PROJECTING THE CLIMATE PENALTY ON $PM_{2.5}$ POLLUTION WITH SPATIAL DEEP LEARNING

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ABSTRACT

The climate penalty measures the effects of a changing climate on air quality due to the interaction of pollution with climate factors, independently of future changes in emissions. This work introduces a statistical framework for estimating the climate penalty on soot pollution ($PM_{2.5}$), which has been linked to respiratory and cardiovascular diseases and premature mortality. The framework evaluates the disparities in future $PM_{2.5}$ exposure across racial/ethnic and income groups—an important step towards informing mitigation public health policy and promoting environmental equity in addressing the effects of climate change. The proposed methodology aims to improve existing statistical-based methods for estimating the climate penalty using an expressive and scalable predictive model based on spatial deep learning with spatiotemporal trend estimation. The proposed approach will (1) use higher-resolution climate inputs, which current statistical approaches to estimate the climate penalty cannot accommodate; (2) integrate additional predictive data sources such as demographics, geology, and land use; (3) consider regional dependencies and synoptic weather patterns influencing $PM_{2.5}$, deconvolving the effects of climate change from increasing air quality regulations and other sources of unmeasured spatial heterogeneity.

1 INTRODUCTION

Air pollution is one of the leading mortality risk factors worldwide. In 2019, up to 6.7 million deaths worldwide were attributed to cardiovascular diseases likely caused by air pollution exposure (Murray et al., 2020; Brauer et al., 2021). Particularly concerning is soot pollution from fine particulate matter with a diameter less than 2.5 µm ($PM_{2.5}$). These small particles can travel deep into the lungs, and some may even enter the bloodstream (EPA, 2023). Several studies have found significant evidence that $PM_{2.5}$ is linked to respiratory and cardiovascular disease (Brook et al., 2010) and premature mortality (Wu et al., 2020; Pelucchi et al., 2009; Laden et al., 2006). Due to its significant public health and economic consequences (Wu et al., 2020), it is crucial to understand how $PM_{2.5}$ will be affected by climate change, which is believed to increase air pollution concentrations (East et al., 2022). This effect is known as the *climate penalty*, and it measures the effects of a changing climate on $PM_{2.5}$ concentration due to the interaction of pollution with climate factors, independently of future changes in emission levels (Fiore et al., 2022). Here we introduce a novel statistical framework (summarized in Fig. 1) for estimating the climate penalty allowing us to produce higher-resolution predictions and use more predictors than existing statistical approaches. Our scientific aim is to predict the climate penalty on $PM_{2.5}$ under a constellation of climate change scenarios and use these projections to evaluate the disparities in future $PM_{2.5}$ exposure across racial/ethnic and

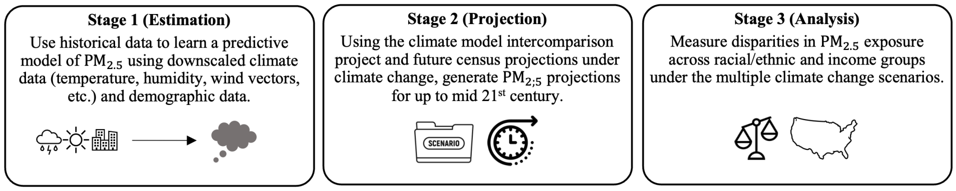

Figure 1: Proposed workflow.

income groups. The findings have the potential to inform mitigation policy aiming to protect public health and promote environmental equity when addressing the effects of climate change.

Accurately characterizing the climate penalty is challenging due to the complex interactions between atmospheric patterns and $PM_{2.5}$ (Tai et al., 2010). For instance, higher temperatures increase $PM_{2.5}$ due to increasing oxidation rates and fire emissions. By contrast, the effect of relative humidity and cloud cover may vary by different $PM_{2.5}$ components and geographic locations (Tai et al., 2010; Koch et al., 2003). $PM_{2.5}$ levels are also affected by regional or *synoptic* weather patterns occurring at a larger spatial scale (Shen et al., 2015; Leung et al., 2018). Thishan Dharshana et al. (2010) estimate that synoptic systems derived from wind patterns such as cold frontal passages and maritime inflow accounted for 30% of the daily variability in $PM_{2.5}$ in the US. The full effects of synoptic patterns on $PM_{2.5}$ are still not fully understood, and quantifying them remains an open, challenging task (Shen et al., 2017; Tec et al., 2023).

Estimating the climate penalty with chemical transport models (CTMs) has been the subject of much attention within the atmospheric modeling community (Racherla & Adams, 2006; Hong et al., 2019; Val Martin et al., 2015; Fiore et al., 2022; East et al., 2022; Day & Pandis, 2015; Tai et al., 2012; Jacob & Winner, 2009). Yet CTMs show considerable uncertainty and low consistency among each other (Shen et al., 2017; East et al., 2022). And developing empirical calibration methods remain an open research problem (Turnock et al., 2020; East et al., 2022; Cheng et al., 2021). For these reasons, statistical methods to project air pollution have been proposed to complement projections based on CTMs (Shen et al., 2017). This paper introduces a statistical framework for estimating the climate penalty considering the complex relationship between climate and $PM_{2.5}$. It combines state-of-the-art deep learning architectures for spatial feature learning with carefully designed spatio-temporal trend modeling. Spatial feature learning allows learning from synoptic weather patterns, socio-demographic data, and other predictors strongly influencing $PM_{2.5}$ (Shen et al., 2017; Tec et al., 2023). Random effects and time trend modeling are used to deconvolve the effects of a changing climate from the downward trend in air pollution due to increasing air quality regulation (EPA, 2011; Hu et al., 2014), as well as from other sources of unmeasured spatial heterogeneity (Urdangarin et al., 2022; Shen et al., 2017). Notice that our goal differs from forecasting using spatiotemporal patterns $PM_{2.5}$ (e.g., Wen et al. (2019); Liang et al. (2023)). We aim instead to project $PM_{2.5}$ under a constellation of climate change scenarios at interdecadal time scales (Shen et al., 2017).

2 METHODS

We will use the following notation convention. The observed $PM_{2.5}$ grid is denoted $\boldsymbol{Y}_t$. We denote the climate grid as $\boldsymbol{W}_t$ and the grid of all other covariates, such as local emissions and demographic information, as $\boldsymbol{X}_t$. We denote them Fig. 2 summarizes our proposed model. The observed $PM_{2.5}$ is predicted from two latent vectors $\boldsymbol{Z}_t$ and $\boldsymbol{U}_t$ of arbitrary dimension representing the measured and unmeasured spatio-temporal which will be combined using attention-like mechanisms (Vaswani et al., 2017).

Spatial feature learning of climate impacts on PM2.5. The measured spatio-temporal variation $\boldsymbol{Z}_t$ is extracted from the climate and covariate grids ($\boldsymbol{W}_t$ and $\boldsymbol{X}_t$) using a subnetwork for spatial feature learning. Various design choices for this subnetwork will be evaluated and compared, including convolutional architectures (He et al., 2016; Ronneberger et al., 2015; Liu et al., 2022; Tec et al., 2023) and vision transformers (Vaswani et al., 2017; Zhang et al., 2023; Nguyen et al., 2023).

Spatio-temporal trends and heterogeneity modeling. For the unmeasured variation term $\boldsymbol{U}_t$, we will draw from the literatures of meteorological detrending (Henneman et al., 2015) and spatial ran-

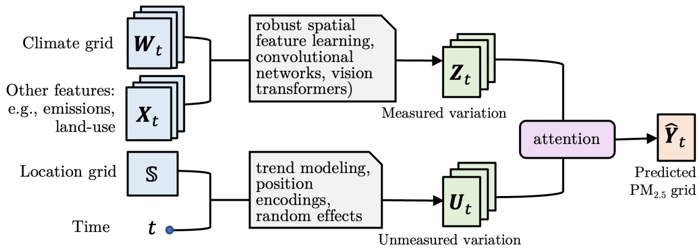

Figure 2: Proposed predictive model with various design choices.

dom effect modeling (Gelfand et al., 2010; Besag, 1974). For instance, Wells et al. (2021) model a pollutant's time series using an indicator for the year and a seasonal component. Qiu et al. (2022) estimate a debiased linear temporal trend using double machine-learning (Chernozhukov et al., 2018). We will also investigate machine learning-driven strategies based on learning position encoders with attention (Vaswani et al., 2017). These trends will be estimated at each location. Ensuring spatial smoothness may improve the estimates and reduce overfitting, so we will investigate and evaluate using auto-regression (CAR) (Besag, 1974). For our final future projections, $\boldsymbol{U}_t$ will be held constant. This is so because it represents unmeasured variation, and thus it is cannot be known under a distributional shift. But recall that the climate penalty measures the impact of climate change on $\mathrm{PM}_{2.5}$, factoring out the changes in other sources of pollutant emissions. Thus, it is logical to make projections of future $\mathrm{PM}_{2.5}$ values holding $\boldsymbol{U}_t$ constant to its last estimated value.

Evaluation metric. Disparities of air pollution exposure under future projected $\mathrm{PM}_{2.5}$ will be measured using the standardized metrics proposed by Jbaily et al. (2022). To select the final neural network architecture for predicting $\mathrm{PM}_{2.5}$, we will use the mean-squared error evaluated at a future dataset not used during training. We do this because we aim to evaluate the prediction of $\mathrm{PM}_{2.5}$ under a distributional shift of W_t. Notice, however, that a systematic control of the effect of a distributional shift is not possible using real data due to the covariates and unmeasured factors changing simultaneously. Thus, to further isolate the effect of climate in our evaluation, we will generate semi-synthetic datasets that are highly representative of $\mathrm{PM}_{2.5}$. Semi-synthetic datasets are produced from a simulated or estimated model of the outcome variable, allowing us to evaluate performance under a controlled distributional shift. Finally, we remark that the distributional shift perspective motivates us to investigate potential training methods that specifically target robustness in such scenarios. These methods include invariant risk minimization (Arjovsky et al., 2019), risk extrapolation (Krueger et al., 2021), and Fishr (Rame et al., 2022). However, it is not entirely obvious that they will perform better than standard empirical risk minimization (likelihood estimation).

3 Data Sources

We will consider the shared socio-economic pathways (SSP) scenarios and the climate model intercomparison projects (CMIP6). Our primary source for projected weather data is NASA Earth Exchange Global Daily Downscaled Projections dataset (NEX-GDDP-CMIP6) (Thrasher et al., 2022), designed for studies of climate change impact. This dataset contains nine climate variables at high-resolution (roughly $\sim$28 km or 0.25°), including temperature, relative humidity, precipitation, etc. We will consider the period 2000–2050, focusing on the conterminous US due to more data availability. Unfortunately, we could not find downscaled wind direction data. Yet these data can be incorporated at the coarser resolution of 200km directly from the CMIP6 project (O'Neill et al., 2016). Interestingly, Höhlein et al. (2020) argue that convolutional architectures are effective for wind vector downscaling, suggesting that even if included at a coarser resolution, the spatial feature learning layer may extract relevant information. Climate data will be enhanced with topographical and land use information from the US Geological Survey (Rabbitt, 1989) and demographic information will be gathered from the US Census Bureau (2011), which are proxys for greenhouse emissions. When evaluating future projections, demographic patterns will be either fixed constant or scaled accordingly to current migratory and national trends (US Census Bureau, 2017; Ambinakudige & Parisi, 2017). Our combined dataset will be shared publicly on the dataverse (King, 2007) to facilitate future research.

Source	Description
NEX-GDDP-CMIP6	Climate variables at 0.25° x 0.25° resolution with historic daily data and projections under climate change up to 2100.
Di et al. (2019)	$PM_{2.5}$ at 1×1 km resolution. Daily historic surface 2000–2015.
US Geological Survey	Land cover and land use created using satellite imagery and other data sources.
US Census	Demographic and socio-economic variables by census track.

Table 1: Summary of Data sources

4 Concluding Thoughts

This work holds the potential to inform planning and preparedness with an improved understanding of how the changing climate will impact air quality and public health. By highlighting inequities in $PM_{2.5}$ exposure, the study can help understand the relation between the expected changes to air quality exposure and inequity. However, it is important to acknowledge that the methodology is subject to uncertainties, limitations, and assumptions about the future. While these assumptions are necessary and shared among existing frameworks, transparent communication of these considerations is very important, and the results cannot be interpreted without them.

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