

Wildfire gas emission and its impact on crop yields

by

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B.S., China Agricultural University, 2016

M.S., China Agricultural University, 2019

AN ABSTRACT OF A DISSERTATION

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DOCTOR OF PHILOSOPHY

Department of Agronomy
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Abstract

Wildfire activities are more frequent due to the effects of global warming and climate change. It causes a lot of damage in terms of impact on agriculture and air quality through the emission of large amounts of trace gases and particular matters. A critical step to quantify the wildfire related air pollution impacts on crop productivity is firstly to assess the emission of primary gas- and particle-phase emissions (e.g. Carbon Monoxide (CO), nitrogen dioxide (NO₂)). Therefore, using NO₂ and CO data measured by the Tropospheric Monitoring Instrument (TROPOMI), together with fire counts and fire radiative power (FRP) from MODIS, we analyzed the temporal and spatial variation of NO₂ and CO column densities over three selected areas covering savanna and temperate forest vegetation in Australia 2019-2020 bushfires in Chapter 2. The $\Delta\text{NO}_2/\Delta\text{CO}$ emission ratio and emission factor were also estimated. The $\Delta\text{NO}_2/\Delta\text{CO}$ emission ratio was found to be 1.57 ± 1.71 for temperate forest fire and ranged from 2.0 ± 2.36 to 2.6 ± 1.92 for savanna fire. For savanna and temperate forest fires, satellite-derived NO_x emission factors were found to be 1.48 g kg^{-1} and 2.39 g kg^{-1} , respectively, whereas the CO emission factors are 107.39 and 126.32 g kg^{-1} , respectively. This study demonstrates that the large-scale emission ratio from the TROPOMI satellite for different biomass burnings can help identify the relative contribution of smoldering and flaming activities in a large region and their impacts on the regional atmospheric composition and air quality.

Next, we estimate how air pollution from fire smoke influences soybean yield over the non-wildfire-prone Midwestern farmlands of the United States (U.S.) in Chapter 3. We develop robust statistical models, based on historical crop data, fire smoke products as well as climate data, and satellite-based ground-level fine particulate matter (PM_{2.5}) pollution. We observed increased exposure to heavy smoke days during the growing season in the Midwest region, ranging from 2 to 48 days on average during 2008-2022. Relative yield change due to smoke exposure has been worsened over all states, with the largest trend in North Dakota by a rate of -1.7 % per decade and the lowest in Illinois at a rate of -0.4 % per decade. Our result confirms that a substantial decline in yield loss from PM_{2.5} indicates that smoke pollution control has had widespread benefits on soybean yield. However, wildfires already affected PM_{2.5} trend in the U.S. in recent years, and the trend of wildfire specific PM_{2.5} reduced yield was the largest in North Dakota with a rate of $1.4 \text{ \% dec}^{-1}$. Increasing smoke-related PM_{2.5} suggests the yield gain

benefiting from the Clean Air Act in the non-wildfire-prone Midwestern U.S. is declining. Our findings call for attention to yield damage from exposure to the smoke plume under climate warming-induced frequent and more severe wildfires due to fuel aridity.

Last, in Chapter 4, we analyze the variation of total precipitable water and its response to temperature at the global scale, our results indicate a global increase in total precipitable water (TPW) of $\sim 2\%$ per decade from 1993 to 2021. These variations in TPW reflect the interactions of global warming feedback mechanisms across different spatial scales. Our results also revealed a significant near-surface temperature (T_{2m}) warming trend of $\sim 0.15\text{ K}$ per decade during 1958-2021. This consistent warming at a rate of $\sim 0.21\text{ K}$ per decade after 1993 corresponds to a strong water vapor response to temperature at a rate of 9.5% K^{-1} globally, with land areas warming approximately twice as fast as the oceans. The relationship between TPW and T_{2m} showed a variation around $6 - 8\%$ K^{-1} in the $15\text{--}55^\circ\text{N}$ latitude band, aligning with theoretical estimates from the Clausius–Clapeyron equation.

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Last, in Chapter 4, we analyze the variation of total precipitable water and its response to temperature at the global scale, our results indicate a global increase in total precipitable water (TPW) of $\sim 2\%$ per decade from 1993 to 2021. These variations in TPW reflect the interactions of global warming feedback mechanisms across different spatial scales. Our results also revealed a significant near-surface temperature (T_{2m}) warming trend of $\sim 0.15\text{ K}$ per decade during 1958-2021. This consistent warming at a rate of $\sim 0.21\text{ K}$ per decade after 1993 corresponds to a strong water vapor response to temperature at a rate of 9.5% K^{-1} globally, with land areas warming approximately twice as fast as the oceans. The relationship between TPW and T_{2m} showed a variation around $6 - 8\%$ K^{-1} in the $15\text{--}55^\circ\text{N}$ latitude band, aligning with theoretical estimates from the Clausius–Clapeyron equation.

Table of Contents

List of Figures	x
List of Tables	xv
Acknowledgments.....	xvi
Chapter 1 - Introduction.....	1
1.1 Background and Motivation	1
1.2 Scope of Dissertation	3
Chapter 2 - Estimation of biomass burning emission of NO ₂ and CO from 2019-2020 Australia fires based on satellite observations	4
2.1 Introduction.....	4
2.2 Data Used.....	6
2.3 Methods Used for Calculating Emission Ratio and Emission Factor.....	9
2.4 Results and Discussion	12
2.5 Summary and Conclusions	16
2.6 Data availability	17
2.7 Acknowledgments	17
Chapter 3 - Wildfire smoke induced PM _{2.5} impact on soybean yield.....	27
3.1 Introduction.....	27
3.2 Data and Method.....	29
3.3 Results.....	33
3.4 Discussion and conclusion.....	37
3.5 Data availability	38
3.6 Acknowledgments	39
Chapter 4 - Global total precipitable water variations and trends during 1958-2021.....	45
4.1 Introduction.....	45
4.2 Data and Method.....	47
4.3 Results and Discussion	50
4.4 Further Discussion	55
4.5 Conclusions.....	58
4.6 Data availability	59

4.7 Acknowledgments	60
Chapter 5 - Conclusions and Applications.....	67
References	69
Appendix A - Supplemental Information for Chapter 3	92
Appendix B - Supplemental Information for Chapter 4	105

List of Figures

Figure 2.1 Total fire counts from August 2019 through January 2020 at $0.5^\circ \times 0.5^\circ$ resolution.	
Three $10^\circ \times 10^\circ$ (latitude $\times$ longitude) areas indicate regions of interest in this study.	18
Figure 2.2 An example of emission analysis for a fire event, with MODIS fire pixels indicated (black points) and the center of the fire event indicated by a red star. (a) Map of TROPOMI NO_2 column density over Australia on 6 November 2019. The red box in southeast Australia marks the fire event location. (b) The original TROPOMI NO_2 column density with the wind direction is indicated by a white arrow. The red arrow indicates the plume direction. (c) The excess NO_2 after 1) removing background column density from original NO_2 and 2) rotating the entire pixels examined to align with the wind direction, thus a 20 km downwind distance area was selected and used to estimate the NO_2 emission.	19
Figure 2.3 Daily fire radiative power (FRP) from August 2019 through January 2020 for Area 1 (green), Area 2 (blue), and Area 3 (red). Several distinct periods are highlighted to show a significant increase in FRP, covering 1-24 October and 1 November - 3 December (Area 1), 4 – 13 September (Area 2), 7 - 18 November and 28 November - 29 December (Area 2), 5 - 17 November (Area 3), and 28 December - 6 January (Area 3).	20
Figure 2.4 Monthly average NO_2 (a-f) and CO (g-l) column density from August 2019 through January 2020. Three $10^\circ \times 10^\circ$ (latitude $\times$ longitude) areas indicate regions of interest in this study.	21
Figure 2.5 Time series of daily maximum NO_2 (a) and CO (b) total column densities from August 2019 through January 2020 as well as daily mean NO_2 (c) and CO (d) for three highlighted areas: Area 1 (green), Area 2 (blue), and Area 3 (red). Results for Areas 1 and 2 are displayed by the left Y axis and results for Area 3 are displayed by red colours of the right Y axis.	22
Figure 2.6 The relationship between daily ΔCO (mol m^{-2}) and daily ΔNO_2 (mmol m^{-2}) in Savanna regions (a for Area 1, b for Area 2, and c for Area 3) and temperate forest regions (d for Area 3 only). The colour bars are coded by daily FRP, data points with black edges are the days with high FRP (highlighted periods) in Figure 4. The blue markers represent the monthly average relationship between ΔCO and ΔNO_2 with day-to-day variabilities shown represented by the error bars. ER stands for the total emission ratio expressed by overall mean plus and minus one standard deviation.	23

Figure 2.7 The relationship between daily ΔCO (mol m^{-2}) and daily ΔNO_2 (mmol m^{-2}) was derived from TROPOMI for all regions. The slope of linear fit with an intercept at zero represents the combustion efficiency of different fire types.	24
Figure 2.8 Scatter plots of TROPOMI-derived NO_x and CO emissions (g s^{-1}) versus MODIS FRP in Savanna regions (a, d for Area 1, b, e for Area 2) and temperate forest regions (c, f for Area 3). The black line indicates the regression line estimated from ordinary least squares regression with the intercept fixed at zero. Slopes are shown with a 95% confidence interval. The color represents the plume height of the corresponding fire events. Emissions and FRP are on log scales.	25
Figure 2.9 NO_2 line density decay curves of three example fire events (each color represents a fire event) in Area 2. The embedded histogram shows the frequency distribution of NO_2 lifetime estimated from all three areas.	26
Figure 3.1 (a) Averaged smoke-influenced days per growing season month (May-October) across all counties and (b) smoke-influenced days change from 2008 to 2022 using Hazard Mapping System smoke dataset. The dark blue line is the average days among all counties and the shaded areas show counties where smoke days are at 75% and 95% position. (c) Average days and (d) spatial distribution of trends of smoke-influenced days during the growing season (May-October) from 2008 to 2022.	39
Figure 3.2 The effects of increased smoke days on soybean yields from 2008 to 2022, the graphs surrounding the maps represent the overall state changes in yield. The solid line indicates the mean and shaded areas indicate 5%-95% confidence intervals by 1,000 bootstrap estimates. Trends were significant and estimated using the ordinary least squares method of linear regression. Yield loss is represented as the percentage change relative to mean yield. Trend unit: $\% \text{ dec}^{-1}$	40
Figure 3.3 The average yield loss relative to soybean mean yield due to the increase of smoke-influenced days during 2008-2012 (triangle) and 2018-2022 (cycle) at North Dakota, South Dakota, Minnesota, Wisconsin, Michigan, Iowa, Illinois, Indiana, Ohio, and Missouri state. The error bar is 5%-95% confidence intervals from 1000 times bootstrap. The Y-axis is ordered based on latitudes.	41
Figure 3.4 The spatial distribution of yield loss due to wildfire-specific smoke contributed to $\text{PM}_{2.5}$ relative to soybean mean yield from 2008 to 2022.	42

- Figure 3.5 The differential impact on soybean yields between 2018-2022 and 2008-2012 periods that caused by wildfire-specific $PM_{2.5}$ and total $PM_{2.5}$. The yield loss difference is calculated as a relative change to overall mean yield corresponding to each period (light diamond indicates wildfire-specific smoke $PM_{2.5}$, dark diamond indicates total $PM_{2.5}$). The error bars are calculated by 1,000 times bootstrapping. 43
- Figure 3.6 Wildfire-specific smoke $PM_{2.5}$ and total smoke $PM_{2.5}$ impacts on soybean yields expressing as a percent change relative to overall mean yields from (a) North Dakota, (b) South Dakota, (c) Minnesota, (d) Wisconsin, (e) Michigan, (f) Iowa, (g) Illinois, (h) Indiana, (i) Ohio, and (j) Missouri (blue color for wildfire-specific smoke $PM_{2.5}$ and orange color for total $PM_{2.5}$). The solid line in a-j indicates the mean estimate across 1,000 bootstrap estimates and shaded areas indicate 5th and 95th percentiles. Trends were significant and estimated using the ordinary least squares method of linear regression. (Unit: % dec⁻¹). 44
- Figure 4.1 Time series of monthly TPW anomalies (mm) over (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, (e) SH polar, (f) ocean area, (g) land area, and (h) the globe from the ERA5 (blue) and JRA-55 (red) during the period 1958–2021. A 12-month running smoother was applied to each time series shown. The trends are shown for 1958-2021 (light color) and 1993-2021 (dark color) periods with 95% confidence intervals in brackets. The vertical line indicates the year of 1993. 61
- Figure 4.2 Monthly total precipitable water (TPW) trend (% dec⁻¹) from 1993 to 2021 from (a) ERA5 and (b) JRA-55. The hatch areas represent trends that are not statistically significant at a 95% confidence level. 62
- Figure 4.3 Trends of surface air temperature (T_{2m}) from 1958 to 2021 for ERA5 (a) and JRA-55 (b). The differential trends between T_s and T_{2m} trends for ERA5 (c) and JRA-55 (d). The hatch areas indicate trends that are not statistically significant. Trend units: K dec⁻¹. 63
- Figure 4.4 Monthly T_{2m} and T_s anomaly over (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, (e) SH polar, (f) ocean, (g) land, and (h) the globe from the ERA5 (blue) and JRA-55 (red) data sets during the period of 1958 to 2021. A 12-month running smoother was applied to all time series. The

trends are shown for 1958-2021 (light color) and 1993-2021 (dark color) periods with 95% confidence intervals in brackets. The vertical line indicates 1993 year.....	64
Figure 4.5 (a) The ratio (% K ⁻¹) of the TPW trends and the surface air temperature (T _{2m}) trends from 1993 to 2021 in ERA5. (b) Same as (a) but for JRA-55. The hatch areas represent ratios that are not statistically significant at the 95% confidence level.	65
Figure 4.6 The meridional means of change of TPW response to T _{2m} for ERA5 (blue) and JRA-55 (red) over (a) globe, (b) land, and (c) ocean base using data from 1993 to 2021. The dashed lines represent the theoretically expected Clausius-Clapeyron response based on the climatological zonal mean temperature from the trend analysis.....	66
Figure A- 1 The histogram of soybean growing season. Each bar represents the total number of when more than 50% of acreage within a state-year reaches a crop stage (e.g. blooming) or practice (e.g. planting) from 2008 to 2022.	93
Figure A- 2 An example of smoke density map on August 1 st , 2021. The data is provided by the NOAA Office of Satellite and Product Operations as part of the Hazard Mapping System Fire and Smoke Product, available: https://www.ospo.noaa.gov/Products/land/hms.html#data , accessed January 11, 2024.	94
Figure A- 3 The Locations of EPA PM _{2.5} air pollution monitors from 2008 to 2022. The total number of each class monitor is 213 for <10 years, and 154 for > 10 years, data source: https://aqs.epa.gov/aqswweb/airdata/download_files.html	95
Figure A- 4 Time series change of total smoke-impacted days per growing season month (May-October) from 2008 to 2022	96
Figure A- 5 The Probability density estimates of observed daily average PM _{2.5} for smoke-influenced (red line) and smoke-free (blue line) for soybean emerge to setting pod period (June-August) from 2008 to 2022 in (a) North Dakota, (b) South Dakota, (c) Minnesota, (d) Wisconsin, (e) Michigan, (f) Iowa, (g) Illinois, (h) Indiana, (i) Ohio, (j) Missouri state.	97
Figure A- 6 Sensitivity contour plots for the t-value of: (a) the GDD (b) the EDD.....	98
Figure A- 7 The effects of increased smoke days on soybean yields from 2008 to 2022, the graphs surrounding the maps represent the overall state changes in yield. The solid line indicates the mean and shaded areas indicate 5%-95% confidence intervals by 1,000 bootstrap estimates. Trends were significant and estimated using the ordinary least squares	

method of linear regression. Yield loss is represented as the percentage change relative to mean yield. Trend unit: % dec ⁻¹ .	99
Figure A- 8 The sensitivity of corn (orange) and soybean (blue) response to (a) smoke days during May to October, (b) total PM _{2.5} , and (c) wildfire PM _{2.5} during June to August over segment years with different start years (range from 2008 to 2013) and same year (2022). Empty scatters mean the coefficients are not significant.	100
Figure B-1 Detected change points for monthly temperature during 1958-2021 in (a) ERA5 and (b) JRA55. (c) The timeseries of Oceanic Niño Index (ONI) from 1958 to 2021. There is a total 21,307 of grids for PMF-test over the ocean.	106
Figure B-2 Histogram of years with detected change points for total precipitable water in ERA5 (a) and JRA-55 (b). (c) The timeseries of Oceanic Niño Index (ONI) from 1958 to 2021.	107
Figure B- 3 The variability of TPW and expected TPW calculated from regression with temperature for ERA5 (a) and JRA-55 (b). (c) The timeseries of Oceanic Niño Index (ONI) index from 1981 to 2021. Discrepancies are marked by triangles.	108
Figure B- 4 The relationship of monthly T _{2m} and T _s over land, ocean, and global for ERA5 (first column) and JRA-55 (second column).	109
Figure B- 5 The same as Figure R4 but for (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, and (e) SH polar.	110
Figure B- 6 Trend comparisons with radiosondes: (a-b) TPW trends' difference (mm dec ⁻¹) between radiosonde observations and ERA5 and JRA-55 from 1979-2019. (c-d) Same as (a-b) but for temperature trends' difference (K dec ⁻¹). A total of 331 radiosonde observations were used in the analysis.	111
Figure B-7 Trend comparisons with satellite observations from 2003-2021: Total precipitable water (TPW) trends over oceans for (a) ERA5, (b) JRA-55, (c) AIRS satellite, and (d) SSMI satellite. The hatch areas represent trends that are not significant at a 95% confidence level.	112

List of Tables

Table A- 1 Minimal sensitivity reporting of the reduced form regression, robust value ($RV_{q=1}$ and $RV_{q=1, \alpha=0.05}$), and partial R^2 of treatment with the outcome are sensitivity statistics.	101
Table A- 2 The bounds of unobserved confounders: the residual variation of the treatment ($R^2_{D \sim Z X}$) and residual variation of the outcome ($R^2_{Y \sim Z D, X}$)	102
Table A- 3 Ordinary least squares (OLS), Reduce Form, and IV Estimates for soybean from June to August: Satellite-Based $PM_{2.5}$ Sample, standard errors are included in the bracket for soybean.	103
Table A- 4 Smoke impact during May to September, Ordinary least squares (OLS), Reduce Form, and IV Estimates for soybean from June to August: EPA Monitor-Based $PM_{2.5}$ Sample, standard errors are included in the bracket for soybean.....	104

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Chapter 1 - Introduction

1.1 Background and Motivation

Fire is a natural phenomenon within the Earth System and plays an important role in the biosphere, hydrosphere, and atmosphere (Scott et al., 2013; Ward et al., 2012). It is one of the largest sources of trace gases and aerosols worldwide accounting for more than 20% of carbon monoxide and nitric oxide global emissions (Andreae, 2019; Wiedinmyer et al., 2011). During the last decade, the number of large and destructive wildfires increased in many regions (Flannigan et al., 2009). Increasing temperature and drought are projected to increase the occurrence and intensity of wildfires and lengthen the fire seasons (climate science report), which has happened in the western United States, Canada and Australia (Keywood et al., 2013; A. L. Westerling et al., 2006).

Agriculture, from property and soil health to workers' health and crop productivity in downwind regions, is one of the sectors that are susceptible to fires (Kabeshita et al., 2023). In addition to damaged land and loss of property, the impacts of fires on climate and air quality are a major concern. Crops in downwind regions can be impacted by changes in air quality and photosynthetically active radiation that stem from smoke. Finer particular matter (PM_{2.5}) and ozone are two risk factors when exposed to biomass burning smoke. To understand the elements that contribute to downwind PM_{2.5} and ozone pollution, a critical first step is to quantify primary gas and particle-phase emissions (e.g., CO, NO_x). The emission ratio is a common value that has been used in numerous studies to quantify emissions for various fire conditions and fuel types (e.g., Konovalov et al., 2016; Lama et al., 2019). Current estimates of emission factors are primarily based on field measurements or laboratory studies in a limited spatial and temporal coverage (Roberts et al., 2020; Lindaas et al., 2021). Satellite instruments can eliminate those difficulties and obtain information on fire emissions over large regions. The TROPOspheric Monitoring Instrument (TROPOMI) is a new satellite instrument that has demonstrated improved accuracy and high spatial resolution that facilitates investigations of trace gases from space compared to other sensors. Therefore, using a more accurate and finer resolution satellite to parameterize wildfire emission based on CO and NO_x ratio is useful to enhance modeling efforts to precisely capture the chemical transformation of wildfire smoke, which is our motivation for the second chapter.

Wildfire emission has a very high PM_{2.5} emission per unit of burned fuel compared to anthropogenic, industrial, or vehicular emissions (Daniel Jaffe et al., 2022). Thus, wildfires can result in a severe deterioration of surface air quality near the source. Meanwhile, the smoke from long-time burning lofts high into the atmosphere travels long distances from source fires and potentially affects ground-level pollution thousands of kilometers. The non-wildfire-prone Midwestern U.S., as the downwind of the western U.S., has been exposed to smoke more frequently and reached seasonal maximum smoke occurrences during the summertime which is also an important time for Midwestern crop growth (Kaulfus et al., 2017). Fire smoke containing a mixture of particulate matter and gases impacts crop productivity by changing air quality and photosynthetically active radiation (PAR). The relationship between smoke plumes and crop yields is complex because it depends on the balance between harmful and beneficial impacts on crop productivity. O₃, nitrogen oxides (NO_x) and acyl peroxy nitrates from smoke are known to reduce crop yield. Enhanced O₃ damages plant tissue thereby impeding the process of photosynthesis (Hong et al., 2020; Ninneman & Jaffe, 2021). PM_{2.5} impacts crops by reducing total radiation and increasing diffuse radiation, the main impact of changing radiation depends on the balance between the two. Multiple studies quantified the PM_{2.5} attributed to wildfire smoke impact on human health (e.g., Aguilera et al., 2021; Burke et al., 2021) but few studies related to agricultural yields. Therefore, quantifying the magnitude of PM_{2.5} from wildfire smoke's impact on crop yield is important, underlining the major motivation for chapter three in this thesis.

Wildfires, from burned areas to season length and frequency, have been increasing globally (Pausas & Keeley, 2021). It's a consequence of climate change not only because greenhouse gas emissions continue to rise but also water vapor feedback within the climate system. The global average temperature has increased by around 1.1 °C since the 1800s, driven by the human-induced burning of fossil fuels that release greenhouse gases (Masson-Delmotte, Valérie, et al., 2023). When temperatures rise due to increased carbon dioxide levels, the warmer atmosphere retains more moisture in the form of water vapor, then, the water vapor contributes to greenhouse warming as a greenhouse gas. This positive feedback loop demonstrates that increased water vapor is a consequence of global warming. Therefore, evaluating the long-term trend of water vapor change and its relationship with temperature is important for understanding the role of

water vapor in climate change and the impact of water vapor feedback on global warming, underlining the major motivation for chapter four.

1.2 Scope of Dissertation

In this thesis, we first assess the influence of trace gases and particular matters from wildfire on air quality and crop yield. Then, we analyze the change of the largest greenhouse gas-total precipitable water, and the response to temperature change. The following paragraphs provide an overview of the chapters in this thesis. Chapter 2 is a research article published in *Atmospheric Chemistry and Physics* journal. In this chapter, I assess the impact of Australian bushfires during 2019-2020 on air quality by analyzing CO and NO₂ trace gases. I use the integrated mass enhancement method combined with data from the TROPOMI satellite to estimate trace gas concentrations and emission ratios. In Chapter 3, I develop robust statistical models, based on historical soybean crop data, fire smoke products as well as climate data, and satellite-based ground-level PM_{2.5} pollution, to characterize the effect of smoke days and the wildfire specific PM_{2.5} pollution on soybean yield over the growing season in non-wildfire-prone Midwestern farmlands in the United States (U.S.). Chapter 4 is a research article published in *Hydrology and Earth System Sciences* journal. In this chapter, I investigate the total precipitable water and temperature relationship from 1958 to 2021 using reanalysis datasets. The results confirm the increase of total precipitable water and a strong response to temperature. Finally, in Chapter 5, we provide a summary of the conclusions and the applications.

Chapter 2 - Estimation of biomass burning emission of NO₂ and CO from 2019-2020 Australia fires based on satellite observations

Wan, N., Xiong, X., Kluitenberg, G. J., Hutchinson, J. M., Aiken, R., Zhao, H., & Lin, X. (2023). Estimation of biomass burning emission of NO₂ and CO from 2019–2020 Australia fires based on satellite observations. *Atmospheric Chemistry and Physics*, 23(1), 711-724. doi: <https://doi.org/10.5194/acp-23-711-2023>

2.1 Introduction

As a consequence of climate change, extreme climatic conditions are conducive to large wildfires around the world, resulting in extensive social, economic, and environmental impacts (Bowman et al., 2017; Filkov et al., 2020). The year 2019 was the warmest and driest year on record to date in Australia (Abram et al., 2021). The high temperature aggravated the impact of low rainfall that led to low soil moisture conditions. Recently it was reported that the strong positive Indian Ocean Dipole was one of the main influences on Australia's climate in 2019 (Annual Australian Climate Statement 2019, 2022), leading to very low rainfall across Australia. High temperatures, combined with low rainfall and high winds further exacerbated evaporative demand, resulting in canopy dieback and increasing high fire danger indices (Boer et al., 2020; Nolan et al., 2020; Abram et al., 2021). It was Australia's record-breaking temperature and extremely low precipitation in 2019 and 2020 that caused these unprecedented fire disasters (Abram et al., 2021) which also resulted in significant ecological, social, and economic impacts. These mega-fires in 2019 and 2020 burned more than 8 million hectares of vegetation including more than 70% of forests, woodlands, and shrublands, and 816 native vascular plant species across the south-east of the continent (Godfree et al., 2021). Thirty-three lives were lost and more than 3,000 homes destroyed as a direct result of the fires (Filkov et al., 2020), while approximately 417 perished and 3,151 hospitalizations occurred as a result of smoke inhalation (Borchers et al., 2020). The direct economic loss was estimated at \$20 billion (Wilkie, 2020).

Fire events are considered to be the largest source of global carbon emissions, especially in grasslands and savannas (44 %) and woodlands (16 %) (Van der Werf et al., 2010). Also, the open biomass burning produced 20 % of global nitrogen oxides (NO_x) and one-third to one-half

of carbon monoxide (CO) emissions (Wiedinmyer et al., 2011). Nitrogen oxides undergo smog photochemistry and convert to ozone (O₃) leading to increased tropospheric O₃, whereas CO is the leading sink of the hydroxyl radical (OH) and one of the precursors to tropospheric O₃ (Fowler et al., 2008). Emission ratios (ER), defined as the ratio of an excess trace gas concentration (ΔX , i.e., the mixing ratio of species X) and the excess concentration of a reference gas (ΔY) have been widely used to characterize combustion over large fire source regions (Van der Werf et al., 2010, 2017). The amount of substances emitted from the burning of a particular type of land cover depends on the fuel type and completeness of combustion. For example, a relatively large amount of NO₂ is emitted during hotter and cleaner flaming combustion whereas a larger quantity of CO is emitted during the smoldering combustion phase. Therefore, the emission ratio metric can be considered as a proxy for combustion efficiency to distinguish flaming from smoldering combustion (Andreae and Merlet, 2001). Previous studies related to CO and NO₂ emissions have been reported from anthropogenic (e.g., vehicles emission in urban regions), fossil fuel (e.g., coal and gas-fired power plant), and wildfire sectors based on surface and satellite observations (Zhao et al., 2011; Konovalov et al., 2016; Lama et al., 2019). Besides ER, emission factor (EF), which is defined as the amount of gas released per kg of dry fuel burned (g kg^{-1}), is another widely used metric to provide emission information. It varies greatly based on individual fire conditions and fuel types. Current estimates of EFs are primarily based on laboratory studies or field measurements in limited spatial and temporal coverage (Roberts et al., 2020; Lindaas et al., 2021). Satellite remote sensing instruments can eliminate those difficulties and obtain information on emissions from burning conditions and fuel types over large regions. The TROPospheric Monitoring Instrument (TROPOMI) is the satellite instrument onboard the Copernicus Sentinel 5 Precursor launched by the European Space Agency and the overpass time is about 1:30 PM local time (Veefkind et al., 2012). The TROPOMI has demonstrated improved accuracy and high spatial resolution that facilitate investigations of trace gases from space compared to other sensors, such as the Ozone Monitoring Instrument and Measurement of Pollution in the Troposphere (Van der Velde et al., 2020).

Burning in Australia is responsible for 14.4 % of the global annual burnt area although the land of Australia only accounts for 6 % of the Earth's land area (Giglio et al., 2013). Most of these fires occur in the semi-arid and tropical savannas that cover the northern part of the continent (Russell-

smitha et al., 2007), but large bushfires also occur in the temperate forests of southeast Australia (Cai et al., 2009). Through a multiple-year surface observations, the annual pattern of some trace gas emissions (e.g., CO) has been identified and specific emission ratios that are based on carbon monoxide (i.e., $\text{CH}_2\text{O}/\text{CO}$, $\text{C}_2\text{H}_2/\text{CO}$, $\text{C}_2\text{H}_6/\text{CO}$) from Australian savanna fires have been investigated (Paton-Walsh et al., 2010; Smith et al., 2014; Desservettaz et al., 2017). However, there are relatively few studies related to emissions from temperate forest fires in Australia (Paton-Walsh et al., 2010; Possell et al., 2015; Guérette et al., 2018) and few studies have documented NO_2 and CO emissions from Australian savanna and temperate forest fires over large regions.

Therefore, the objective of this study is to characterize the emission ratio and emission factor of NO_2 and CO over large savanna and temperate forest fires in Australia in 2019 and 2020 using TROPOMI satellite observations. Our paper structure is as follows: Sections 2 and 3 describe the datasets and methods used. In Section 4, we report the fire intensity, and daily maximum and mean NO_2 and CO column densities observed during 6 months in 2019 and 2020 (i.e., 1 August 2019 to 31 January 2020) over fire hotspot regions. The emission ratios of NO_2 relative to CO for savanna and temperate forest fires are also examined. Finally, we estimated the EF using satellite-derived NO_x and CO emissions. Section 5 is a summary and conclusion.

2.2 Data Used

2.2.1 GFED4s database

The Global Fire Emission Database version 4 with small fires (GFED4s) provides global estimates of monthly and daily burned area, emissions, and fractional contributions of different fire types with $0.25^\circ \times 0.25^\circ$ spatial resolution (Randerson et al., 2012). This database uses the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 5.1 MCD64A1 burned area product and includes small fires for emission estimates (Giglio et al., 2013). Six fuel classifications are estimated using the land cover type product from MODIS and the University of Maryland classification scheme in the GFED4s database, including temperate forest, boreal forest, deforested and degraded land, peatland, agricultural waste burning, and herbaceous fuel type which is composed of shrubland, savanna and grassland (Van der Werf et al., 2017). The vegetation fires that occurred in Australia from August 2019 through January 2020 were classified as savanna and temperate forest fires based on GFED4s. Highlighted in Figure 2.1 are

the three areas of interest employed in this study. The three selected areas include two savanna fire areas in northwestern (Area 1) and northeastern (Area 2) Australia, as well as an area with both savanna and temperate forest fires in southeast (Area 3) Australia (Fig. 2.1). To be consistent for the three areas, we chose the same study period that covers all fires from August 2019 through January 2020.

2.2.2 TROPOMI CO, NO₂, and fire plume data

The total column density of CO from TROPOMI was estimated from spectral radiance measurements from the shortwave to infrared spectral ranges around 2.3 μm that are sensitive to CO absorption with a daily $5.5 \times 7 \text{ km}^2$ resolution (Landgraf et al., 2016; Borsdorff et al., 2018). Previous studies have shown that TROPOMI was able to capture the variability of daily CO as a result of atmospheric transport of pollution (Borsdorff et al., 2018; Schneising et al., 2020). The NO₂ tropospheric column density is detected from TROPOMI's 405 – 465 nm wavelength bands with a $5.5 \times 3.5 \text{ km}^2$ resolution. Although there exists a negative bias of approximately 30% in the lower tropospheric columns because of cloud pressure and the *a priori* NO₂ profile used in air mass factor calculations (Lambert et al., 2018), it is still appropriate to use TROPOMI NO₂ to quantify fire burning efficiency (Lama et al., 2019; Van der Velde et al., 2020). We chose an improved NO₂ dataset from Van Geffen et al. (2022), which showed that, on average, the corrected NO₂ tropospheric vertical column densities are 10 % to 40 % larger than the raw data, especially over large, polluted regions. Different algorithms are used to estimate NO₂ and CO in TROPOMI instrument channels which also provide quality assurance values (i.e., *qa_value*) to help filter raw data under unclear sky conditions and/or other problematic retrievals. In our study, we collected CO retrievals with a *qa_value* larger than 0.5 and NO₂ retrievals with a *qa_value* larger than 0.75. The CO total column density and NO₂ tropospheric column density were then converted to units of moles per square meter (mol m^{-2}) and millimoles per square meter (mmol m^{-2}), respectively. The TROPOMI also provides aerosol layer height (ALH) data that are based on the O₂ absorption band at near-infrared wavelengths (Graaf et al., 2019). The ALH data were used to define the main vertical wind layer which was required for the emission estimation procedure described in Section 3.2, and we added plume height data from the Global Fire Assimilation System (GFAS) as alternative values to use when ALH data were unavailable.

All data were then re-sampled to $0.05^\circ \times 0.05^\circ$ spatial resolution through an areal weighted interpolation using the Harp package from Python (Niemeijer, 2017).

2.2.3 MODIS fire radiative power (FRP) and fire events

The FRP represents the instantaneous radiative energy that is released from actively burning fires and is related to the rate of biomass combustion (Wooster et al., 2003), the emission rate of trace gases, and aerosol emissions (Kaiser et al., 2012). The MODIS instrument is onboard both the Earth Observation System Terra and Aqua satellites of the National Aeronautics and Space Administration and measures radiance in spectral channels to detect fires at a 1 km spatial resolution (Kaufman et al., 1998). The MODIS near real-time active fire products data (MCD14DL) were used to identify fire events from August 2019 through January 2020. For each day, fire pixels (i.e., $1 \times 1 \text{ km}^2$ grid cells) located within a 20 km distance of one another were aggregated into a “fire event” forming a rectangular polygon with $\pm 50 \text{ km}$ crosswind distance and 100 km downwind distance. The polygons were defined for the purpose of completing the emission calculation in Section 4.3. The fire event’s center was set as the average latitude and longitude of all fire pixels, weighted by each pixel’s FRP which is related to trace gas emission and widely used to estimate fire intensity (Wooster et al., 2003; Li et al., 2018). We retained only fire events for which the total FRP was larger than 200 Megajoule per second (MJ s^{-1}). It should be noted that MODIS does not provide all fire event data due to cloudy days.

2.2.4 Wind

Wind fields, which include wind speed and direction, were obtained from the hourly ERA-5 reanalysis dataset from the European Center for Medium-range Weather Forecast (ECMWF). This dataset provides meteorological variables for 37 vertical layers from 1000 hPa to 1 hPa from 1979 to the present at $0.25^\circ \times 0.25^\circ$ horizontal resolution (Hersbac et al., 2020). We first interpolated ERA-5 wind fields data at TROPOMI overpass time (1:30 PM at local time) and resampled to $0.05^\circ \times 0.05^\circ$ resolution grids. Then, the data were vertically interpolated to the averaged ALH level within each fire event. For fire events without valid ALH data, the GFAS plume height data were used as a replacement. Otherwise, an average plume height over each area was used when both ALH and GFAS datasets were unavailable. The mean plume height was 822 hPa for Area 1, 866 hPa for Area 2, and 833 hPa for Area 3.

2.3 Methods Used for Calculating Emission Ratio and Emission Factor

2.3.1 Emission ratio (ER)

Excess trace species concentration (ΔX) is defined as the difference between concentrations of species X in the fire plume (X_{fire}) and in the ambient background (X_{bg}). Usually, ΔX is divided by a reference species (ΔY), such as CO or CO₂, to get the emission ratio (ER) between those two emitted compounds (i.e., $\Delta X/\Delta Y$). In our study, a local sampling method similar to that employed by Van der Velde et al. (2020) was used to calculate the ER. To calculate excess gas concentration over the three selected $10^\circ \times 10^\circ$ areas (Fig. 2.1), daily TROPOMI data were first re-sampled into a $0.05^\circ \times 0.05^\circ$ spatial resolution grid. Next, co-located NO₂ and CO column densities from TROPOMI were obtained from locations where NO_x and CO values were available from the GFED4s database in the three selected areas (Fig. 2.1). The X_{fire} plume value was calculated as the average of all selected column densities. The corresponding ambient background X_{bg} value was calculated as the average of all values inside a $5^\circ \times 5^\circ$ subregion upwind of the biomass burning region but within the three $10^\circ \times 10^\circ$ study areas. The upwind direction was determined by interpolating the surface daily ERA-5 wind data to the time and location of TROPOMI observations. The background subregions were determined by visual inspection through examining the predominant direction of the individual plume. Excess NO₂ and CO concentration were determined from the expressions $\Delta NO_2 = NO_{2_{fire}} - NO_{2_{bg}}$ and $\Delta CO = CO_{fire} - CO_{bg}$, respectively, and the emission ratio was thus calculated as $ER = \Delta NO_2 / \Delta CO$. Days with inadequate data coverage (when the missing area exceeded 25% of the selected area in a single day) in either the background or study areas were removed during computation. And the overall emission ratio for each area was calculated by averaging the daily emission ratios in the studied area. Although CO and NO₂ also have strong anthropogenic sources, we minimized the influence of anthropogenic sources by selecting pixels collocated with FRP pixels.

2.3.2 Emissions from satellite measurement and emission factor (EF)

In our study, downwind flux was estimated using an integrated mass enhancement method that has been used in previous studies (Mebust et al., 2011; Adams et al., 2019; Griffin et al., 2021). Since the 2018-2019 fire events in Areas 1 and 2 were larger than those in 2020-2021, the period

from August 2020 through January 2021 was used as the background data for both CO and NO₂ column densities, to represent emissions under less intense fire conditions. To improve background robustness for daily gas column density, we removed raw column density values that were above the 99th percentile on each day in each area, then refilled back by interpolation using the nearest neighbouring data. The means and standard deviations of the background data indicated that the background selected did not have a strong systematic variation. The background values for CO ranged from 0.018 ± 0.001 to 0.032 ± 0.002 mol m⁻², and the background values for NO₂ ranged from 0.007 ± 0.002 to 0.011 ± 0.005 mmol m⁻². The daily column density was then calculated by subtracting corresponding monthly background values from raw daily column density values. When estimating CO and NO₂ emission from biomass burning, we excluded the TROPOMI dataset over the areas with pyrocumulus (PyroCb) events between 29-31 December 2019 and 4 January 2020 based on the PyroCb activity dataset of Peterson et al. (2021) because the flux method should be used under no PyroCb development condition (Griffin et al., 2021). Fire pixels were grouped based on distance as described in Section 2.3 and surrounding rectangles were defined. The total mass, m (g), emitted by fires is the product of daily column density and area (Eq. 1).

$$m = VCD \cdot A, \quad (1)$$

where VCD (mol m⁻²) is the daily vertical column density after subtracting background values, A is the rectangle area (m²). A line density derived from a plume traveling gaussian model over downwind under assumptions of constant wind without diffusion and deposition (Adams et al., 2019) is expressed as Eq. 2.

$$L(x) = L_0 \cdot e^{-kt} = L_0 \cdot e^{-\frac{x}{\tau\mu}}, \quad (2)$$

where L_0 (mol m⁻¹) is the concentration over the fire center calculated by integrating VCD (mol m⁻²) from ± 50 km crosswind direction, the lifetime τ is the inverse of reaction rate coefficient k ($\tau = 1/k$), and t is the time for emitted gas transport from the fire center to downwind distance x . μ is averaged wind speed at the mean ALH level in the rectangle. $L(x)$ (mol m⁻¹) is the line density at x downwind distance. The total mass m also equals the integral of gas density from the fire center to x distance (Eq. 3).

$$m = \int_0^x L_0 \cdot e^{-\frac{x}{\tau\mu}} dx = L_0 \cdot \tau \cdot \mu \cdot \left(1 - e^{-\frac{x}{\tau\mu}}\right) = L_0 \cdot \tau \cdot \frac{x}{t} \cdot \left(1 - e^{-\frac{x}{\tau\mu}}\right), \quad (3)$$

Therefore, $t = x/\mu$ is the residence time inside the areas from the fire center to downwind distance x . $L_0 x t^{-1}$ equals to the emission rate E ($g\ s^{-1}$). Therefore, the relationship between total mass and the emission rate can be expressed as:

$$E = \frac{m}{\tau \cdot \left(1 - e^{-\frac{x}{\tau\mu}}\right)}, \quad (4)$$

In this study, the downwind distance x was set as 20 km based on previous studies (Adams et al., 2019; Griffin et al., 2021), therefore the area in Eq. 1 is the area of 20 km downwind distance. We used Eq. 4 to estimate the emission rate with constant wind and estimated lifetime by using Eq. 2. Figure 2.2 (a) - (c) shows an example of calculating emission with a fire event that occurred in Area 3 of southeastern Australia (29.2° S, 151.5° E) on 6 November 2019, where the FRP fire pixels were grouped and TROPOMI data background column density values were removed. The location for the center of the fire was set at the averaged latitude and longitude of all fire pixels (the red star), then the mean wind direction was calculated. Lastly, the TROPOMI data plume direction (red arrow) was rotated to align with the wind direction. We derived CO and NO₂ emission flux in $g\ s^{-1}$ based on Eq. 4 and a NO₂/NO_x ratio of 0.75 was used to convert NO₂ to NO_x. Previous studies (Yurganov et al., 2011; R'Honi et al., 2013; Whitburn et al., 2015) indicated a 7-day or 14-day effective lifetime for CO, so a 7-day effective lifetime was used in our study determined through a sensitivity test discussed in Section 4.3. For the short lifetime NO₂, Mebust et al. (2011) assumed a 2-hour effective lifetime based on the fitted lifetimes from the OMI tropospheric NO₂ columns whereas Tanimoto et al. (2015) used 2 hours or 6 hours as the effective lifetimes. In our study, Eq. 2 was used to estimate the NO₂ lifetime by fitting an exponential to $L(x)$ as a function of downwind distance and wind speed. Finally, we used the emission coefficient ($g\ MJ^{-1}$), an energy-based coefficient, which is defined as the mass of pollutants emitted per unit of radiative energy. The emission coefficient was estimated as the slope of the linear relationship between emission estimates and FRP, with an intercept fixed at zero (Vermote et al., 2009). For both savanna and temperate forest fires, we converted regression emission coefficients to the EFs using an energy-to-mass factor of $0.41 \pm 0.04\ kg\ MJ^{-1}$, which is the average of the $0.368 \pm 0.015\ kg\ MJ^{-1}$ and $0.453 \pm 0.068\ kg\ MJ^{-1}$ values reported by others (Wooster et al., 2005; Freeborn et al., 2008; Vermote et al., 2009). It should be noted that

recirculating plumes have not been taken into account in our analysis, which may cause some degree of uncertainty in our emission ratio estimates.

2.4 Results and Discussion

2.4.1 Temporal evolution of fire intensity and total column density

The majority of fire-affected regions during these extreme fire events were located in Area 3 in southeast Australia (Fig. 2.1) where the largest cumulative fire counts exceeded 1,000. Fire frequencies were much lower in Areas 1 and 2 where the largest cumulative fire counts did not exceed 700. The fire-affected areas were dominantly located either in far northern oceanic boundaries of Areas 1 and 2 or in the south-eastern oceanic boundary of Area 3 (Fig. 2.1). From the fire data product of MCD14DL, the daily FRP observations showed a few distinct periods of peak fire events (Fig. 2.3), including three weeks from October 1st to 24th and four weeks from November 1st to December 3rd in Area 1, and three weeks for Area 2 from November 28th to December 29th. For Area 3, there were two short FRP peaks in November and early January. The highest FRPs during these periods of peak fire events were 4.45×10^4 , 4.44×10^4 , 1.01×10^6 MJ s⁻¹ for Areas 1, 2, and 3, respectively. The most intensive fire events were observed in October and November 2019 for Area 1, in December 2019 for Area 2, and in January 2020 for Area 3 (Fig. 2.3). Within these six months, both NO₂ and CO column density distributions showed a larger mean value for each month over Area 3 compared to the other two study regions (Fig. 2.4). These higher NO₂ and CO column density observations reflect the larger FRP over Area 3 (Figs. 2.3 and 2.4). As expected, the daily maximum NO₂ column density in Area 3 was nearly double that of the other two areas (Fig. 2.5a) but their mean values were comparable (Fig. 2.5c), indicating highly fluctuated NO₂ densities on a fire day. On the other hand, daily maximum CO column density was nearly 10 times higher in Area 3 than those estimated for Area 1 and Area 2 (Fig. 2.5b), suggesting the role of different fuel and fire combustion types. The maximum daily column densities were observed as 1.26 mmol m⁻² for NO₂ on 28th November, and 2.3 mol m⁻² for CO on 4 January in Area 3. For the daily mean total column densities, both NO₂ and CO are significantly different for all three areas under the two-sample t-test. Again, the daily mean CO was more sensitive to the FRP compared to NO₂ (Fig. 2.5d). In addition, significant increases in CO and NO₂ mean values in Area 3 were observed in early January, which certainly was

associated with the large FRP values that were detected on 30 December 2019, and 4 January 2020 (Fig. 2.3) by MODIS satellites.

2.4.2 Emission ratio (ER) in savanna and temperate forest

Different from the calculation of gas concentrations, the excess gas concentration (expressed as ΔX) is derived by removing the impact of potentially varying amounts of background concentration and thus represents the gas emissions related to fire activities. The averaged ERs derived from savanna fires were 2.34, 2.60, and 2.03 for Areas 1, 2, and 3, respectively. The ER for temperate forests in Area 3 was, on average, 1.57 during the six months of this study period (Fig. 2.6). As expected, ΔNO_2 and ΔCO both increased with increasing FRP (high FRP periods were highlighted in Fig. 2.3 to correspond to points with black edge markers shown in Fig. 2.6) for both savanna and temperate forest-dominated landscapes, but there was a clear distinction between savanna and temperate forest fires. For the savanna fires, ΔNO_2 approached 0.05 mmol m⁻² whereas changes in ΔCO were much less at 0.03 mol m⁻² across all three study areas. However, ΔNO_2 (up to 0.08 mol m⁻²) and ΔCO (up to 0.08 mol m⁻²) for temperate forest fires in Area 3 were both larger in magnitude and variability. ΔCO and ΔNO_2 emissions in temperate forest regions showed a larger enhancement compared to savanna fires. The ΔNO_2 and ΔCO in temperate forests exceeded those in savanna fires within the same region because temperate forest fuels consisted mainly of eucalyptus trees (Godfree et al., 2021). The relatively high ΔNO_2 and small ΔCO in the savanna portion of the three burning areas showed that the flaming combustion phase was dominant in savanna fires as this phase tends to produce higher NO₂ as previous research has shown (Andreae and Merlet, 2001). The day-to-day variability in ΔNO_2 was larger than the day-to-day variability in ΔCO . The ΔCO emission ranged from 0 to 0.08 mol m⁻² whereas ΔNO_2 emission ranged from 0 to 0.08 mmol m⁻². Compared to the result of Van der Velde et al. (2020), who estimated $\Delta NO_2/\Delta CO$ ERs between 3.58 and 6.2 for savanna fires, the ER values in our study were lower and ranged between 2 and 2.8. The ER for temperate forest combustion reported here (1.5) was also lower than the results from Young et al. (2011), which was 5 ± 2 mmol mol⁻¹, suggesting a complex interaction between dominant vegetation and local atmospheric turbulence during fire events. Although there are uncertainties from TROPOMI, there were distinct ERs clearly resulting from savanna and temperate forest combustion (Fig. 2.7). This result suggests that temperate forest fires emitted larger CO per unit NO₂ compared to

savanna fires, indicating less efficient combustion in temperate forest fires than in savanna fires (Fig. 2.7).

One possible reason for different ER values was the different land surface sensitivities of TROPOMI in CO and NO₂ measurements (Val Martin et al., 2018; Van der Velde et al., 2020). Previous studies have shown that tropospheric NO₂ measurement was less sensitive to sources in the planetary boundary layer than CO measurements, which causes underestimation of ΔNO_2 (Borsdorff et al., 2018; Van der Velde et al., 2020). A second reason is the highly reactive property of NO₂. The short lifetime of NO₂ makes the daily values underestimated compared to CO which gas has a relatively long lifetime. In addition, the natural variability of atmospheric composition (e.g., tropospheric O₃, water vapor) and different measurement techniques may contribute to the measurement uncertainty.

2.4.3 Satellite-derived emission factor (EF)

After deriving the NO₂ and CO emissions for fire events, we calculated the emission coefficient (g MJ⁻¹) using satellite-derived emissions and FRP. The 95 % confidence intervals of the slope were computed based on the student's t-distribution test. Figure 2.8 shows the relationship between TROPOMI-derived NO_x, CO emissions and MODIS FRP for savanna and temperate forest fires in three areas. The FRP explains 40 % to 56 % variance in NO_x emissions with the highest R² in temperate fires in Area 3 and lowest in savanna fires in Area 1. For CO emission, the FRP explained 35 % to 51 % variance with the highest R² in savanna fires and the lowest in temperate fires. The variability may relate to multiple uncertainties including the satellite retrieval and emission estimate approach as we discussed below. Comparing different fire types, the NO_x emission coefficient in savanna fires in Area 1 is the largest (0.98 g MJ⁻¹), with 95% confidence intervals of 0.9 – 1.06 g MJ⁻¹, CO emission coefficient in temperate forest fires in Area 3 is the largest (55.93 g MJ⁻¹), with 95 % confidence intervals of 50.7 – 61.17 g MJ⁻¹.

To compare with previous studies, we converted emission coefficients to EFs by applying a conversion factor $K = 0.41 \text{ kg MJ}^{-1}$ (Vermote et al., 2009). For NO_x, the satellite-derived EFs range from 1.48 to 2.39 g kg⁻¹ in savanna fires which are slightly lower than the value 2.49 g kg⁻¹ of Jin et al. (2021) who used TROPOMI NO₂ data with updating *a priori* profile and the values

2.5±1.3 g kg⁻¹ from Andreae (2019) that represent an updated compilation of EFs over the past 20 years. For temperate forests, the satellite-derived EF_{NO_x} is 1.51 g kg⁻¹, which is also less than the value 3 g kg⁻¹ of Andreae (2019). For CO, the satellite-derived EF_{CO} in savanna fires ranges from 107.39 to 126.32 g kg⁻¹ and those values are larger than the values 69 ± 20 g kg⁻¹ of Andreae (2019) but in the range of the field measurement (ranging 15 to 147 g kg⁻¹) from SAFIRED campaign savanna fires in Australia (Desservettaz et al., 2017). Our satellite-derived EF_{CO} in temperate forest fires is 136.41 g kg⁻¹ which is close to the value 113 ± 50 g kg⁻¹ of Andreae (2019) and the field measurements of Guérette et al. (2018), which ranged from 101 to 118 g kg⁻¹ in Australia temperate forest fires.

Our NO_x EFs is smaller than those reported in previous studies while CO EFs is the opposite. One source of this variance is because of aerosol smoke impact on the CO and NO₂ volume column density retrieval process. Hirsch et al. (2021) found that unprecedented bushfires in Australia caused record-breaking levels of aerosols, as TROPOMI CO values were monitored using radiances in the shortwave infrared bands so that the smoke aerosol does not have a strong effect on measurements. Schneising et al. (2020) show that the uncertainty due to smoke aerosol during several Californian wildfires was about 5 %. However, smoke aerosols have always affected TROPOMI NO₂ observations in the ultraviolet-visible region when estimating fire emissions. Previous studies showed an implicit aerosol correction can be applied to retrieval algorithms (Griffin et al., 2021) and without this correction, a bias of more than 40% over polluted regions could be introduced (Lorente et al., 2017), suggesting that the estimated daily CO net emission was much more accurate than the estimated NO₂ emissions. The uncertainty in the satellite emission method (e.g., the lifetime used in emission estimation) can also be a cause of variance. Figure 2.9 shows as example of fits for NO₂ in Area 2, and the embedded histogram shows the frequency distribution of NO₂ lifetime ranging from 1 to 4 hours over all three areas. Thus, an average of 2.5 hours for NO₂ selected in our computation was optimal for calculating emission. To test the uncertainty related to different lifetime choices, Adams et al.'s (2019) test was followed. Fluxes were recalculated by replacing the default lifetime ($\tau_{NO_2} = 2.5$ hours, $\tau_{CO} = 7$ days) into alternate lifetimes ($\tau_{NO_2_{lower}} = 1$ hour, $\tau_{NO_2_{upper}} = 4$ hours, and $\tau_{CO_{lower}} = 14$ days), then the percent difference between EFs were calculated. The largest deviation from the default settings was defined as the uncertainty (Adams et al., 2019). For CO, the uncertainty

based on the 14-day lifetime was smaller (less than 1 %) whereas the uncertainty based on the largest 4-hour lifetime was larger for NO₂ (37 % in savanna fires in Area 1).

2.5 Summary and Conclusions

The 2019-2020 black summer fires in Australia emitted large amounts of trace gases and aerosols. In this study, we focused on the analysis of two trace gases: CO and NO₂. Based on the total columns (mean and maximum) from TROPOMI observations and the fire intensity from MODIS in late 2019 to early 2020, we estimated the ERs of NO₂ relative to CO for each day over three selected areas with savanna and temperate forest vegetation. For temperate forest fires, the ER was 1.57 ± 1.71 which is consistent with previous studies. For savanna vegetation fires, the ER ranged from 2.0 ± 2.36 to 2.6 ± 1.92 , which is slightly lower compared to other studies. These differences could be traced back to different measurement techniques used, their spatial resolutions, nonlinear sensitivities to gas densities in the boundary layer, and larger NO₂ natural variability due to its short lifetime, all of which suggest that further validation of satellite products and investigations of more cases are required. For example, aircraft measurements from NASA airborne campaigns could be used to validate TROPOMI satellite-derived CO and NO₂ concentrations. The satellite-derived concentrations and emission estimates also could be compared with simulations from dynamical models (e.g., Weather Research and Forecasting model coupled to Chemistry, Community Modeling and Analysis System). Further advanced techniques to improve the calibration and retrieval algorithm could be used to improve the estimates of emissions and emission factors. For instance, even though we used the improved TROPOMI NO₂ data from Van Geffen et al. (2022) in this study, it still has a negative bias when compared with ground-based observations, which probably is due to the relatively coarse resolution ($1^\circ \times 1^\circ$) of the *a priori* profiles used. Taking advantage of higher-resolution profile shapes can lead to better retrieval of tropospheric columns over emission hotspots (Douros et al., 2022). Additionally, considering the short lifetime of NO₂, the NO₂ tropospheric column could be corrected using boundary layer temperature and OH concentration, as described in the work of Lama et al. (2019)

Using the methods from Mebust et al. (2011) and Adams et al. (2019), net emission fluxes were estimated by using a 14-day CO effective lifetime and a 2.5-hour NO₂ effective lifetime, and EFs were calculated. The TROPOMI-derived NO_x EFs were 1.48 g kg⁻¹ and 1.51 g kg⁻¹ for savanna and temperate forest fires, respectively, which are lower than previous studies while the CO EFs were 107.39 g kg⁻¹ for savanna fires and 136.41 g kg⁻¹ for the temperate forest. Our study on both savanna and temperate forest fire emissions demonstrates the capability and limitations of TROPOMI data for the study of the regional variability of combustion characteristics and their impacts on regional atmospheric composition and air quality. Benefiting from the global coverage of TROPOMI and its high spatial resolution, the method used in our study could be applied to different vegetation wildfires at various scales, even the burning of fossil fuel in megacities.

2.6 Data availability

TROPOMI CO, NO₂ and ALH data are available from NASA Goddard Earth Sciences (GES) Data and Information Services Center (DISC, <https://disc.gsfc.nasa.gov/datasets/>). MODIS FRP data are available from NASA Earth Data Fire Information for Resource Management Systems (<https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms>). GFED4s fire emissions are available from <https://www.geo.vu.nl/~gwerf/GFED/GFED4/>. Wind data from the European Center for Medium-range Weather Forecast (ECMWF) is available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-preliminary-back-extension>.

2.7 Acknowledgments

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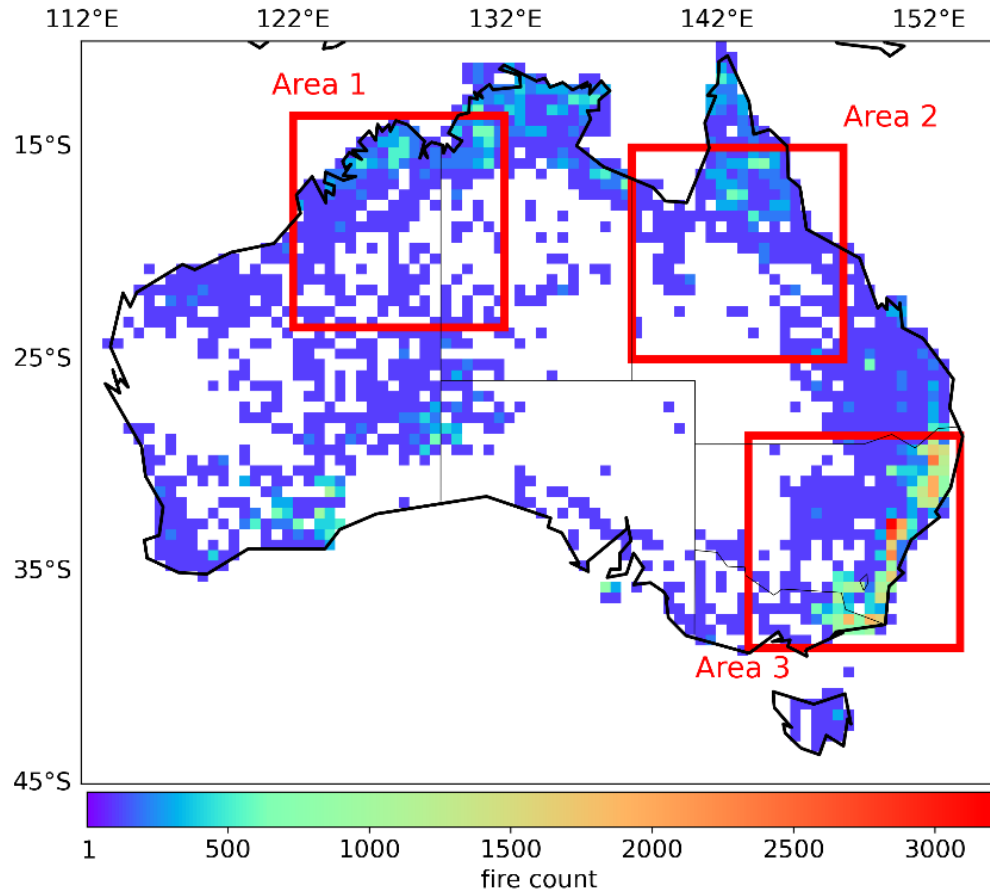


Figure 2.1 Total fire counts from August 2019 through January 2020 at $0.5^\circ \times 0.5^\circ$ resolution. Three $10^\circ \times 10^\circ$ (latitude $\times$ longitude) areas indicate regions of interest in this study.

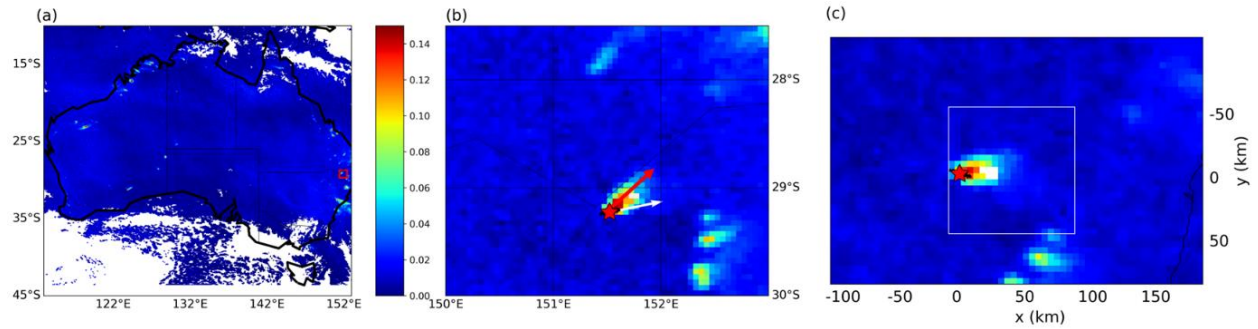


Figure 2.2 An example of emission analysis for a fire event, with MODIS fire pixels indicated (black points) and the center of the fire event indicated by a red star. (a) Map of TROPOMI NO₂ column density over Australia on 6 November 2019. The red box in southeast Australia marks the fire event location. (b) The original TROPOMI NO₂ column density with the wind direction is indicated by a white arrow. The red arrow indicates the plume direction. (c) The excess NO₂ after 1) removing background column density from original NO₂ and 2) rotating the entire pixels examined to align with the wind direction, thus a 20 km downwind distance area was selected and used to estimate the NO₂ emission.

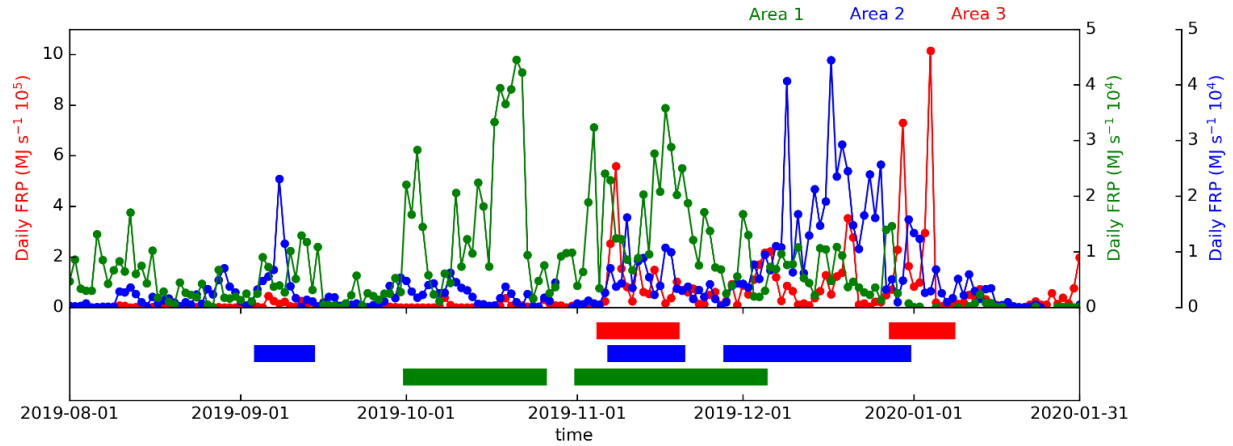


Figure 2.3 Daily fire radiative power (FRP) from August 2019 through January 2020 for Area 1 (green), Area 2 (blue), and Area 3 (red). Several distinct periods are highlighted to show a significant increase in FRP, covering 1-24 October and 1 November - 3 December (Area 1), 4 – 13 September (Area 2), 7 - 18 November and 28 November - 29 December (Area 2), 5 - 17 November (Area 3), and 28 December - 6 January (Area 3).

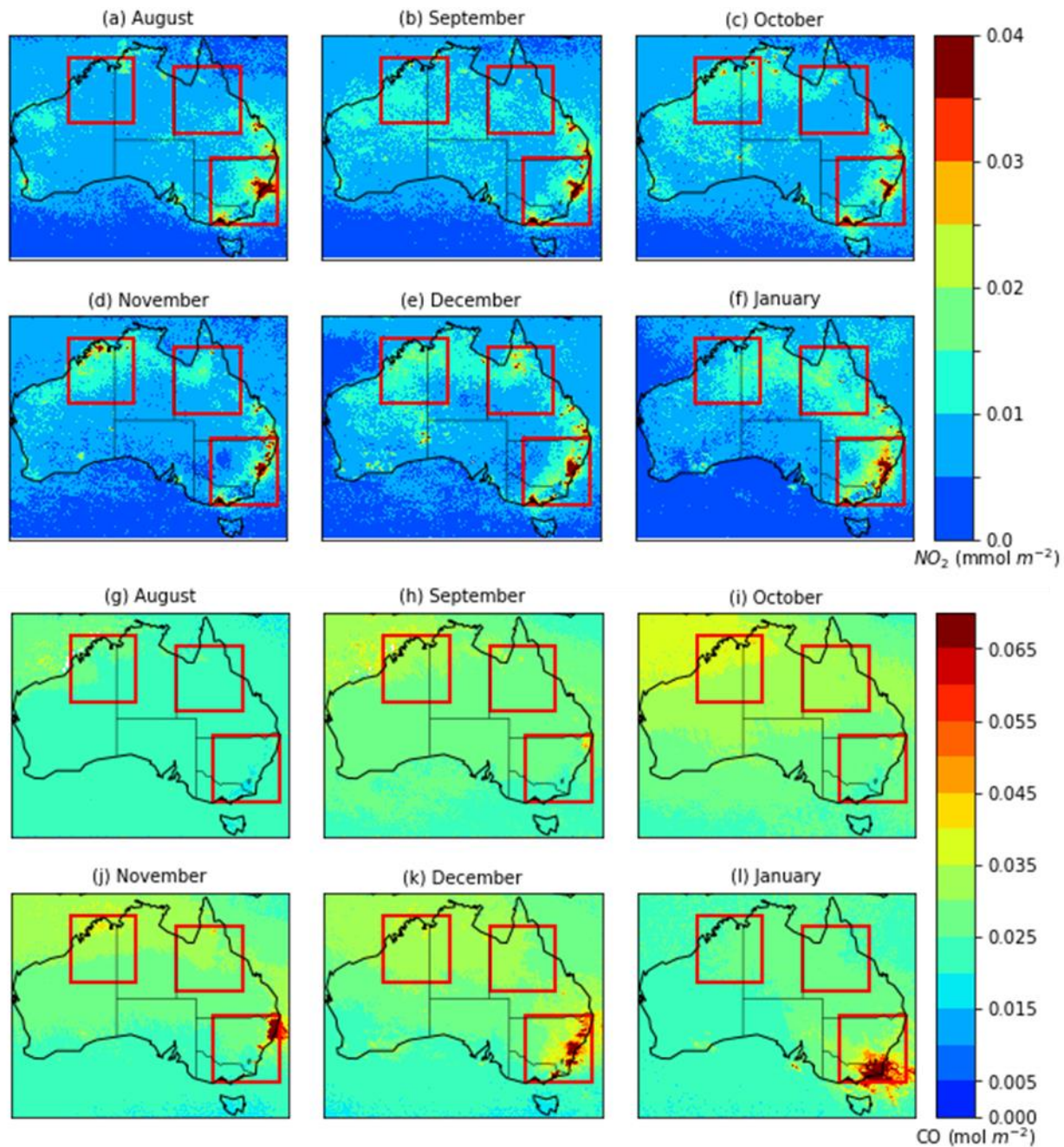


Figure 2.4 Monthly average NO_2 (a-f) and CO (g-l) column density from August 2019 through January 2020. Three $10^\circ \times 10^\circ$ (latitude $\times$ longitude) areas indicate regions of interest in this study.

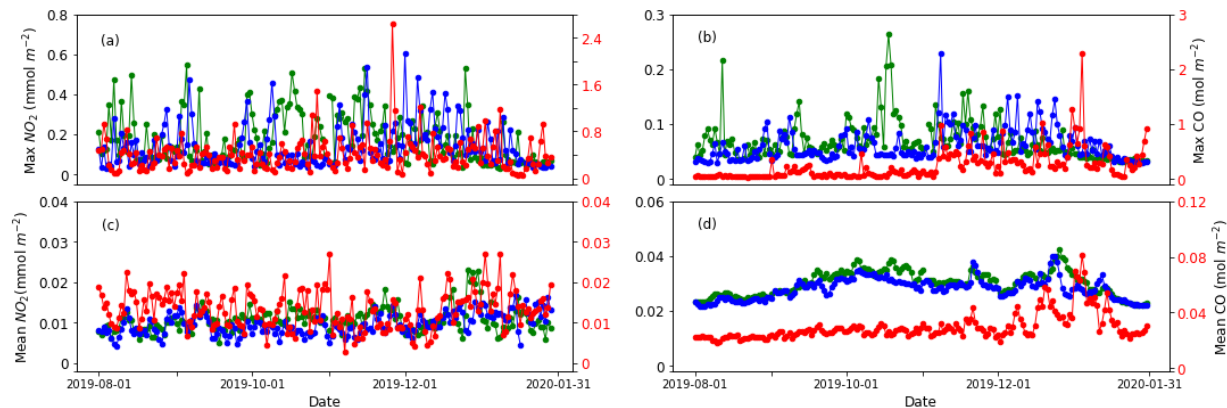


Figure 2.5 Time series of daily maximum NO₂ (a) and CO (b) total column densities from August 2019 through January 2020 as well as daily mean NO₂ (c) and CO (d) for three highlighted areas: Area 1 (green), Area 2 (blue), and Area 3 (red). Results for Areas 1 and 2 are displayed by the left Y axis and results for Area 3 are displayed by red colours of the right Y axis.

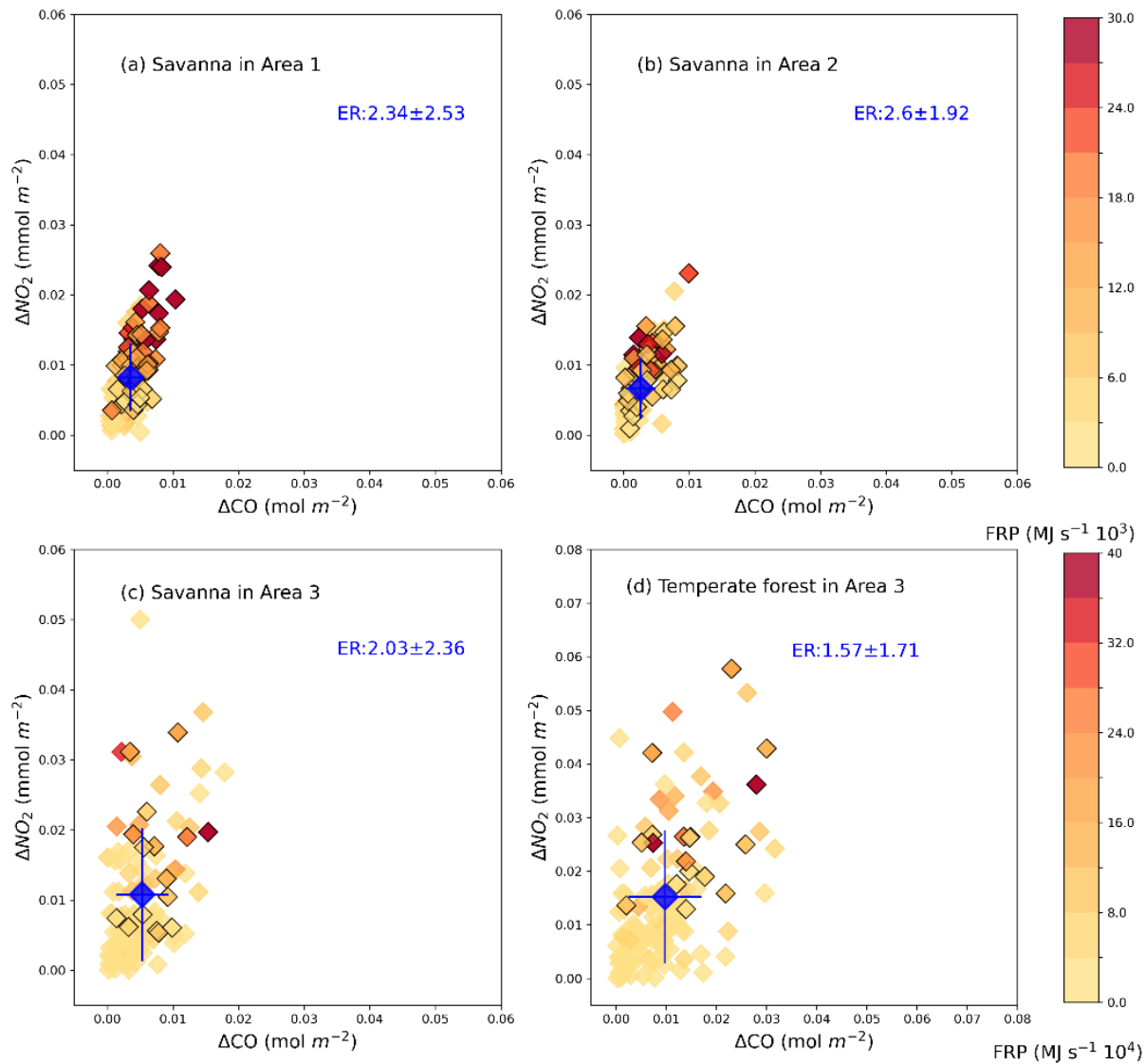


Figure 2.6 The relationship between daily ΔCO (mol m^{-2}) and daily ΔNO_2 (mmol m^{-2}) in Savanna regions (a for Area 1, b for Area 2, and c for Area 3) and temperate forest regions (d for Area 3 only). The colour bars are coded by daily FRP, data points with black edges are the days with high FRP (highlighted periods) in Figure 4. The blue markers represent the monthly average relationship between ΔCO and ΔNO_2 with day-to-day variabilities shown represented by the error bars. ER stands for the total emission ratio expressed by overall mean plus and minus one standard deviation.

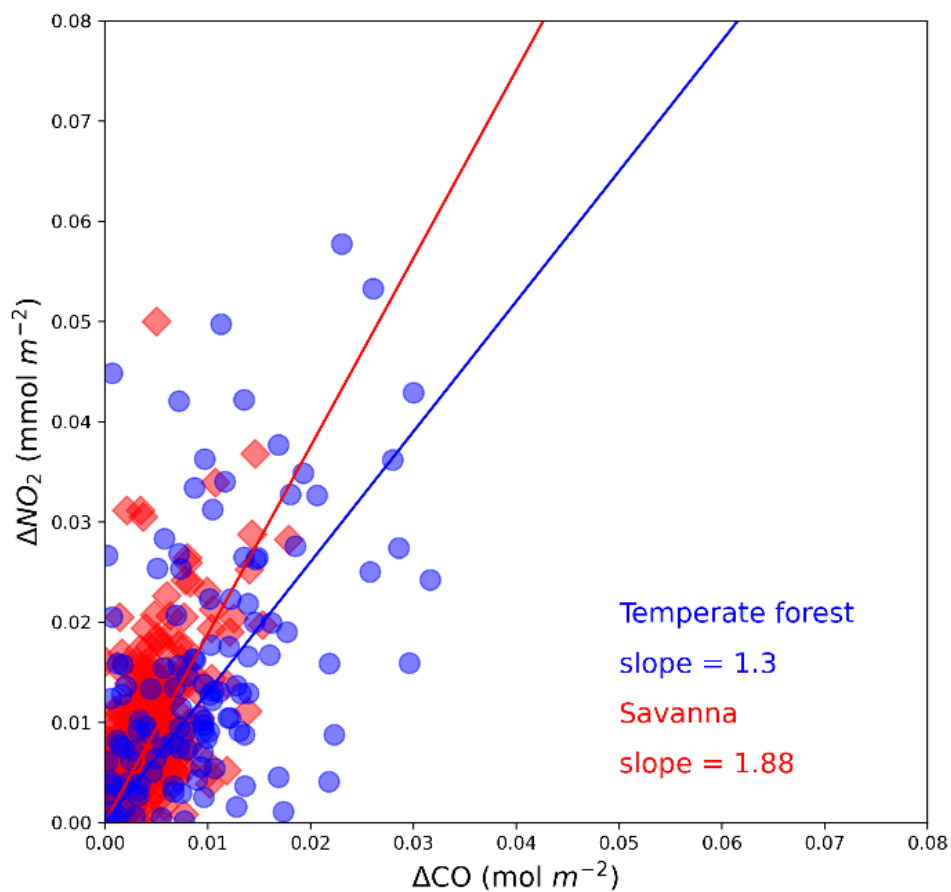


Figure 2.7 The relationship between daily ΔCO (mol m^{-2}) and daily ΔNO_2 (mmol m^{-2}) was derived from TROPOMI for all regions. The slope of linear fit with an intercept at zero represents the combustion efficiency of different fire types.

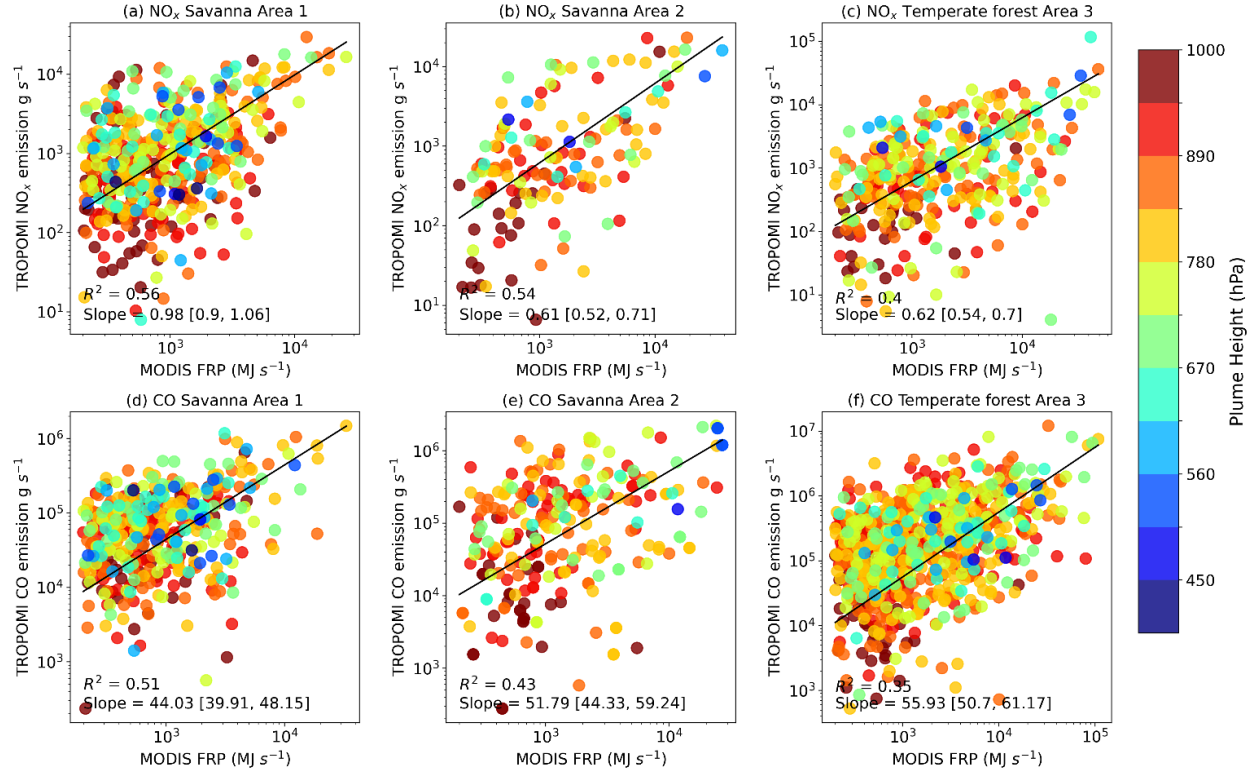


Figure 2.8 Scatter plots of TROPOMI-derived NO_x and CO emissions (g s⁻¹) versus MODIS FRP in Savanna regions (a, d for Area 1, b, e for Area 2) and temperate forest regions (c, f for Area 3). The black line indicates the regression line estimated from ordinary least squares regression with the intercept fixed at zero. Slopes are shown with a 95% confidence interval. The color represents the plume height of the corresponding fire events. Emissions and FRP are on log scales.

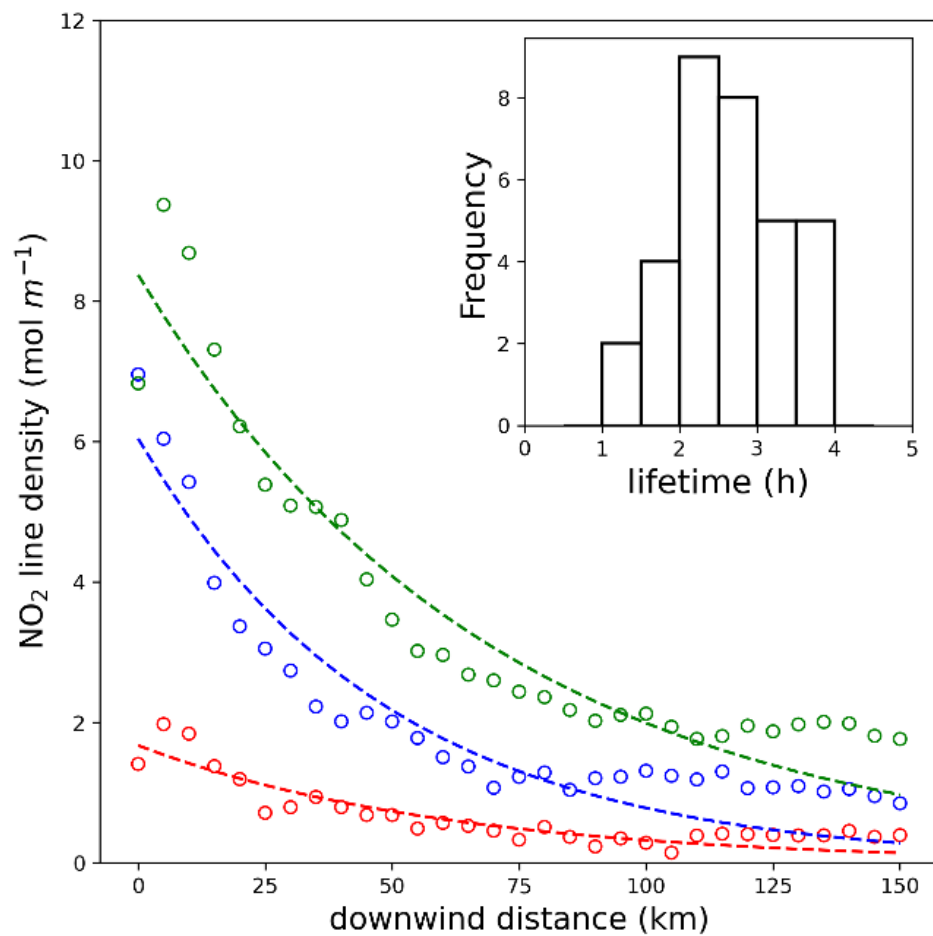


Figure 2.9 NO₂ line density decay curves of three example fire events (each color represents a fire event) in Area 2. The embedded histogram shows the frequency distribution of NO₂ lifetime estimated from all three areas.

Chapter 3 - Wildfire smoke induced PM_{2.5} impact on soybean yield

3.1 Introduction

Over the past decades, wildfires have happened more frequently with longer fire seasons and widespread burned areas due to climate change increased temperature and drought in the continental United States (CONUS) (Burke et al., 2021; Westerling, 2016). Compelling evidence indicates a triple increased fire frequency and nearly quadrupled burned area in CONUS since the 1980s, reaching the second-largest burned area on record in 2020 (Iglesias et al., 2022; Kabeshita et al., 2023) and those phenomena are projected to continue to increase (Ford et al., 2018). The rise in wildfire activity has coincided with a considerable increase in the number of smoke days across the United States. The Midwestern U.S., an intensive agricultural area, has been exposed to fire smoke frequently in recent years, particularly during the summer when smoke occurrences reach their seasonal peak (Kaulfus et al., 2017). This is also the critical period for crop growth in Midwestern U.S.. Smoke climatology shows that biomass burning can result in a severe deterioration of surface air quality near the source. Meanwhile, the smoke from long-time burning lofts high into the atmosphere, travels long distances from source fires, and can potentially affect ground-level air quality thousands of kilometers away. Therefore, although the Midwestern U.S. is not a wildfire-prone region, smoke exposure is on the rise since it's downwind of Northwest, Southwest, and Rocky Mountains in U.S. as well as Canada during fire seasons from June to September (Brey et al., 2018). The zonal transport that is attributed to Bermuda high in the Gulf of Mexico and an upper-level anticyclone dominating the southwest, combined with a southerly component in the upper troposphere that transports smoke from high latitude boreal fires in Canada (Brey et al., 2018; Miller et al., 2011) and Siberian fires (Jaffe et al., 2004) lead to convergence of smoke plume and the peak occurrence of smoke during summer seasons over the North Central U.S. (Kaulfus et al., 2017), where the climatology of smoke occurrence days from 2005 to 2016 reached a maximum number of 15% of total days on an annual basis.

Wildfire smoke containing a mixture of particulate matter and gases impacts crop productivity by changing air quality and affecting photosynthetically active radiation (PAR). The relationship between smoke plumes and crop yields is complex because of both harmful and beneficial

impacts on crop productivity. O₃, nitrogen oxides (NO_x), and acyl peroxy nitrates from smoke are known to reduce crop yield. Wildfire smoke can enhance O₃ production, then, O₃ damages plant tissues by generation free radicals, thereby impeding the process of photosynthesis (Hong et al., 2020; Ninneman and Jaffe, 2021). Multiple studies showed that exposure to O₃ can reduce annual and perennial crop yields (Burney and Ramanathan, 2014; He et al., 2022; Mcgrath et al., 2015). Additionally, smoke can impact crops by changing PAR. For example, a decrease in total PAR can reduce productivity, but an increase in diffuse fraction can offset the yield losses (Hemes et al., 2020; Corwin et al., 2022). Particulate matter (PM) is a main component of wildfire smoke and it has been shown to increase ground-level pollution, especially the total primary fine particulate matter measuring 2.5 µm or less in diameter (PM_{2.5}) (Burke et al., 2021). Although few studies were related to the effect of PM on crop production, the main idea of those studies was that PM can decrease total solar radiation and augment diffuse portions of solar radiation. Lobell & Burney (2021) and Zhou et al. (2018) quantified the adverse effect on crop yields. However, accounting for the change of diffusion and scattering light with modeling results, Schiferl and Heald (2018) found the beneficial effect of PM on production by increasing diffusion radiation offsets the reduction in yield associated with O₃ damage. These studies estimated the total PM_{2.5} from all sources impacted on yields although these emissions sources include both anthropogenic and natural sources that might change the variations of PM_{2.5}.

Clean air benefiting from a multi-decadal decline in air pollution concentrations, in part a result of anthropogenic emissions regulation, has been observed in most regions of the U.S. (Aldy et al., 2022; Burke et al., 2023; EPA, 2015). The significant improvement in air quality since 1999 has contributed to around 20% of crop yield gain in the U.S. (Lobell and Burney, 2021).

However, recent studies showed that air quality improvement, specifically, the PM_{2.5} variations and trends, are stagnating or even reversing across nearly all states, and wildfire smoke has been proven to influence the PM_{2.5} trends in nearly three-quarters of states since at least 2016 that offset the benefits from reductions in PM_{2.5} by regulating human-made emissions (Burke et al., 2023; O'dell et al., 2019). Most studies quantified that the PM_{2.5} attributed to wildfire smoke impact on human health (Aguilera et al., 2021; Burke et al., 2021) but few studies related to agricultural crop yields were investigated. As wildfires have increased in area size and fire severity in recent years (Burke et al., 2023), agricultural benefits from the clean air may change

or offset due to the increased wildfire-specific PM_{2.5}. Therefore, quantifying the magnitude of PM_{2.5} from wildfire smoke impact on crop yield, especially the trend changes, plays an important role in the impact of climate change on global food production and security.

This paper assesses the effect of exposure to smoke days on soybean and corn yields in the Midwestern U.S. from 2008 to 2022. The objective of the study is (1) to estimate the sensitivity of soybean and corn yield to exposure to smoke days, and (2) how wildfire smoke impact on yield through increasing PM_{2.5}. We established a statistical approach that accounts for the spatiotemporal climate variations and crop exposure to heavy smoke days to estimate the relative yield changes due to wildfire smoke present during the soybean growth period. In addition, we used an instrumental variable approach to quantify the effect of smoke days on yields through increased PM_{2.5} pathway and compare the trend changes of total PM_{2.5}.

3.2 Data and Method

3.2.1 Datasets

The annual county-level rainfed soybean and corn yield in t ha⁻¹ and harvested area during 2008-2022 were collected in North Dakota (ND), South Dakota (ND), Minnesota (MN), Wisconsin (WI), Michigan (MI), Iowa (IA), Illinois (IL), Indiana (IN), Ohio (OH), and Missouri (MO) states from the U.S. Department of Agriculture (USDA)'s National Agricultural Statistics Service database. In order to precisely map soybean exposures to fire smoke plumes, the USDA's soybean cropland Data layer (CDL) at a 30 m spatial resolution is combined with the smoke products described below across the continental US. We defined the soybean growing season based on the historical timing of planting to maturity (Figure A-1). This corresponds to May to June as the vegetative stage and July to August as the reproductive stage. Daily minimum temperature, maximum temperature, and precipitation with a grid resolution of 5 km for each state, named nClimGrid-Daily (Durre et al., 2022), were obtained from the National Centers for Environmental Information. Growing degree days (GDD) between 10 °C and 30°C, extreme degree days (EDD) above 30°C, precipitation, and square of precipitation were calculated from May 1 and October 31 for each county.

We collected smoke plume data from the National Oceanic and Atmospheric Administration National Environmental Satellite, Data, and Information Service Hazard Mapping System (HMS) fire and smoke products during 2008-2022. HMS utilizes multiple geostationary and polar-orbiting environmental satellites to monitor fires. And the outline areas of smoke during daylight hours were generated by trained satellite analysts. The Geographic Information System (GIS) files outlining the extent of smoke across North America are provided each day. The smoke density is classified into low, medium, and high categories that approximately correspond to PM_{2.5} concentrations of <10, 10-21, and >21 $\mu\text{g m}^{-3}$, respectively. An example of smoke plume data on August 1st, 2021, is shown in Fig. A-2. HMS smoke polygons in 2009 are not classified into smoke density classes and instead replaced by a dataset from Liu, which used random forest modeling to assign smoke densities (Liu et al., 2023). We first took the union of smoke polygons for each smoke density at daily level from May to October. If an area was under a light and heavy smoke plume in one day, we classified it as being exposed to a high-density plume, rather than a low-density plume, for that day. To calculate the number of days that cropland is exposed to smoke, the daily-level smoke polygon (Fig. A-2) was rasterized into images at 30 m resolution pixels to match with CDL pixels. Considering the small number of heavy- and medium-density smoke plumes, we grouped and defined them as heavy-density smoke. In addition, smoke may be aloft and doesn't affect ground-level air quality, especially for light smoke, our study focuses on how heavy smoke impacts yield. Because the HMS product is derived from top-down satellite imagery, its detection capability is limited by cloud cover, and it doesn't include smoke's vertical information or smoke sources (e.g., wildfires, agricultural fires). Smoke plume overlap hours in the Midwest are mainly attributed to wildfires from U.S. wildfire-prone regions (Northwest and Southwest) and Canada (Brey et al., 2018). Therefore, we defined the smoke over the Midwest region are wildfire smoke. Then, each CDL pixel was assigned a binary classification: 1 represents this pixel (soybean cropland) was exposed to smoke and 0 represents no exposure. We aggregated the daily pixel to the monthly level by summing the number of days that each pixel was exposed to smoke. Last, we averaged all pixels within a county to define "smoke-influenced days" as the number of days in which a county was exposed to heavy smoke from May to October.

For PM_{2.5} air pollution data, we chose monthly average ground-level PM_{2.5} concentrations (µg m⁻³) at 0.01° x 0.01° which are estimated by combining aerosol optical depth retrievals from satellite's products, chemical transport model, and ground surface observations (Van Donkelaar et al., 2021). We aggregated pixel PM_{2.5} to the county level from June to August. The ground-level PM_{2.5} observation data from the Environmental Protection Agency's (EPA) Air Quality System are also selected for supplemental analyses.

3.2.2 Method

We first use a panel fixed effect regression to estimate the effect of smoke exposure on crop yield:

$$yield_{i,t} = \beta_1 * GDD_{i,t} + \beta_2 * EDD_{i,t} + \beta_3 * P_{i,t} + \beta_4 * P_{i,t}^2 + \beta_5 * smk_{i,t} + \beta_6 * t_i + \theta_i + \varepsilon_{i,t} \quad (1)$$

Where $yield_{i,t}$ is yield in county i and year t , $GDD_{i,t}$, $EDD_{i,t}$, $P_{i,t}$ and $P_{i,t}^2$ are accumulated temperature and precipitation predictors from May to October. A squared precipitation term was included to account nonlinear response of yield to precipitation. θ_i is county fixed effect accounting for time-invariant factors that vary across counties (i.e., soil property and fertility). smk is smoke days and β_6 represents time trend of yield. Coefficient β_5 is the main quantity of interest, the impact of changes in smoke days on yield is ($Y_{i, smk}$) as $\beta_5 * smk_{i,t}$. The coefficients in Equation (1) were estimated using a fixed panel regression with standard errors clustered at the county level and the model was run 1,000 bootstrap times to get robust coefficients.

Fire smoke can affect yield through multiple pathways, including altering surface radiation and impacting air quality by increasing PM_{2.5} and O₃ level. Here we specify the air quality pathway as the change in PM_{2.5}. Before we estimate the yield loss due to the increased wildfire specific PM_{2.5}, we confirm the increased daily PM_{2.5} on smoke days using daily PM_{2.5} observations from EPA monitors shown in Fig. A-3. Days from June to August from 2008 to 2022 were classified as smoke-free and smoke-influenced days based on whether smoke is present overhead. Then, Kolmogorov–Smirnov test is used to test if PM_{2.5} in smoke-free and smoke-influenced days are statistically significant differences ($p < 0.05$).

After confirming the relationship between smoke and $PM_{2.5}$ from surface observations, we characterize the yield loss due to smoke specific surface $PM_{2.5}$ using two-stage least square regression with an instrumental variable (IV). Specifically, we used smoke days from June to August as the instrumental variable to isolate the effect of wildfire specific $PM_{2.5}$ on yield loss. The first stage (Eq.2) estimates the relationship between smoke days and $PM_{2.5}$. The second stage (Eq.3) is a regression of yield on the predicted value of $PM_{2.5}$ from first stage, including all same controls as Eq. 2. We used temperature and precipitation as control variables because both variables have different impacts on $PM_{2.5}$ level and crop yield. Meanwhile, all control variables used in the first stage should be included in the second stage to keep IV regression to be consistent (Wooldridge, 2010).

$$PM_{2.5,i,t} = \beta_1 * GDD_{i,t} + \beta_2 * EDD_{i,t} + \beta_3 * P_{i,t} + \beta_4 * P_{i,t}^2 + \beta_5 * smk_{i,t} + \beta_6 * t_i + \theta_i + \varepsilon_{i,t} \quad (2)$$

$$yield_{i,t} = \beta_p * \overline{PM_{2.5,i,t}} + \beta_1 * GDD_{i,t} + \beta_2 * EDD_{i,t} + \beta_3 * P_{i,t} + \beta_4 * P_{i,t}^2 + \beta_5 * t_i + \theta_i + \varepsilon_{i,t} \quad (3)$$

Where $GDD_{i,t}$, $EDD_{i,t}$, $P_{i,t}$ and $P_{i,t}^2$ are weather controls in county i and year t . County fixed effect θ_i and a time trend t_i are included in both stages. $PM_{2.5,i,t}$ is the satellite-derived data and the wildfire-specific $PM_{2.5}$ impact on yield ($Y_{i, PM_{2.5}}$) is calculated as $\beta_5 * smk_{i,t} * \beta_p$. Numerous diagnostic statistics are used to confirm the validation and robustness. First, the Wu–Hausman test (Greene, 2012) was selected to test if our IV regression is different from the Ordinary Least Squares regression (OLS), p-value should be significant to prove the IV regression is necessary. Second, the F-statistic in the first-stage was chosen to test if smoke days is a strong instrument, the statistical result should be larger than the threshold of 19.93 for a 10% maximum relative bias to avoid weak instruments, as recommended by (Andrews and Stock, 2005). Third, a bias analysis was used to assess sensitivity in terms of how much of the residual variation in the instrument or outcome can be predicted by an unmeasured confounder (Cinelli and Hazlett, 2022). Here we introduce the “reduce-form” which is a regression of yield on smoke days including all same controls as Eq. 2. Our two-stage approach estimates the direct causal effect of smoke days on yield. Because IV estimator is equal to the ratio of the reduce-form and the first-stage regression coefficients, residual biases can bring the IV estimate to zero only if they can bring the reduced-form estimate to zero (Cinelli and Hazlett, 2022). Therefore, if the bias

analysis on reduce-form shows that the omitted variables are not strong enough to make the coefficient 0, the same holds for the IV estimator. According to (Cinelli and Hazlett, 2022), we did the bias analysis on reduce-form and compared the partial R-square and robust variable (SI text, Tables A-1&A-2, Fig. A-6). Results confirmed that smoke days is a strong instrument and the IV regression is different from OLS. In addition, bias analysis revealed that the unobserved confounders should explain at least 4.5% of the residual variance of both smoke days and yield are strong enough to bring the estimated coefficient to 0. All regressions (Eq.1-3) were also repeated at EPA monitoring stations level. Based on smoke days and PM_{2.5} pollution sensitivities given by Eq.1-3, we then determine the crop yield responses as percentage changes in yields (i.e., relative yield change) as follows:

$$\% RY_i = \frac{Y_{i,t} - \bar{Y}_{i,t}}{\bar{Y}_{i,t}} \times 100 \quad (4)$$

RY_i is relative yield change, is the yield change for county i due to exposure to smoke days ($Y_{i,smk}$) or smoke specific PM_{2.5} pollution ($Y_{i,PM2.5}$), $\bar{Y}_{i,t}$ represents the mean yield over multiple years for county i .

3.3 Results

3.3.1 Smoke frequency during the growing season

Monthly smoke frequency during growing seasons over the study region is characterized in Fig. 3.1a. Days affected by smoke increased from planting month (May) and reached a peak in August. Smoke-influenced days then declined in September and less in October. This averaged monthly distribution is consistent with year-month change in Fig. A-4. The months that smoke reaches maximum are consistent with the peak in wildfires in the western U.S. and high latitude boreal forests (Giglio et al., 2006). Between 2008 and 2022, annual smoke days of growing season ranged from 2 to 48 on average across all counties (Fig. 3.1b). Several years with intense smoke have been documented, for example, 2012, 2018 and 2021, resulting in 14, 16 and 48 days affected by smoke, respectively. The rise of smoke days is consistent with the growing wildfire frequency, burned areas, and lengthened seasons (Burke et al., 2021; Kabeshita et al., 2023). The spatial distribution of smoke days from 2008 to 2022 shows that upper Great Plains states are the most impacted (Fig.3.1c), with a maximum number of 63 days exposure to smoke on average over the region of ND and MN, and extends southward into SD and IA. The peak

occurrence of smoke over the upper Great Plains is the consequence of the transport associated with the Bermuda high in the Gulf of Mexico and a dominant upper-level anticyclone in the southwest, combined with a southerly upper tropospheric component carrying smoke from Canadian boreal fires and Siberian fires (Jaffe et al., 2004; Kaulfus et al., 2017; Miller et al., 2011). A gradient of smoke days is observed from northwest to southeast and the minimum smoke days is found in OH state. The spatial variability of the trends in smoke days is shown in Fig. 3.1d. The smoke days have trended upwards throughout most regions, particularly the maximum trend of around 28 days dec⁻¹ in ND and SD.

3.3.2 Yield response to exposure to heavy smoke days

Overall, the negative effects of exposure to smoke days on soybean and corn yield were found across all states in Midwest region (Fig. 3.2 and Fig. A-7). Relative corn yield change was less than 1%. However, the magnitudes of negative effects were larger as much as 4% relative to mean soybean yield over the upper Great Plains including the western regions of ND, and SD states in extreme years. Meanwhile, upper Great Plains states are also the relatively low-yield (around 0.03 t ha⁻¹ at multi-year average) areas of soybean (Li et al., 2023). Fire smoke damages were less than 1% yr⁻¹ relative to mean yield over IL, IN, and OH states where the most soybeans are produced and yield is high as much as 4.3 t ha⁻¹ (Li et al., 2023). The spatial maps of yield loss due to exposure to smoke days show a similar pattern with the average of smoke days (Fig. 3.1c). The relative yield change due to smoke were varied at the state level due to the variations of smoke days can differ by a factor of 3 from year to year (O'dell et al., 2019). As the smoke days increased over the past 15 years (Fig. 1b), the decline in yield has intensified across all states, with the most significant decrease observed in ND at a rate of $-1.7 \pm -0.7\%$ per decade, while IL experienced the lowest decline at a rate of -0.4% per decade, respectively. The negative impact of smoke days has been even more detrimental since about 2016 when wildfire smoke significantly influenced surface air quality (Burke, 2023). Relative yield change was highest in North Dakota at a rate of $-2.3 \pm 1.6\%$ per decade and lowest in Illinois at a rate of $-0.7 \pm 0.4\%$ per decade over the past 10 years. A dramatic increase in relative yield change was documented in 2012 in IA and MO states that experienced a severe, widespread drought in the same year (Smith and Matthews, 2015). Meanwhile, the extreme wildfires in 2012 which is the third highest number of acres burned on record since 1960 (Hoover and Bracmort, 2015) as well as in

2021 made farmland exposed to more heavy smoke days and damaged crop yield. On the contrary, relative yield change in 2016 were close to zero in all states although the number of wildfire acres burned in 2016 was the 7th, the number of heavy smoke days is small (Fig. A-4) and the daily average PM_{2.5} from smoke is small (Childs et al., 2022).

In order to further examine relative yield change due to exposure to smoke days, we compared soybean relative yield change between two periods, 2008–2012 to 2018–2022, with 5-year windows used to avoid undue influence from exceptional years, such as 2012 (Fig. 3.3). For soybean, all states experienced an average relative yield change of -0.4% from 2008 to 2012, worsening to -1.1% from 2018 to 2022, with a gradient decline from high to low latitude states. In addition, ND experienced the greatest yield loss, changing from -0.7 % $\pm$ 0.35% at a 95% CI in the early years to -2.1 % $\pm$ -0.9 % in the latest years. Relative yield change in IA, IL, and MO states were -0.4 %, -0.2%, and -0.3% during 2008-2012, respectively, which were -0.9 %, -0.7 %, and 0.9 % during the last five years. In general, our result suggests that high latitude states experienced more yield loss, and with the increase of smoke days, more worsen in yield loss was present in recent years.

3.3.3 PM_{2.5} pollution attributed to smoke impact on yield

Recent studies (e.g., Burke et al., 2021) indicate that up to 25% of primary PM_{2.5} pollution in the U.S. can be attributed to wildfire events in recent years. The daily PM_{2.5} probability densities under smoke-free and smoke-influenced conditions, observed from June to August across all states, exhibit a rightward skew and are significantly distinct (Fig. A-5). These distributions are further skewed rightward when the smoke is present, leading to an increased frequency of higher surface PM_{2.5}. We found a positive relationship between smoke days and PM_{2.5}, indicating that one additional smoke day increased the mean PM_{2.5} of exposure by 0.14 μm^{-3} ($p < 0.01$) from June to August (Table S3). For soybean yield, an increase of 1 μm^{-3} in wildfire specific PM_{2.5} during June-August decreased soybean yield at the rate of 0.01 t ha⁻¹ (Table S3). However, wildfire specific PM_{2.5} doesn't have a significant impact on corn yield (Fig. S8). Our main analysis uses satellite-based measures of ground-level PM_{2.5} concentrations for the study regions, and we got a similar estimate of smoke and PM_{2.5} relationship when using observations from EPA ground-level monitors within a small number of counties (Table S4). However, the Wu-

Hausman test of significance for IV regression was not significant, an unexpected result. Fig. 3.4 reveals the spatial distribution of smoke impact on yield through increasing ground-level PM_{2.5}. Yield loss is as little as 1% over most counties but as large as 4% over northwest ND where exposure the most smoke days shown in Fig. 3.1.

To better understand the effect of smoke days on soybean yield through increased PM_{2.5} concentrations, the difference in average annual yield loss between 2018–2022 and 2008–2012 is shown in Fig. 3.5. Owing to the anthropogenic emissions regulation in U.S., PM_{2.5} pollution level significantly dropped in the growing season of soybean, resulting in a decline in yield loss over all states except ND shown as the positive difference in Fig.3.5. Yield benefits from clean air increase with decreasing of latitude and opposite to the spatial distribution of smoke days. However, the negative difference in Fig.3.5 reveals that wildfire specific PM_{2.5} impact on yield is increasing over all states. Although the relative yield change due to wildfire PM_{2.5} is less than 1% in east north central states (Fig.3.4, Fig.3.5), the negative effects could become larger under a warming climate and frequent extreme fires in the future.

The impact of PM_{2.5} on soybean yields across various states reveals a noteworthy trend. Fig. 3.6 illustrates the impact of wildfire-specific smoke and total PM_{2.5} variations on yields. Our results suggest a general negative impact of PM_{2.5} on soybean yields, with the degree of impact varying by state or location. For example, the total PM_{2.5} showed a reduction in yield with a trend of -3.4% dec⁻¹ in ND, whereas a trend of 6.7% dec⁻¹ in OH. States except ND benefit from reducing total PM_{2.5} that yield loss from PM_{2.5} pollution decreased over the past 15 years. In 2008, PM_{2.5} has reduced average yields by 11% with the highest in OH (-19.6%) and lowest in SD (-11.5%). yield loss from PM_{2.5} pollution in 2022 was decreased with the highest in IA (-6%) and lowest in ND (-11%). Therefore, relative yield change due to PM_{2.5} pollution is significant but declines during 2008-2022, ranging from -3.4 % dec⁻¹ in ND to 6.7 % dec⁻¹ in OH. However, wildfire-specific PM_{2.5} reduce yield at a different trend. The relative yield change in soybeans due to wildfire-specific PM_{2.5} pollution was as low as 1% across all states in 2008. This impact increased across all states, particularly after 2016, when wildfire smoke was shown to influence PM_{2.5} trends. The wildfire specific PM_{2.5} pollution on yield was as much as -1.4% dec⁻¹ in ND and less than -1% dec⁻¹ over the rest of states over past 15 years.

3.4 Discussion and conclusion

In the present study, we developed robust statistical models to characterize the effect of smoke days and the wildfire specific PM_{2.5} pollution on soybean yield over the growing season in the Midwestern U.S. from 2008 to 2022. Overall, we show that exposure to heavy smoke days increased during the soybean growing season in the Midwest region. Days with heavy smoke plumes have a negative impact on yield, especially in more northern regions (e.g. WI, SD, and ND states). Meanwhile, our analysis implicates larger smoke-days-specific yield loss in recent years as the number of heavy smoke days increased under more frequent extreme wildfires. The gradient of yield loss increases from low to high latitude. Moreover, we find PM_{2.5} pollution level significantly dropped in the growing season of soybean, resulting in a decline in yield loss over all states except ND over the past 15 years. However, the damage of PM_{2.5} pollution from the wildfire source to soybean yield expresses the opposite change in that an increasing trend of yield loss happened in all states. The contribution of smoke PM_{2.5} to average PM_{2.5} has become larger in recent years (e.g., 2018, 2021) and is expected to continue under a warming climate (Burke et al., 2023). Corn yield loss due to exposure to smoke days is less than 1% (Fig. S7). Result shows that total PM_{2.5} has a negative impact but the wildfire-specific PM_{2.5} has no significant impact on corn yield during 2008-2022. Smoke (aerosols) and PM_{2.5} impact crop yield through changes in direct and diffuse solar radiation. While previous research has highlighted that the C4 plant is generally more responsive to decreases in direct light compared to C3 plants (Kanniah et al., 2012), corn is believed to enhance light utilization efficiency because of a higher canopy than soybean, particularly under diffuse light conditions associated with increased aerosol levels (Emmel et al., 2020). C4 crops benefit more from a change in light quantity and quality because of slower light-saturated than C3 (Strada et al., 2015). Our analysis reveals that soybean yield is sensitive to smoke compared to corn, and consistent with the response of corn and soybean to aerosols (Liu and Desai, 2021)

Our study considers smoke plumes' impact on yield through increasing ground-level PM_{2.5} pollution, however, there are other pathways of smoke impact crop yield that deserve further investigations, such as potential O₃ damage. Wildfires can enhance O₃ production and impact air pollution across the U.S. (Ninneman and Jaffe, 2021). Smoke in the Midwest region originates

from wildfires occurring in the western United States or from Canada (Burke et al., 2021; Jethva et al., 2019). The long distance from fire source, combined with plume dilution rate, time of day, and meteorological condition, makes it challenging to directly link production loss directly to the O₃ attributable to wildfires. Despite this, Hong et al. (2020) observed O₃-induced declines in production for perennial crops in California where is one of the wildfire-prone in the U.S. Therefore, further investigation is necessary to connect production losses and O₃ attributed to wildfires.

Our results underline the gradient of yield loss increases from low to high-latitude regions due to exposure to smoke plumes. Extreme wildfires not only have evident consequences on both local and distant air quality but can also impact crop production thousands of kilometers away. As wildfires have happened more frequently with longer fire seasons as well as widespread burned areas in the western U.S., crop yield in the Midwest region is expected to be exposed to more heavy smoke and damage. In addition, increasing wildfire PM_{2.5} contribution may decline the yield gain benefiting from total PM_{2.5} reduction. Last, under a warming climate, soybean production may expand to the north to take advantage of moderate temperatures (Hoffman et al., 2020), this shift in production towards more smoke-influenced areas (e.g. WI, SD, and ND states), farmers might need to navigate a choice between increase in temperature and more frequently smoke exposure.

3.5 Data availability

All data used for this study is freely available. The county-level rainfed soybean yield is openly available from USDA https://www.nass.usda.gov/Data_and_Statistics/. The nClimGrid-Daily weather data is available from <https://www.ncei.noaa.gov/products/land-based-station/nclimgrid-daily>. The Information Service Hazard Mapping System (HMS) fire and smoke product is from <https://www.ospo.noaa.gov/Products/land/hms.html>. The cropland layer is from <https://croplandcros.scinet.usda.gov/>. The satellite-derived PM_{2.5} dataset is from <https://sites.wustl.edu/acag/datasets/surface-pm2-5/>

3.6 Acknowledgments

We thank Stephen Watson for editing the paper. His work continues to be at the highest professional level.

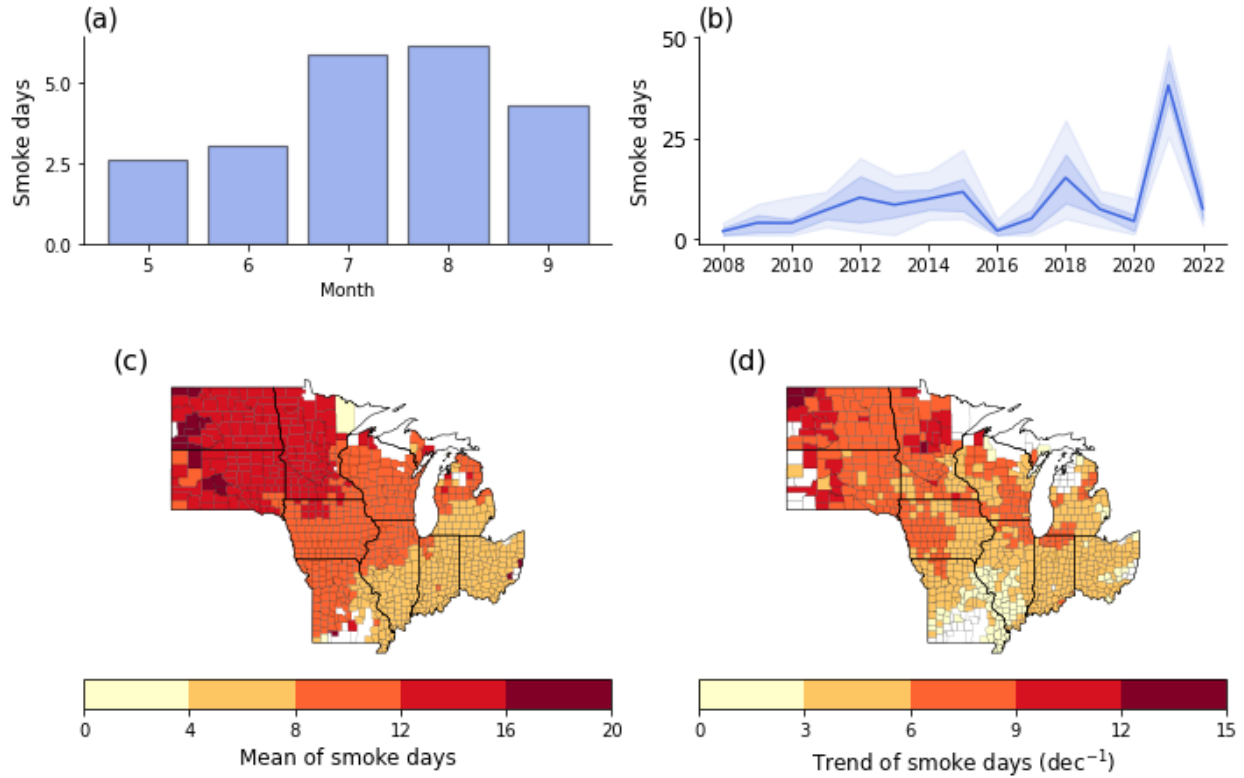


Figure 3.1 (a) Averaged smoke-influenced days per growing season month (May-October) across all counties and (b) smoke-influenced days change from 2008 to 2022 using Hazard Mapping System smoke dataset. The dark blue line is the average days among all counties and the shaded areas show counties where smoke days are at 75% and 95% position. (c) Average days and (d) spatial distribution of trends of smoke-influenced days during the growing season (May-October) from 2008 to 2022.

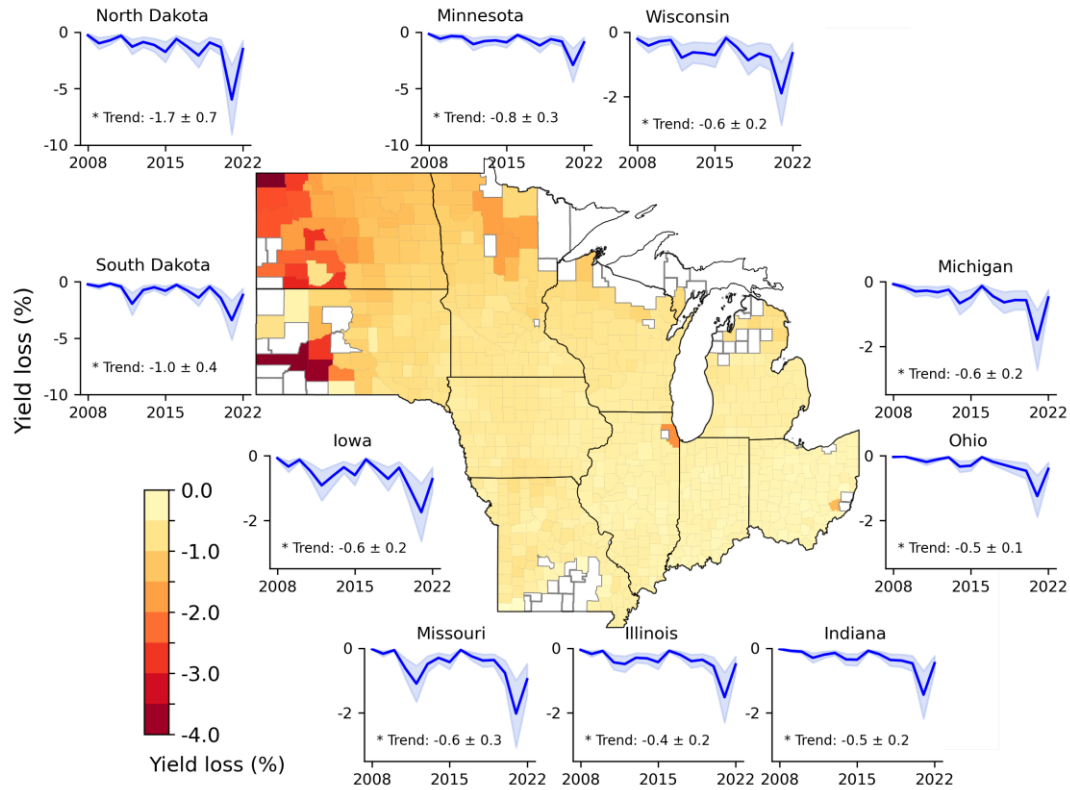


Figure 3.2 The effects of increased smoke days on soybean yields from 2008 to 2022, the graphs surrounding the maps represent the overall state changes in yield. The solid line indicates the mean and shaded areas indicate 5%-95% confidence intervals by 1,000 bootstrap estimates. Trends were significant and estimated using the ordinary least squares method of linear regression. Yield loss is represented as the percentage change relative to mean yield. Trend unit: % dec⁻¹.

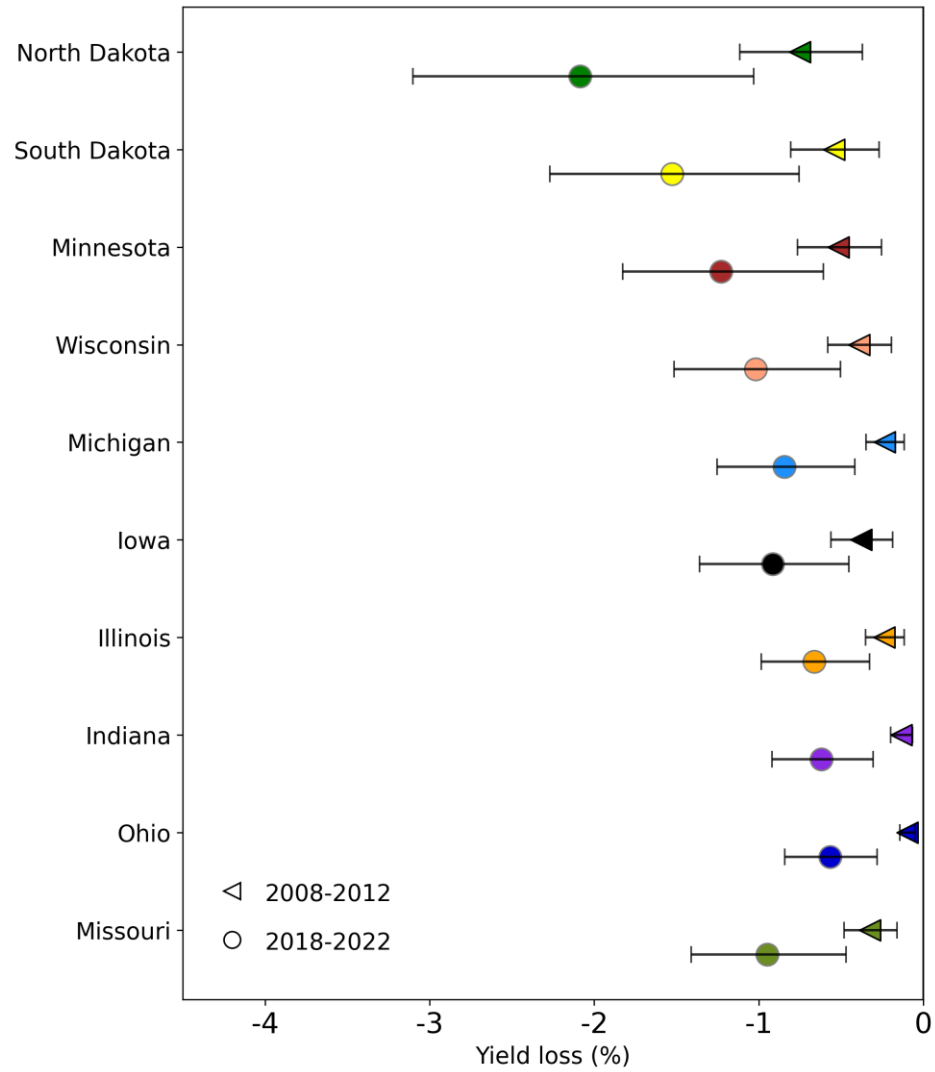


Figure 3.3 The average yield loss relative to soybean mean yield due to the increase of smoke-influenced days during 2008-2012 (triangle) and 2018-2022 (circle) at North Dakota, South Dakota, Minnesota, Wisconsin, Michigan, Iowa, Illinois, Indiana, Ohio, and Missouri state. The error bar is 5%-95% confidence intervals from 1000 times bootstrap. The Y-axis is ordered based on latitudes.

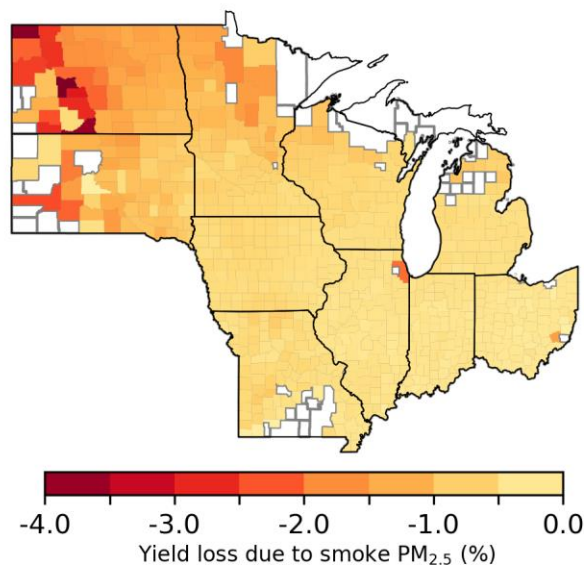


Figure 3.4 The spatial distribution of yield loss due to wildfire-specific smoke contributed to PM_{2.5} relative to soybean mean yield from 2008 to 2022.

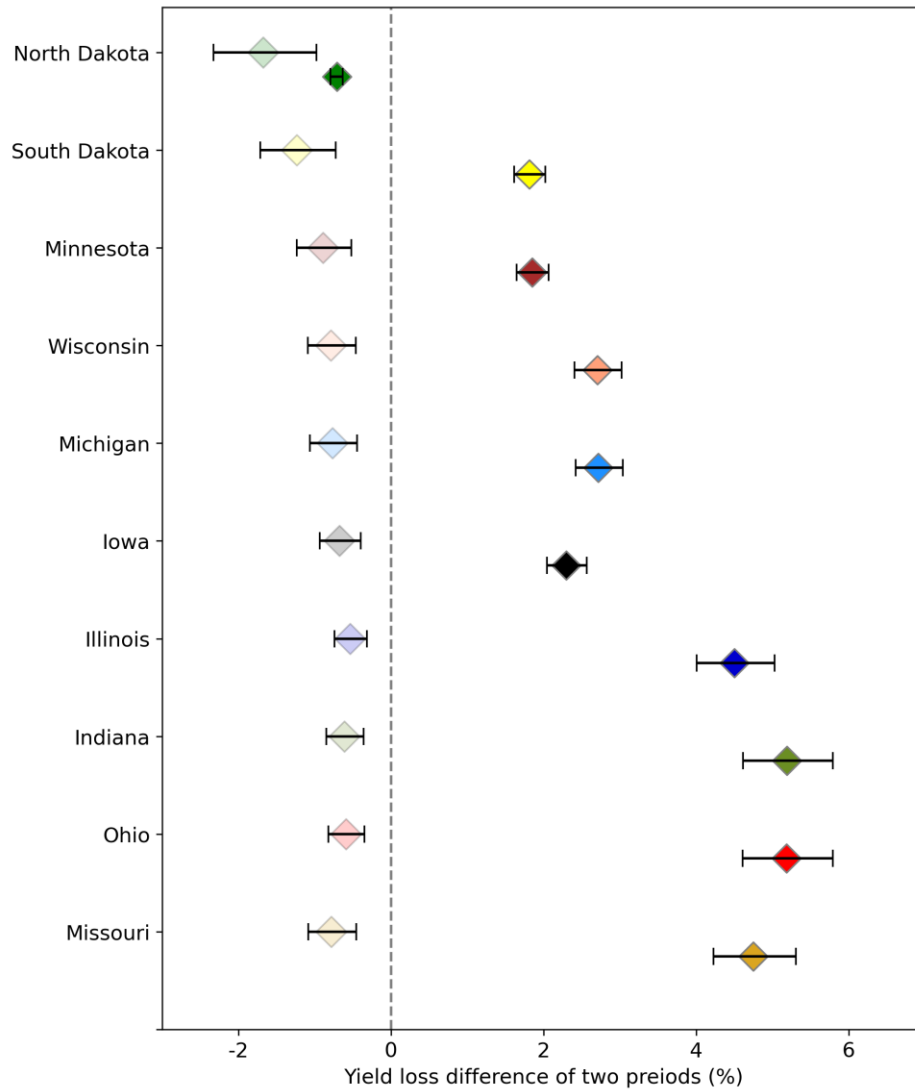


Figure 3.5 The differential impact on soybean yields between 2018-2022 and 2008-2012 periods that caused by wildfire-specific PM_{2.5} and total PM_{2.5}. The yield loss difference is calculated as a relative change to overall mean yield corresponding to each period (light diamond indicates wildfire-specific smoke PM_{2.5}, dark diamond indicates total PM_{2.5}). The error bars are calculated by 1,000 times bootstrapping.

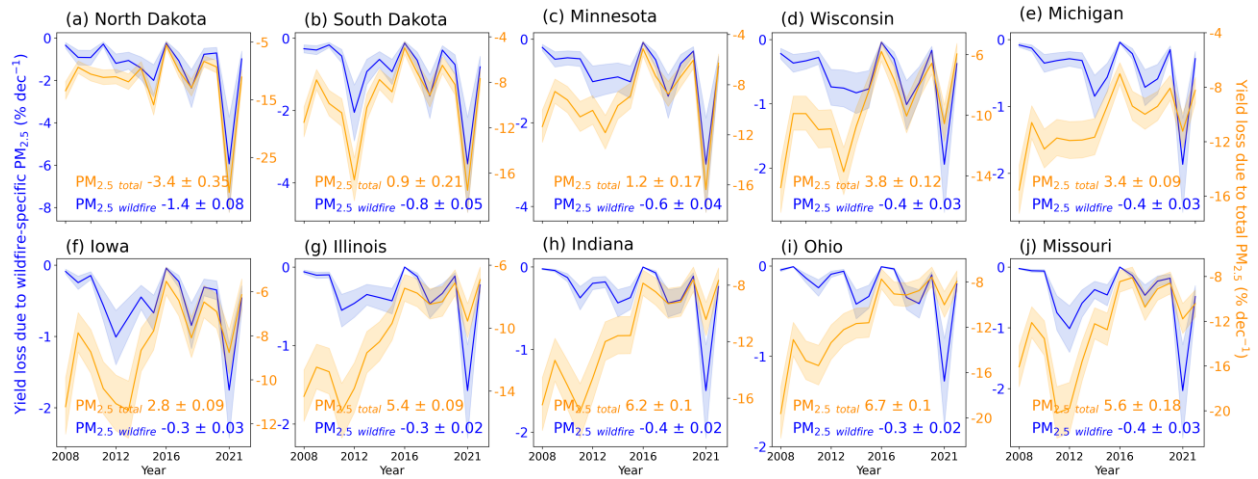


Figure 3.6 Wildfire-specific smoke PM_{2.5} and total smoke PM_{2.5} impacts on soybean yields expressing as a percent change relative to overall mean yields from (a) North Dakota, (b) South Dakota, (c) Minnesota, (d) Wisconsin, (e) Michigan, (f) Iowa, (g) Illinois, (h) Indiana, (i) Ohio, and (j) Missouri (blue color for wildfire-specific smoke PM_{2.5} and orange color for total PM_{2.5}). The solid line in a-j indicates the mean estimate across 1,000 bootstrap estimates and shaded areas indicate 5th and 95th percentiles. Trends were significant and estimated using the ordinary least squares method of linear regression. (Unit: % dec⁻¹).

Chapter 4 - Global total precipitable water variations and trends during 1958-2021

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4.1 Introduction

As the most critical greenhouse gas in the Earth's atmosphere, water vapor plays a key role in atmospheric processes from the microscale (including the formation of clouds and precipitation) to the global scale, and is related to the Earth's radiation budget, hydrological cycle, and climate change (Held and Soden, 2006; Lacis et al., 2010; Ruckstuhl et al., 2007). The amount of water vapor is primarily controlled by the air temperature when the relative humidity (especially over the ocean) remains unchanged in the low troposphere. The total precipitable water (TPW), also known as the column-integrated amount of water vapor from the surface to the top of the atmosphere, increases by 6-7% with a 1 K increase in air temperature according to the Clausius-Clapeyron equation and thus enhances the strength of global warming with strong positive feedback due to the greenhouse effect (Held and Soden, 2006, O'Gorman and Muller, 2010) particularly in upper troposphere whereas changes at lower levels are strongly linked with precipitation, influencing the frequency and intensity of extreme weather events (Trenberth, 1998; Trenberth et al., 2003). Therefore, evaluating the long-term trend of TPW change and its relationship with temperature is important for understanding the role of water vapor in climate change and the impact of water vapor feedback on global warming.

Because of the short residence time of water vapor in the atmosphere, studies in terms of long-term water vapor trends and their variability still face challenges. The two main categories of water vapor data include observations collected from various weather station networks and satellites, as well as reanalysis datasets integrated with simulations and observations. The former has difficulty in evaluating long-term trends due to discontinuities, insufficient spatial densities, and coverage (Dee et al., 2011). For example, radiosonde observations have the issue of spurious discontinuities or changes in variability due to shifts in instruments and observational methods

(Dee et al., 2011; Trenberth et al., 2005). However, multiple observations have been homogenized and thoroughly quality-checked in recent years. For example, the ground-based measurements of Global Navigation Satellite Systems (GNSS) integrated water vapor from 1994-2021 (Bock, 2022) and provided evidence of global moistening (Douville et al., 2022). The in-situ observations from the Radiosounding HARMonization (RHARM) dataset (Madonna et al., 2022) enhance the spatial consistency of estimated trends and align more closely with a contemporary atmospheric reanalysis. In addition, the homogenized temperature data presented by Zhou et al. (2021) exhibited spatially consistent trends and temporally stable variations, and didn't show the erroneous tropospheric cooling observed in various reanalyses including ERA5 and raw datasets, across North China and Mongolia. This accuracy of temperature can help in increasing the confidence in tropospheric temperature and water vapor, as well as in enhancing the quality of atmospheric reanalysis products. Temperature and humidity extremes from HadISDH by Willett (2023) are also designed for long-term regional trends. The latter reanalysis dataset has issues of data quality that suffered from biases and errors from assimilated data during the satellite era, causing concerns about their reliability for detecting climate trends (Dai et al., 2011; Schröder et al., 2016; Trenberth et al., 2011). Trenberth et al. (2005) evaluated the performance of global reanalyses, satellite, and radiosonde datasets on TPW and found that the Special Sensor Microwave Imager Sounder (SSM/I) dataset provided by Remote Sensing Systems (RSS) is the only source with reliable means, variabilities, and trends for TPW over oceans after 1988. The discontinuity and inaccurate data in 1992 due to changes in satellite instruments was highlighted by Trenberth et al (2015) and this spurious variability in water vapor existed in reanalyses up to the present. Numerous studies have analysed trends and variations in atmospheric water vapor distribution on both global and regional scales, primarily utilizing early versions of reanalysis datasets and satellite observations, albeit over relatively short study periods (e.g., Borger et al., 2022; Parracho et al., 2018; Wang et al., 2016; Zhang et al., 2019, 2021). New generation reanalysis datasets (JRA-55 and ERA5) provide a better option for climate studies because of advanced modeling and data assimilation systems, with better accuracy, and fewer homogeneity issues (Hersbach et al., 2020; Kobayashi et al., 2015; Douville et al., 2022). JRA-55 showed a better performance in studying multidecadal variability and climate change than previous reanalysis datasets (Kobayashi et al., 2015). Many studies have confirmed that ERA5 was the best or among the highest-performing reanalysis products

(Taszarek et al., 2021; Yuan et al., 2023) although inhomogeneity still remains; for example, water vapor associated with changes in SSMI instruments (Trenberth et al., 2015) and unreliability of tropical water vapor in ERA5 and ground-based observations before 1993 (Allan et al., 2022). Therefore, the latest ERA5 and JRA-55 were selected in this study to analyze long-term TPW changes and their relationship with temperatures at regional and global scales.

The near-surface air temperature (2m air temperature, T_{2m}) describes the thermodynamic temperature at a 1.5-2 m height while surface skin temperature (T_s) refers to ‘radiometric surface temperature’ that is governed by the terrestrial radiation balance (Jin et al., 1997; Jin and Dickinson, 2010). Recent studies investigated how the TPW responds to changes in surface temperature using modeling estimation, satellite observations, or ground-based observation systems (Allan et al., 2022; Alshawaf et al., 2017; Borger et al., 2022; O’Gorman and Muller, 2010; Wang et al., 2016; Yuan et al., 2021), and many global surface temperature observational datasets use sea surface temperature (SST) over ocean and T_{2m} over land (e.g., HadCRUT, Morice et al., 2021). Different from prior studies, we use the newest and longest available reanalysis datasets to discuss the difference of T_{2m} and T_s , and the relationship between trends in TPW and T_{2m} from 1993 to 2021 along with additional analysis using radiosonde data as well as AIRS and SSMI(S) satellite measurements since 2003.

In this study, we focus on answering the following questions: (1) To what extent has the TPW changed and what is the difference between the variations of T_{2m} and T_s on a multi-decade scale? (2) What is the relationship between trends of TPW changes and temperature changes? The results from reanalysis dataset are compared with radiosonde data as well as AIRS and SSMI(S) satellite measurements. We discuss the difference of results among datasets and their potential discontinuities in datasets. Therefore, this paper is organized as follows. In section 2, we introduce the datasets and methods. In section 3, the TPW variations and the differences of T_{2m} and T_s are compared with radiosonde and satellite observations over land and ocean. Sections 4 and 5 provide the discussion and conclusion.

4.2 Data and Method

4.2.1 Datasets

Two reanalysis datasets containing TPW and temperature (T_{2m} , T_s) from 1958 to 2021 were used in this study, these being ERA5 (Hersbach et al., 2020) and JRA-55 (Kobayashi et al., 2015). For ERA5, skin temperature, T_s , is the temperature estimated from the surface energy balance. For JRA-55, skin temperature is a diagnostic variable computed from the surface upward longwave radiation under the assumption that the surface is a black body. We used monthly reanalysis datasets from January 1958 to December 2021 for TPW and temperatures. Both TPW and temperature variables in these two datasets were regridded into $1^\circ \times 1^\circ$ resolution data using a bilinear interpolation method before analyzing (Zhuang, 2018).

The Atmospheric Infrared Sounder (AIRS) instrument captures a precisely calibrated, spectrally detailed dataset of both infrared and microwave radiances. It offers quality temperature and humidity profiles throughout the troposphere (Tian et al., 2020). Satellite observation from version 7 of AIRS (Tian et al., 2020) was used for comparison with the reanalysis from 2003 to 2021. The total column water vapor (kg m^{-2}) is calculated as the average of daytime (TotH2OVap_A) and nighttime modes (TotH2OVap_D). In addition, the column-integrated water vapor from the Special Sensor Microwave Imager and the Special Sensor Microwave Imager Sounder (SSMIS) from 2003-2021 (Wentz et al., 2015) are selected for comparison with reanalysis datasets.

We also used *in-situ* observations from the Radiosounding HARMonization (RHARM) dataset (Madonna et al., 2022), which applied the new algorithm to the Global Climate Observing System Reference Upper-Air Network (GRUAN) data and used observation measurement instead of reanalysis data as a reference to calculate and adjust for systematic effects on temperature and humidity. RHARM provides homogenized temperature and relative humidity profiles at two observation times (0000 and 1200 UTC) for radiosonde stations globally from 1979 to 2019. Therefore, T_{2m} used in this study from radiosonde observation was taken from the temperature observed at the lowest layer. Relative humidity and temperature from the surface to 500 hPa level are used to calculate precipitable water.

4.2.2 Methods

Monthly TPW and temperature anomalies were calculated by the base period of 1958-2021 for reanalysis datasets and discussed the trends of long-term (1958-2021) and short-term (1993-2021) periods. We divided the globe into five areas: tropical regions (23.5°S–23.5°N), temperate (23.5°S–66.5°S in Southern Hemisphere (SH) and 23.5°N–66.5°N in Northern Hemisphere (NH)), and polar regions (66.5°S–90°S in SH and 66.5°N–90°N in NH). These regions respectively cover approximately 40%, 26%, and 8% of the Earth's surface. The regional average values, presented by different latitude bins, were calculated with a cosine (latitude) weighting factor to account for the convergence of grid points for each region. For the global distribution, all datasets were re-sampled into 1° x 1° resolution using spatial-averaging resampling, then the area-weighted average of anomalies was computed to formulate a global time series.

For all trend analyses in TPW and temperature (T_s , T_{2m}) series, we first calculated globe, land and ocean average values, then, we selected the Seasonal Kendall (SK) test (Hirsch et al., 1982) using the Theil-Sen slopes (Sen 1968; Theil, 1992) to calculate relative TPW trends (% dec⁻¹) (Zhai and Eskridge, 1997) and temperature trends for both T_s and T_{2m} (K dec⁻¹). The statistical significance of all linear correlations and trends used was performed at a 95% confidence level for all analyses conducted in this study. The TPW responses to temperature from 1993 to 2021 is calculated as the ratio of TWP trends and T_{2m} trends.

Due to daily data missing in radiosonde observations, valid data required at least 10 days of data available within a month, and at least two-thirds of the total months had to have valid monthly data (345 months for 1979-2019). Each month had to have at least 28 years of valid data at each station to calculate monthly climatology. Trend analysis is also from Sen's estimate of the slope (Sen 1968) for these observations. Thereby, a set of 331 radiosonde stations were selected in this study. To facilitate the comparison, interpolated reanalysis data from radiosonde stations were selected to compare with the observation data. We calculated the trend difference between reanalyses and observations to assess how effectively each reanalysis product captures changes in observed TPW over 1979-2019.

To detect potential discontinuity within temporal sequence of total water vapor and temperature in reanalysis dataset, we applied penalized maximal F test (PMF test, Wang et al., 2006, 2013;

Wang, 2018) to detect temporal discontinuity points on each grid over ocean during 1958-2021. The discontinuities were documented if testing statistic's p-value was less than 0.01 (Zhou et al., 2021).

4.3 Results and Discussion

4.3.1 TPW Trends

Figures 4.1a-e show the temporal variations of monthly TPW anomalies over tropical, temperate, and polar regions. Overall, in terms of latitude bands, these trends differ little between the two reanalysis datasets. Specifically, ERA5 gives a $0.6 \text{ \% dec}^{-1}$ moistening rate whereas the JRA-55 shows a $0.96 \text{ \% dec}^{-1}$ moistening rate over the tropical regions for the whole period 1958-2021. A notable decrease in TPW is shown during the 1980s to 1990s over tropical regions in ERA5, which is consistent with ERA-interim (Allan et al., 2014) but inconsistent with satellite microwave data (Allan et al., 2022). This discrepancy seems to originate in the tropical lower troposphere over ocean. Since SSM/I satellite became available and were used in ERA5 after 1987 (Hersbach et. al., 2020), there has been some spurious variability in TPW, notably in January 1992 (Trenberth et al., 2015). However, a strong agreement of TPW after 1993 is shown between SSM/I observations and ERA5 (Allan et al., 2022). In addition, data after 1993 show fewer change points based on PMF-test results on grid boxes over the ocean (Figure B-2). Thus, the 1993-2021 time series of TPW benefiting from in-situ and satellite observations is expected to produce more reliable water vapor variability. ERA5 gives a $1.46 \text{ \% dec}^{-1}$ moistening rate whereas the JRA-55 shows a $1.43 \text{ \% dec}^{-1}$ moistening rate over the tropical regions from 1993 to 2021. Trends are 1.86 in NH temperate and $3.89 \text{ \% dec}^{-1}$ in NH polar regions for ERA-5 while values are about 1.56 (0.89) $\text{ \% dec}^{-1}$ over temperate but are not significant over polar in SH for ERA5 (JRA-55) during 1993-2021. The TPW trends increase in the NH is larger than those in the SH although they showed strong month-to-month variabilities (coefficient of variation, CV, is 0.7 on average) in the NH, which are consistent with the global distribution (Fig. 4.1).

Figures 4.1f-h depict these trends of TPW estimated over the ocean, land, and the globe. It is noticeable that monthly TPW anomalies showed a consistent and statistically significant increase, yielding a rate of 0.58 (0.85), 0.88 (1.07), and 0.65 (0.89) $\text{ \% dec}^{-1}$ for ERA5 (JRA-55) during 1958-2021 over ocean, land, and the globe, respectively. However, those trends increase

at a rate of 1.72 (1.21), 1.19 (2.22) and 2.12 (1.91) % dec⁻¹ for ERA5 (JRA-55) after 1993. The monthly TPW anomalies showed a similar variability over ocean, land, and globally (CVs, around 0.4), and displayed significant interannual variations, which had been dominated by ENSO events (Trenberth et al., 2005; Wang et al., 2016). The distinct turning points may be attributed to the intensity of ENSO events. For example, one of the most powerful ENSO events during the 1997/1998 El Niña led to a significant tropical TPW increase, attributable to the warming in the equatorial Pacific (Wagner et al. 2005). The 2015/2016 El Niño caused a moistening TPW trend over tropical regions (Garfinkel et al., 2018). The trend of TPW during 1988-2003 was likely associated with the decadal variation of Interdecadal Pacific Oscillation from a warm period (1977-1998) to a cold period (1999 to 2003) (Dong and Dai, 2015). The TPW trend for recent period including 1997/98 event will likely be similar (Wang et al. 2016). In addition, Patel and Kuttippurath (2023) also shows a strong correlation (0.81) between Pacific Decadal Oscillation and TPW variability in the tropics.

Based on timeseries of TPW in Fig. 4.1, Fig. 4.2 shows the decadal trends in TPW calculated from ERA5 and JRA-55 after 1993. In general, the two reanalysis datasets showed similar trend patterns of global TPW distribution, with upward trends as the dominant change of TPW, indicating a rise in moisture in response to global warming since the end of the twentieth century (Santer et al., 2006). TPW trends are largely positive and statistically significant over North Africa, Europe and the NH polar region. In addition, Simpson et al. (2023) found that near-surface water vapor, as measured by surface observations, hasn't increased over arid and semi-arid regions since 1980, a discrepancy compared to predicted results from simulations. These findings indicate there might be misrepresentations of hydroclimate-related processes in simulations since climate models showed moistening trends associated with the increase in water vapor-holding capacity of a warmer atmosphere. On the other hand, decreasing TPW trends show a dipole structure over the Southern Ocean in both reanalysis datasets which can be attributed to the change of the ENSO phase (Trenberth et al., 2005). In contrast, these two reanalysis datasets show opposite trends over eastern Africa including the Sudan where ERA5 trends are negative, whereas JRA-55 trends are positive. The reason for opposite trends in reanalyses is likely due to the different representations of large-scale moisture transport, surface-atmosphere processes, and their data assimilation (Parracho et al., 2018). Chen and Liu (2016)

and Parracho et al. (2018) also showed decreasing trends in North Africa using ERA-Interim reanalysis for 1979-2014 and 1980-2016, and the biases in rainfall over West Africa might also exist in ERA-Interim reanalysis (Dunning et al., 2016). In terms of TPW trend over arid and semi-arid regions from 1980 to 2020 in reanalysis dataset (figure not shown), it also shows a different trend, comparing observation from Simpson et al. 2023, that only TPW over southwest United States in ERA5 and central Africa in JRA-55 significantly decreased.

4.3.2 Trends in temperature

In contrast to TPW, temperature in ERA5 is relatively stable for the pre-satellite era and aligned with independent datasets, although some notable discrepancies exist in accurately representing specific regional variations (Hersbach et al. 2020). The global trends of temperature between 1958-2021 exhibit widespread warming over large regions in both reanalysis datasets, except for some of small areas located in the SH and northern Atlantic (Fig. 4.3). Large land areas experience warming temperature changes of greater magnitude compared to the surrounding oceans (Fig. 4.3) and the strongest warming occurred in the Arctic (Fig. 4.3). Greater warming is observed over mid-latitude than tropical regions in NH, consistent with Zeng et al. (2021). Cooling in the North Atlantic is also observed by Li et al. (2022) when using observation datasets. This arises from strengthened local convection and heat dissipation from the ocean induced by the overlying atmosphere. Meanwhile, the North Atlantic cooling appears most significant in February in the northern hemisphere while it becomes net warming in August (Allan and Allan, 2020). Some studies connect this phenomenon to changes in ocean circulation based on modeling results (Drijfhout et al., 2012). In addition, based on model simulations without considering variable ocean currents, He et al. (2022) explained that the warming hole is driven by enhanced surface westerly wind removing heat from the ocean surface. For the SH, the polar region also experiences the strongest warming trends, similar to the trend's magnitudes by Clem et al. (2020). There is a slight difference between two reanalysis datasets for differential trends (ΔT) between T_s and T_{2m} at the global scale, especially over the ocean area where ΔT trends are negative in ERA5 and positive in JRA-55. The ΔT shows a similar pattern only over the tropic land region (Fig. 4.3d). Although air and surface temperatures are closely related, they are physically distinct. The difference may be affected by changes of regional and seasonal vegetation ecosystems, land use, and land cover (Gulev et al., 2021; Masson-Delmotte, 2022).

The ability of atmospheric reanalyses to effectively constrain variations in T_s and T_{2m} trends is limited because the sea surface temperatures in atmospheric reanalyses were obtained from globally observed and interpolated products (Rayner et al. 2003). In contrast, the estimation of air temperature depends on model parameterizations and assimilated observations, which do not incorporate marine air temperature (Simmons et al., 2017). The strong correlations between T_{2m} and T_s are further discussed in SI (Fig. B-4 & B-5). Overall, T_{2m} and T_s show very similar interannual variations and the trends aren't significantly different. Therefore, we only present T_{2m} variations and its relationship with water vapor.

The general warming since the late 1970s revealed by T_{2m} over different latitude bins in both datasets agree with each other when viewing the spatial distribution of magnitudes globally (Fig. 4.4), manifested by much larger warming in the Arctic at a rate (all temperature rates given as $K\ dec^{-1}$) of ~ 0.45 , which is three times warming than the global average rate (~ 0.15) (Figs. 4.4h). During the 1979-2021 period, this Arctic amplification of warming was markedly pronounced, occurring at rates 3.5 times faster than the global average warming rate documented by surface climate observations (Rantanen et al., 2022) in ERA5 data and 4 times faster in JRA-55 data. The potential causes of the Arctic amplification may be linked to sea ice decline, changes in atmospheric and oceanic heat contents, or changes in atmospheric moisture transport (Graversen, 2006; Screen and Simmonds, 2010; Zhang et al., 2008). The Arctic warming is concentrated in the lower troposphere (Allan et al. 2022) and reached $\sim 0.74\ K\ dec^{-1}$ after 1993, thus leading to increases in water vapor as shown in Fig. 4.1a. Antarctic warming is at a rate of $\sim 0.24\ K\ dec^{-1}$ over the past 64 years and consistent warming at $\sim 0.23\ K\ dec^{-1}$ after 1993. In addition, the warmer and colder years are linked to the ENSO events and further cause the distinct turning points of TPW (Fig. 4.1). The datasets exhibit a clear consensus regarding the increased temperature of both land and ocean areas over the years. The land experienced greater warming at a rate exceeding 0.2 for T_{2m} compared to the oceans' warming, leading to a land-to-ocean warming ratio ranging from 1.8 to 2.3 (Fig. 4.4). The explained reasons for the land-ocean contrast in warming rates is the influence of temperature and humidity on lapse rate, which results in a smaller reduction in lapse rate over land areas compared to the ocean, leading to a greater warming effect on land surfaces than on ocean surfaces (Joshi et al., 2008). Additionally, the restriction of moisture in the land boundary layer directly contributes to an intensified

warming of land surfaces, which, in turn, raises the lapse rate over the land (Joshi et al., 2008). Byrne & O’Gorman (2018) further extended Joshi’s theory in a quantitative way. They investigated the contrast of land/ocean warming from surface observations and model simulations at the global scale and indicated that amplified land temperature increases were the consequence of reduced relative humidity over land.

4.3.3 TPW change response to temperature

TPW is expected to increase with air temperature by about 7% per K according to the Clausius–Clapeyron equation if the relative humidity in the lower troposphere is constant (Trenberth et al., 2005; O’Gorman and Muller, 2010). This relationship is determined by the ratio ($dTPW/dT$) of TPW trends and temperature trends from 1993 to 2021 (Fig. 4.5). The $dTPW/dT$ ratio shows a similar pattern but different magnitude between two reanalysis datasets. The TPW increases significantly around 11.2% (10.9%), 5.8% (9.4%), and 9.5% (8.9%) per K for ocean, land, and globe for ERA5 (JRA-55). These rates are larger than 6% per K at a global scale based on observational HadCRUT5 (Allan et al., 2022). A disagreement involving TPW trend and tropospheric temperature trend between observation and modelling simulation is also shown in Santer et al. (2009, 2021). The $dTPW/dT$ ratio increases significantly around 6% per K over eastern North America and Europe for both ERA5 and JRA-55 (Fig. 4.5). However, the relationship between TPW patterns and rising surface temperatures does not always follow the Clausius-Clapeyron equation, especially over some areas of Asia, central Africa, Australia and South American where TPW response to rising surface temperatures is negative without significance (Fig. 4.5). Regions with higher data density and homogeneity, such as North America and Europe, are likely to exhibit more realistic trends. Meanwhile, the shifts in wind patterns over regions can influence the local meteorological conditions over time, resulting in fluctuations in relative humidity, which in turn can cause deviations in water vapor changes from thermodynamic predictions. Negative $dTPW/dT$ occurs over the southern tropical ocean, where sea surface temperature was increased (Fig. 4.3) but precipitable water appears to be decreased slightly (Fig. 4.1); thus, the TPW change is contrary to what might be expected from the thermodynamic response to changes in temperature. Water vapor moves from one location to another through circulation, and the trend of vertical motion at 500 hPa could be further

investigated to reveal the ascent and convective activity as well as its relationship to decreasing water vapor (Zveryaev and Allan, 2005).

In addition to the global patterns of spatial dTPW/dT ratios, the ratio's latitude dependency is an interesting subject (Fig. 4.6) between 55° S and 55° N. Although the TPW response values show strong variations across latitudes, the ratios show a similar changing pattern over the globe and ocean, which varies across the theoretical Clausius-Clapeyron curves of dTPW/dT ratios (Figs. 4.6a). The dTPW/dT ratios are close to the Clausius-Clapeyron response curves in NH mid- to high-latitudes over the ocean, but larger than 6% per K in the SH (-40 to -20°N band) over the ocean. Such strong latitude dependency and the discrepancy between land and ocean areas are associated with zonal relative humidity changes and possible amplification of surface warming over land relative to the ocean (O’Gorman and Muller, 2010) (Figs. 4.6c). In arid areas, due to a lack of water, warming doesn’t result in increased water vapor; conversely, water vapor changes could be amplified or suppressed in monsoon regions due to dynamics (Fasullo, 2011). Multiple other studies also confirm the “dry gets drier, and wet gets wetter” paradigm over land (Xiong et al., 2022). Likewise, an analysis of the salinity index in Cheng et al. (2024) showed that salty areas are getting saltier and fresh areas are getting fresher; and that over the ocean wet areas are getting wetter and dry areas are getting drier. There are two stronger TPW response zones, located in the southern mid-latitude and the tropics over the globe (Figs. 4.6a, c). This result is nearly the same when drawn from multiple models of climate simulations for both historical and projected climate scenarios (O’Gorman and Muller, 2010). For land areas, in addition to two stronger response zones similar to the globe and ocean, a local maximum was found in the sub-tropical areas of the NH and SH (Fig. 4.6). The ratios for the land region are mainly lower than the theoretical ratio (around 7% per K) and these ratios are even negative in SH mid-latitudes where is the arid and semi-arid regions. Comparing these ratios between reanalyses, their discrepancies are greater over ocean, which probably contributes to their discrepancies over the globe (Fig. 4.6).

4.4 Further Discussion

The reanalysis dataset combines various observations to create a coherent global dataset using an atmospheric general circulation model. It provides spatially coherent and consistent data with

global coverage, which makes it valuable for climate research (e.g., Allan et al., 2022; Urraca and Gobron, 2023). By assimilating multiple data sources and employing a physics-based model, reanalyses can effectively address uncertainties and minimize the presence of unrealistic values. However, it is worth mentioning that discontinuities in the time series may still occur in reanalysis datasets when satellites and conventional observations are transited, newly added, and removed during the assimilation process (Long et al., 2017). In order to get a general picture of discontinuities in the reanalysis data, we calculated the discontinuity from 1958 to 2021 for each grid box of temperature and TPW over the ocean, where there is a strong relationship between water vapor and temperature along with significantly increased trends (Figs. 4.1 and 4.3). We applied the PMF test on each grid of the reanalysis dataset and selected the significance level of 0.01 to detect discontinuities (Zhou et al., 2021). The years with detected discontinuities (after counting all change points within the same year) of both temperature and TPW are shown in Figures B-1 and B-2. Discontinuities for temperature are relatively frequent before 1980 in both reanalysis datasets (Fig. B-1a, b) and are relatively less frequent after 1980 for ERA5 except for 1992-1995, 1998, and 2015 when strong El Niño (1992, 1998, 2015) or La Niña (1995) events or Pinatubo eruption in June 1991 and volcanic eruptions in 1992 occurred (Fig. B-1c). It reveals that the detected change points during 1990-2021 in ERA5 might be associated with the result of abrupt climate changes. Previous studies also demonstrated the reliability of ERA5 air temperature for the warming trend of the global ocean (He et al., 2023; Wang et al., 2019). For TPW, discontinuities show a similar pattern as the temperature in ERA5, in which water vapor before 1980 has relatively more discontinuities. In addition, change points are fewer after 1980 except for the largest discontinuity in 1991-1992 (Fig. B-2a) in ERA5 and in 1996-1997 in JRA-55 (Fig. B-2b). Trenberth et al. (2015) highlighted that the discontinuity and inaccurate values in 1992 are the result of changes in satellite instruments. A strong agreement between SSMI(S) observations and ERA5 is shown after 1993 (Allan et al., 2022), and fewer discontinuities are presented from 1993 to 2021 (Fig. B-2a). Meanwhile, discontinuities in JRA-55 are larger and distributed in all decadal periods even in normal years (Fig. B-2b, c). Because TPW is highly dependent on temperatures and has a strong relationship with temperature over ocean, we further detected TPW discontinuities by comparing TPW and the expected TPW (TPW_{ept}) calculated from regression with temperature (Figure B-3) during 1981-2021 when temperature shows fewer change points (Figure B-1). The discrepancy points between TPW and TPW_{ept} are obvious over

1987, 1998, 1999, and 2015 in both analysis data, indicating the strong effect of ENSO events on the change of TPW. For ERA5, these discontinuities occurred in 1992 and 1995 when TPW_{ept} increased but TPW decreased in ERA5 (Fig. B-2), in which the discontinuity in 1992 also existed in ERA-I (Trenberth et al., 2015). For JRA-55, discrepancy points occurred in 1984 and 1995. Due to lack of reliable observations before 1979, it is not recommended to use adjusted or statistically homogenized timeseries for trend analysis without metadata confirmation (e.g., the homogenized observations) (Wang and Feng, 2013). Although several discontinuities are detected in years after 1993 for TPW (Fig. B-2), a strong agreement of TPW between ERA5 and SSMI satellite might indicate reliable TPW trends (Allan et al., 2022). For the surface temperatures, most of the discontinuities occur before the satellite era, therefore the long-term trend analysis for temperatures in reanalysis datasets after 1979 should be more reliable, and removing the effect of discontinuities located in the pre-satellite period on longer-term trends needs further investigation. In terms of temperature discontinuity identified (Figure B-1), the longer temperature trends should be more reliable by using surface observation networks' datasets (Pielke et al., 2007).

The RHARM radiosonde observations (Madonna et al., 2022), which are mostly located in the NH land and available from 1979-2019, are completely independent of reanalysis data in terms of calculating and adjusting temperature and humidity. Compared with TPW trends from reanalysis data, moistening TPW in the NH polar region and Asia show the best agreement with radiosondes, with more than 90% and 60% of stations' trend differences within $\pm 0.2 \text{ mm dec}^{-1}$, respectively (Fig. B-6). In addition, TPW trend differences are within $\pm 0.2 \text{ mm dec}^{-1}$ at more than 54% of stations in Europe and North America (Fig. B-6). Moistening TPW trends in Western Europe and South Asia and drying TPW trends in Western North America are consistent with the results from both reanalysis data and GPS observations (Parracho et al., 2018). Overall, ERA5 and JRA-55 show good agreement with observations at regional scales. Specifically, TPW shows better agreement in North America and the NH polar region.

After evaluating the reanalysis data with radiosonde observations on land, water vapor data from AIRS and SSMI(S) satellites are used to evaluate the accuracy of reanalysis over oceanic regions from 2003 to 2021 (Fig. B-7). Except for the drying trends of the Northern Atlantic Ocean in the

short-term period, the spatial drying trend patterns in the two reanalysis datasets are similar to the long-term trends (Fig. 4.2) although they are not statistically significant. The surface air over tropical oceans increased in water vapor at a rate of $1.6\% \text{ dec}^{-1}$ for ERA5 and $1.9\% \text{ dec}^{-1}$ for JRA-55 on average, with a similar moistening rate shown in SSMI(S) ($1.1\% \text{ dec}^{-1}$) but not in AIRS data ($0.05\% \text{ dec}^{-1}$) since 2003. This result is consistent with Allan et al. (2022). The good agreement between the reanalyses and SSMI(S) is likely be attributed to the assimilation of all-sky radiances collected by the SSMI(S) satellite into the ERA5 and JRA-55 (Hersbach et al., 2020; Kobayashi et al., 2015). Although radiance measurement from AIRS is also introduced in ERA5 but not in JRA-55 (Hersbach et al., 2020; Kobayashi et al., 2015), the TPW from AIRS does not produce a strong global moistening and disagrees with reanalysis data and SSMI(S) microwave data and climate models, as well as Global Navigation System GPS (Allan et al., 2022; Douville et al., 2022).

4.5 Conclusions

Atmospheric reanalyses are widely used in the assessment of global climate change and their accuracy has advanced in recent years. Our study, bolstered by the latest ERA5 and JRA-55 reanalysis datasets, presents notable trends in the total precipitable water (TPW), surface temperature (T_s), and 2-meter temperature (T_{2m}) from 1993 to 2021. Beginning with TPW anomalies, a rise in moisture in response to global warming occurred from 1958-2021. However, due to data discontinuities in reanalysis data before 1993, more dependable trends have been identified. Post-1993, a moistening trend is observed at rates of 1.72% (ERA5) and 1.19% (JRA-55) per decade over oceans, 1.21% (ERA5) and 2.23% (JRA-55) per decade over land, and 2.12% (ERA5) and 1.90% (JRA-55) per decade globally. the 1993-2021 period begins from a cooler, drier year after the eruption of Mt. Pinatubo in 1991 (Soden et al., 2002), however, this event didn't significantly affect the long-term trend. When considering regional TPW trends, we identified statistically significant moistening trends over North Africa, Europe, and Northern Hemisphere polar regions since 1993. These findings, which are in concert with prior studies (Borger et al. 2022; Trenberth et al. 2005; Wang et al. 2016), point to the solitary exception of the South Pacific Ocean, where TPW trends registered as negative. The observed warming pattern is unlike coupled simulation, with warming more prominent in the tropical warm pool, which can increase stability in these subtropical subsidence regions (Andrews et al., 2022).

Reanalysis TPW showed an agreement with radiosonde observations over North America after 1979 and with SSMI(S) satellite but not AIRS measurement.

Building upon the analysis of TPW, our study further explored the temperature trends based on T_{2m} and T_s from ERA5 and JRA-55. Despite a general global warming trend (~ 0.15 K per decade), certain areas of the Southern Hemisphere and the North Atlantic Ocean demonstrated cooling since 1958. Terrestrial regions displayed a faster warming rate compared to oceanic regions, with a ratio of roughly 2:1, corroborating findings from Swaminathan et al. (2022). Arctic warming was particularly pronounced, registering three times the global average during 1958-2021, and escalating to around four times from 1979 to 2021 and around $6.5\% \text{ K}^{-1}$ of water vapor response to temperature. While Antarctic warming was more modest at 0.2 K per decade over the past 64 years, a sharp increase to over 0.6 K per decade was observed post-1980.

Last, we examined the TPW response to surface temperature changes, noting deviations from the Clausius-Clapeyron relation. In the ERA5 dataset, we identified TPW increases of around 11.2% , 5.8% , and 9.5% per K for ocean, land, and globe, respectively after 1993. These increased rates were higher in the JRA-55 dataset, with values at 10.9% , 9.4% , and 8.9% per K, respectively. Importantly, these response ratios were not uniform globally, presenting a variation between 6 and $8\% \text{ K}^{-1}$ between latitudes $15 - 55^\circ\text{N}$ and increasing toward southern high latitudes over oceans. The most substantial ratios for deviations in TPW responses were discovered in the southern high latitudes across land, ocean, and the globe. Because of the importance of atmospheric water vapor in the global energy balance and hydrological cycle, it has received much attention in recent years (this study; Trent et al., 2023; Douville and Willett, 2022; Patel and Kuttippurath, 2023; Shao et al., 2023; Ding et al., 2022). In the near future, results from these studies need to be synthesized to further quantify atmospheric water vapor, its relationship with surface temperature, and associated uncertainties. These results can then be used to better evaluate climate models and constrain these models' future projections.

4.6 Data availability

All data used for this study is freely available. The ERA5 dataset is openly available from ECMWF: <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalyses-era5-single-levels->

[monthly-means?tab=overview](#). The JRA-55 dataset is available from <https://rda.ucar.edu/datasets/ds628.0/>. The AIRS satellite data is from https://disc.gsfc.nasa.gov/datasets/AIRS3STD_006/summary. The SSMI(S) satellite is from www.remss.com/missions/ssmi. The Radiosounding HARMonization dataset is from <https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-observations-igra-baseline-network?tab=doc>. We thank Dallas Staley for editing and finalizing the paper and Ryan Maue's motivation for writing this paper.

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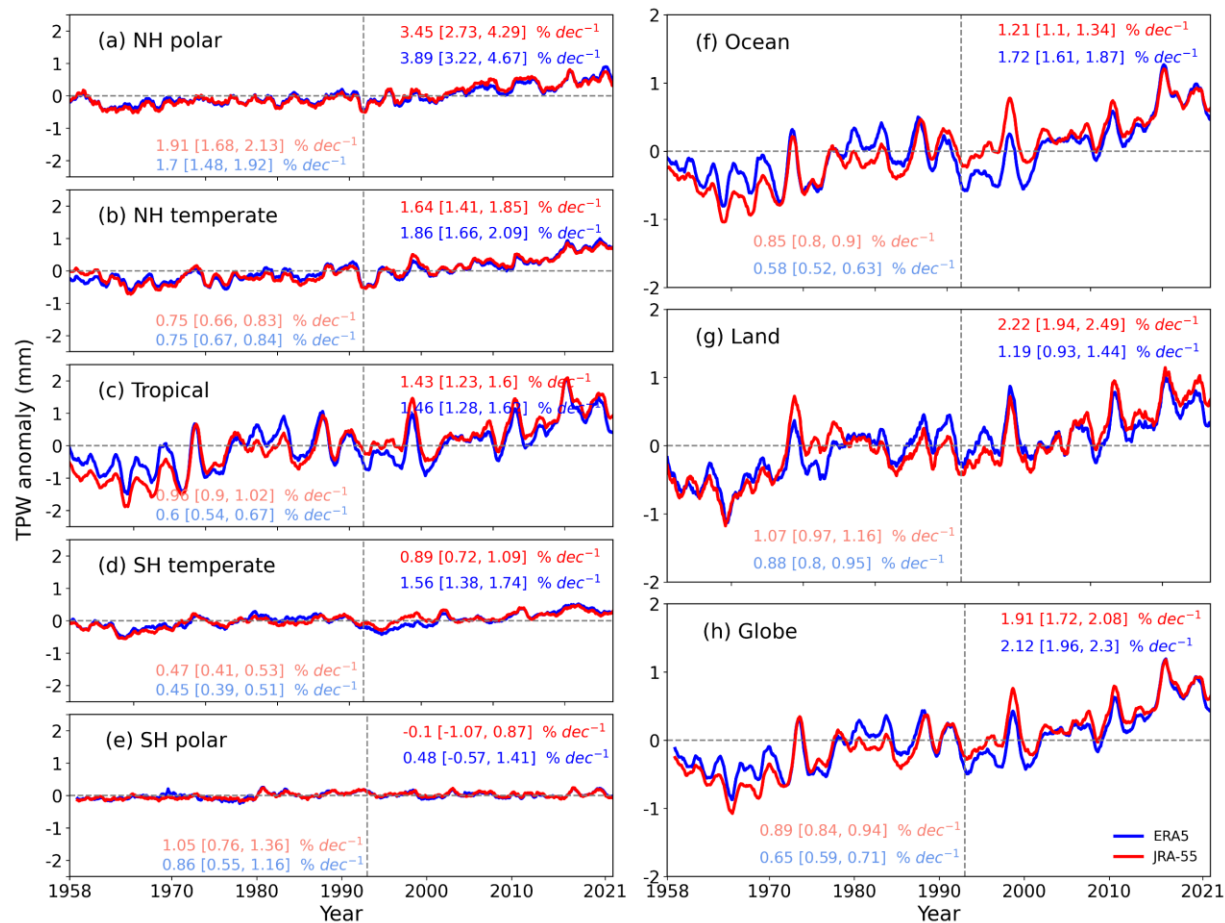


Figure 4.1 Time series of monthly TPW anomalies (mm) over (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, (e) SH polar, (f) ocean area, (g) land area, and (h) the globe from the ERA5 (blue) and JRA-55 (red) during the period 1958–2021. A 12-month running smoother was applied to each time series shown. The trends are shown for 1958–2021 (light color) and 1993–2021 (dark color) periods with 95% confidence intervals in brackets. The vertical line indicates the year of 1993.

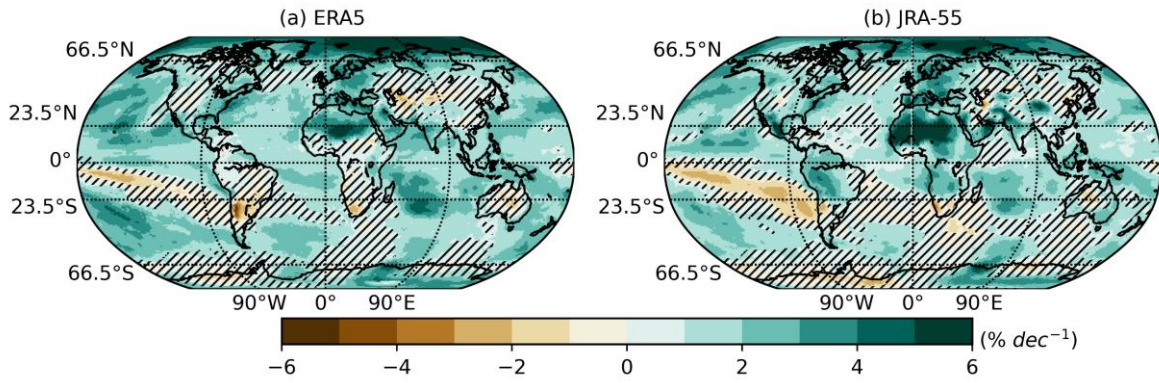


Figure 4.2 Monthly total precipitable water (TPW) trend ($\% \text{ dec}^{-1}$) from 1993 to 2021 from (a) ERA5 and (b) JRA-55. The hatch areas represent trends that are not statistically significant at a 95% confidence level.

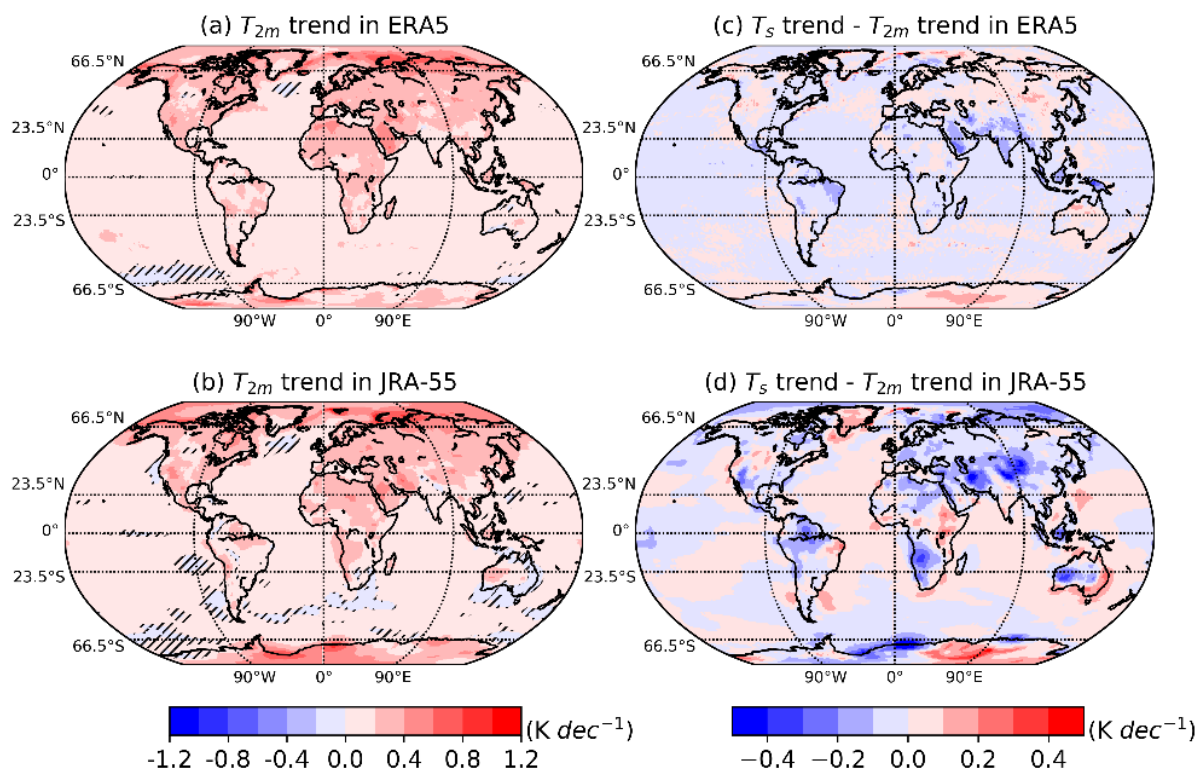


Figure 4.3 Trends of surface air temperature (T_{2m}) from 1958 to 2021 for ERA5 (a) and JRA-55 (b). The differential trends between T_s and T_{2m} trends for ERA5 (c) and JRA-55 (d). The hatch areas indicate trends that are not statistically significant. Trend units: $K dec^{-1}$.

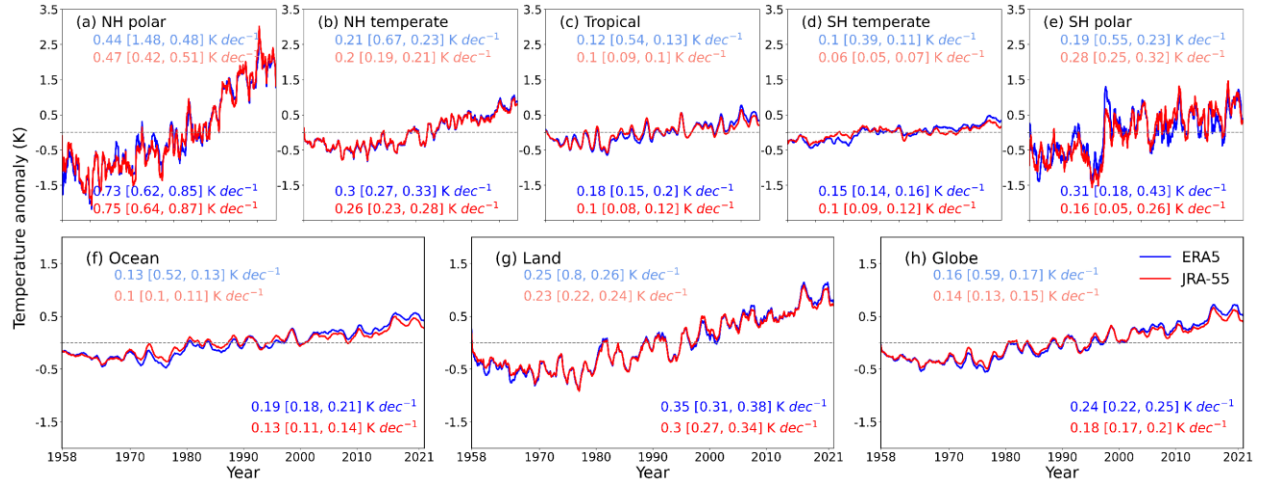


Figure 4.4 Monthly T_{2m} and T_s anomaly over (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, (e) SH polar, (f) ocean, (g) land, and (h) the globe from the ERA5 (blue) and JRA-55 (red) data sets during the period of 1958 to 2021. A 12-month running smoother was applied to all time series. The trends are shown for 1958-2021 (light color) and 1993-2021 (dark color) periods with 95% confidence intervals in brackets. The vertical line indicates 1993 year.

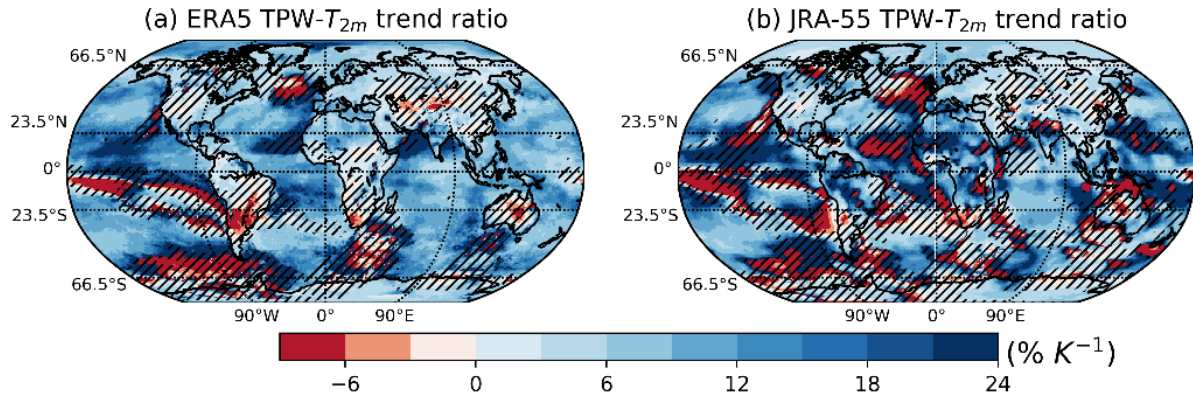


Figure 4.5 (a) The ratio (% K^{-1}) of the TPW trends and the surface air temperature (T_{2m}) trends from 1993 to 2021 in ERA5. (b) Same as (a) but for JRA-55. The hatch areas represent ratios that are not statistically significant at the 95% confidence level.

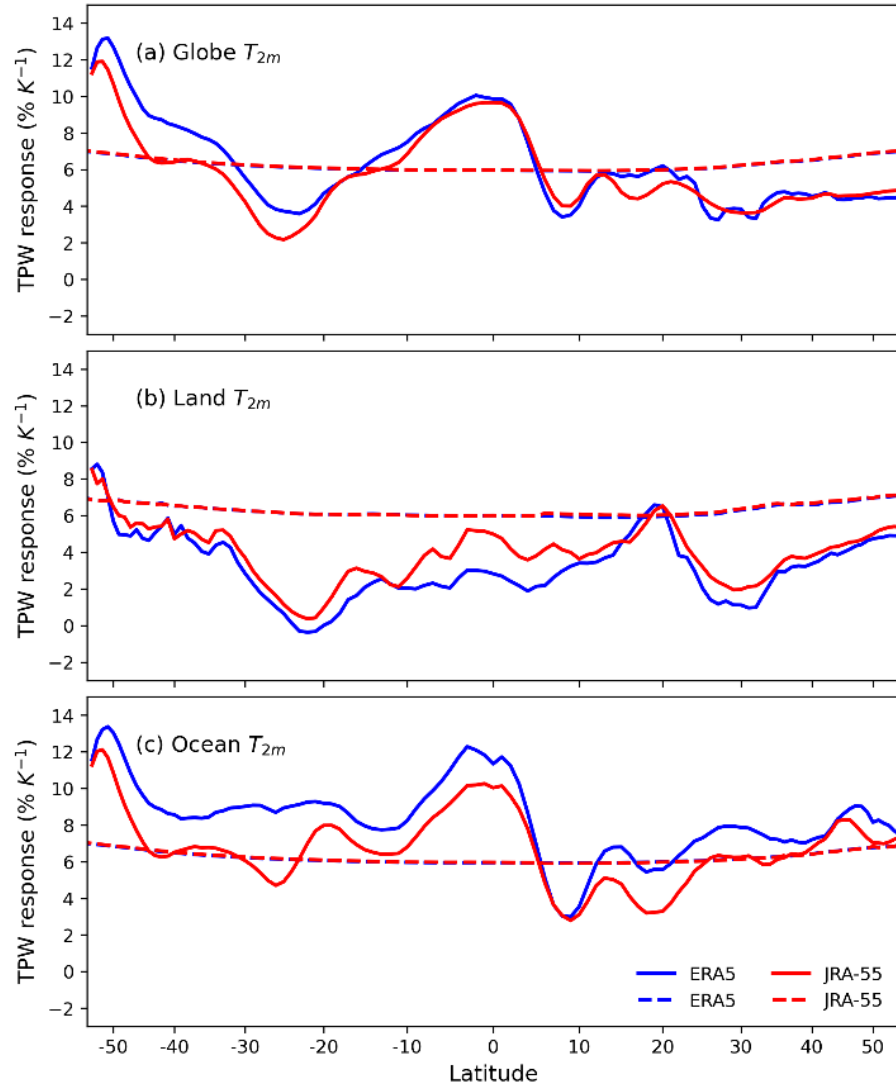


Figure 4.6 The meridional means of change of TPW response to T_{2m} for ERA5 (blue) and JRA-55 (red) over (a) globe, (b) land, and (c) ocean base using data from 1993 to 2021. The dashed lines represent the theoretically expected Clausius-Clapeyron response based on the climatological zonal mean temperature from the trend analysis.

Chapter 5 - Conclusions and Applications

The advent of large earth systems data like densely distributed observation networks, a large number of earth observation satellites, and improved modeling data, allowed statistic and computer science to be applied in research of large-scale comparisons across different regions to uncover the cause-effect relationship among huge datasets, solving the shortcomings of traditional field experiments that are limited in scale and may not capture the full complexity of real-world conditions. In this dissertation, I leveraged multi-source datasets (e.g., satellite remote sensing, surface observation and reanalysis datasets) and data-driven methods to conduct research toward understanding wildfire emission and its impact on agricultural productivity, as well as the trend of water vapor and its response to temperature under a warming climate. Specifically, my thesis integrated theories and methods from satellite remote sensing, atmospheric, biological, and statistics to 1) estimate the emission ratio from the Australian 2019/2020 bushfire with different vegetation fires, 2) quantify the magnitude of soybean yield loss due to air pollution from wildfires, 3) analyze the precipitable water and temperature change from 1958 to 2021 and quantify the relationship between water vapor and temperature.

First, I used an integrated mass enhancement method combined with data from a finer resolution satellite -TROPOMI- to quantify the emission of CO and NO₂ trace gases over savanna and temperate forest vegetation fires from the Australian 2019/2020 bushfire. The $\Delta\text{NO}_2/\Delta\text{CO}$ emission ratio was found to be 1.57 ± 1.71 for temperate forest fire and ranged from 2.0 ± 2.36 to 2.6 ± 1.92 for savanna fire. For savanna and temperate forest fires, satellite-derived NO_x emission factors were found to be 1.48 g kg^{-1} and 2.39 g kg^{-1} , respectively, whereas the CO emission factors are 107.39 and 126.32 g kg^{-1} , respectively. Our study demonstrates that the large-scale emission ratio from the TROPOMI satellite for different biomass burnings can help identify the relative contribution of smoldering and flaming activities in a large region and their impacts on the regional atmospheric composition and air quality.

Second, I used robust statistical models to investigate how wildfire smoke impacts soybean yield in non-wildfire-prone Midwestern US and the magnitude of yield loss due to air pollution from wildfire smoke. The results reveal that the heavy smoke days increased during the soybean's growing season from 2008 to 2022. Days with heavy smoke plumes have a negative impact on

yield, especially in more northern regions (e.g. Wisconsin, South Dakota, and North Dakota). Moreover, our results confirm that a decline in soybean yield loss because of reduced PM_{2.5} air pollution over the past 15 years. However, the damage of PM_{2.5} pollution from the wildfire source to soybean yield expresses the opposite change in that an increasing trend of yield loss happened in all states. The increases in wildfire smoke which other studies show are expected to continue under a warming climate, will offset the reduction of air pollution as the result of regionally based air quality regulation that focuses on controlling human-induced emissions. Our findings call for attention to yield damage from exposure to the smoke plume under climate warming-induced frequent and severe wildfires.

Third, we provide a valuable update on the regional changes in atmospheric water vapor content and surface temperature since 1958 based on the reanalysis dataset and observations. Our results indicate a global increase in total precipitable water (TPW) of ~2 % per decade from 1993 to 2021. These variations in TPW reflect the interactions of global warming feedback mechanisms across different spatial scales. Our results also revealed a significant near-surface temperature (T_{2m}) warming trend of ~0.15 K per decade during 1958-2021. Its consistent warming at a rate of ~0.21 K per decade after 1993 corresponds to a strong water vapor response to temperature at a rate of 9.5 % K⁻¹ globally, with land areas warming approximately twice as fast as the oceans. The relationship between TPW and T_{2m} showed a variation around 6 - 8% K⁻¹ in the 15-55 °N latitude band, aligning with theoretical estimates from the Clausius–Clapeyron equation.

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Appendix A - Supplemental Information for Chapter 3

The bias from Cinelli & Hazlett's method (2022) provided a robustness value (RV) for bringing the point estimate of smoke days exactly to zero ($RV_q=4.5\%$). It means that unobserved confounders that at least explain 4.5% of the residual variance both of the smoke days and of the yield to make the coefficient of smoke days is zero. In our result (Tables A-1), for precipitation (prcp and prcp2), the residual variation of the treatment ($R^2_{D \sim Z|X}$) and residual variation of the outcome ($R^2_{Y \sim Z|D, X}$) are both less than 4.5%, it means unobserved confounders like precipitation can't affect our results. For GDD and EDD, only $R^2_{D \sim Z|X}$ is less than 4.5%, then we plot the Sensitivity contour plots (figure A-6). The figure reveals that, at the 5% significance level, the null hypothesis of zero effect would still be rejected given confounders once, twice, or three times as strong as GDD. However, confounders as strong as EDD are sufficient to bring the reduced form, and hence also the IV estimate, to a region that is not statistically different from zero. That is if we are concerned that omitted variables as strong as EDD might exist, our result is biased.

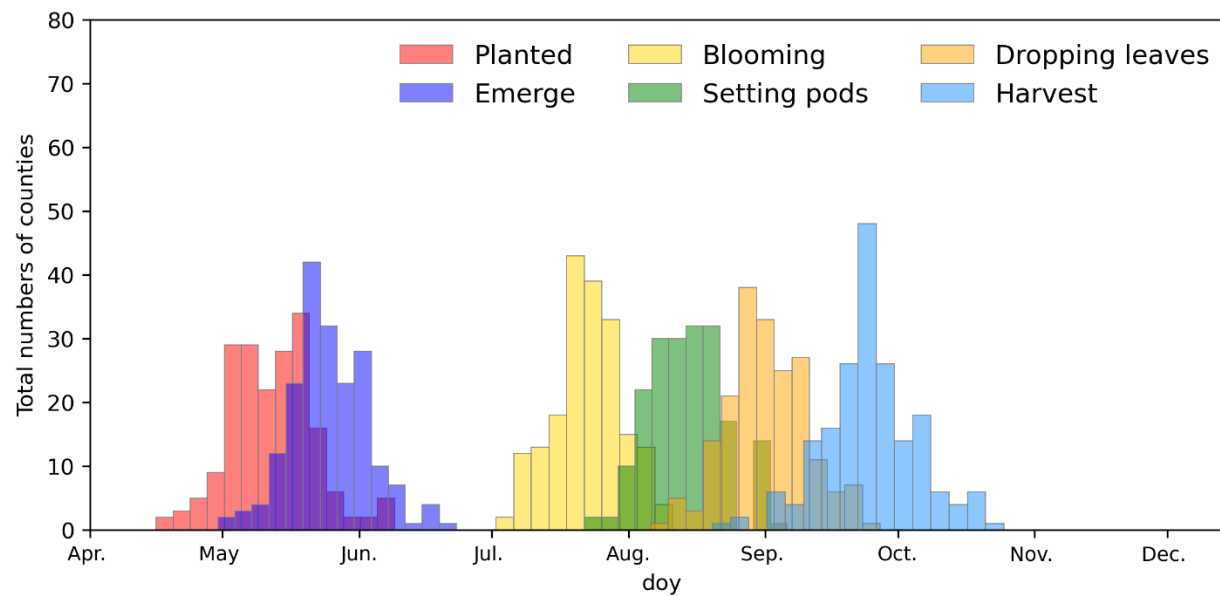


Figure A- 1 The histogram of soybean growing season. Each bar represents the total number of when more than 50% of acreage within a state-year reaches a crop stage (e.g. blooming) or practice (e.g. planting) from 2008 to 2022.

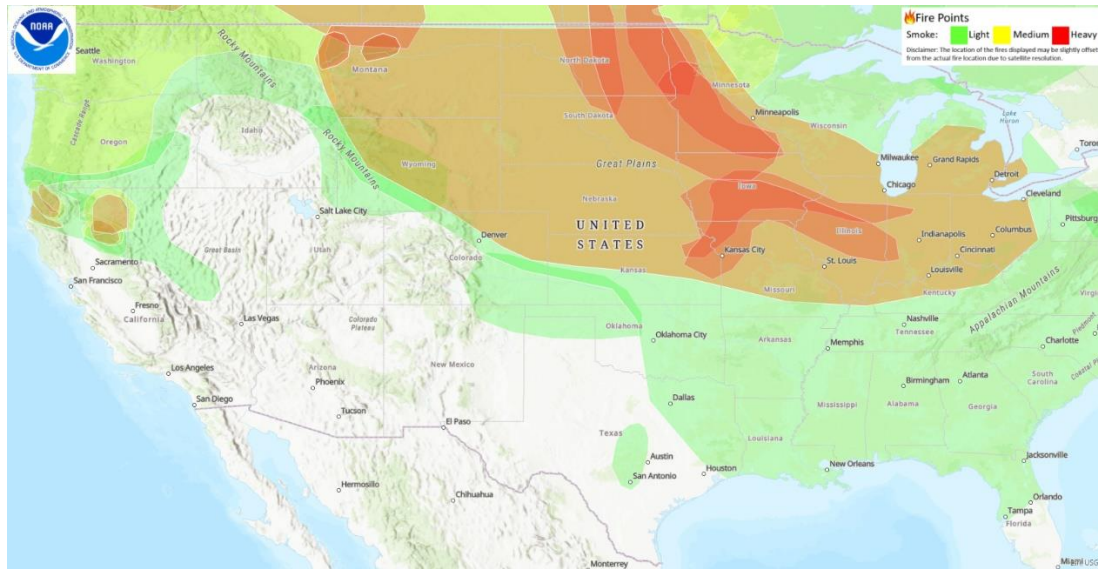


Figure A- 2 An example of smoke density map on August 1st, 2021. The data is provided by the NOAA Office of Satellite and Product Operations as part of the Hazard Mapping System Fire and Smoke Product, available: <https://www.ospo.noaa.gov/Products/land/hms.html#data>, accessed January 11, 2024.

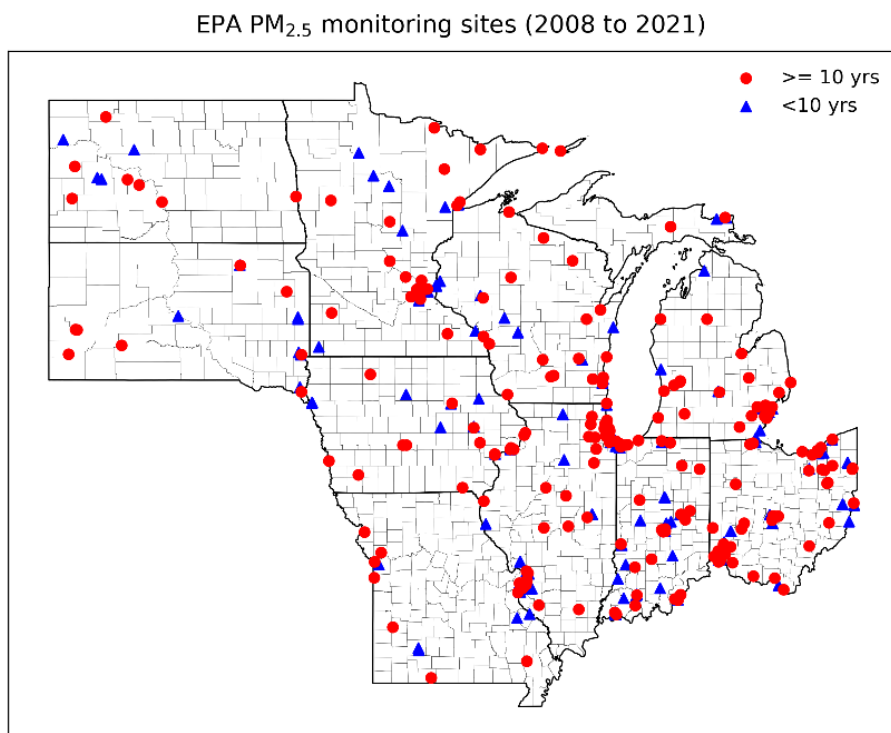


Figure A- 3 The Locations of EPA PM_{2.5} air pollution monitors from 2008 to 2022. The total number of each class monitor is 213 for < 10 years, and 154 for > 10 years, data source: https://aqs.epa.gov/aqsweb/airdata/download_files.html

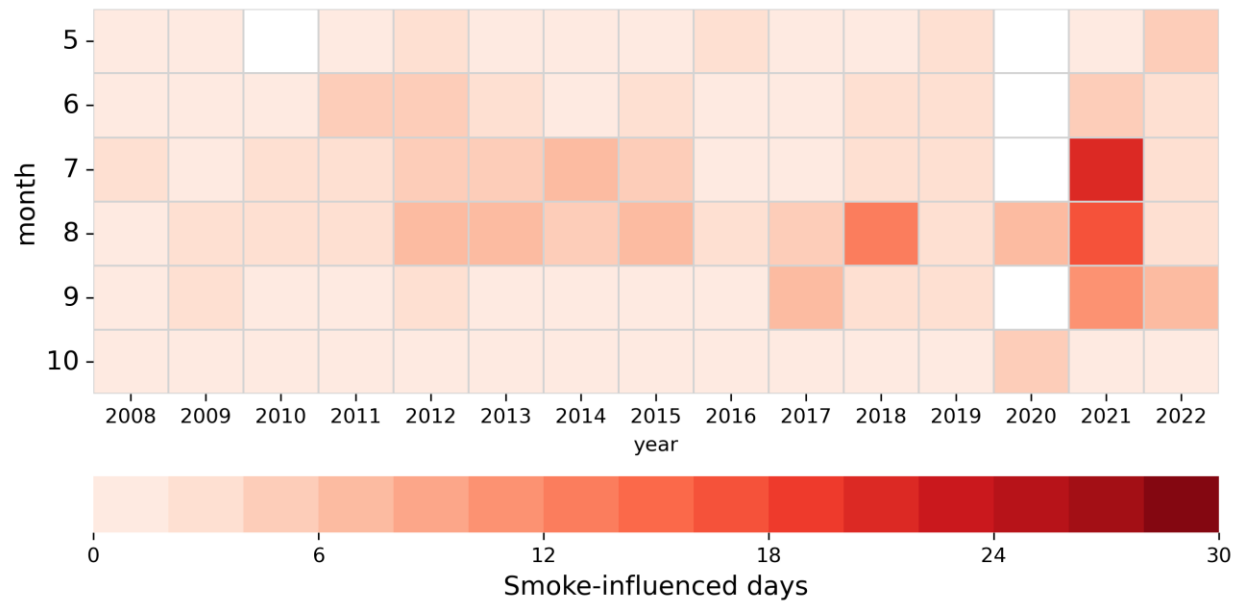


Figure A- 4 Time series change of total smoke-impacted days per growing season month (May-October) from 2008 to 2022

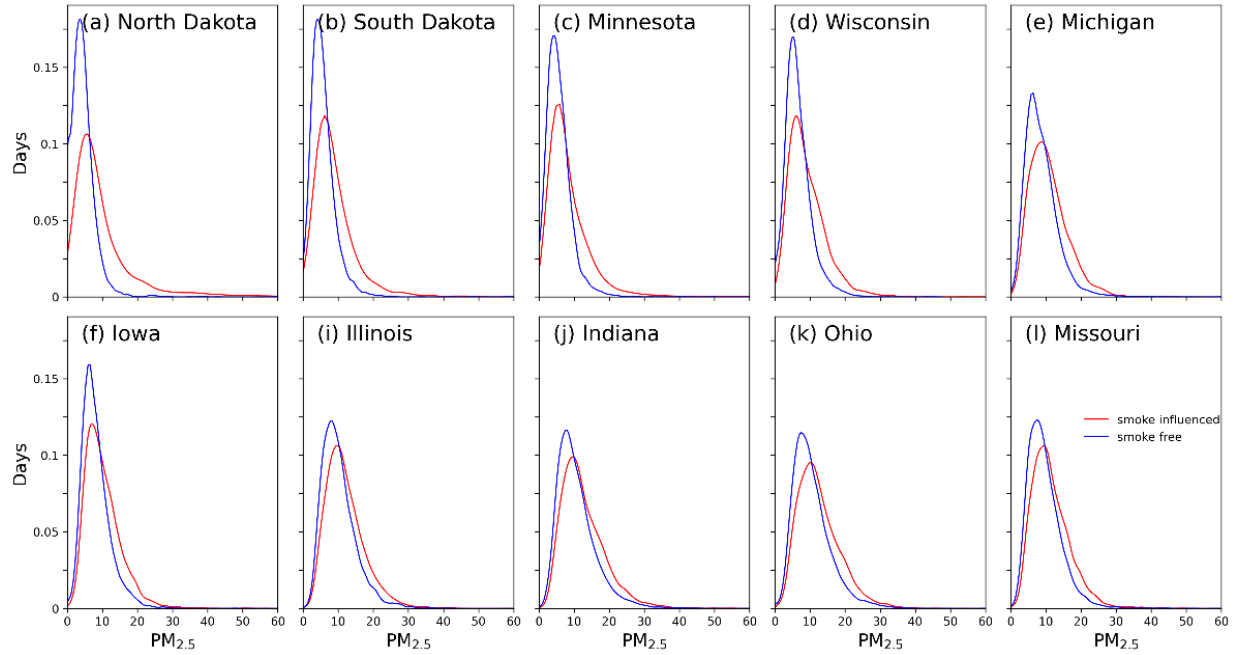


Figure A- 5 The Probability density estimates of observed daily average PM_{2.5} for smoke-influenced (red line) and smoke-free (blue line) for soybean emerge to setting pod period (June-August) from 2008 to 2022 in (a) North Dakota, (b) South Dakota, (c) Minnesota, (d) Wisconsin, (e) Michigan, (f) Iowa, (g) Illinois, (h) Indiana, (i) Ohio, (j) Missouri state.

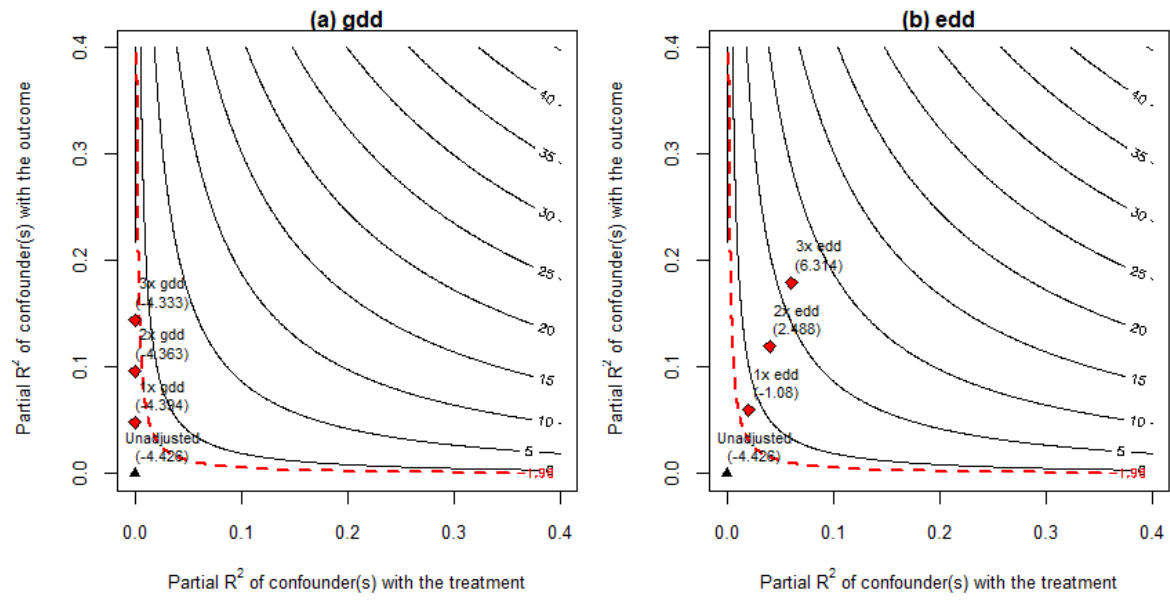


Figure A- 6 Sensitivity contour plots for the t-value of: (a) the GDD (b) the EDD.

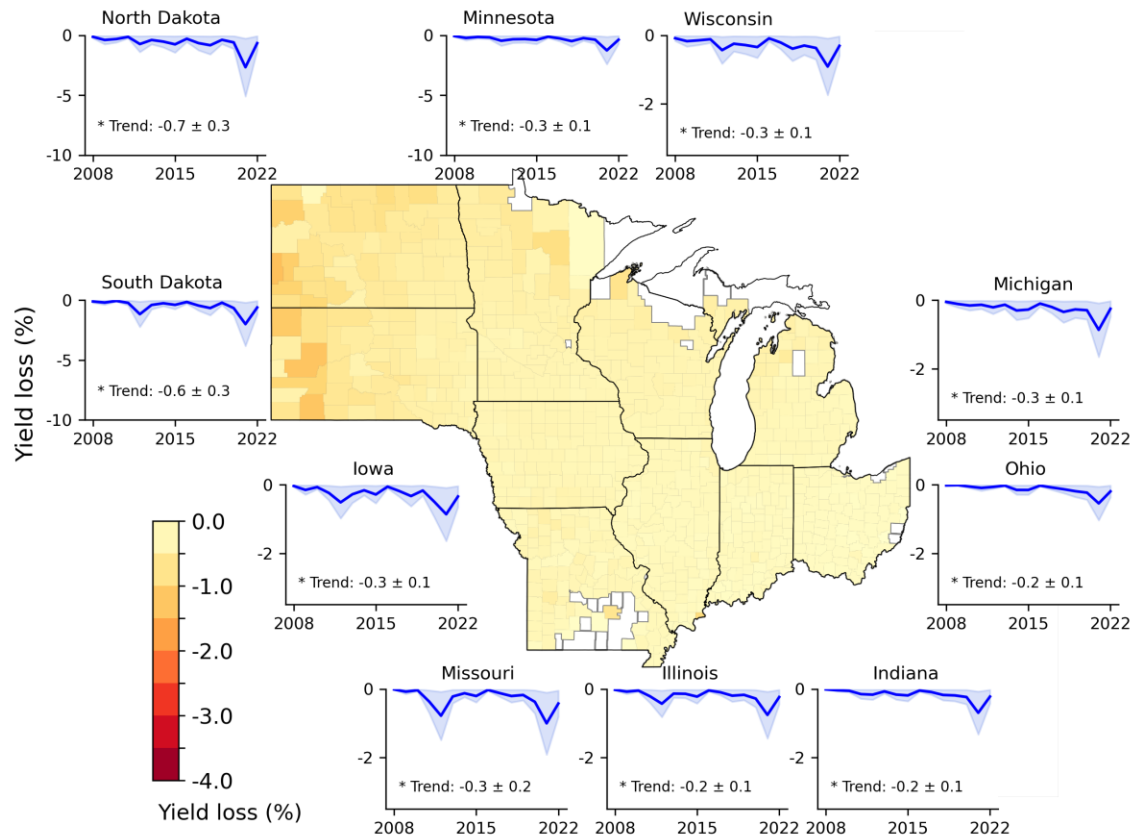


Figure A- 7 The effects of increased smoke days on soybean yields from 2008 to 2022, the graphs surrounding the maps represent the overall state changes in yield. The solid line indicates the mean and shaded areas indicate 5%-95% confidence intervals by 1,000 bootstrap estimates. Trends were significant and estimated using the ordinary least squares method of linear regression. Yield loss is represented as the percentage change relative to mean yield. Trend unit: % dec⁻¹.

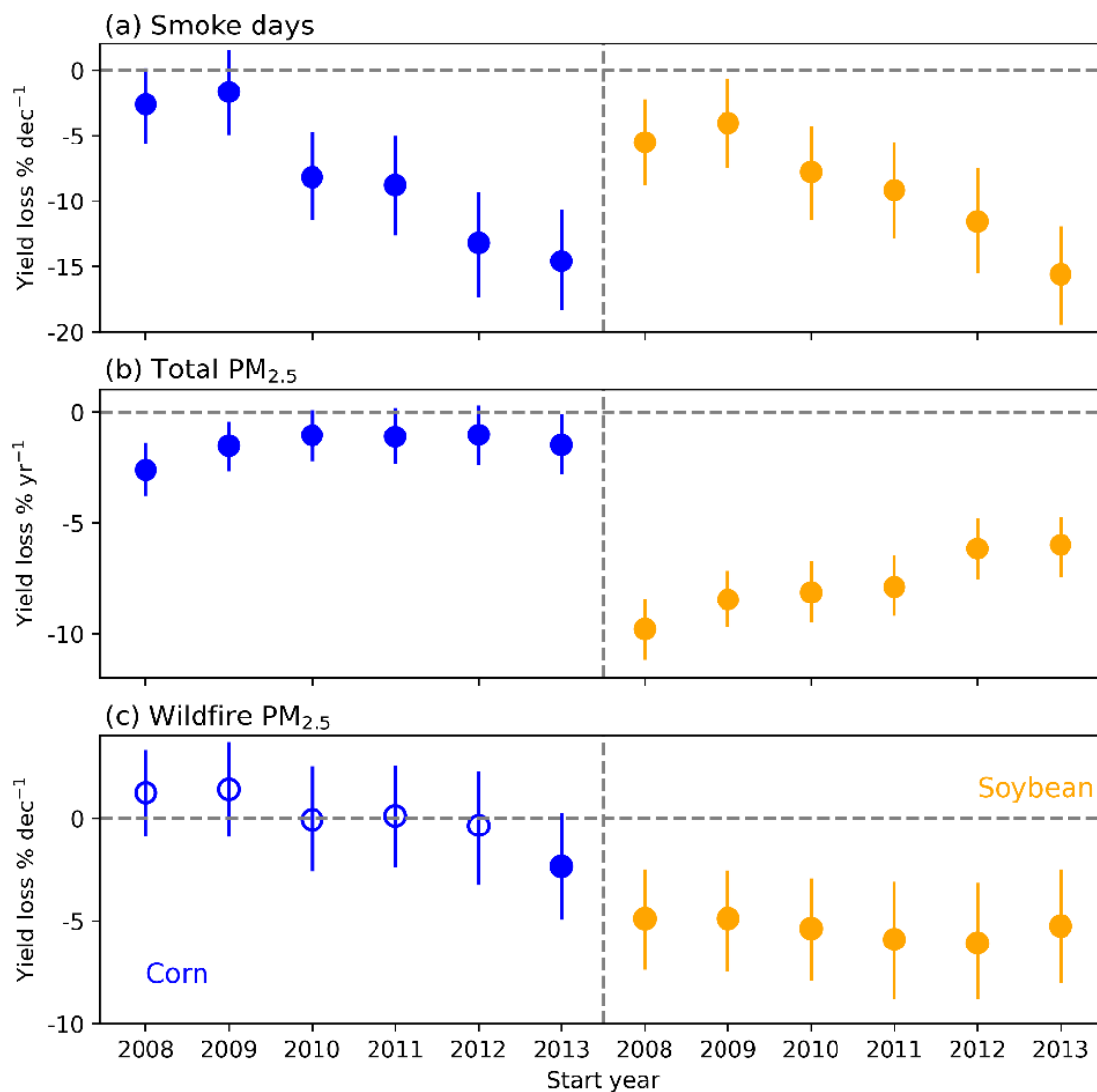


Figure A- 8 The sensitivity of corn (orange) and soybean (blue) response to (a) smoke days during May to October, (b) total PM_{2.5}, and (c) wildfire PM_{2.5} during June to August over segment years with different start years (range from 2008 to 2013) and same year (2022). Empty scatters mean the coefficients are not significant.

Table A- 1 Minimal sensitivity reporting of the reduced form regression, robust value ($RV_{q=1}$ and $RV_{q=1, \alpha=0.05}$), and partial R^2 of treatment with the outcome are sensitivity statistics.

Outcome: yield						
Treatment	Estimate	Std. Error	t-value	$R^2_{Y \sim D X}$	$RV_{q=1}$	$RV_{q=1, \alpha=0.05}$
Smoke days	-0.0018	0.0004	-4.43	0.21%	4.5%	2.5%

Table A- 2 The bounds of unobserved confounders: the residual variation of the treatment ($R^2_{D \sim Z|X}$) and residual variation of the outcome ($R^2_{Y \sim Z|D, X}$)

	$R^2_{D \sim Z X}$	$R^2_{Y \sim Z D, X}$
Prcp	0.07%	6.7%
Prcp ²	0.03%	5.7%
GDD	0	4.8%
EDD	2%	6.0%

Table A- 3 Ordinary least squares (OLS), Reduce Form, and IV Estimates for soybean from June to August: Satellite-Based PM_{2.5} Sample, standard errors are included in the bracket for soybean.

soybean	Average sources			Isolate wildfire-specific	
	Smoke impact (May-Sep.)	OLS	Reduce form	IV first stage	IV second stage
	Yield	Yield	Yield	PM _{2.5}	Yield
PM _{2.5}		-0.037* (0.003)	/	/	-0.013* (0.003)
smoke days	-0.002* (0.004)	/	-0.002* (0.0004)	0.1357* (0.002)	/
GDD	0.002* (0.0000)	0.002* (0.00007)	0.002* (0.00007)	0.008* (0.0002)	0.002* (0.00007)
EDD	-0.003* (0.0001)	-0.002* (0.0001)	-0.002* (0.0001)	-0.004* (0.0002)	-0.002* (0.0001)
P	0.0024* (0.0002)	0.005* (0.0002)	0.005* (0.0002)	-0.0011* (0.0006)	0.005 (0.0002)
P ²	-0.000018 (0.0000)	-0.000005* (0.0000)	-0.000005* (0.0000)	-0.000001* (0.0000)	-0.000006 (0.0000)
year	0.05* (0.001)	0.04* (0.001)	0.05* (0.001)	-0.33* (0.002)	0.05* (0.001)
Wu-Hausman					P<0.01
F-statistic				P<0.01	
Observations	10066	10066	10066	10066	10066
Adjusted R ²	0.77	0.77	0.77	0.82	0.77
county fixed	Yes	Yes	Yes	Yes	Yes

* p<0.01

Table A- 4 Smoke impact during May to September, Ordinary least squares (OLS), Reduce Form, and IV Estimates for soybean from June to August: EPA Monitor-Based PM_{2.5} Sample, standard errors are included in the bracket for soybean.

soybean	Smoke impact (May-Sep.) Yield	Average sources		Isolate wildfire-specific	
		OLS	Reduce form	IV first stage	IV second stage
		Yield	Yield	PM _{2.5}	Yield
PM _{2.5}		-0.01* (0.009)	/	/	-0.001 (0.01)
smoke days	0.0006 (0.001)	/	-0.0001 (0.004)	0.12* (0.003)	/
GDD	0.001* (0.0001)	0.001* (0.0001)	0.001* (0.0002)	0.007* (0.0005)	0.001* (0.0002)
EDD	-0.002* (0.0003)	-0.001* (0.0003)	-0.001* (0.0009)	-0.002* (0.0009)	-0.001* (0.0003)
P	0.004* (0.001)	0.005* (0.0002)	0.006* (0.001)	-0.0001 (0.002)	0.006 (0.001)
P ²	-0.0000* (0.0000)	-0.0000025* (0.0000)	-0.000002* (0.0000)	-0.000001 (0.0000)	-0.000002 (0.0000)
year	0.05* (0.005)	0.05* (0.003)	0.05* (0.004)	-0.34* (0.02)	0.05 (0.003)
Wu-Hausman					P=0.65
F-statistic				P<0.01	
Observations		2643	2643	2643	2643
Adjusted R ²		0.74	0.74	0.68	0.74
county fixed		Yes	Yes	Yes	Yes

* p<0.01

Appendix B - Supplemental Information for Chapter 4

B.1 The relationship of T_s and T_{2m}

The comparison of long-term changes between T_s and T_{2m} in reanalyses over the ocean, land, and globe as shown in Figure B-4. T_s and T_{2m} show very similar interannual variations although some discrepancies exist in years, especially prior to the 1980s. The two are much closer thereafter when multiple satellite observations are assimilated in reanalyses, indicating the overall coupling between T_s and T_{2m} . In addition, the correlation of T_s and T_{2m} is strong (>0.9) and the trends aren't significantly different (student t-test) over ocean, land, and global regions. For the variability over different latitude bins in Fig. B-5 the discrepancy is the largest over polar area, with values around 0.4 K in JRA-55 and 0.2 K in ERA5. The difference between T_s and T_{2m} decreases after 1979 as more observations become available. Meanwhile, the trends of T_s and T_{2m} for the same latitude region aren't significantly different.

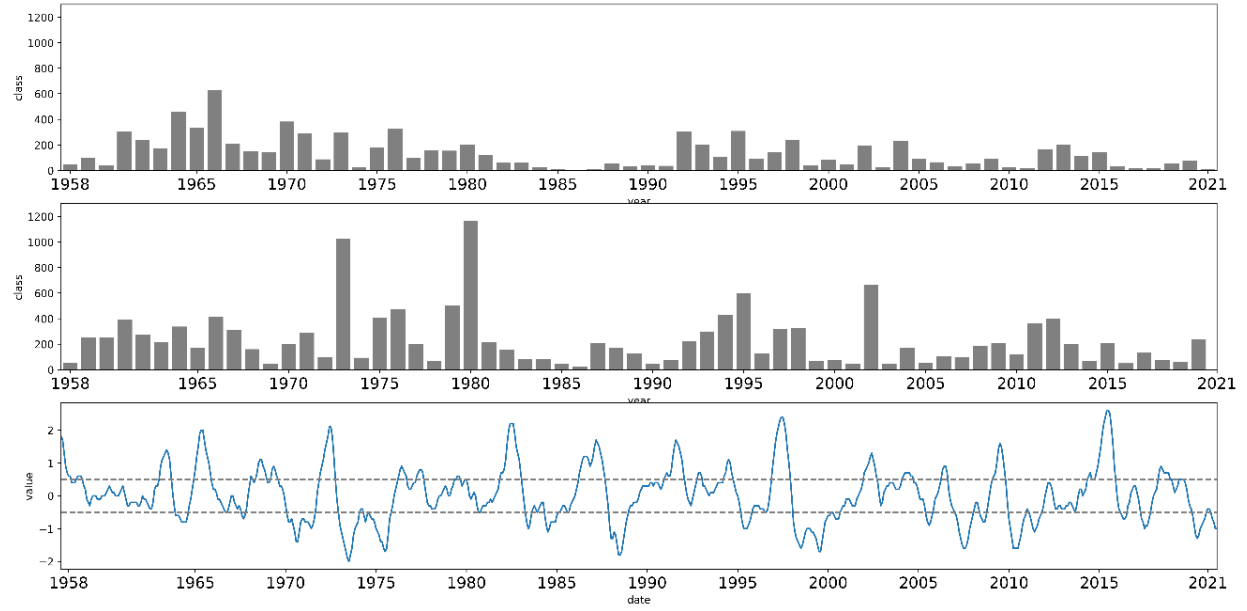


Figure B-1 Detected change points for monthly temperature during 1958-2021 in (a) ERA5 and (b) JRA55. (c) The timeseries of Oceanic Niño Index (ONI) from 1958 to 2021. There is a total 21,307 of grids for PMF-test over the ocean.

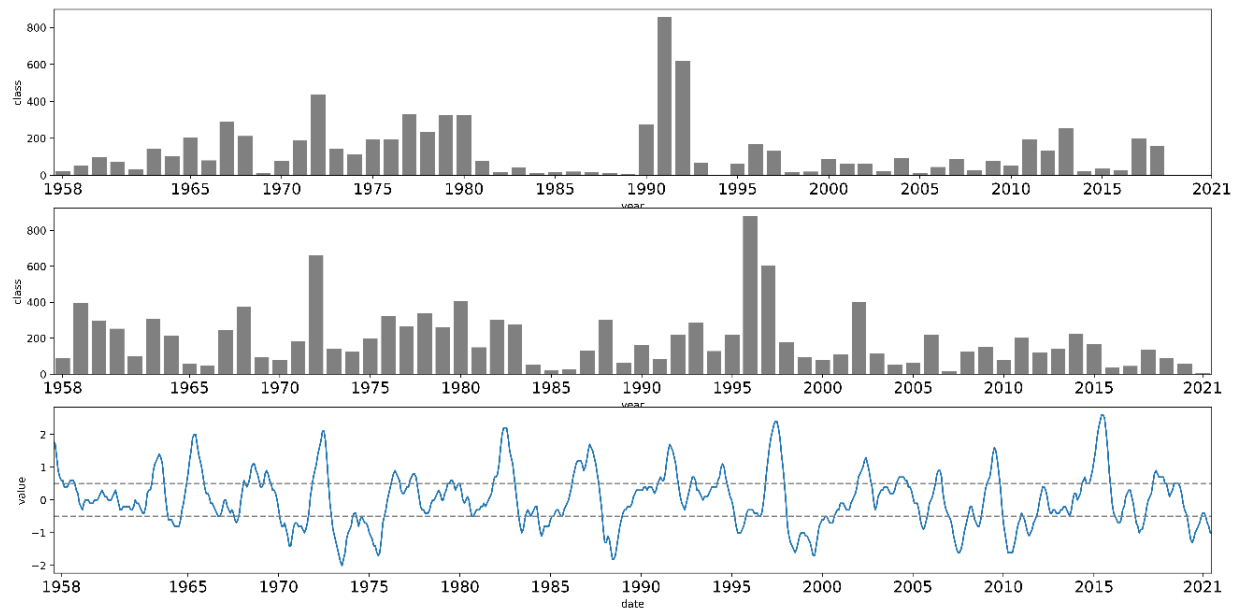


Figure B-2 Histogram of years with detected change points for total precipitable water in ERA5 (a) and JRA-55 (b). (c) The timeseries of Oceanic Niño Index (ONI) from 1958 to 2021.

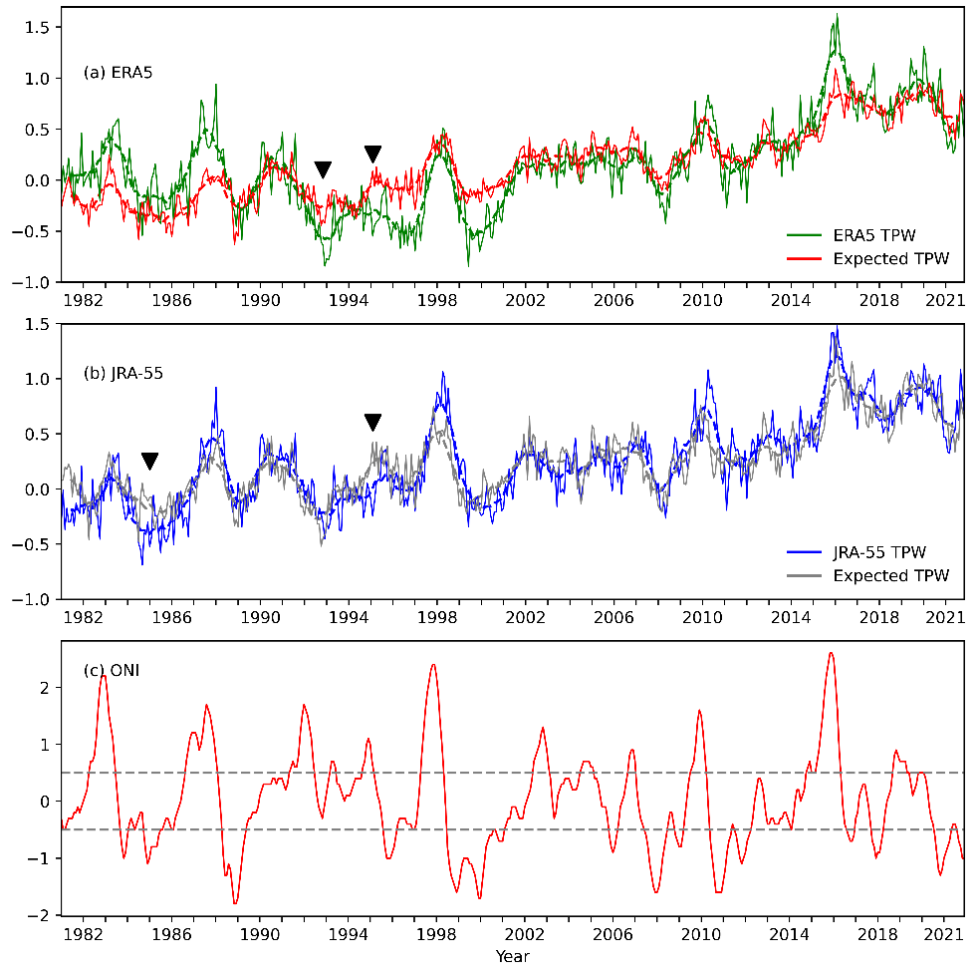


Figure B- 3 The variability of TPW and expected TPW calculated from regression with temperature for ERA5 (a) and JRA-55 (b). (c) The timeseries of Oceanic Niño Index (ONI) index from 1981 to 2021. Discrepancies are marked by triangles.

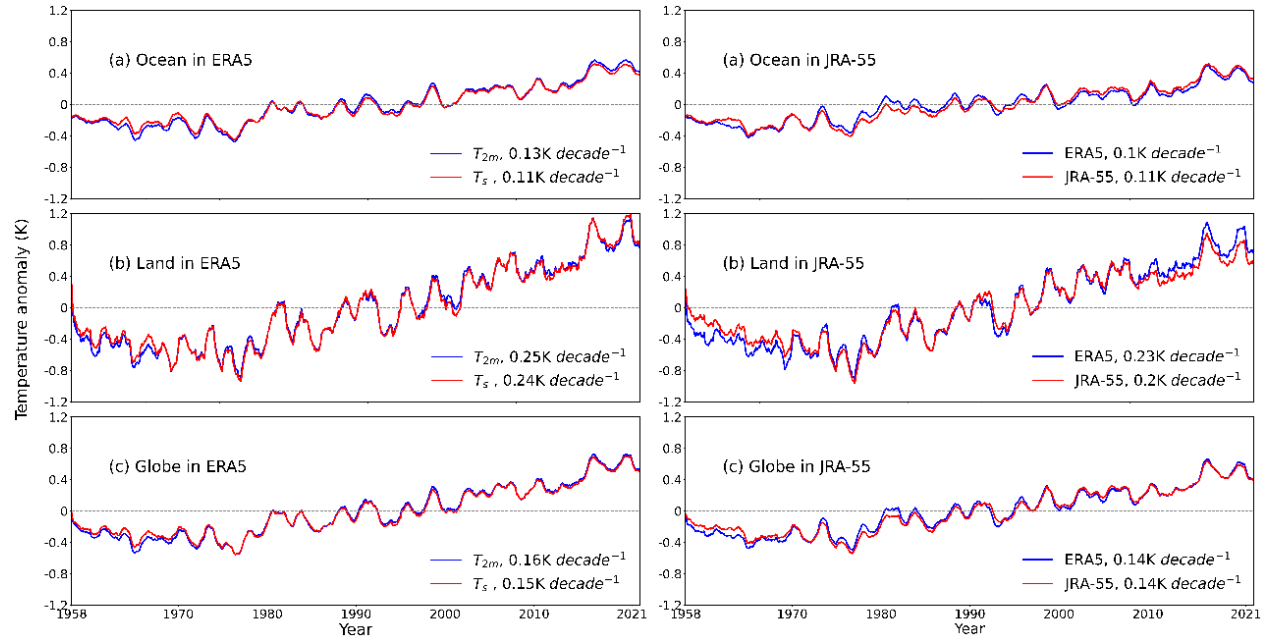


Figure B- 4 The relationship of monthly T_{2m} and T_s over land, ocean, and global for EAR5 (first column) and JRA-55 (second column).

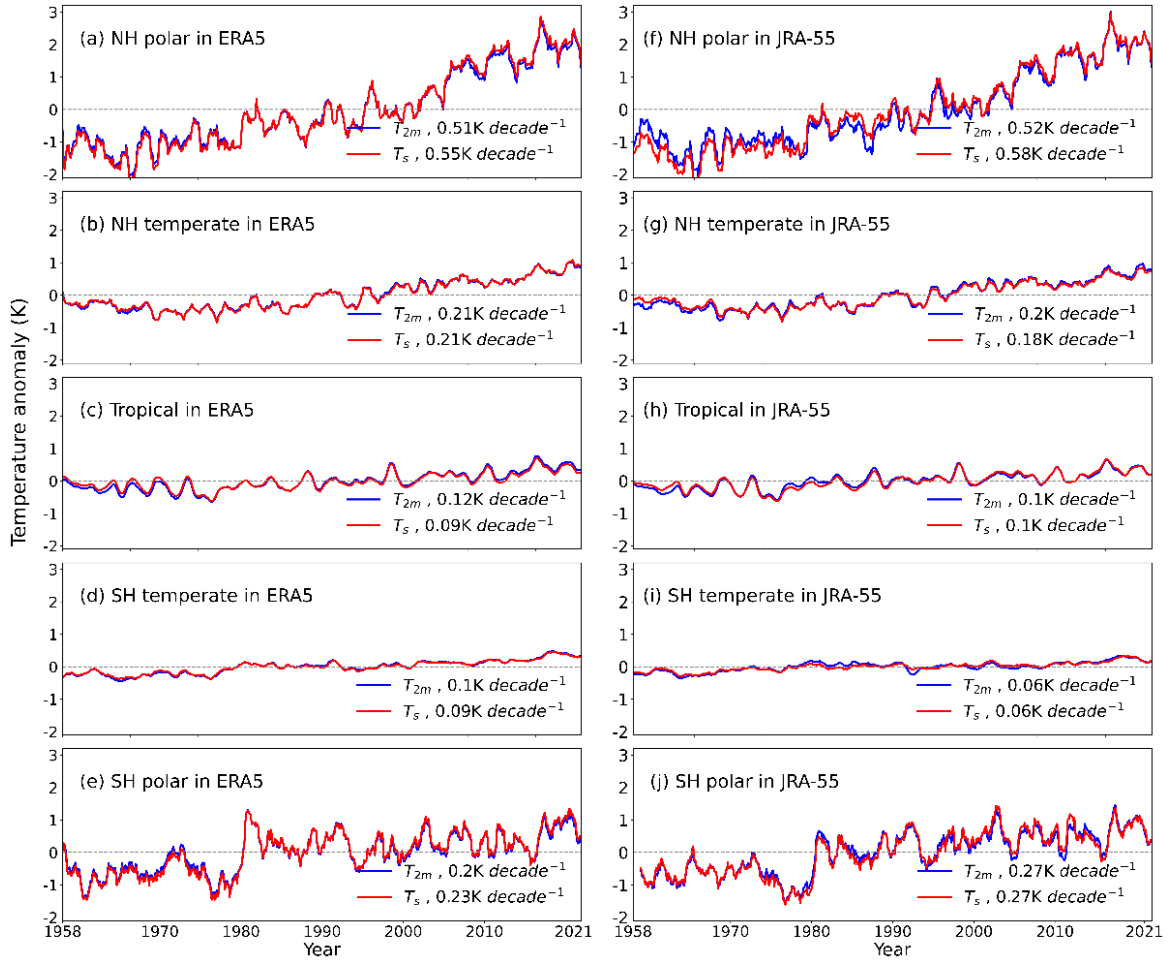


Figure B- 5 The same as Figure R4 but for (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, and (e) SH polar.

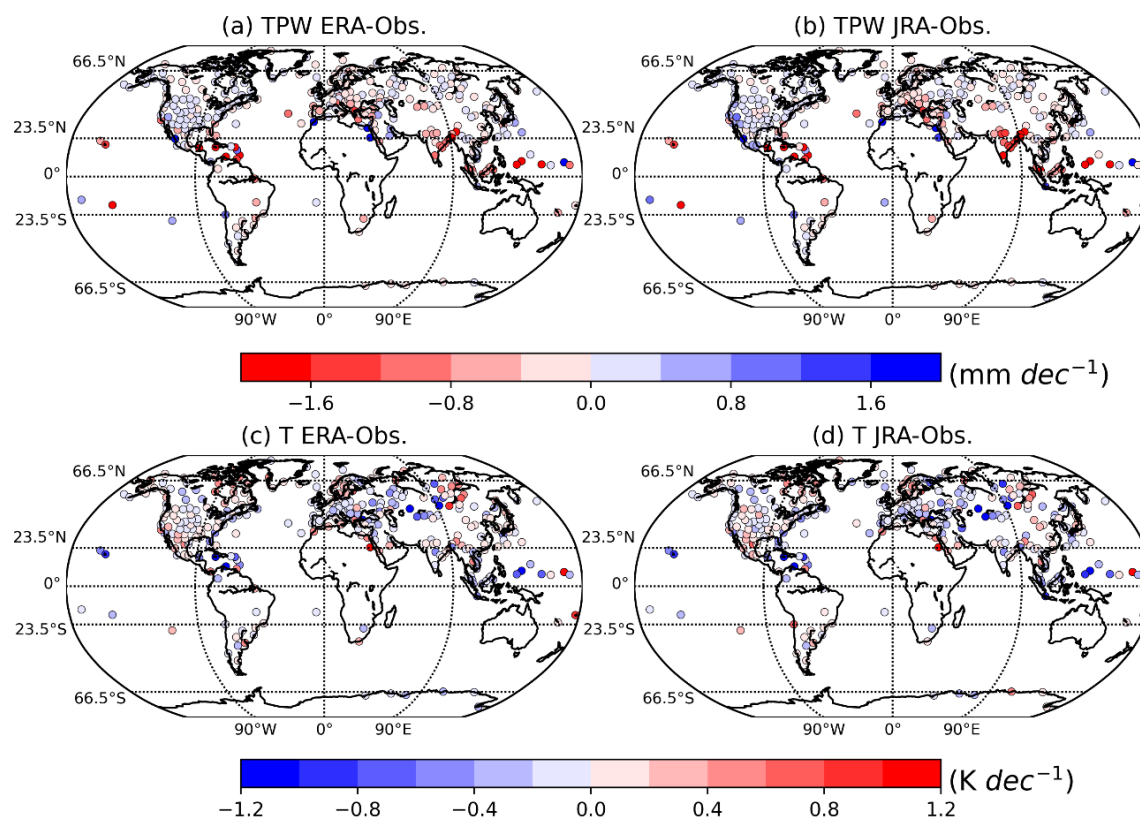


Figure B- 6 Trend comparisons with radiosondes: (a-b) TPW trends' difference ($mm\ dec^{-1}$) between radiosonde observations and ERA5 and JRA-55 from 1979-2019. (c-d) Same as (a-b) but for temperature trends' difference ($K\ dec^{-1}$). A total of 331 radiosonde observations were used in the analysis.

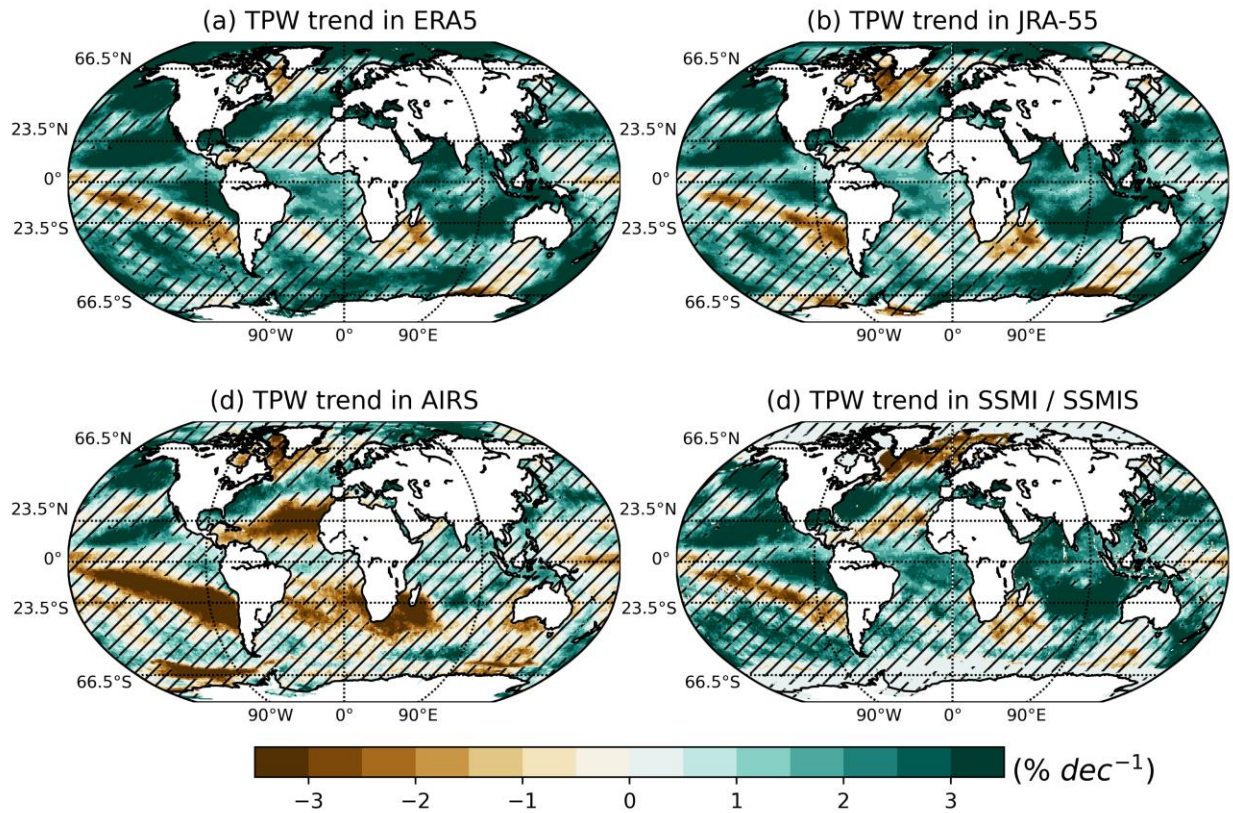


Figure B-7 Trend comparisons with satellite observations from 2003-2021: Total precipitable water (TPW) trends over oceans for (a) ERA5, (b) JRA-55, (c) AIRS satellite, and (d) SSMI satellite. The hatch areas represent trends that are not significant at a 95% confidence level.