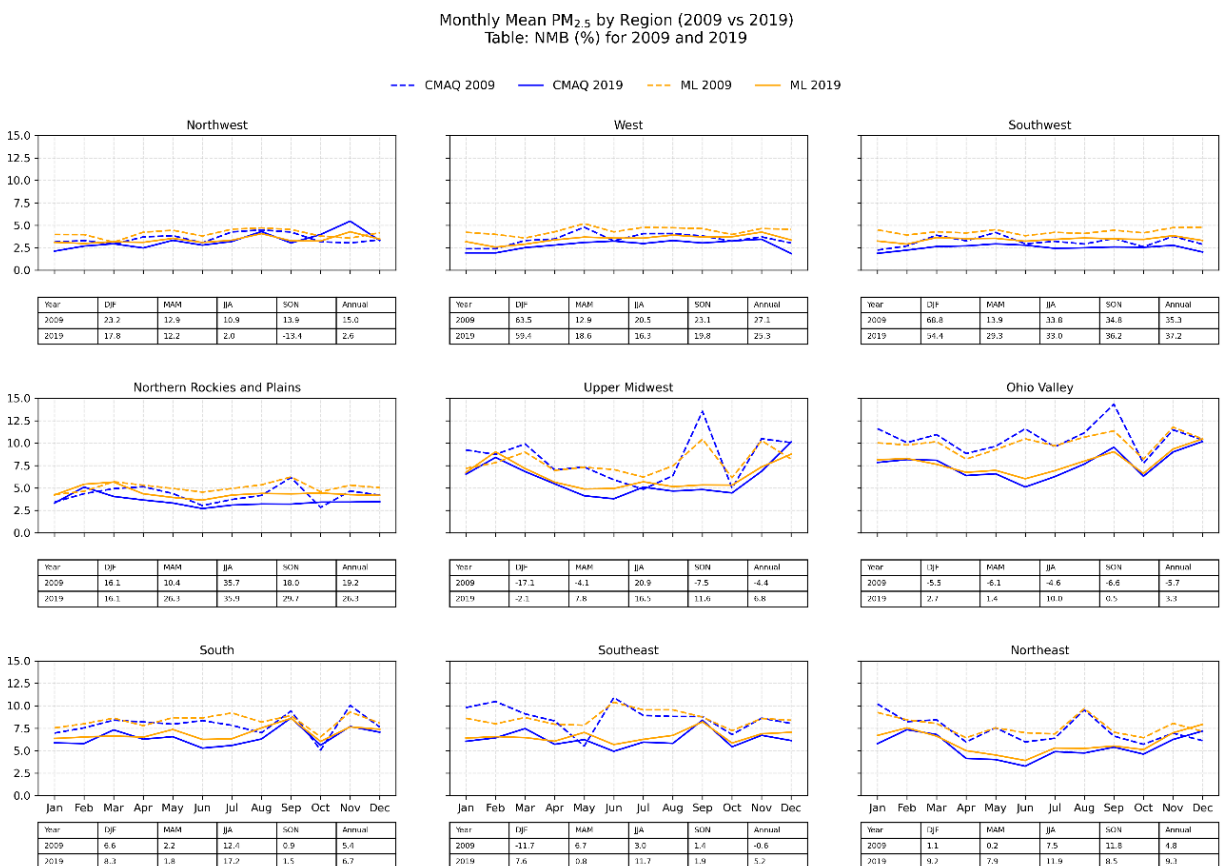


Figure 3.5 Monthly mean PM_{2.5} concentrations by NCEI climate region for 2009 and 2019 from CMAQ and machine learning predictions. Table below each panel shows normalized mean bias (NMB, %) for the two years.

Figure 3.5 presents monthly average PM_{2.5} concentrations by NCEI-defined climate region, allowing for evaluation of both spatial and seasonal variability in model behavior.

CMAQ shows clear regional and seasonal gradients, in the Upper Midwest, concentrations drop from over $8 \mu\text{g}/\text{m}^3$ in 2009 to below $6 \mu\text{g}/\text{m}^3$ in 2019, with peak values typically occurring in January and July. The RF model captures the general direction of seasonal evolution but underestimates the magnitude of summer-to-winter contrasts in rural or topographically complex regions such as the Northwest, Northern Rockies, and Southwest. In these regions, the RF predictions are consistently higher than CMAQ estimates, especially in spring and summer months, indicating possible overfitting to urban patterns or insufficient representation of low-emission environments during model training. Such discrepancies are important because they can propagate into exposure assessments, especially for rural populations, which are often underrepresented in air quality monitoring but remain highly vulnerable due to reliance on local agricultural activities (Reid *et al* 2019).

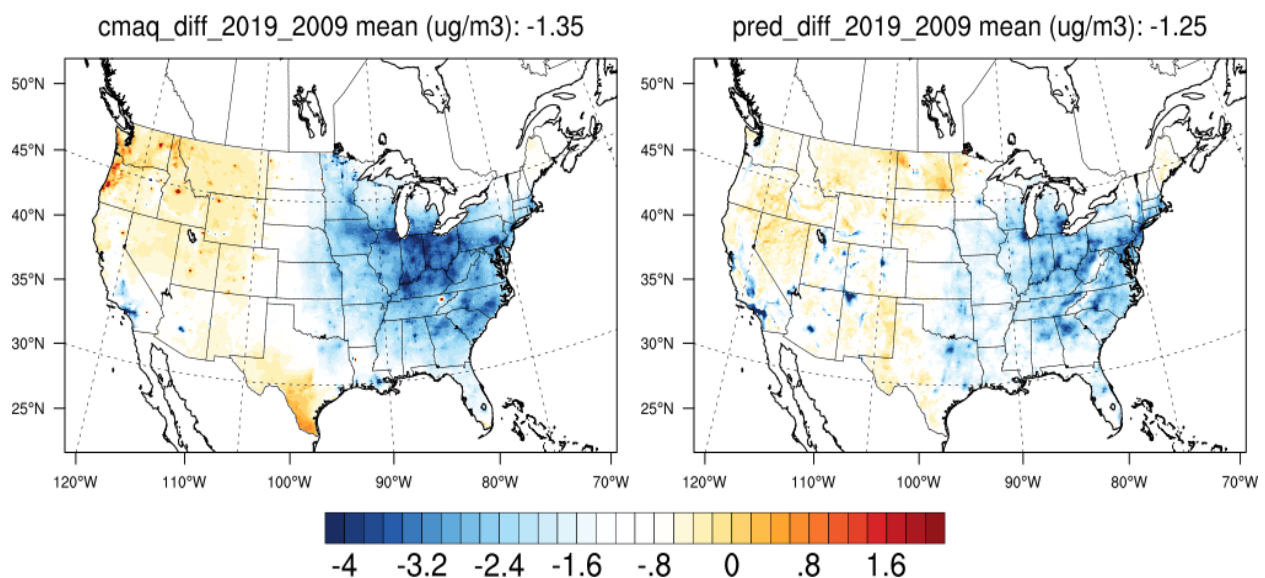


Figure 3.6 Spatial distribution of decadal $\text{PM}_{2.5}$ changes (2019 minus 2009) simulated by CMAQ and predicted by the machine learning model.

Figure 3.6 maps the spatial distribution of annual mean $\text{PM}_{2.5}$ differences between 2009 and 2019 for both CMAQ and RF outputs. CMAQ simulations reveal widespread reductions of more than $2 \mu\text{g}/\text{m}^3$ across the Midwest, Great Lakes, and parts of the Southeast, reflecting major

emission control efforts over the decade. In contrast, RF-predicted reductions are more moderate in these regions, often ranging from 1 to 1.5 $\mu\text{g}/\text{m}^3$, and appear less pronounced over the Central Plains and Interior West. Some regions such as Texas and parts of California even show marginal increases or near-zero trends in RF predictions, diverging from the corresponding CMAQ outputs. These spatial discrepancies suggest that while the RF model reproduces the

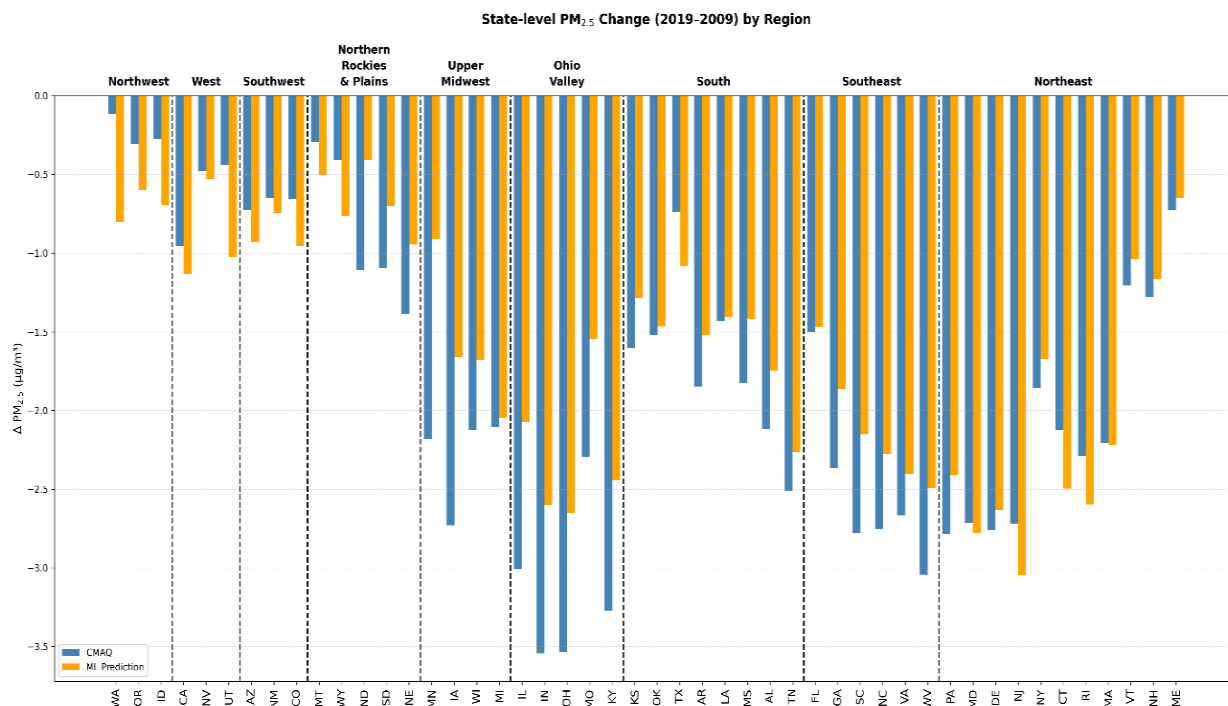


Figure 3.7 State-level PM_{2.5} changes (2019 minus 2009) by NCEI climate region from CMAQ and machine learning predictions.

direction of change, it underestimates regional heterogeneity in emission responses, particularly where monitoring data is sparse. This underestimation aligns with earlier evaluations of ML-based PM_{2.5} models, which highlighted the risk of “spatial smoothing” when the models rely heavily on features correlated with urban emission patterns but fail to capture secondary formation or long-range transport dynamics (Just *et al* 2020, Li *et al* 2024b).

Figure 3.7 quantifies these differences at the state level, grouping the results by the nine NCEI regions. CMAQ simulations show the largest state-level reductions in the Ohio Valley and

Southeast, where annual mean concentrations dropped by 2.0 to 2.5 $\mu\text{g}/\text{m}^3$. RF predictions show similar directional trends but with reduced magnitude, typically 0.5 to 1.5 $\mu\text{g}/\text{m}^3$ across the same states. In under-monitored areas such as the Northern Rockies and Upper West, the RF model frequently predicts minimal change or even slight increases, failing to reflect CMAQ-simulated declines. Notably, states like Colorado and Kansas, which combine complex topography with rural emission patterns, show the widest disagreement between the two models. These inconsistencies reinforce the importance of incorporating additional rural and regional monitoring networks (e.g., CASTNET and IMPROVE) to improve ML training sets and reduce reliance on urban-dominated samples. Without such adjustments, ML frameworks may systematically underestimate the benefits of air quality regulations in cleaner regions, leading to biased policy evaluations (Shaddick *et al* 2020). These spatial and temporal discrepancies set the stage for a quantitative comparison of CMAQ and machine learning predictions in the following analysis.

Overall, Figure 3.4-3.7 reveal that while machine learning models trained on multi-year datasets can approximate national trends in $\text{PM}_{2.5}$ decline, their performance varies substantially across space and time. CMAQ provides stronger spatial gradients and region-specific trend patterns, whereas RF predictions tend to smooth over these variations and produce more conservative estimates of change. The consistent underestimation of reductions in rural regions and the persistence of elevated predictions in cleaner areas suggest that sample imbalance remains a primary limitation. These findings demonstrate the value of hybrid testbeds that integrate CMAQ simulations with ML models, as they can highlight where ML predictions deviate most strongly from physical process-based simulations, thereby guiding targeted improvements in feature engineering, sampling strategies, and monitoring network design (Wei

et al 2023, Wang *et al* 2023).

Monthly PM_{2.5} was summarized for the nine NCEI climate regions: Northwest, West, Southwest, Northern Rockies and Plains, Upper Midwest, Ohio Valley, South, Southeast, and Northeast. CMAQ simulations and machine-learning (ML) predictions were mapped to a common grid and masked by state identifiers to delineate each region. For every region and month, spatial means were computed across all masked grid cells after averaging over hours. Annual means were obtained by averaging the twelve monthly regional means. Seasons were defined as DJF for December, January, and February; MAM for March, April, and May; JJA for June, July, and August; and SON for September, October, and November. December was taken from the same calendar year as the corresponding January and February to maintain consistency with the plotted panels.

To quantify the degree of consistency between CMAQ and ML predictions, the normalized mean bias (NMB) was computed for each climate region and season as defined below:

$$NMB(\%) = \frac{\sum(P_i - O_i)}{\sum O_i} \times 100 \quad (3.1)$$

where P_i and O_i denote the ML and CMAQ monthly regional means within the period of interest. Positive values indicate ML overestimation relative to CMAQ, and negative values indicate underestimation. Seasonal and annual NMBs were computed for 2009 and 2019 and reported beneath each panel of Figure 3.5.

Across the United States, ML and CMAQ both capture the decadal decline in PM_{2.5} from 2009 to 2019. Annual NMB magnitudes are generally small in the eastern regions and larger in parts of the West and Southwest. For example, the Ohio Valley remains close to neutrality at the annual scale, with values on the order of a few percent in both years, while the West and

Southwest retain clearly positive annual biases. The Northwest shows a marked improvement, with the annual NMB decreasing from roughly fifteen percent in 2009 to only a few percent in 2019. In contrast, the Northern Rockies and Plains exhibit an increase in annual NMB from about twenty percent to more than a quarter, indicating a growing positive bias. The Southeast changes sign at the annual scale, moving from a slight underestimation in 2009 to a slight overestimation in 2019. The Upper Midwest maintains a small positive annual bias in both years, and the Northeast shows a moderate increase but remains within a range that is modest compared with the western domains.

Seasonal behavior explains much of this regional contrast. Wintertime biases are particularly pronounced in the western United States. In the West and Southwest, DJF NMB values are very large and strongly positive in both 2009 and 2019, with the West near sixty percent and the Southwest above fifty percent, which is consistent with cold-season accumulation under stable conditions and with differences in how background levels are represented by ML and CMAQ. Summer also contributes positively to several regions. The West and Southwest display persistent positive JJA biases, and the Upper Midwest shows positive summer NMBs in both years, although the magnitude is smaller in 2019. By contrast, the Ohio Valley exhibits seasonal NMBs that are mostly within a few percent of zero, and the Northwest shifts toward neutrality across seasons, which together explain the substantial reduction in its annual bias. The Southeast illustrates a clear seasonal rebalancing, with winter changing from a negative to a positive NMB and summer increasing, consistent with the sign change at the annual scale.

Overall, the Figure 3.4-3.7 indicate strong alignment between ML and CMAQ in the eastern United States, typically with annual NMB near or below ten percent, and larger

systematic differences in several western regions, especially in winter and, where wildfire influence is common, in summer. These regional differences in NMB indicate that bias patterns may depend not only on geography and season but also on concentration levels, which is examined next. These patterns underscore the role of monitoring density, regional emissions, meteorological regimes, and extreme events in shaping apparent ML–CMAQ consistency at regional and seasonal scales.

Here we compare machine-learning (ML) predictions with CMAQ using a hexagonal density plot of grid-cell pairs and a concentration-binned summary. The scatter shows strong nationwide coherence between products, with a coefficient of determination near 0.83. The normalized mean bias is about +22 percent when referenced to CMAQ, indicating a systematic elevation of ML relative to CMAQ at the national scale. The ordinary least-squares slope is approximately 0.79, which is consistent with a compressed dynamic range in ML: values near the low end are elevated and values near the high end are reduced relative to CMAQ. Extremes are rare but informative. Grid cells that are extreme in CMAQ but not in ML account for roughly 0.07 percent of the domain, and cells that are extreme in ML but not in CMAQ account for roughly 0.13 percent, indicating occasional misses of very high concentrations and occasional spurious high values in lower-background settings.

The binned analysis, which groups grid cells by CMAQ concentration and reports the share with ML greater than or less than CMAQ together with the mean relative difference, reveals a pronounced concentration dependence (Figure 3.8). In the lowest bins, from 0 to 3 $\mu\text{g}/\text{m}^3$ and from 3 to 6 $\mu\text{g}/\text{m}^3$, ML exceeds CMAQ for most grid cells and the mean relative difference is large and positive, on the order of +54 percent and +19 percent, respectively. Near the middle range, around 6 to 9 $\mu\text{g}/\text{m}^3$, the mean difference is close to neutral. At higher

Spatial Consistency (ML vs CMAQ), 2019 (Annual)

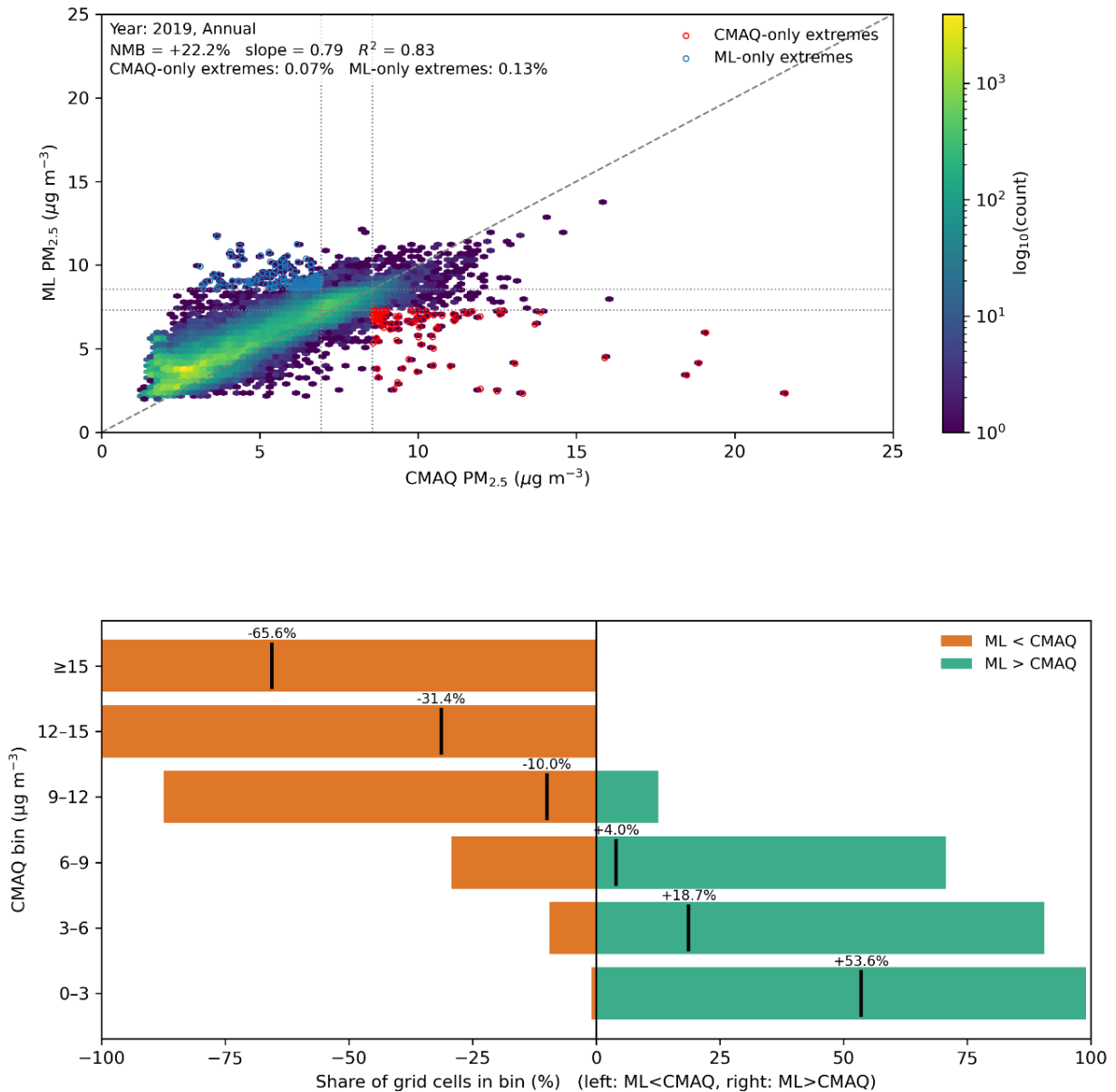


Figure 3.8 Concentration-binned comparison between CMAQ and machine learning PM_{2.5} estimates for 2019, showing grid-cell scatter (top) and relative bias by concentration range (bottom).

concentrations the sign reverses: between 9 and 12 $\mu\text{g/m}^3$ the mean relative difference is modestly negative, near -10 percent, and it becomes increasingly negative in the 12 to 15 $\mu\text{g/m}^3$ and $\geq 15 \mu\text{g/m}^3$ bins, reaching approximately -31 percent and -66 percent. Together with the

sub-unit slope, these patterns indicate a consistent tendency for ML to raise cleaner backgrounds and to damp the highest concentrations.

The most plausible explanations combine statistical shrinkage and representativeness. Regression-to-the-mean behavior in the learning algorithm, limited training coverage at the highest quantiles, and imperfect predictors for wintertime stagnation and smoke-affected summers can all contribute to underestimation at the top end and overestimation at the bottom end. For applications that depend on accurate exposure gradients, these results argue for a simple post-processing bias correction that is conditional on concentration, for example quantile mapping or bin-wise calibration, and for targeted evaluation in regimes dominated by winter inversions and wildfire smoke.

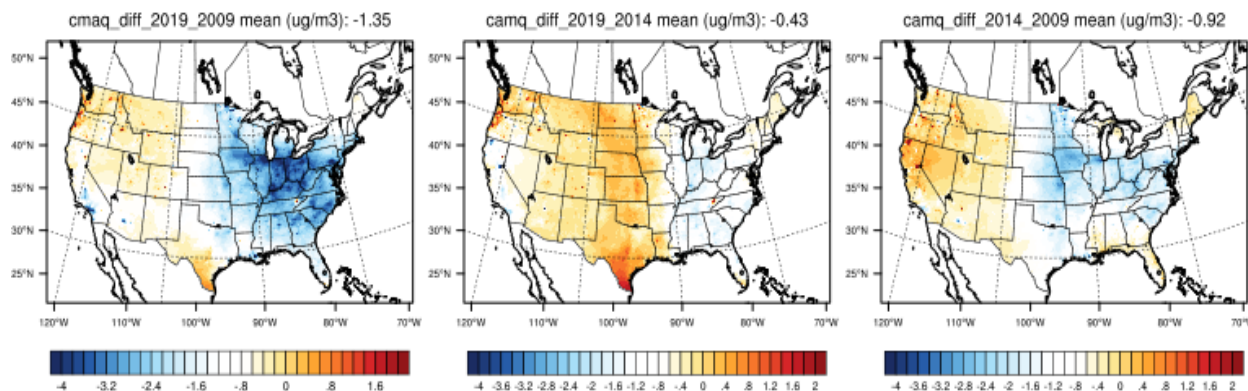


Figure 3.9 Spatial and temporal changes in CMAQ-simulated PM_{2.5} concentrations across the contiguous United States for 2009, 2014, and 2019.

Figure 3.9 illustrates the spatial and temporal changes in PM_{2.5} concentrations derived from CMAQ data. It shows the differences in PM_{2.5} levels between different years, highlighting a general decrease in PM_{2.5} from 2009 to 2019, with an average decrease of -1.35 $\mu\text{g}/\text{m}^3$. However, when this decade is divided into two periods, the changes are not uniform. Between 2014 and 2019 the decrease is only -0.43 $\mu\text{g}/\text{m}^3$, while from 2009 to 2014 the decrease is almost double. This indicates that while PM_{2.5} levels are generally decreasing, the rate of decrease has slowed

over time. Spatially, the figure shows a contrasting trend across the United States: PM_{2.5} levels are decreasing in eastern regions, but increasing in western regions. The most severe areas of PM_{2.5} have shifted from the far eastern U.S. to central regions, such as Texas, between 2009 and 2014. This spatial shift suggests that relying on traditional machine learning models, which tend to overestimate PM_{2.5} in the West and underestimate it in the East, could lead to significant biases in PM_{2.5} predictions. These temporal and spatial patterns are consistent with national emission inventory records showing substantial reductions in SO₂ and NO_x emissions after 2009 due to regulatory controls, whereas increases in wildfire activity and oil and gas operations contributed to western PM_{2.5} burdens in the 2010s (McDuffie *et al* 2021, Pye *et al* 2022). These findings collectively highlight the concentration-dependent nature of model bias and underscore the need for post-processing calibration and evaluation under emission- and meteorology-specific regimes. Building on these results, the next section evaluates how the spatial distribution of monitoring networks influences the accuracy and generalization of PM_{2.5} predictions.

3.5.3 Influence of Monitoring Network Distribution on Prediction Accuracy

To evaluate how monitoring coverage affects prediction bias and spatial generalization, Figure 3.10 compares the spatial distribution of monitors, CMAQ-modeled concentration distributions, and RMSE as a function of distance from observation sites across three representative years. Over time, from 2009 to 2019, there has been a gradual increase in the number of monitoring sites, particularly in urban areas. However, despite this increase, monitors remain heavily concentrated in cities, leaving rural areas less covered. The middle column of the figure shows density plots of PM_{2.5} concentrations as modeled by CMAQ for each of the three years. The black dashed lines indicate the peak of the density distribution for each year, which shows a leftward shift from a log concentration of 9 µg/m³ in 2009 to 7.8 µg/m³ in 2014, and

further to $7.1 \mu\text{g}/\text{m}^3$ in 2019. This shift reflects a general decrease in $\text{PM}_{2.5}$ concentrations over time. However, regardless of the year, the label values (representing ground truth data) do not fully capture the entire density distribution generated by the CMAQ model. The peak and distribution of the label values consistently show a rightward shift compared to the CMAQ results, indicating that relying solely on label data for predictions may lead to an overestimation of total $\text{PM}_{2.5}$ concentrations. This bias highlights the challenge of “urban skew” in monitoring, where station locations overrepresent polluted cores while underrepresenting rural or background conditions, leading to inflated estimates when extrapolated nationally (Shaddick *et al* 2020).

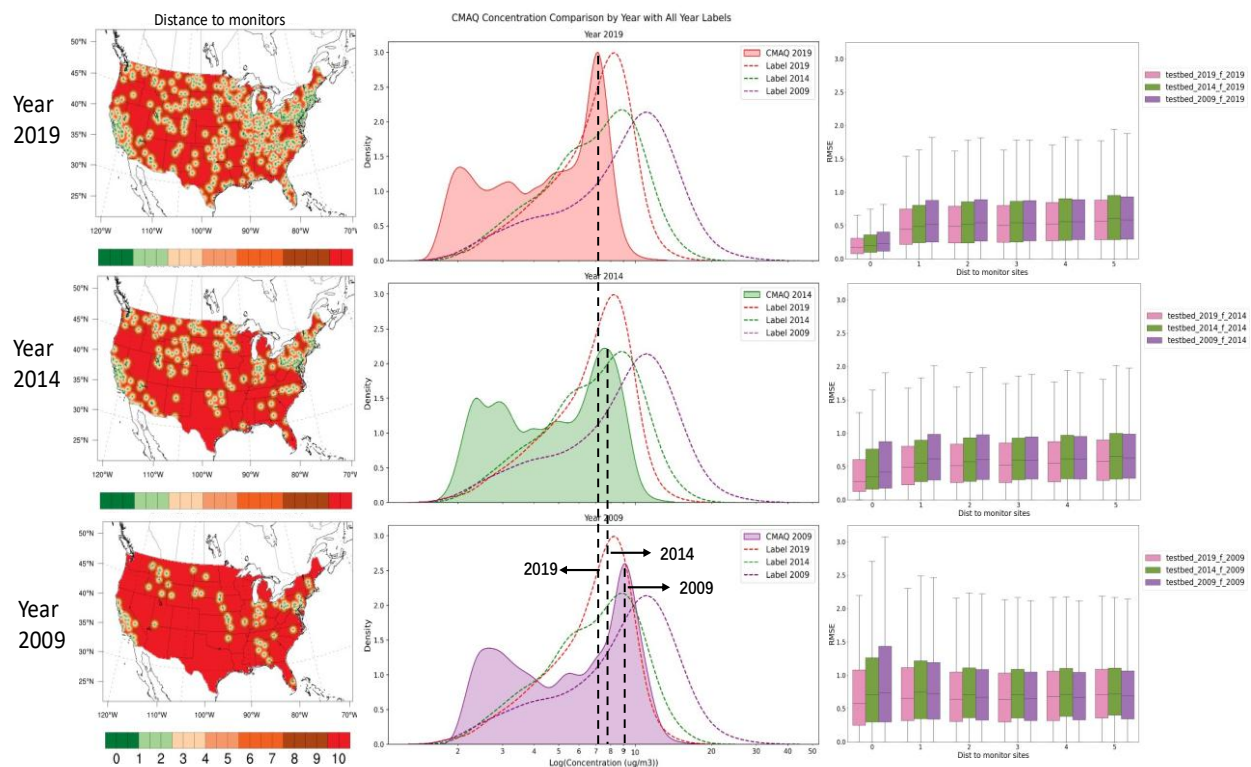


Figure 3.10 Spatial coverage of EPA monitoring networks, CMAQ-modeled $\text{PM}_{2.5}$ distributions, and distance-dependent prediction errors (2009, 2014, 2019).

The right column of the figure shows box plots representing the RMSE values obtained when using Random Forest models to predict $\text{PM}_{2.5}$ at different distances from the monitor sites, using the label positions from different years as a reference. The results clearly show that the

RMSE increases with distance from the monitoring sites for all years, highlighting the challenge of making accurate predictions in areas far from monitors. In particular, predictions using 2019 tag positions tend to have lower RMSE values, indicating better model performance.

Furthermore, predictions for 2019 consistently result in the lowest RMSE, regardless of which year's label positions are used as a reference. These results highlight the importance of balancing the distribution of monitoring sites across regions to improve the accuracy of PM_{2.5} predictions. Concentrating monitors in urban areas while neglecting rural regions can lead to significant biases and inaccuracies, especially in areas far from existing monitors. Therefore, achieving a more even distribution of monitoring sites is critical to improving the reliability of PM_{2.5} predictions over the entire study area. This reinforces the call for integrating multiple monitoring networks (AQS, CASTNET, IMPROVE) to reduce spatial bias and improve generalization, particularly in under-monitored western and rural regions (Hand *et al* 2019, Wei *et al* 2023).

Figure 3.11 demonstrates how combining multiple monitoring networks improves spatial coverage and prediction accuracy. The upper row shows PM_{2.5} predictions generated using only AQS data, while the lower row incorporates CASTNET and IMPROVE sites to form a combined network. Each panel includes both spatial prediction maps and monitor site distributions, allowing visual comparison of coverage and model performance. The AQS-only model shows strong prediction skill in densely monitored urban corridors such as the Northeast and Great Lakes regions but performs poorly in sparsely monitored western and central areas. Adding CASTNET and IMPROVE sites substantially increases coverage in these regions, filling large observational gaps across the Rocky Mountains, Northern Plains, and interior Southwest.

The hybrid model produces lower national mean bias and RMSE values compared with the AQS-only model. It also yields smoother spatial gradients that better align with the

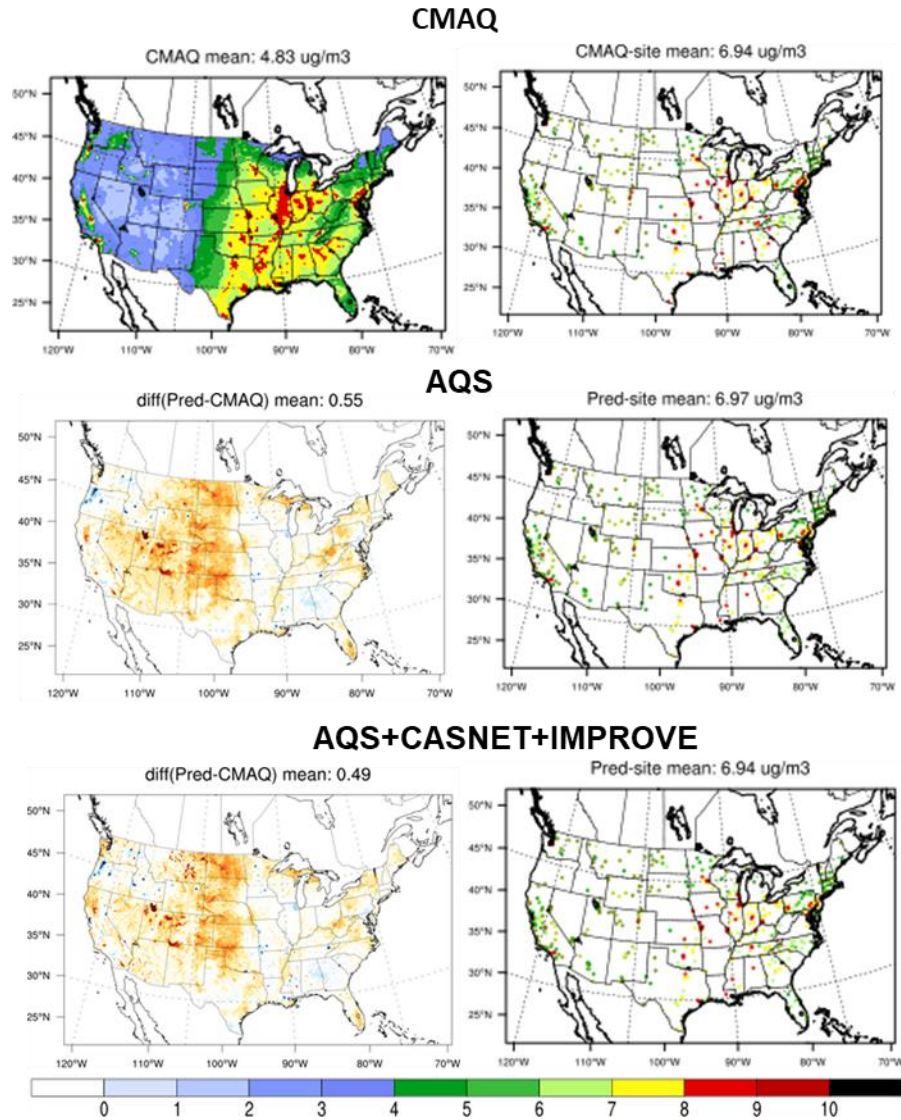


Figure 3.11 Improvement of PM_{2.5} prediction accuracy through multi-network integration (AQS, CASTNET, IMPROVE).

underlying CMAQ fields. This improvement is particularly evident in the western United States, where the addition of CASTNET and IMPROVE reduces overestimation of PM_{2.5} that previously occurred in data-sparse regions. In the Midwest and Southeast, the combined network enhances spatial continuity by linking urban and rural subdomains, reducing abrupt transitions near monitoring boundaries. These changes indicate that the inclusion of rural and background sites helps constrain the upper and lower bounds of concentration estimates and improves

regional consistency.

Building on the integration results, Figure 3.12 evaluates the performance of Random Forest models trained separately using AQS, CASTNET, and IMPROVE data as label sources for 2019. The left column shows the spatial distribution of monitoring sites for each data source, and the distances of these sites to other areas. Among the three, CASNET has the fewest monitoring sites, followed by IMPROVE, while AQS has the most. When comparing the spatial prediction results with the CMAQ output, it is evident that all three sources tend to overestimate $PM_{2.5}$ concentrations overall. However, the spatial discrepancies vary by region. In the western United States, all three label sources lead to overestimates. In the eastern United States, predictions based on AQS data lead to overestimates in some areas, while CASNET data tend to significantly underestimate $PM_{2.5}$ concentrations. IMPROVE data, on the other hand, result in moderate underestimations. These contrasting patterns highlight the influence of network design on prediction bias: urban-heavy networks like AQS tend to overpredict due to emission density, whereas rural-focused networks like IMPROVE may underpredict by missing urban plumes. CASTNET, with its mixed urban–rural distribution, provides a more balanced representation, improving overall generalization (Schwede and Lear 2014, Simon and Amos 2011).

Further analysis of the RMSE values at different distances from the monitoring sites shows that predictions using CASNET data yield the lowest RMSE values, followed by AQS, with IMPROVE yielding the highest RMSE. In addition, the RMSE values for all three sources increase with distance from the monitoring sites, indicating that predictions become less accurate as one moves away from the data points. The superior performance of CASNET can be attributed to its balanced coverage of over 90 rural, suburban, and urban sites, providing a more representative data set. In contrast, IMPROVE data points are concentrated in rural and remote

areas and lack urban information, while AQS, despite having the largest number of sites, is primarily focused on urban regions, leading to overestimation when used as a label for predictions. This finding underscores the importance of network complementarity: combining AQS for urban cores, IMPROVE for remote areas, and CASTNET for mixed coverage could yield a hybrid dataset that reduces spatial bias in ML training and better captures the full exposure gradient (Di *et al* 2019, Wei *et al* 2023).

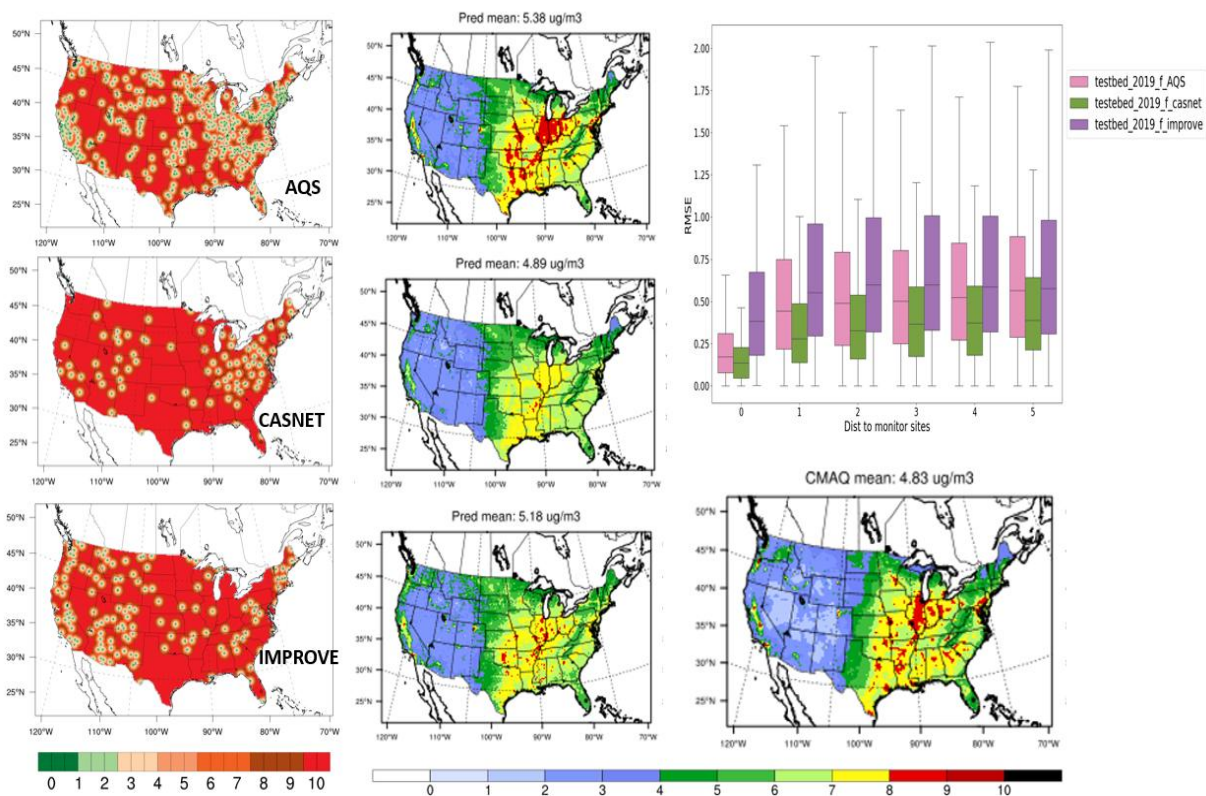


Figure 3.12 Comparative performance of Random Forest PM_{2.5} predictions using AQS, CASTNET, and IMPROVE as label networks (2019).

3.5.4 Performance of Deep Learning Methods for PM_{2.5} Prediction

Building upon previous analyses of monitoring network influence, this section examines how deep learning architectures, particularly ResNet and its temporal variant, enhance prediction accuracy relative to tree-based approaches. ResNet, known for its powerful feature extraction

capabilities, is compared to traditional machine learning models such as random forest (RF) and gradient boosting methods (XGBoost, LightGBM), as well as other deep learning variants such as DeepRF and ResNet with temporal features (ResNet_temporal). Figure 3.14 shows the spatial distribution of PM_{2.5} concentrations for 2019 as predicted by different models, including the ground truth data from CMAQ. The figure shows that while all models capture the general spatial patterns of PM_{2.5}, there are differences in the predicted concentrations, especially in regions with higher pollution levels. The right panel (e) shows how the prediction errors vary with distance from the monitoring sites, illustrating that the errors tend to increase with distance from the monitoring sites, which is a common challenge in air quality modeling.

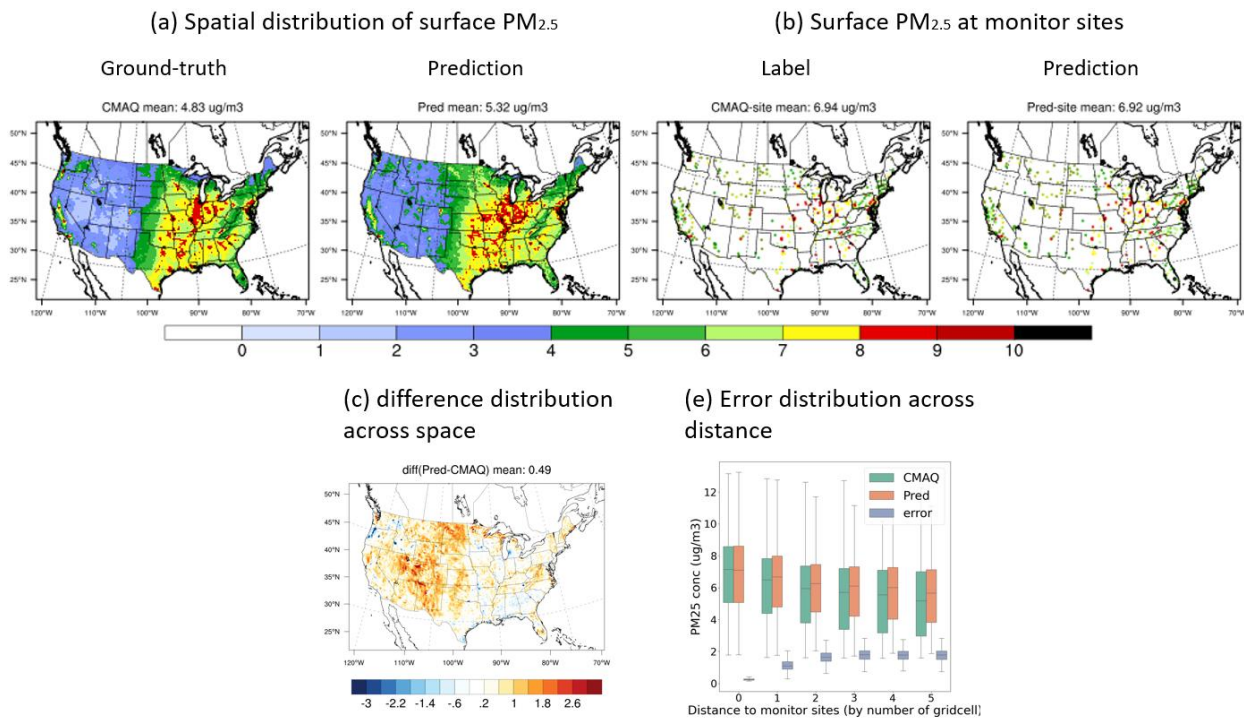


Figure 3.13 Spatial distribution of surface PM_{2.5} and error analysis for 2019.

ResNet's advantage lies in its ability to learn hierarchical representations of features through residual blocks, allowing the model to capture nonlinear interactions between emissions, meteorology, and atmospheric chemistry that simpler algorithms may miss (He *et al* 2016, Song

et al 2020). This makes it particularly effective in regions with complex pollution dynamics, such as the eastern U.S. with strong anthropogenic sources, or the western U.S. where wildfire smoke and dust events drive episodic $PM_{2.5}$ peaks.

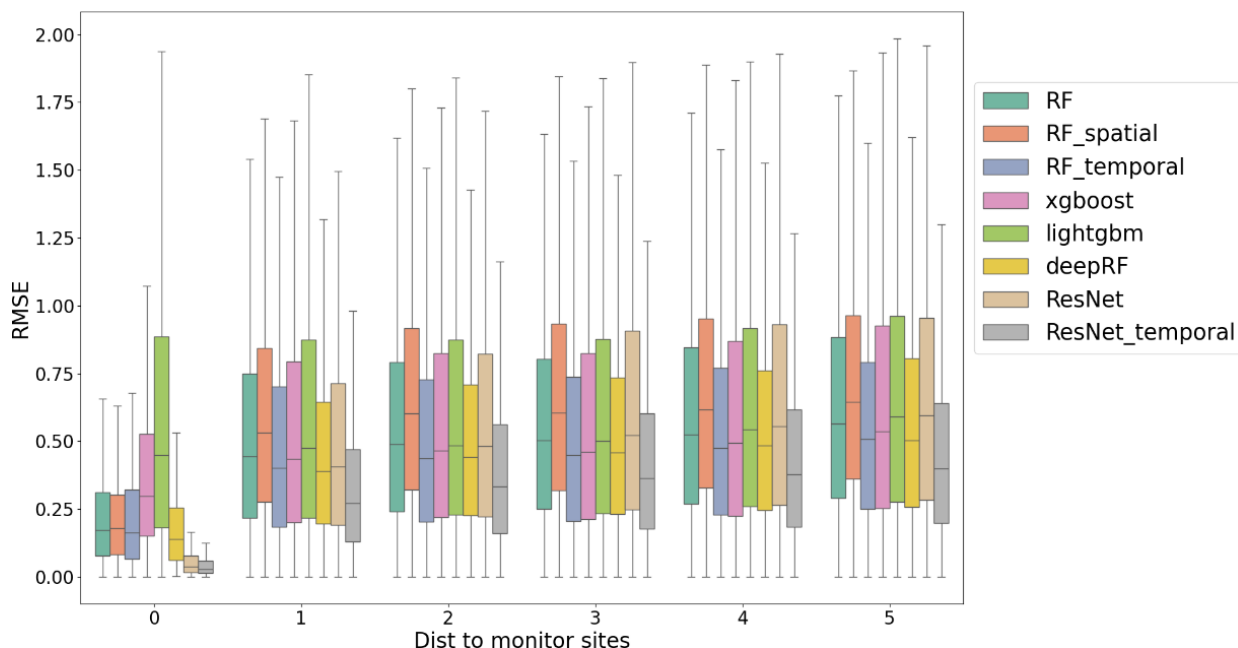


Figure 3.14 RMSE comparison of traditional and deep learning models across distance.

To quantitatively evaluate performance, RMSE values were computed for different models as a function of distance from monitoring sites. Figure 3.14 further explores the performance comparison by showing RMSE values at various distances from monitoring sites for different models. The box plots show that the ResNet and ResNet_temporal models generally yield lower RMSE values compared to traditional models such as RF and gradient boosting methods, especially at greater distances from monitoring sites. This indicates that ResNet, especially when incorporating temporal features, improves the ability of the model to generalize and more accurately predict $PM_{2.5}$ concentrations over a larger spatial domain. Incorporating temporal features into ResNet (ResNet_temporal) appears to provide a significant benefit, reducing prediction errors even further compared to ResNet alone. This improvement suggests

that ResNet_temporal can capture persistence effects of PM_{2.5} formation and transport, such as multi-day stagnation or wildfire smoke plumes, which purely spatial models may fail to represent. Our results are consistent with recent applications of spatiotemporal deep learning in air quality research, which demonstrate that CNN- or ResNet-based architectures outperform tree-based models in regions with sparse monitoring networks (Li *et al* 2024b, Wei *et al* 2023). Importantly, ResNet’s ability to reduce error growth with distance highlights its potential to bridge urban–rural gaps in exposure assessments, a critical issue for addressing environmental equity in air pollution research (Clark *et al* 2022).

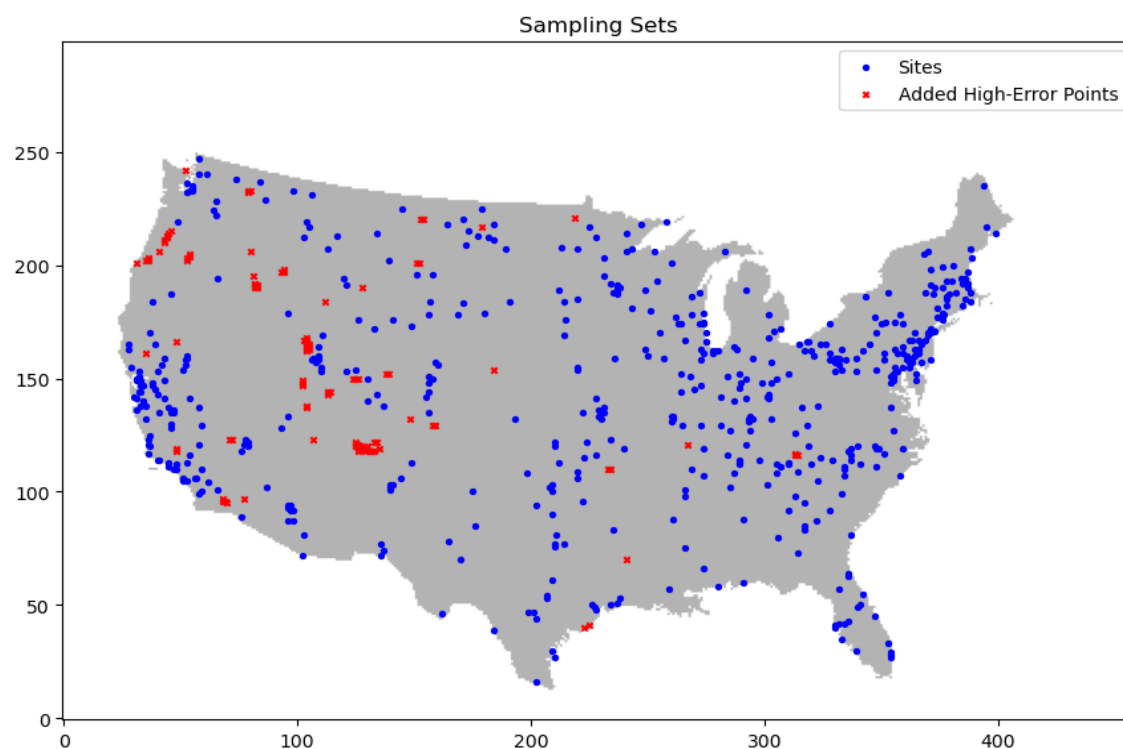


Figure 3.15 Spatial distribution of monitoring sites and sampled high-error grid cells. Blue dots denote existing monitoring sites, while red crosses indicate newly sampled high-error locations identified based on model–simulation discrepancies.

After evaluating overall model performance, we further analyzed the spatial characteristics of model–simulation discrepancies and identified regions that contributed disproportionately to total prediction errors. As shown in Figure 3.15, high-error grid cells are

primarily concentrated in the western and central United States, particularly along the Rocky Mountains, the Great Basin, and parts of the arid Southwest. These regions correspond to areas with complex topography, limited monitoring coverage, and strong episodic variability from dust storms and wildfire smoke, which collectively increase predictive uncertainty. In contrast, the eastern United States, with denser monitoring networks and more stable meteorological regimes, exhibits smaller and more spatially consistent errors. This spatial contrast highlights the dependence of model accuracy on observation density and data representativeness.

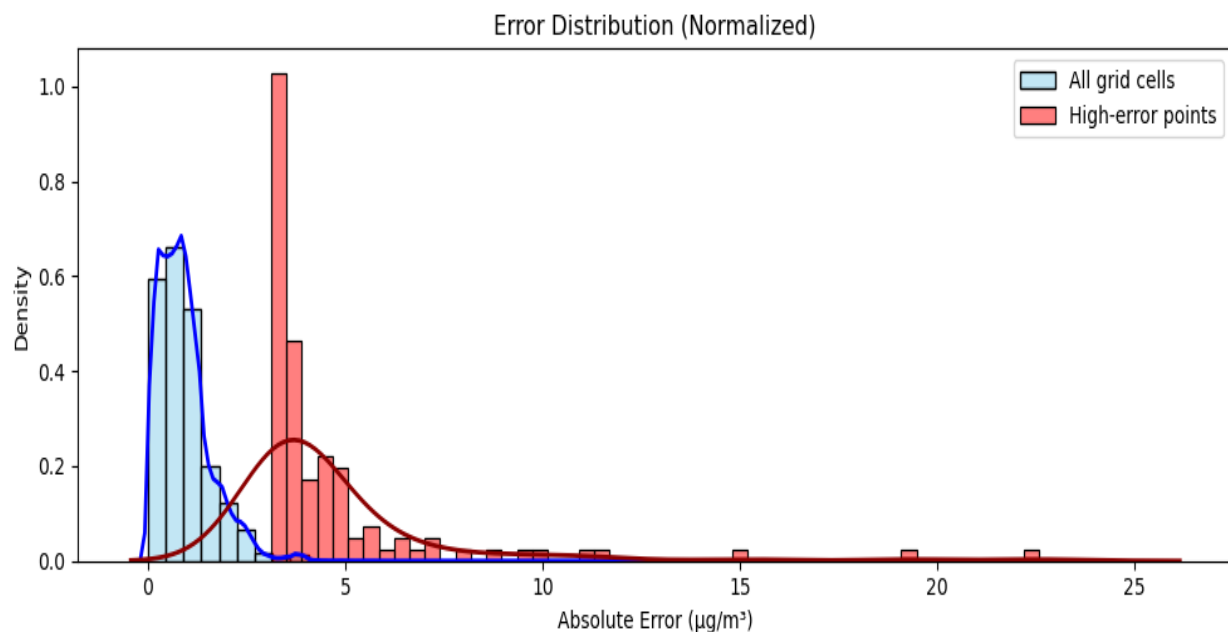


Figure 3.16 Normalized error distributions for all grid cells and high-error locations. Histogram and kernel density estimates show that errors at high-error points (red) are systematically larger and shifted toward higher values compared to all grid cells (blue).

To quantify these differences, Figure 3.16 compares normalized error distributions between all grid cells and the subset of high-error locations. The high-error group displays a right-shifted and broader distribution, with a mean bias approximately three times larger than the domain-wide median. This indicates that large errors are not randomly scattered but spatially structured, often linked to regions with highly variable emissions, terrain-induced meteorological

gradients, or gaps in satellite retrieval coverage. The skewed distribution also implies that a small fraction of grids contributes disproportionately to the total domain error, emphasizing the need for targeted model refinement in these regions.

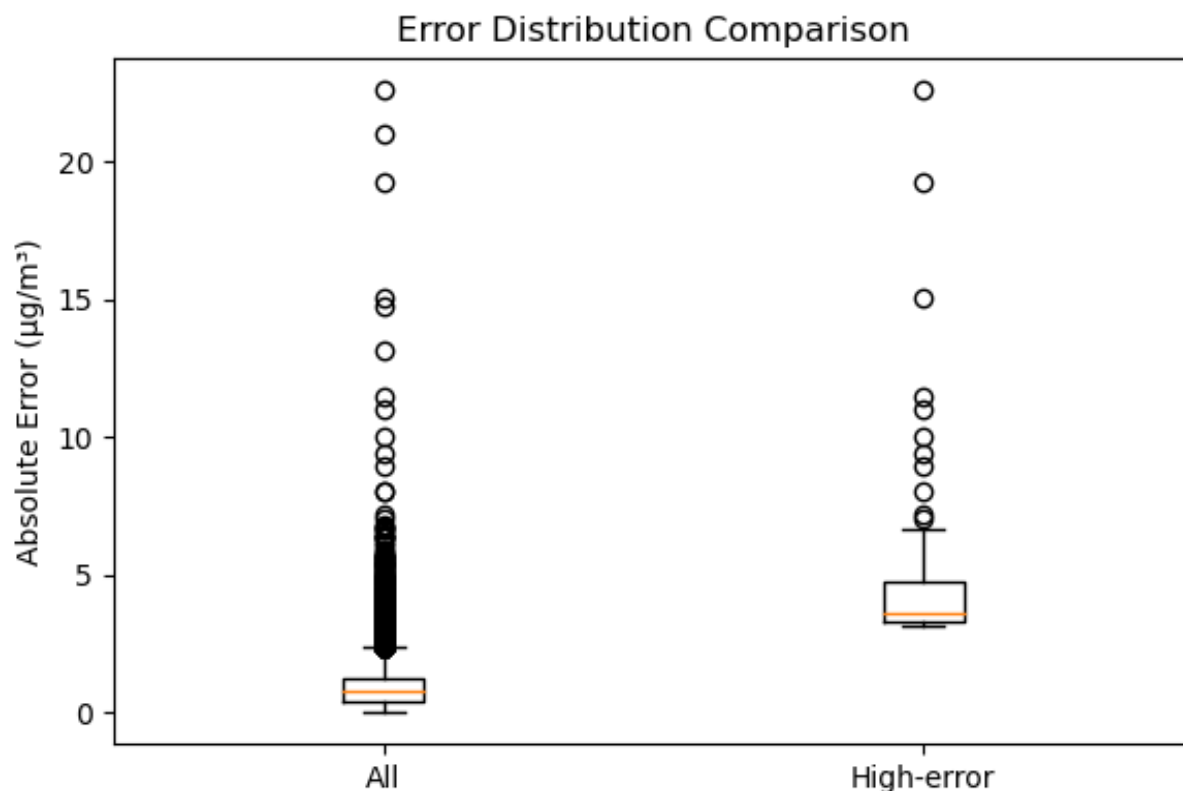


Figure 3.17 Boxplot comparison of absolute errors between all grid cells and high-error regions. The median and interquartile range of the high-error group are significantly higher, demonstrating the effectiveness of the sampling strategy in capturing model underperformance regions.

The boxplot comparison in Figure 3.17 further reinforces these findings. Median absolute errors in the high-error subset are significantly higher than those across all grid cells, and their interquartile range is nearly doubled. Outliers exceeding $10 \mu\text{g}/\text{m}^3$ are most common in western basins and fire-prone areas, indicating that these localized conditions consistently drive model divergence. The spatial clustering of such errors suggests that the model bias is systematic rather than random. Incorporating these high-error regions into an adaptive sampling strategy, by

prioritizing them as supplemental training data, can reduce systematic bias and improve generalization across under-monitored areas. This targeted refinement is essential for achieving spatially balanced PM_{2.5} predictions and for enhancing the reliability of exposure assessments across the continental United States.

3.6 Discussion

This study evaluates the effectiveness of machine learning models in predicting surface PM_{2.5} concentrations over the United States, with a specific focus on how spatial and temporal sampling influence prediction accuracy. Our results indicate that although Random Forest and other baseline models reproduce the overall spatial distribution of PM_{2.5}, they tend to overestimate concentrations in regions far from monitoring sites, especially across the central and southeastern United States, where monitoring density is low and secondary aerosol formation dominates. These errors persist even when models are trained on multiple years of data (2009, 2014, 2019), indicating that increasing temporal coverage alone cannot resolve sample-imbalance issues rooted in spatially clustered monitoring networks. This observation echoes findings from (Li *et al* 2024b) and (Ma *et al* 2023), who similarly reported that data sparsity in rural areas introduces systematic uncertainties, even when multi-year training datasets are used.

Incorporating spatiotemporal features improves model performance across both traditional and deep learning frameworks. As shown in Figure 3.15, models that include temporal or neighborhood information (RF_temporal, ResNet_temporal) consistently yield lower RMSE values at increasing distances from monitoring sites. Temporal features, in particular, enhance the model's ability to capture persistence and lagged effects associated with multi-day pollution episodes such as stagnation or wildfire smoke (Hu *et al* 2017), leading to improved

generalization in regions with limited observations (Vargo 2020). These improvements demonstrate that integrating temporal context reduces bias and complements algorithmic advances provided by deep learning architectures.

The spatial error analysis further reveals that model inaccuracies are not uniformly distributed but are instead concentrated in specific regions. High-error cells, primarily located across the western and central United States, coincide with areas of complex terrain, sparse monitoring, and episodic sources such as wildfires and dust storms. The heavy right tail of the error distribution (Figures 3.17–3.18) indicates that a small fraction of grid cells contributes disproportionately to total model uncertainty. These systematic biases suggest that improving PM_{2.5} predictions in under-monitored regions requires targeted retraining and adaptive sampling strategies rather than uniform model updates. Such approaches would enhance both spatial representativeness and environmental equity by prioritizing areas most affected by model underperformance.

Our study also reveals concerning implications for health exposure assessment. For example, overestimation of PM_{2.5} in the clean-air western U.S. (e.g., parts of Nevada and Utah) may inflate public health risks and trigger unwarranted regulatory actions. Conversely, underestimation in polluted but poorly monitored areas (e.g., central Texas, Ohio Valley) may mask real exposure burdens and delay necessary interventions. These biases have direct implications for environmental justice, as rural and socioeconomically disadvantaged regions—often home to marginalized populations—are disproportionately affected by either misdiagnosed or overlooked air quality problems. This reinforces concerns raised in recent environmental equity literature (Clark *et al* 2022, Tessum *et al* 2021), which show that communities of color and low-income populations are frequently underrepresented in monitoring networks yet bear

disproportionate pollution burdens.

Another key finding is the systematic distortion of annual trends. Although national PM_{2.5} levels declined from 2009 to 2019, models trained on urban-centric data tend to underestimate this reduction, especially in the eastern U.S., where regulatory improvements were most effective. Such distortions can obscure the long-term benefits of emission controls and undermine policy evaluations. For example, Xue and Ullrich highlighted that urban-weighted sampling can mask emission control success in regional trend analyses, leading to discrepancies between modeled and observed improvements (Xue and Ullrich 2022). Our findings confirm that machine learning frameworks must explicitly account for monitoring-site bias to avoid misleading conclusions about regulatory efficacy.

While deep learning models such as ResNet and ResNet_temporal show promising improvements, their performance is still contingent on input data quality. Current reliance on daytime satellite AOD creates blind spots for nighttime and cloudy conditions. Future work should explore additional data sources (e.g., nighttime satellite products, ground-based LiDAR) and techniques (e.g., domain adaptation, synthetic data augmentation) to improve prediction robustness in data-sparse regions. Recent studies demonstrate that multimodal integration of satellite, chemical transport models, and sparse ground networks can substantially reduce uncertainties, especially in regions with limited observations (Jiang *et al* 2021, Sun *et al* 2023).

In conclusion, this study underscores that addressing sample imbalance requires not only algorithmic innovations but also more equitable spatial data collection. Our results suggest that failure to correct spatial biases can result in health exposure errors exceeding 1–2 µg/m³, particularly in rural America, which is large enough to alter regulatory decisions and exacerbate health disparities. These findings call for coordinated efforts to expand monitoring in

underrepresented regions and to integrate more spatially diverse data into training pipelines. Such an approach would align with the U.S. EPA's recent calls for modernizing the national air quality monitoring system (Wooley *et al* 2024), ensuring that advances in machine learning are matched by improvements in the underlying data infrastructure.

3.7 Conclusion

This study systematically evaluates the performance of machine learning and deep learning models for surface PM_{2.5} prediction across the continental United States using a CMAQ–ML testbed. The results demonstrate that incorporating spatial and temporal features markedly improves prediction accuracy, particularly in data-sparse regions where conventional models tend to overestimate PM_{2.5}. Models enhanced with temporal information, such as RF_temporal and ResNet_temporal, achieved up to a 15 percent reduction in RMSE at distances greater than 150 km from monitoring sites, indicating their ability to capture persistence and lagged effects associated with multi-day pollution events such as stagnation or wildfire smoke.

While the integration of spatiotemporal features improves performance overall, systematic biases remain. High-error grid cells are concentrated in the western and central United States, coinciding with areas of complex topography, limited monitoring, and episodic sources like dust and wildfires. These spatially structured errors indicate that a small fraction of grid cells contributes disproportionately to total model uncertainty, underscoring the continuing influence of sample imbalance in the ground-observation network. Deep learning models such as ResNet and ResNet_temporal reduce these regional discrepancies by better learning nonlinear interactions between emissions, meteorology, and chemistry, yet the results confirm that algorithmic advances alone cannot fully overcome the lack of spatially representative data.

The analysis further highlights the policy relevance of these biases. Overestimation in

clean-air western regions could inflate health burden estimates, while underestimation in polluted but under-monitored areas such as central Texas and the Ohio Valley may obscure true exposure risks. These biases have implications for environmental equity, as rural and socioeconomically disadvantaged regions remain underrepresented in monitoring networks. Addressing these disparities will require both improved modeling strategies and more equitable data collection.

Future research should focus on expanding temporal and spatial coverage through multimodal data fusion. Integrating nighttime satellite observations (e.g., VIIRS), geostationary data from GOES-R, and high-resolution platforms such as TROPOMI can provide near-continuous coverage to fill data gaps (Van Donkelaar *et al* 2021, Hammer *et al* 2020). Combining national monitoring systems like CASTNET and IMPROVE with low-cost community sensors may also enhance representativeness in rural regions (Malings *et al* 2020). Such approaches will improve model generalization and support real-time air quality assessment under diverse environmental conditions.

Overall, this study establishes a high-resolution, physically consistent CMAQ–ML framework that integrates observational, satellite, and modeled data to improve PM_{2.5} prediction accuracy and spatial equity. By revealing how monitoring density, feature selection, and model architecture jointly influence predictive performance, this framework provides actionable insights for both model development and regulatory applications. As national air quality standards continue to tighten (Wooley *et al* 2024), achieving accurate and equitable PM_{2.5} exposure estimates will be critical to guiding emission control policies, protecting vulnerable populations, and ensuring that the benefits of clean air are shared across all regions of the United States.

CHAPTER 4 SOCIOECONOMIC AND HEALTH IMPLICATIONS OF DROUGHT AND AIR POLLUTION

4.1 Research Question

This chapter investigates the socioeconomic and health implications of increasing drought variability and air pollution across the contiguous United States. It examines how changes in drought patterns and fine particulate matter (PM_{2.5}) pollution jointly affect population exposure, public health, and economic productivity. The research is guided by four key questions: (1) How does exposure to drought and PM_{2.5} vary across different demographic and socioeconomic groups? (2) What are the projected health burdens associated with increasing exposure to these environmental stressors? (3) What are the economic costs of air pollution—related health impacts, and how do they differ between urban and rural areas? (4) What policy and adaptation strategies can most effectively mitigate these adverse effects? By addressing these questions, the chapter establishes a foundation for linking climate projections, air quality modeling, epidemiological analysis, and economic valuation.

4.2 Introduction

Drought and air pollution are two major environmental challenges that directly affect human health and societal well-being. Climate change has intensified drought variability, leading to more frequent and severe dry periods in some regions, while others experience alternating wet and dry extremes. These shifts threaten water resources, agricultural productivity, and ecosystem stability. At the same time, air pollution, especially fine particulate matter (PM_{2.5}), remains a significant public health concern. Exposure to elevated PM_{2.5} concentrations contributes to respiratory and cardiovascular diseases, premature mortality, and losses in labor productivity.

The coexistence of drought and air pollution often amplifies their individual impacts.

Drought increases air pollution by promoting wildfires, reducing soil moisture, and enhancing dust emissions, which elevate particulate concentrations. These processes disproportionately affect vulnerable populations such as children, older adults, and those with pre-existing health conditions. The resulting health burden imposes substantial economic costs through higher medical expenditures, reduced work capacity, and broader social disruptions.

Although previous studies have investigated the physical mechanisms and regional trends of drought and air pollution separately, fewer have quantified their combined health and economic impacts at high spatial resolution. This chapter builds upon recent advances in climate and air quality modeling to provide an integrated assessment. It couples drought indices and PM_{2.5} fields with population exposure data and epidemiological evidence to quantify the human and economic costs of these environmental stressors across the contiguous United States.

4.3 Objective

The overarching goal of this chapter is to quantify the health and economic burdens associated with the combined effects of drought and air pollution under a changing climate. Specifically, the study aims to estimate population exposure to drought conditions and fine particulate matter (PM_{2.5}) using high-resolution climate and air quality data, assess the associated health risks with a focus on premature mortality and major respiratory and cardiovascular diseases, quantify the economic losses resulting from drought- and pollution-related health outcomes including direct medical costs and productivity losses, and identify vulnerable populations that experience disproportionate impacts due to socioeconomic disparities and environmental inequities. Through these objectives, the chapter seeks to establish an integrated framework for evaluating how climate-driven environmental stressors influence public health and economic resilience across the United States.

4.4 Methods and Data

This study employs an integrated framework consisting of three components: (1) population exposure estimation, (2) health impact estimation, and (3) economic cost analysis. By combining high-resolution environmental datasets with epidemiological models and socioeconomic indicators, the framework links drought and air pollution exposures with their public health and economic consequences.

4.4.1 Population Exposure Estimation

Population exposure was quantified for both drought and fine particulate matter ($PM_{2.5}$) by overlaying environmental datasets with demographic and socioeconomic information.

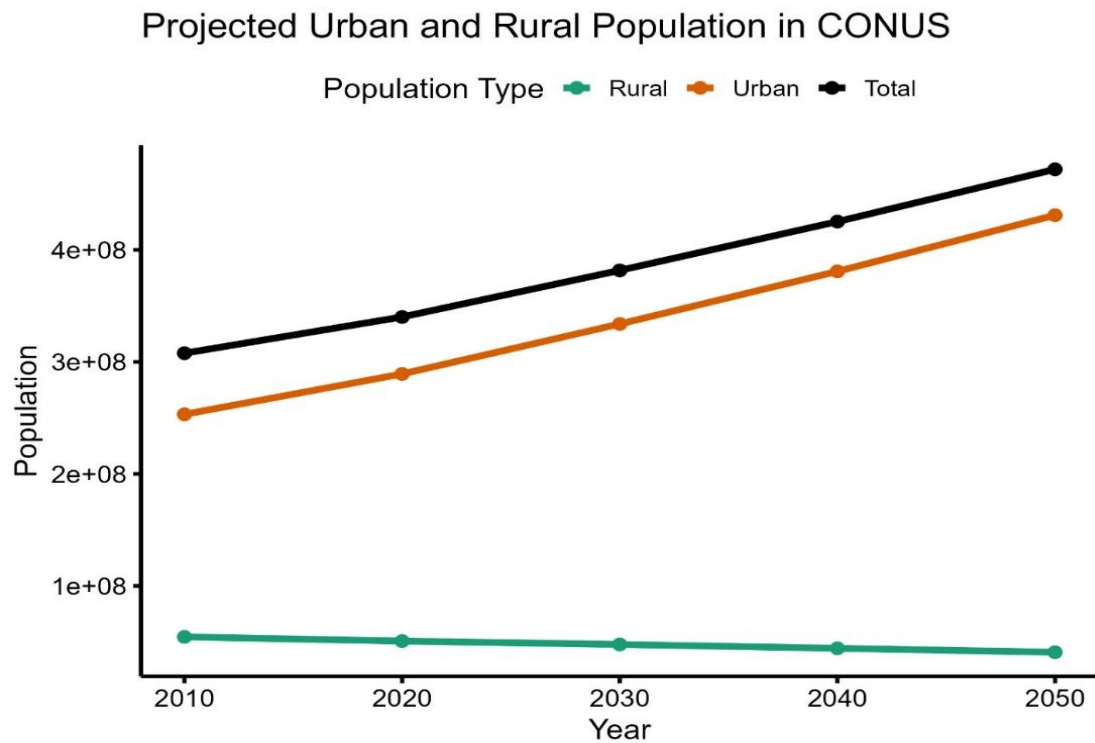


Figure 4.1 Projected Urban and Rural Population Growth in CONUS (2010–2050).

Drought exposure. For the population exposure analysis, we used the Global 1-km Downscaled Population Base Year and Projection Grids dataset (SSPs, Revision 01), which

provides global urban, rural, and total population projections at a 1-km resolution from 2000 to 2100 in 10-year intervals (Jones and O'Neill 2016, Jones *et al* 2020). Urban and rural populations are classified based on census-defined urban areas and a spatial downscaling model incorporating national-level urbanization projections. Urban areas are determined using the Global Human Settlement Layer (GHSL) and national urbanization definitions, while rural areas include all remaining non-urban grid cells. Figure 4.1 illustrates projected changes in urban, rural, and total populations across the CONUS under the SSP5-8.5 scenario from 2010 to 2050, showing continued urban population growth and relatively stable rural populations.

This classification enables the identification of high population density regions overlapping with projected drought conditions, offering insights for drought risk management and adaptation planning. To assess drought impacts on human populations under the SSP5-8.5 scenario, we build upon the downscaling framework developed by Rastogi *et al* (Rastogi *et al* 2022), which applied a six-member CMIP6 ensemble dynamically downscaled using RegCM4 and bias-corrected statistically.

The regional statistics for ScPDSI, SPI-12, and SPEI-12 were derived through a multi-step process. First, each drought index was calculated at the grid level for every individual model in the ensemble: ScPDSI was based on soil moisture dynamics, while SPI-12 and SPEI-12 were derived from precipitation and precipitation minus PET, respectively. Second, the gridded values were spatially averaged over the nine climatically consistent regions defined by the National Centers of Environmental Information (NCEI), ensuring that regional drought characteristics captured spatial climatic variability. Third, we computed the multi-model ensemble mean by averaging regional values across all models to reduce the influence of individual model biases and provide robust regional estimates. Fourth, for long-term drought analysis, decadal trends in

the 10th, median, and 90th percentiles of ScPDSI across the contiguous United States from the 1980s to the 2050s were calculated to evaluate shifts in drought regimes. Probability distributions of drought categories (D0-D4) were also derived to examine changes in drought frequency and severity. Finally, to assess human exposure, population data were interpolated to match the drought index grid resolution using bilinear interpolation, and exposure to various drought severity levels was quantified separately for urban and rural populations. We acknowledge that these estimates are based on the SSP5-8.5 population scenario, which represents a high-growth, fossil-fueled development pathway. As population projections are subject to considerable uncertainty, especially beyond mid-century, future work could incorporate multiple SSPs to evaluate a broader range of exposure outcomes. This would help to capture the uncertainty associated with demographic change and improve the robustness of risk assessments.

The SSP5-8.5 scenario, representing an extreme high-emission future, is chosen to assess the upper bounds of future drought severity, though additional warming levels (e.g., 1.5°C and 2°C) should be explored in future studies to account for broader uncertainties. This scenario is particularly useful for stress-testing adaptation and resilience strategies by providing insights into potential worst-case outcomes, even if actual emissions trajectories diverge. Nevertheless, uncertainties remain in population projections, including migration dynamics, urban expansion patterns, and socioeconomic development pathways, which may deviate from SSP assumptions. Recognizing these uncertainties underscores the need for cautious interpretation and motivates sensitivity analyses in future work.

PM_{2.5} exposure. Air pollution fields were derived from an ensemble of satellite-based aerosol optical depth retrievals, chemical transport model (CMAQ) simulations, and ground-

based observations from EPA’s Air Quality System (AQS), CASTNET, and IMPROVE networks. To address uneven monitoring coverage, population-weighted exposure (PWE) was calculated as:

$$PWE = \frac{\sum_i Pop_i \times C_i}{\sum_i Pop_i} \quad (4.1)$$

where Pop_i is the population in grid cell i and C_i is the modeled $PM_{2.5}$ concentration.

Stratification by urban–rural classification allows evaluation of disparities in exposure patterns and helps identify vulnerable groups in monitor-sparse regions.

4.4.2 Health Impact Estimation

Health impacts in this study were quantified using two complementary epidemiological frameworks tailored to the specific characteristics of drought exposure and $PM_{2.5}$ exposure. Although both approaches rely on established concentration response evidence, they differ in their underlying functional forms and the type of exposure metrics used. The two frameworks are based on distinct epidemiological evidence and therefore cannot be applied interchangeably. To maintain conceptual and methodological clarity, drought related health impacts and $PM_{2.5}$ related health impacts were evaluated separately using the procedures described below.

Drought-related health impact estimation. Drought-attributable health impacts were quantified using a population attributable fraction approach. This method links drought severity categories to health risks through relative risk estimates derived from epidemiological and meta analytical studies. For each drought category (D0 through D4), the number of excess cases attributable to drought exposure was calculated as:

$$Excess\ Cases = Population\ Exposed \times \left(\frac{y_0}{100,000} \right) \times (RR - 1) \quad (4.2)$$

where y_0 is the baseline annual incidence per 100,000 population, and RR is the relative risk associated with the drought severity level. Population exposure was defined as the number

of individuals experiencing drought conditions (D0 to D4) based on SPI-12, SPEI-12, and ScPDSI classifications. Baseline incidence rates were obtained from national U.S. health statistics and U.S. EPA BenMAP default values to maintain consistency with the PM_{2.5} analysis.

Relative risks were drawn from peer reviewed epidemiological studies reporting increases in mortality, respiratory hospitalizations, asthma exacerbations, and COPD admissions during drought and co-occurring environmental stressors during drought periods, such as heat, dryness, and reduced air quality (Rau *et al* 2025, De Vita *et al* 2024, Gwon *et al* 2025). To reflect the intensification of health risks with increasing drought severity, relative risks were parameterized to increase progressively from D0 to D4. Baseline incidence rates and drought specific relative risks used in this study are summarized in Table 4.1.

Table 4.1 Baseline incidence rates and relative risks (RR) for drought-related health outcomes in the CONUS.

Health endpoint	Baseline incidence (y ₀ , per 100k·yr)	RR (D0)	RR (D1)	RR (D2)	RR (D3)	RR (D4)	References
All-cause premature mortality	800	1.010	1.015	1.030	1.050	1.070	(Lynch <i>et al</i> 2020, Berman <i>et al</i> 2017)
Cardiovascular mortality	300	1.012	1.018	1.035	1.055	1.075	(Berman <i>et al</i> 2017, Stanke <i>et al</i> 2013)
Respiratory mortality	200	1.015	1.022	1.040	1.060	1.085	(Gwon <i>et al</i> 2023, Lynch <i>et al</i> 2020)
Asthma ER visits	1000	1.020	1.030	1.050	1.070	1.100	(Stanke <i>et al</i> 2013, Lynch <i>et al</i> 2020)
COPD admissions	500	1.015	1.025	1.045	1.065	1.090	(Gwon <i>et al</i> 2023, Stanke <i>et al</i> 2013)

* Baseline incidence rates (y₀) are expressed as annual cases per 100,000 population. Relative risks are stratified by drought severity (D0–D4), consistent with SPI-12, SPEI-12, and ScPDSI classification thresholds.

PM_{2.5}-related health impact estimation. Health impacts associated with long term PM_{2.5} exposure were estimated using a log linear concentration response (C–R) function widely applied in global and national burden of disease assessments. This approach relates incremental changes in PM_{2.5} concentration to relative changes in risk and allows impacts to be quantified at the grid level.

For each grid cell i , the number of PM_{2.5}-attributable cases was calculated as:

$$\Delta Y = \sum_i [P_i \times \frac{y_0}{100000} \times (e^{\beta \Delta C_i} - 1)] \quad (4.3)$$

where P_i is the exposed population in grid cell i , y_0 is the baseline incidence rate (per 100,000 population), β is the concentration response coefficient, and ΔC_i is the PM_{2.5} concentration above the counterfactual threshold C_0 , which was set to 5 $\mu\text{g}/\text{m}^3$. C–R coefficients and baseline incidence rates for PM_{2.5} related endpoints were obtained from large cohort studies and meta analyses, including the American Cancer Society extended follow up, nationwide Medicare analyses, and multi city studies of respiratory and cardiovascular morbidity (Krewski 2009, Di *et al* 2017, Pope III *et al* 2002, Brook *et al* 2010, Zanobetti and Schwartz 2009, Zheng *et al* 2015, Atkinson *et al* 2014). The values used in this study are summarized in Table 4.2 (Premature mortality, Cardiovascular mortality, Respiratory mortality, Asthma emergency room visits, and COPD admissions).

To evaluate the differences between CMAQ simulations and ML-based predictions, we calculated both grid-level and aggregated health impacts at the state and national scales. State-level totals were obtained by summing across all grid cells within each state boundary, while national-level estimates were derived by summing across the entire domain. Additionally, we constructed cumulative distribution functions to examine the spatial distribution of health impact differences by sorting grid cells according to their population-weighted distance to the nearest air

quality monitor.

Table 4.2 Concentration–response coefficients (β) and baseline incidence rates (y_0) for health endpoints associated with PM_{2.5} exposure.

Health endpoint	β per 10 $\mu\text{g}/\text{m}^3$	Baseline incidence (y_0 , per 100k/year)	Reference(s)
Premature mortality (≥ 30 yrs, all-cause)	0.006	~800	(Krewski 2009, Di <i>et al</i> 2017)
Cardiovascular mortality	0.010	~300	(Brook <i>et al</i> 2010)
Respiratory mortality	0.012	~200	(Pope III <i>et al</i> 2002, Krewski 2009)
Asthma exacerbation (ER visits)	0.015	~1000	(Zheng <i>et al</i> 2015, Sacks <i>et al</i> 2020)
COPD hospital admissions	0.008	~500	(Atkinson <i>et al</i> 2014, Zanobetti and Schwartz 2009)

* Concentration–response coefficients (β) represent the percentage change in risk per 10 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} exposure, converted to per 1 $\mu\text{g}/\text{m}^3$ in calculations. Baseline incidence rates (y_0) are approximate values derived from U.S. Centers for Disease Control and Prevention (CDC) national health statistics and U.S. EPA BenMAP default values. References are drawn from large-scale cohort studies and meta-analyses commonly used in health impact assessments.

4.4.3 Economic Cost Analysis

Economic cost analysis quantifies the monetary burden associated with the health impacts of drought and PM_{2.5} exposure. Health impacts for each hazard were first estimated using the epidemiological frameworks described in Sections 4.4.1 and 4.4.2. The resulting excess cases were then monetized using two valuation approaches: the Cost of Illness (COI) and the Willingness to Pay (WTP) methods. The COI approach reflects direct medical expenditures, including hospital admissions, emergency department visits, outpatient care, and medication costs, while the WTP approach captures broader societal costs, such as productivity losses and the valuation of avoided premature mortality. Mortality was monetized using a Value of a Statistical Life (VSL) consistent with U.S. EPA guidelines.

Drought-related economic costs. Drought-related economic burdens were derived from

the excess health cases estimated using the relative risk based framework in Equation 4.2.

Drought exposure was characterized using SPI-12, SPEI-12, and ScPDSI, with severity categories D0 through D4, for the period 2010 to 2050. For each year, drought index, drought category, and population type (total, urban, and rural), we combined gridded drought–population data, baseline incidence rates, and endpoint specific relative risks to obtain drought-attributable excess cases for premature mortality, cardiovascular mortality, respiratory mortality, asthma emergency room visits, and COPD hospital admissions.

Economic costs for each endpoint were calculated by multiplying drought-attributable excess cases by the corresponding unit cost expressed in 2019 United States dollars. Mortality outcomes were valued using a VSL of 11.5 million dollars per case, applied consistently across all mortality endpoints. Morbidity outcomes were valued using unit costs of 500 dollars per asthma ER visit and 25 000 dollars per COPD admission. Annual drought-related economic costs were then aggregated to national totals by endpoint and drought index. For selected years, premature mortality costs were further decomposed by drought category to quantify the relative contributions of mild, moderate, severe, and extreme droughts, forming the basis of the components shown later in Figure 4.6.

PM_{2.5}-related economic costs. PM_{2.5}-related economic costs were evaluated separately using excess cases derived from the concentration–response framework in Equation 4.3. Grid-level excess cases for 2019 were computed for both CMAQ-simulated PM_{2.5} and machine-learning-based PM_{2.5} predictions and then converted to grid-level economic costs using the same mortality and morbidity unit values applied in the drought analysis.

Grid-level costs were first aggregated to obtain national total costs by endpoint for each PM_{2.5} field, providing the basis for the stacked comparison between CMAQ and prediction-based

results in Figure 4.7a. Second, grid cells were grouped according to their population-weighted distance to the nearest regulatory monitor (0–50, 50–100, 100–200, 200–400, and greater than 400 kilometers), and within each bin we summarized the distribution of grid-level cost differences between prediction and CMAQ, as shown in Figure 4.7b. Third, state-level total costs were computed for all states in the contiguous United States, and the five states with the largest total costs were selected for radar plot comparison in Figure 4.7c.

All drought-related and PM_{2.5}-related costs were monetized in 2019 United States dollars and are reported in billions for consistency and readability. All unit cost values, including the Value of a Statistical Life and morbidity cost estimates, were taken from U.S. EPA economic valuation guidelines and national healthcare expenditure datasets such as HCUP and CDC health statistics.

4.5 Results

4.5.1 Population Exposure

Drought exposure. The U.S. population is unevenly distributed, with nearly 80% residing in urban areas, leading to disparities in drought exposure. To assess this, population data were interpolated to match the drought data grid using bilinear interpolation. ScPDSI, SPI-12, and SPEI-12 were classified into five drought categories (D4: Exceptional Drought; D3: Extreme Drought; D2: Severe Drought; D1: Moderate Drought; and D0: Abnormally Dry) and combined with population data to estimate the urban and rural populations affected by each category. Overall, future drought exposure in the U.S. is projected to peak around 2030–2040 before declining toward 2050, with urban areas consistently bearing a greater burden than rural regions, particularly for milder drought categories (D0 and D1). This temporal peak in exposure coincides with projected population growth and urban expansion in climate-sensitive regions, especially

the Sun Belt states (Jones and O'Neill 2016), amplifying the societal relevance of even moderate droughts. The total affected population under SPI-12 reaches 2.7 million in 2030 before dropping to 800,000 in 2050, while ScPDSI projects a more persistent drought exposure, peaking at 3.6 million in 2030 and remaining as high as 1.1 million in 2050. These differences highlight how precipitation-based (SPI-12), temperature-sensitive (SPEI-12), and soil moisture-driven (ScPDSI) drought indices produce distinct projections, with ScPDSI suggesting prolonged drought conditions compared to SPI-12 and SPEI-12, which predict a more variable drought pattern. Such divergence underscores the methodological uncertainty in exposure assessments and the importance of multi-index approaches when quantifying human vulnerability (AghaKouchak *et al* 2015).

Historically, urban populations have been more affected by drought than rural populations, a trend that persists in future projections (Figure 4.2). In 2010, 6.6 million urban residents experienced D0–D4 droughts, compared to 1.1 million in rural areas (SPI-12). The total affected population was 3.5 million under ScPDSI and 2.1 million under SPI-12, highlighting differences across drought indices. This trend continues under SSP5-8.5, with urban drought exposure peaking at 6.4 million in 2030 before declining to 2.8 million by 2050 (SPI-12), while ScPDSI projects a more persistent exposure of 3.6 million in 2030 and 1.1 million in 2050, indicating that soil moisture-based drought estimates predict longer-lasting impacts. These findings are consistent with broader assessments of climate risk in urban settings, where concentrated populations and infrastructure amplify exposure and reduce adaptive capacity compared to dispersed rural areas (Giorgi 2019).

For D0 conditions, urban exposure increases from 1.76 million in 2010 to 2.46 million in 2030 (SPI-12) before dropping to 0.96 million in 2050, while rural exposure declines from 0.35

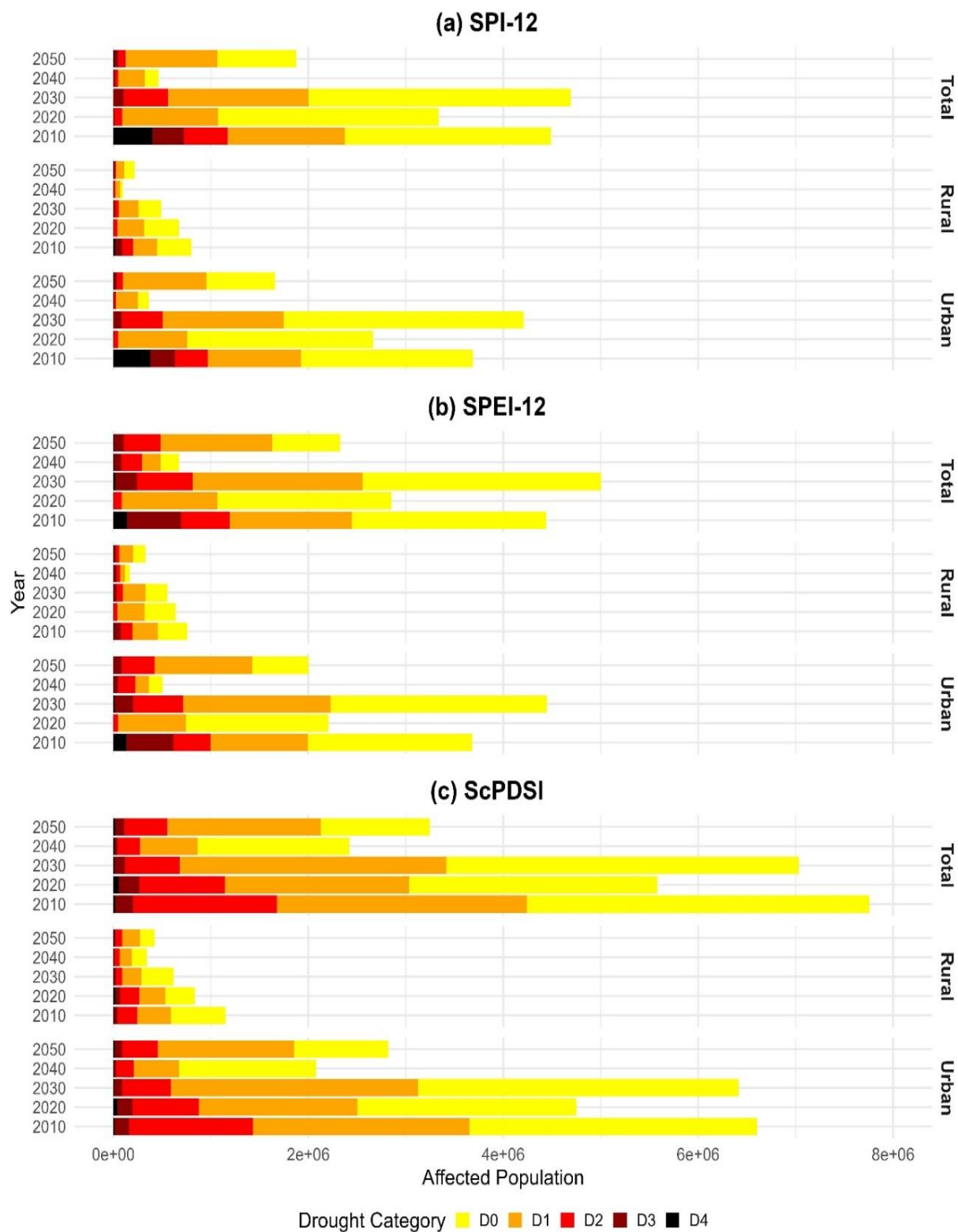


Figure 4.2 Population affected by drought categories in rural and urban areas of the CONUS (2010-2050).

million to 0.1 million over the same period. ScPDSI projects a significantly higher D0 exposure, with urban populations reaching 3.2 million in 2030 and still affecting 1.1 million by 2050. Moderate drought (D1) follows a similar trajectory, with urban exposure peaking at 1.24 million in 2030 (SPI-12) and rural exposure declining from 0.25 million in 2010 to 0.14 million by 2050. ScPDSI estimates indicate a higher persistence, with urban D1 exposure remaining at 2.5 million in 2030 and 1.3 million in 2050, reinforcing the role of long-term soil moisture deficits in driving prolonged drought conditions. This persistence of D0–D1 exposure is particularly critical because mild-to-moderate droughts, though less dramatic than extreme events, often have the greatest cumulative impacts on agriculture, water supply, and health outcomes (Wilhite and Pulwarty 2017).

For severe drought categories, the decline is more pronounced. Severe drought (D2) impacts 420,000 urban residents in 2030 (SPI-12) and 1.4 million in ScPDSI, but by 2050, the affected population drops to 63,000 under SPI-12 and 437,000 under ScPDSI. Extreme drought (D3) peaks at 84,000 urban residents in 2030 (SPI-12) and 101,000 in ScPDSI, while both indices project a decline to 28,000 (SPI-12) and 90,000 (ScPDSI) by 2050. Exceptional drought (D4) consistently affects the smallest population, with urban exposure increasing slightly from 1,321 in 2030 (SPI-12) to 5,141 in 2050, while ScPDSI projects a larger but still minor urban D4 population of 9,000 by 2050. Although absolute numbers of people exposed to D3–D4 remain small, the cascading effects of such extreme droughts—such as regional water crises, wildfire outbreaks, and crop failures—can be disproportionately large relative to population directly exposed (Diffenbaugh *et al* 2015).

PM_{2.5} exposure. PM_{2.5} concentrations were estimated using an ensemble of satellite-derived aerosol optical depth (AOD) retrievals, chemical transport model (CMAQ) simulations,

and surface monitoring data from EPA’s Air Quality System (AQS), CASTNET, and IMPROVE networks. Meteorological variables such as temperature, humidity, and wind were included to capture regional variability in pollutant dispersion and accumulation.

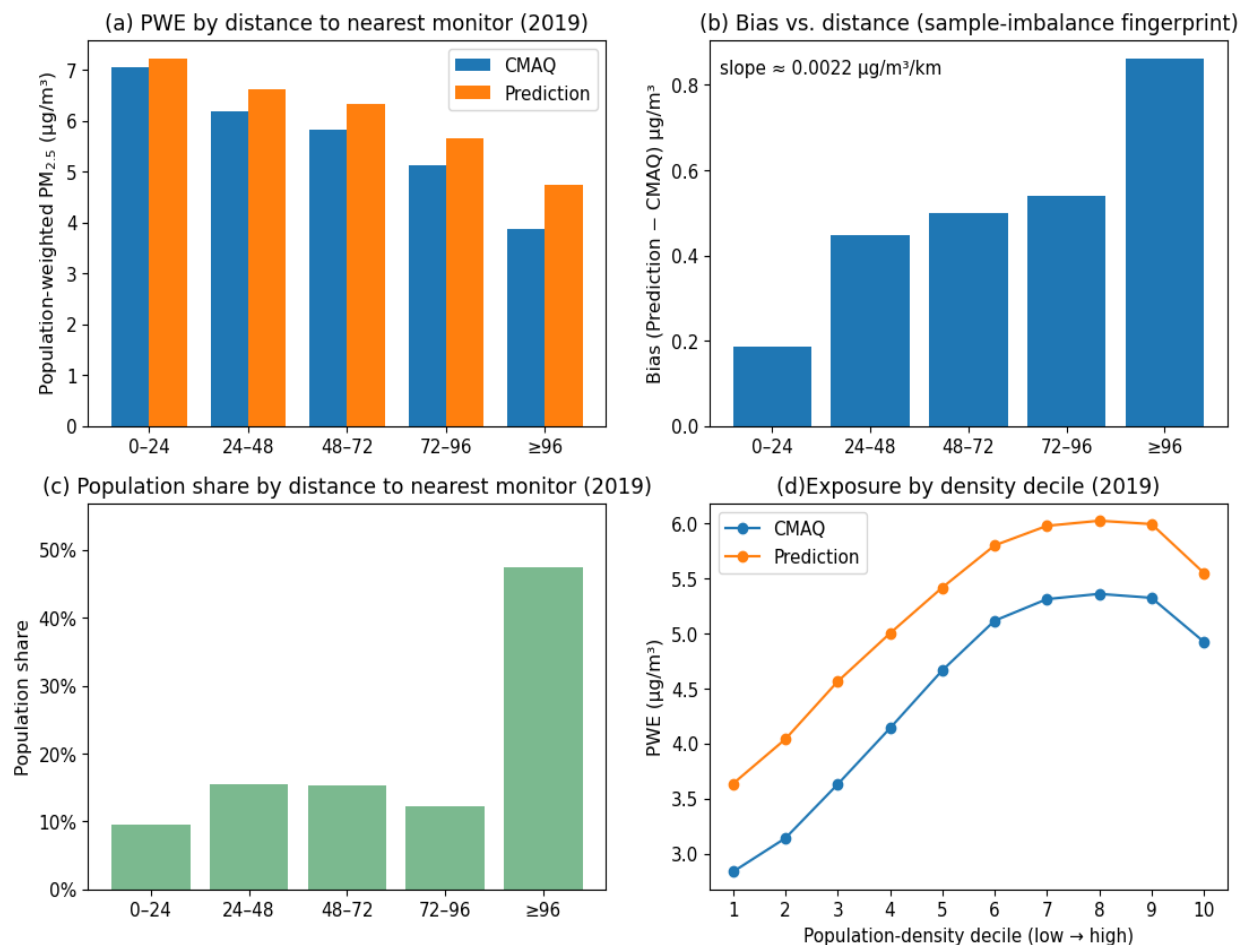


Figure 4.3 Population-weighted exposure and sample-imbalance diagnostics for 2019. (a) PWE ($\mu g/m^3$) for CMAQ and ML prediction by distance to the nearest monitor (0–24, 24–48, 48–72, 72–96, ≥ 96 km). (b) Bias (prediction – CMAQ) by distance; population-weighted linear fit slope $\approx 0.0012 \mu g/m^3 km^{-1}$. (c) Population share in each distance bin, showing that $\sim 48\%$ of the population resides ≥ 96 km from a monitor. (d) Map of distance to the nearest monitor (km), highlighting monitor-sparse regions in the central plains, interior West/mountain areas, and parts of the Southeast. All statistics use WorldPop (regridded to 12 km) for weights.

A key methodological challenge is the uneven spatial distribution of monitors, which creates sample imbalance and systematic bias in exposure estimation. To address this, we computed population-weighted exposure (PWE) using WorldPop (12-km regridded) data as

weights. At the national scale, PWE was $4.98 \mu\text{g}/\text{m}^3$ for CMAQ and $5.62 \mu\text{g}/\text{m}^3$ for the machine learning prediction, a positive bias of $+0.64 \mu\text{g}/\text{m}^3$ ($\approx 13\%$). Distance-stratified diagnostics further revealed that exposure bias increases with distance from the nearest monitor: $+0.19 \mu\text{g}/\text{m}^3$ at 0–24 km, $+0.45$ at 24–48 km, $+0.50$ at 48–72 km, $+0.54$ at 72–96 km, and $+0.86 \mu\text{g}/\text{m}^3$ beyond 96 km. A population-weighted regression gave a slope of approximately $0.0012 \mu\text{g}/\text{m}^3 \text{ km}^{-1}$ ($\approx 0.12 \mu\text{g}/\text{m}^3$ per 100 km).

Crucially, population is not evenly distributed across distance classes. Approximately 10%, 15%, 15%, 12%, and 48% of the U.S. population live at 0–24, 24–48, 48–72, 72–96, and ≥ 96 km, respectively, from the nearest monitor. Thus, nearly half of the population resides in the farthest bin, which is also the bin with the largest positive bias, amplifying the distance-dependent error in the national PWE. Panel maps further indicate that these monitor-sparse regions are concentrated in the central plains, interior West, and parts of the Southeast, consistent with where the largest spatial overestimations were observed.

Together, these results illustrate a two-step mechanism by which monitor-driven sample imbalance propagates into exposure error: (i) bias increases with distance from monitors, and (ii) a large share of the population resides in distant, monitor-sparse regions. Without correction, this mechanism produces exposure inflation of approximately $0.5\text{--}0.9 \mu\text{g}/\text{m}^3$ in rural and remote areas and about $0.64 \mu\text{g}/\text{m}^3$ at the national level, levels that materially affect attainment determinations and health impact assessments. These findings reinforce the importance of augmenting monitoring networks with rural sites (e.g., CASTNET/IMPROVE), applying distance-aware or spatially stratified sampling during model training, and routinely reporting distance–bias relationships alongside conventional performance metrics.

Urban–rural classification. For both drought and $\text{PM}_{2.5}$ exposure analyses, we applied a

consistent urban–rural delineation based on the U.S. Census Urban Areas (2020 vintage). Grid cells whose centroids fall within 24 km of a Census urban polygon were classified as urban, while those outside this buffer were classified as rural. This threshold approximates the spatial footprint of urban influence relative to the 12-km modeling grid. Urban–rural stratification enables a systematic evaluation of disparities in environmental exposure across demographic and socioeconomic groups, which is essential for addressing questions of environmental justice.

4.5.2 Health Impact

Figure 4.4 presents the estimated health impacts attributable to drought in the contiguous United States for the period 2010 to 2050. Three commonly used drought indices (ScPDSI, SPEI-12, and SPI-12) were applied to quantify affected populations, which were then linked with baseline incidence rates and relative risks to estimate excess health cases across multiple endpoints. Panel (a) illustrates the national total number of excess cases stratified by endpoint. The results show substantial variability across both indices and health outcomes. Under ScPDSI, the total number of excess cases reached approximately 10.4 thousand in 2010, declined to 7.6 thousand in 2020, and further decreased to 2.8 thousand in 2040, before slightly recovering to 4.4 thousand by 2050. SPEI-12 followed a similar but more moderate trajectory, with 7.4 thousand excess cases in 2010 and only 3.3 thousand in 2040. SPI-12 consistently produced the lowest burdens, with 5.5 thousand cases in 2030 and only 2.2 thousand by 2050. Across endpoints, asthma emergency room visits accounted for nearly half of the total burden in most years. For example, under ScPDSI in 2010, asthma ER visits represented about 5.2 thousand cases out of the total 10.4 thousand. Respiratory mortality contributed to approximately 2.1 thousand cases, followed by premature mortality (~1.4 thousand) and cardiovascular mortality (~1.0 thousand). COPD admissions contributed less than 1 thousand across all years and indices.



Figure 4.4 Drought-attributable health impacts in the contiguous United States (2010–2050). These results highlight the dominant role of respiratory-related outcomes in shaping the overall health burden of drought. Panel (b) provides a breakdown of premature mortality by urban and rural populations. In all indices, urban populations experienced substantially higher drought-attributable mortality than rural populations. For example, under ScPDSI in 2010, urban premature mortality reached 0.87 thousand cases compared with only 0.15 thousand in rural areas. Even by 2050, when the overall burden had declined, urban premature mortality (0.43

thousand cases) remained more than three times higher than rural premature mortality (0.12 thousand). The same pattern was evident under SPEI-12 and SPI-12, where urban burdens consistently exceeded rural burdens by factors of three to five. This disparity underscores how demographic concentration amplifies drought-related health impacts, particularly in metropolitan regions. Panel (c) focuses on the contributions of drought categories to premature mortality in 2050. The results consistently show that mild to moderate droughts (D0 to D2) accounted for more than 80 percent of the total attributable cases. For instance, under ScPDSI, the total premature mortality in 2050 was 0.9 thousand cases, of which about 0.36 thousand came from D0 and 0.27 thousand from D1. Severe droughts (D3) contributed less than 0.1 thousand, and extreme droughts (D4) were negligible at less than 0.05 thousand. A similar distribution was observed in SPEI-12, where the total burden was 0.7 thousand, and in SPI-12, where the total burden was only 0.4 thousand. Although the relative risks associated with D3 and D4 are higher, their limited frequency and spatial coverage reduce their overall contribution to population-level health outcomes.

Overall, three consistent insights emerge. First, drought-related health burdens are dominated by respiratory outcomes, especially asthma exacerbations and respiratory mortality. Second, urban populations consistently face higher risks than rural populations, with premature mortality burdens that are three to five times larger, reflecting population density and exposure rather than relative vulnerability alone. Third, the majority of drought-related health cases arise from moderate but frequent drought events, rather than from rare extremes. The differences observed across indices further emphasize the methodological sensitivity of drought–health assessments, highlighting the need for careful consideration of drought definitions in future impact studies.

Figure 4.5 illustrates the differences in PM_{2.5}-attributable health burdens between CMAQ simulations and machine learning predictions across states, health endpoints, and population distributions. The state-level results in panel (a) reveal substantial geographic heterogeneity. California exhibits one of the highest totals of premature mortality, with machine learning predictions exceeding CMAQ by approximately 250 to 300 cases. This difference is driven by the combination of large exposed populations in metropolitan regions such as Los Angeles and consistently elevated PM_{2.5} concentrations. Illinois and Ohio also show large discrepancies, with machine learning predicting roughly 180 and 150 more cases than CMAQ, respectively. Virginia and North Carolina display gaps in the order of 100 to 120 cases, whereas states with smaller populations such as Vermont, New Hampshire, and Wyoming show almost no differences, often fewer than five cases. The size of the discrepancy scales with population and exposure levels, which indicates that the two models diverge most where health impacts are largest. Importantly, the ranking of states changes depending on the modeling framework. For example, California and Texas appear comparable in the CMAQ estimates, but machine learning predicts substantially higher totals in California, which could shift state-level priorities in health impact assessments and regulatory decision-making.

Panel (b) disaggregates the national totals by health endpoint and reveals a consistent pattern across outcomes. Asthma emergency room visits dominate the overall burden, with CMAQ estimating 4170 cases and machine learning yielding 5401, a difference of 1231 cases or nearly 30 percent. Premature mortality is the second largest contributor, with 1333 cases from CMAQ and 1726 from machine learning, corresponding to an increase of 393 deaths, also about 30 percent. Cardiovascular mortality rises from 291 to 377, respiratory mortality from 184 to 241, and COPD admissions from 476 to 618. Despite differences in baseline incidence rates and

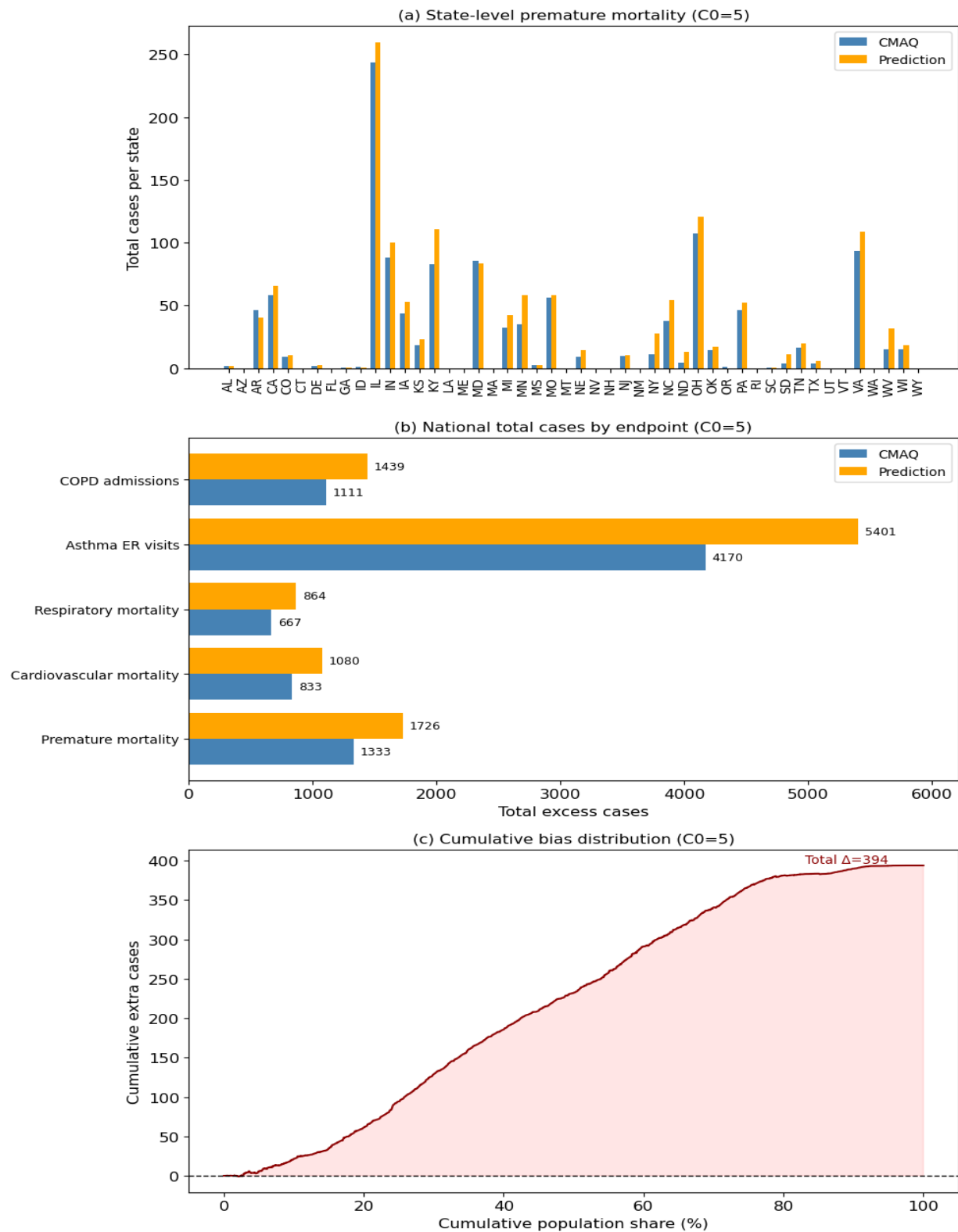


Figure 4.5 Comparison of health burdens attributable to PM_{2.5} exposure between CMAQ and machine learning predictions.

concentration–response coefficients across endpoints, the percentage increase from CMAQ to machine learning remains remarkably consistent, ranging from 28 to 30 percent. This uniformity confirms that the primary source of discrepancy lies in the concentration fields rather than in health effect parameters. CMAQ underestimates PM_{2.5} concentrations relative to machine learning across the domain, and this systematic bias propagates proportionally through each health endpoint.

Panel (c) examines the cumulative distribution of premature mortality differences as a function of population-weighted distance to the nearest monitoring site. The cumulative curve rises steadily, with machine learning producing a total of 394 more premature deaths than CMAQ nationwide. Differences are small for the first quintile of the population, which represents urban cores located within about 20 to 30 kilometers of a monitor. In this group, CMAQ and machine learning predictions diverge by fewer than 30 cases. The slope of the curve becomes steep between 20 and 70 percent of the population share, which corresponds to suburban and semi-urban areas located 40 to 100 kilometers from the nearest monitor. In this middle range, approximately 280 additional premature deaths accumulate in the machine learning estimates, representing more than 70 percent of the total discrepancy. Beyond 70 percent of the cumulative population, which corresponds to sparsely populated rural regions, the curve continues to rise but more gradually, as population counts are smaller. This pattern demonstrates that the differences between CMAQ and machine learning are structured by monitoring network density. CMAQ aligns more closely with machine learning predictions in densely monitored areas, while systematic underestimation emerges in regions with sparse coverage. As a result, the populations most affected by the model discrepancies are those outside the reach of dense monitoring networks, raising concerns about equity in exposure assessment

and health burden estimation.

4.5.3 Economic Cost

Figure 4.6 presents the estimated national drought-related economic costs from 2010 to 2050. The results reveal several key patterns. As shown in Figure 4.6a, the overall burden peaked during the 2010s and 2020s, with national costs exceeding 40 billion USD under the ScPDSI, before declining substantially by mid-century. Premature mortality overwhelmingly dominated the total burden, accounting for the majority of costs across all indices, followed by cardiovascular and respiratory mortality. Morbidity endpoints, such as asthma ER visits and COPD hospitalizations, contributed only marginally. This imbalance reflects the disproportionate economic weight of mortality outcomes in health cost assessments, given both their higher relative risks and their large unit valuation.

Differences across drought indices are highlighted in Figure 4.6b, which shows the temporal trajectory of premature mortality costs from 2010 to 2050. Although all three indices suggested a gradual decline over time, their absolute magnitudes varied substantially. The ScPDSI consistently produced the highest estimates, followed by SPEI-12, with SPI-12 yielding the lowest. By 2050, premature mortality costs were projected to be approximately 5.0, 3.8, and 2.5 billion USD under ScPDSI, SPEI-12, and SPI-12, respectively. These discrepancies underscore the sensitivity of economic burden estimates to the choice of drought index. Since each index is designed to capture different aspects of hydroclimatic variability, the observed spread can be interpreted as a measure of methodological uncertainty that has direct implications for impact assessment and policy.

The contribution of drought categories to premature mortality costs is illustrated in Figure 4.6c. Mild droughts (D0 and D1) were responsible for the majority of costs, contributing 2.4 to



Figure 4.6 National drought-related economic costs by health endpoint, drought index, and drought category.

3.4 billion USD depending on the index, whereas severe and extreme droughts (D3 and D4) contributed very little. This outcome is consistent with the population exposure results discussed earlier, where mild droughts were shown to affect the largest proportion of the population despite

their lower intensity. The economic dominance of mild droughts thus arises from the combination of broad spatial extent and widespread population exposure, which offsets the relatively small increase in relative risk per individual. In contrast, extreme droughts, while carrying higher individual risks, occur less frequently and affect fewer people, thereby resulting in a smaller aggregate burden. This pattern has important implications for adaptation and risk communication. It suggests that focusing only on extreme droughts may underestimate the true economic costs of drought, as the cumulative impact of frequent mild droughts can surpass that of rare severe events.

Taken together, these results demonstrate that the drought-related economic burden on public health is shaped by both the intensity and extent of drought conditions, as well as the methodological choice of drought index. Mortality endpoints dominate the cost estimates, highlighting the high economic value placed on premature deaths. Index differences introduce uncertainty in projected costs, with ScPDSI generally yielding higher burdens. Finally, the predominance of mild droughts in the national cost burden emphasizes the need to account for moderate but widespread events when designing adaptation strategies.

Figure 4.7a shows the stacked national economic costs by health endpoint, directly comparing CMAQ- and prediction-based estimates. Across both models, premature mortality dominates the overall burden, valued at 14.7 billion USD under CMAQ and 19.0 billion USD under the prediction framework. Asthma ER visits represent the second largest component, contributing 45.9 million USD for CMAQ and 59.4 million USD for predictions. Cardiovascular and respiratory mortality add moderate costs of 7.3–11.9 billion USD and 9.2–9.5 billion USD, respectively, while COPD admissions contribute 12.2–15.8 billion USD. In total, prediction-based estimates yield 115.6 billion USD compared to 89.2 billion USD for CMAQ, a national

difference of 26.4 billion USD. The stacked representation highlights that the divergence between the two approaches is not confined to a single endpoint but accumulates across all categories, with asthma ER visits and premature mortality explaining the largest share of the gap.

The distribution of cost differences by distance to the nearest monitoring site is summarized in Figure 4.7b using violin plots. The bulk of the distribution is centered close to zero in all bins, indicating that in most locations the two models agree within a narrow margin. However, the spread of the distribution is substantially wider in the 0–50 km and 100–200 km bins, with cost differences occasionally exceeding ± 0.05 billion USD per grid cell. This indicates that while prediction-based estimates do not uniformly deviate from CMAQ, localized areas near and moderately distant from monitors exhibit large discrepancies. Such discrepancies are likely amplified by high population density combined with modest concentration differences, which translate into disproportionately large cost changes under the exponential concentration-response function.

At the state level, Figure 4.7c summarizes the top five states with the largest total economic costs in 2019 using radar plots. Illinois emerges as the single largest contributor, with costs approaching 2.9 billion USD under both CMAQ and prediction, followed by Ohio, Kentucky, Virginia, and Indiana, each ranging between 1.0 and 1.3 billion USD. In all states, prediction-based estimates exceed CMAQ, though the relative differences are modest compared to national totals. The radar plot reveals that the overall shape of the state-level burden remains consistent between models, but the magnitude of each axis expands under prediction, reinforcing that the discrepancy is largely systematic rather than confined to specific locations.

This chapter provides critical insights into the intersection of climate change, air pollution, and public health, offering policy-relevant recommendations for minimizing

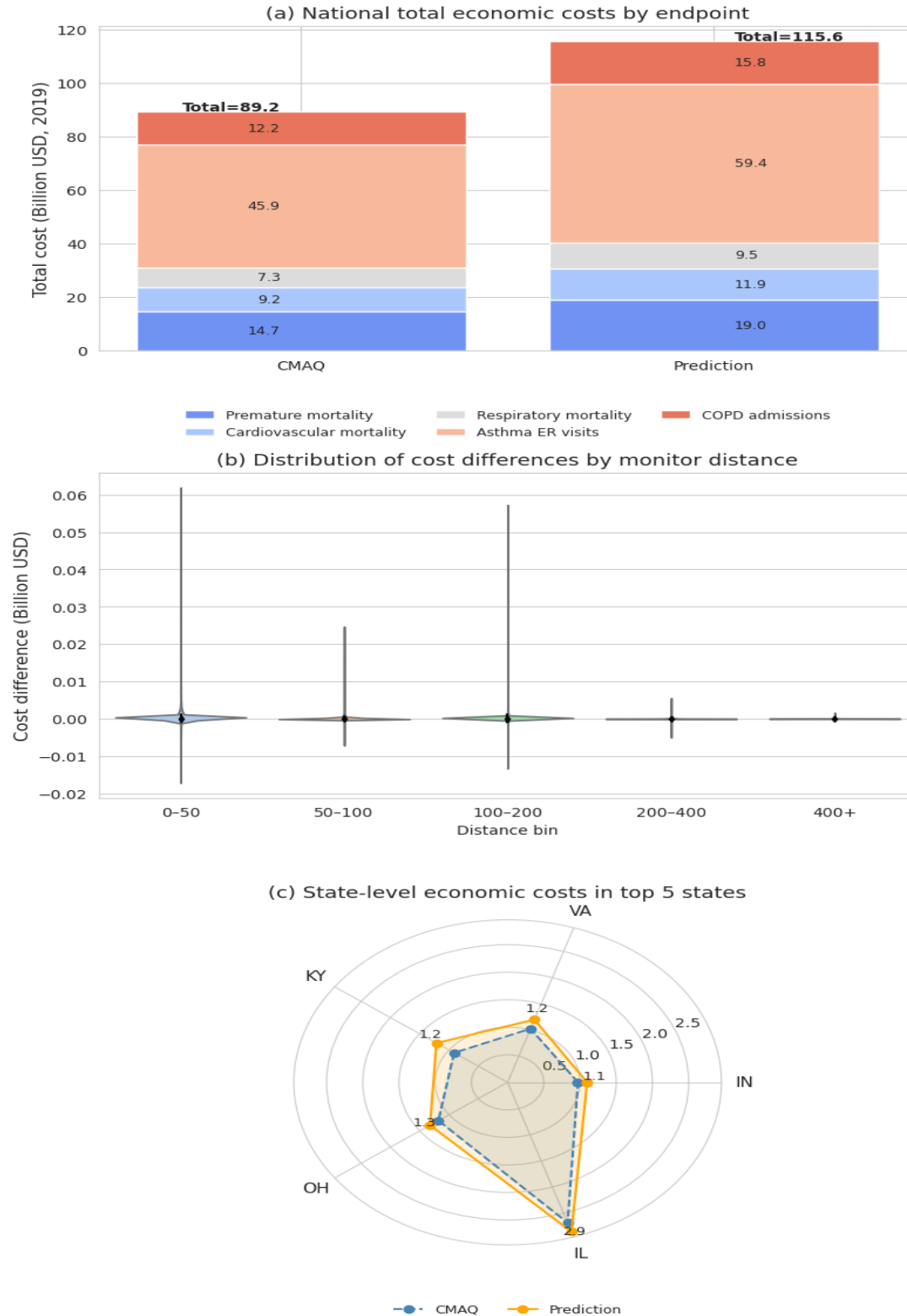


Figure 4.7 National and state-level economic costs of PM_{2.5}-attributable health outcomes in 2019 derived from CMAQ and prediction-based estimates

socioeconomic disparities and enhancing community resilience in the face of worsening environmental conditions.

4.6 Discussion

The results of this chapter demonstrate that both drought and air pollution exert measurable and spatially variable impacts on public health and economic well-being across the United States. The estimated health burdens associated with drought, derived from three independent indices, show a declining trend toward mid-century but reveal persistent disparities between urban and rural populations. The largest health burdens occurred during the early decades, when both drought frequency and population growth were highest in vulnerable regions. Although total drought-attributable cases decrease after 2040, urban populations consistently experience three to five times as many cases as rural populations. This pattern reflects not only higher population density but also the amplified sensitivity of urban systems to environmental stress. Urban heat islands, higher baseline air pollution, and limited vegetation collectively intensify the physiological and environmental impacts of prolonged dryness. These findings are consistent with previous research showing that urban areas often amplify the health effects of meteorological extremes due to compounding exposure pathways and limited adaptive capacity (Wilhite and Pulwarty 2017, Giorgi 2019).

Across the three drought indices, ScPDSI produces the largest health and economic burdens, followed by SPEI-12 and SPI-12. This hierarchy stems from the physical processes that each index represents. ScPDSI incorporates soil moisture dynamics, reflecting cumulative water balance and long-term drought persistence, while SPI and SPEI capture short-term precipitation and temperature anomalies, respectively. As a result, ScPDSI identifies longer and more spatially persistent droughts, which translate into higher cumulative population exposure and greater

estimated health impacts. These differences demonstrate the sensitivity of health impact estimates to the selection of drought metrics. Therefore, applying multiple indices provides a more comprehensive assessment of hydroclimatic stress, helping to capture both rapid meteorological fluctuations and longer-term soil moisture deficits that influence human health outcomes.

The predominance of mild to moderate droughts (D0–D2) in both health and economic burdens highlights that frequent, less intense droughts can generate greater cumulative effects than rare extremes. These events are widespread and recurring, often lasting long enough to disrupt daily life, strain water supplies, and aggravate chronic respiratory conditions. Although the relative risks associated with mild droughts are lower than those of extreme events, their broad spatial extent and large affected populations result in greater aggregate impacts. This finding indicates that public health and adaptation strategies should not focus exclusively on extreme droughts but should also account for the sustained effects of moderate, recurrent dry periods. Expanding early warning systems, investing in water infrastructure, and maintaining healthcare access during prolonged dry spells could substantially reduce cumulative health burdens, particularly in metropolitan regions where exposure remains persistently high.

The analysis of PM_{2.5} exposure adds an important perspective by examining how modeling frameworks influence health impact estimates. Machine learning predictions yielded higher population-weighted exposures and consequently higher health and economic burdens than CMAQ simulations. Although the mean national difference was only about 0.6 µg/m³, it resulted in roughly 30 percent higher estimates of premature mortality and morbidity. This amplification arises because the concentration–response relationship is exponential, meaning that even small underestimations in exposure can produce large differences in health outcomes. The

comparison also reveals a clear dependence on monitoring network density. CMAQ aligns well with machine learning estimates in regions with dense observational coverage but underestimates concentrations in areas that lack monitors, particularly in the central and western United States. Populations living in these monitor-sparse regions therefore face higher exposure uncertainty and may have their health risks underestimated. This spatial imbalance raises critical concerns about environmental equity, as the most data-limited regions are often those with fewer healthcare resources and less adaptive capacity.

Economic cost estimates further underscore the disproportionate influence of mortality outcomes on total national burden. Premature mortality accounts for the majority of total costs due to its high unit valuation and broad exposure base. Although asthma and COPD cases contribute less to total costs individually, their cumulative impacts remain substantial, reflecting ongoing pressure on healthcare systems and local economies. The total drought-related health costs exceeded 40 billion USD during the early decades, while PM_{2.5}-related health costs reached approximately 100 billion USD in 2019. These magnitudes are comparable to national losses from other major weather and climate hazards, illustrating that chronic environmental stressors can generate economic consequences on the same scale as acute disasters. Addressing these challenges requires integrated policy responses that combine improved environmental modeling, comprehensive health surveillance, and equitable mitigation strategies to protect vulnerable populations.

4.7 Conclusion

This study quantified how drought and fine particulate matter exposure affect human health and economic costs across the contiguous United States. By integrating high-resolution environmental datasets with epidemiological relationships, the analysis provided consistent

estimates of population exposure, health outcomes, and financial burdens. The results show that both hazards pose substantial and spatially uneven risks, with urban areas experiencing the greatest impacts due to high population density and accumulated environmental stress.

Drought exposure analysis indicates that future risks peak between 2030 and 2040 before gradually declining toward mid-century. Urban populations remain disproportionately affected throughout the study period. Under the SSP5-8.5 scenario, mild to moderate droughts (D0–D2) account for most of the exposed population and the majority of health impacts. Although severe and extreme droughts (D3–D4) have higher relative risks, their limited spatial coverage and short duration make their contribution to national totals relatively small. These results emphasize that widespread, recurring droughts can have greater cumulative effects on health and economic stability than rare extremes. The findings suggest that focusing adaptation measures solely on exceptional droughts may underestimate the overall burden faced by communities, especially those located in expanding urban regions.

The three drought indices used in this analysis, namely ScPDSI, SPEI-12, and SPI-12, produced consistent patterns in exposure and health outcomes, although the magnitudes differed across the indices. ScPDSI projected the most persistent and extensive drought conditions, resulting in the highest population exposure, health impacts, and associated costs. SPEI-12 showed slightly lower totals due to its sensitivity to short-term temperature variability, while SPI-12 reflected the most rapid recovery because it depends only on precipitation. These differences illustrate the importance of metric selection in assessing climate-driven health risks. Using multiple indices provides a more balanced assessment of hydroclimatic stress and avoids overreliance on a single drought representation.

Health impact results demonstrate that respiratory outcomes dominate drought-related

health burdens, with asthma exacerbations and respiratory mortality contributing to the largest shares of excess cases. Urban areas show premature mortality rates three to five times higher than rural areas, indicating that demographic concentration and environmental co-exposures intensify drought effects. The predominance of respiratory outcomes suggests that both air dryness and dust generation during drought events play a major role in population health degradation. Cardiovascular outcomes contribute less to total cases but remain significant, particularly during prolonged droughts that coincide with elevated temperatures and increased air stagnation.

Economic cost estimates confirm that mortality endpoints are responsible for most of the national financial burden. Under ScPDSI, the total cost exceeded 40 billion USD during the early decades, with premature mortality accounting for more than half of the total. Mild droughts contributed the majority of these costs, primarily because they affect large populations over broad geographic areas. This pattern reinforces the conclusion that cumulative exposure, rather than isolated extremes, determines the long-term economic consequences of drought on public health. Differences among drought indices also produce a wide cost range, demonstrating that methodological uncertainty in drought metrics directly translates into uncertainty in projected financial losses.

The PM_{2.5}-related assessment complements the drought analysis by highlighting the role of exposure estimation methods in shaping health impact outcomes. Machine learning predictions produced population-weighted exposures approximately 13 percent higher than those from CMAQ simulations. This bias, although small in concentration terms, resulted in roughly 30 percent higher national health and economic burdens. The effect was most pronounced in regions located far from monitoring sites, where population coverage is sparse. These findings

demonstrate that exposure underestimation in rural or remote regions can lead to systematic undercounting of affected populations and undervaluation of associated health costs. Expanding monitoring networks and improving hybrid modeling frameworks can therefore enhance both the accuracy and equity of exposure-based health assessments.

Overall, this chapter provides quantitative evidence that mild droughts, persistent air pollution, and uneven data coverage collectively drive a large share of public health and economic impacts across the United States. The results show that even modest environmental stress, when combined with population concentration and data limitations, can produce measurable burdens on health systems and national productivity. Recognizing these combined effects is essential for developing more realistic risk assessments and for guiding policies that address both acute and chronic dimensions of environmental change.

CHAPTER 5 CONCLUSION AND FUTURE WORK

5.1 Summary of Key Findings

This dissertation investigates how climate change alters drought variability and air pollution patterns, and how these environmental changes affect population exposure, health outcomes, and economic costs in the contiguous United States. It integrates high-resolution climate modeling, machine learning-based air quality estimation, and health-economic impact assessment to provide a multiscale understanding of environmental risk.

The analysis of drought evolution under the SSP5-8.5 scenario shows that future drought patterns across the United States will become increasingly variable rather than uniformly intensifying. Instead of a continuous drying trend, regions such as the Southwest and Northern Rockies experience alternating wet and dry periods, resulting in higher hydroclimatic instability. Among the three indices used, the self-calibrating Palmer Drought Severity Index (ScPDSI) captures longer-term and soil moisture-driven drought persistence, while the Standardized Precipitation Index (SPI-12) and the Standardized Precipitation Evapotranspiration Index (SPEI-12) highlight short-term fluctuations influenced by precipitation and temperature. Together, they reveal a shift toward more frequent mild-to-moderate droughts that have broad cumulative impacts on water availability, ecosystems, and human exposure.

The machine learning framework developed in this dissertation provides a systematic evaluation of PM_{2.5} prediction biases and demonstrates how uneven monitoring coverage affects model performance. Traditional algorithms tend to overestimate concentrations in regions far from air quality monitoring sites, especially across the central plains, interior West, and southeastern United States. These biases increase with distance from monitoring stations, producing an average national overestimation of about 0.6 µg/m³. Integrating data from the

CMAQ model, satellite aerosol optical depth retrievals, and extended ground-based networks such as CASTNET and IMPROVE improved model accuracy in rural and under-monitored areas. Deep learning architectures, particularly ResNet with temporal features, further reduced systematic errors, yielding more consistent exposure estimates and better capturing multi-day pollution episodes.

Health impact assessments based on epidemiological concentration–response relationships revealed substantial public health burdens associated with both drought and air pollution. The results show that respiratory and cardiovascular diseases remain the dominant outcomes, with urban populations facing three to five times higher risks than rural populations due to their greater population density and compounded exposure to multiple stressors. Drought-related health burdens were mainly driven by mild-to-moderate droughts (D0–D2), which affected a larger share of the population than rare extremes. Economic analyses showed that mortality outcomes contributed most of the total cost burden, while asthma and COPD cases reflected ongoing strains on public health systems. Together, drought- and pollution-related health impacts translate into tens of billions of dollars in economic losses each year, highlighting the need for coordinated environmental and health policies. Low-income and rural communities remain disproportionately affected, underscoring the importance of expanding monitoring infrastructure and prioritizing equitable adaptation strategies.

5.2 Research Limitations

Several limitations should be recognized when interpreting the results of this study. Although the CMIP6-based climate models used for drought projections provide improved resolution and physical parameterizations, they still contain structural uncertainties that influence projected precipitation and evapotranspiration patterns. The dynamic downscaling framework

employed here reduces large-scale biases but cannot eliminate all inconsistencies among models. Moreover, drought indices such as SPI, SPEI, and ScPDSI were originally developed under stationary climate conditions, and their parameterizations may not fully represent evolving land–atmosphere feedback under a warming climate.

For air pollution estimation, the performance of machine learning and deep learning models remains strongly dependent on the spatial distribution of training data. Sparse monitoring coverage continues to limit accuracy in rural and mountainous regions. Although the integration of CMAQ outputs and satellite data improves generalization, biases persist where observations are sparse or local emission characteristics differ from those represented in training samples. Deep learning models also require large, high-quality datasets, which remain difficult to obtain for under-monitored areas.

Health impact estimates rely on concentration–response functions derived from large cohort studies and meta-analyses. While these relationships are well established, they do not fully capture emerging pollution sources such as wildfire-driven PM_{2.5} or multi-pollutant interactions. Individual-level variability in exposure, such as time spent indoors, occupational differences, or adaptive behaviors, was not explicitly modeled. Economic valuations, while following standard methodologies using the Value of a Statistical Life for mortality and cost-of-illness estimates for morbidity, do not account for long-term productivity losses from chronic illness or potential economic effects of climate-induced migration.

5.3 Future Directions

Future research should continue refining regional climate and air quality models to improve projections of drought and pollution exposure under a changing climate. Enhancing the representation of land–atmosphere coupling, vegetation feedbacks, and groundwater dynamics

will allow more accurate assessment of compound drought processes. Expanding soil moisture and hydrological observation networks can also help validate drought indices and improve early warning systems for water scarcity.

Building upon the CMAQ–ML testbed developed in this dissertation, future studies should explore adaptive sampling and uncertainty quantification approaches to better represent monitor-sparse regions. Integrating physical constraints from chemical transport models with data-driven methods can enhance prediction robustness, especially under extreme or data-limited conditions. The use of new geostationary satellite instruments, such as TEMPO, will allow near-continuous air quality monitoring at high temporal resolution, improving the detection of short-term pollution episodes. Extending these frameworks to multi-pollutant estimation will provide a more comprehensive understanding of atmospheric composition and associated health risks.

Research on health impacts should focus on long-term and compound exposures. Future epidemiological studies can examine how concurrent drought, heat, and air pollution affect vulnerable populations with preexisting respiratory or cardiovascular conditions. Quantifying cumulative and synergistic effects will be crucial for designing adaptive public health interventions. Integrating exposure data with socioeconomic and demographic information can improve assessments of environmental inequality and inform equitable resource allocation.

Policy-oriented research should prioritize expanding the national air monitoring network, especially in rural and low-income urban areas. Incorporating low-cost sensor networks and community-based monitoring can reduce spatial data gaps and improve real-time exposure tracking. Collaboration between environmental agencies and public health institutions will be essential for translating modeling advances into actionable policies. Finally, linking behavioral and economic models with environmental data can help evaluate how individuals respond to

environmental risks and the effectiveness of mitigation incentives.

This dissertation provides an integrated framework that connects physical climate processes, air quality modeling, and health-economic impact assessment. The findings emphasize that addressing environmental challenges requires both technological innovation and equitable policy design. Strengthening monitoring networks, improving exposure models, and integrating multidisciplinary perspectives will be key to reducing health disparities and enhancing resilience to climate-driven environmental change in the coming decades.

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