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**Study on the effects of anthropogenic activities
and climate change on atmospheric environment
by remote sensing technology**

(リモートセンシング手法を用いた人間活動と気候変動が
大気環境に及ぼす影響に関する研究)

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Abstract

Anthropogenic activities play an important role on the change of our atmospheric environment. Urbanization, industrialization, special topography and unfavorable meteorological conditions have induced significant degradation of air quality around the world. Since air quality is closely related to morbidity and mortality from respiratory and cardiovascular diseases, this issue is drawing increasing concern from the environmental health research community, environmental regulatory agencies, industries, as well as the public. Moreover, fossil fuel remains the global major source of energy, which produce massive primary aerosols, SO_2 and NO_x . These gases combining with certain meteorological condition furtherly lead to the formation of secondary aerosols. Human evolution is closely related to the use of fire and air pollutions from biomass burning has been humanity's constant companion for thousands of years. Many researches have revealed that biomass burning account for a large proportion of global biomass consumption and caused severe air pollution.

With respect to climate change, its relationship with atmospheric environment is more subtle and complicate. CO_2 and other greenhouse gas help reduce the back-radiation of heat from the earth to the stratosphere and space which is responsible for the global warming. These temperature changes will have an impact on other air components, such as ozone, and exacerbate air pollution. Ocean, as the biggest carbon sink, is supposed to absorb over 80% of CO_2 . Thus, changes in Sea Surface Temperature (SST) could significantly affect the CO_2 concentration of the Earth.

The main objective of this research is to investigate the effects of anthropogenic activities and climate change on atmospheric environment. This requires various information to explore the features of changing atmosphere and understand the mechanism of the changing process. To achieve this objective, remote sensing data combining with meteorological data and ground-measured data have been used to identify air pollution, climate change, biomass burning, etc. The more specific objectives are outlined below: **i.** analyzing spatial distribution of crop residue burning and $\text{PM}_{2.5}$ (particulate matter with a diameter of 2.5 micrometers or less) change in China. In this part, MODerate Resolution Imaging Spectroradiometer (MODIS) Thermal Anomalies/Fire products and land cover products were used to extract the crop residue burning spots in China. Furtherly, the tempo-spatial distribution of crop residue burning was characterized and the relationship between crop residue burning and $\text{PM}_{2.5}$ change was explored. **ii.** examining the spatial distribution and formation conditions of severe haze pollution in Northeastern China. Combining ground-measured data with satellite data, the $\text{PM}_{2.5}$ pollution episodes in three provinces, Heilongjiang, Jilin and Liaoning, were analyzed. Many factors have been

taken into consideration and I suppose this comprehensive method is effective to find the origin and discover the formation condition of severe PM_{2.5} pollution in Northeastern China. **iii.** analyzing CO₂ concentration changes and their influencing factors in Indonesia. In this part, I proposed a new method to use Orbiting Carbon Observatory 2 (OCO-2) Level 2 products to analyze the distribution of CO₂ in the world's biggest island country, Indonesia. **iv.** investigating the effects of climate and El Niño-Southern Oscillation (ENSO) on the temporo-spatial changes of CO₂ and precipitation in Australia. In this section, combining Greenhouse Gases Observing Satellite (GOSAT) with OCO-2, the relationship between CO₂ and other climate factors in Australia has been explored. Furtherly, the abnormal change of precipitation and CO₂ concentration during the occurrence of ENSO events were presented.

This thesis is made up of six chapters. In Chapter 1, I made a brief introduction of the thesis, which mainly included the research background, research aim and research content. In the last part, Chapter 6, I summarized the new findings and innovative methods in this study. Based on that, I eventually proposed how to conduct future researches. Chapter 2 to Chapter 5 are the main research content and the specific as follows.

Chapter 2: With China as the study area, MODIS MOD14A1 and MCD12Q1 products were used to derive daily crop residue burning spots from 2014, 2015. After vectorization of crop residue burning pixels and with the use of fishnet, burning density distribution maps were eventually completed. Meanwhile, the daily air quality data from 150 cities in 2014 and 285 cities in 2015 were used to obtain daily and monthly PM_{2.5} distribution maps with the Kriging interpolation. The results indicate that crop residue burning occurs in a seasonal pattern, and its spatial distribution is closely related to farming activities. The annual PM_{2.5} in China decreased 11.81% from 2014 to 2015, and the distribution of PM_{2.5} in China's east and north is always higher than in China's west and south. Furthermore, the changes in PM_{2.5} exhibit a hysteresis after crop residue burning in summer and autumn-winter. Regarding summer crop residue burning in China's middle-east, the correlation coefficient r between crop residue burning spots and PM_{2.5} is 0.6921 ($P < 0.01$) in 2014 and 0.5620 ($P < 0.01$) in 2015, while the correlation coefficient of autumn-winter crop residue burning in China's northeast is slightly lower with an r of 0.5670 ($P < 0.01$) in 2014 and 0.6213 ($P < 0.01$) in 2015. In autumn-winter, crop residue burning can induce evident PM_{2.5} increase in China's northeast, and that is more obvious than summer crop residue burning in China's middle-east. Furthermore, when data of summer and autumn-winter crop residue burning from 2014 and 2015 are compared, we can see that the change in number of crop residue burning spots significant affects PM_{2.5} in these regions. Both the summer and autumn-winter crop residue burning areas presented spatial consistency with high PM_{2.5}. By contrast, the

results from many aspects indicated that the crop residue burning in spring did not cause a notable change of PM_{2.5}.

Chapter 3: In this study, I used ground-measured air quality, meteorological data and multiple remote sensing datasets to analyze the severe particulate matter pollution episodes of October and November 2015 in Northeastern China. The results showed that the causes of high PM_{2.5} in three episodes and in each province were completely different. The daily change and spatial distribution of other air components, such as CO, NO₂ and SO₂, were analyzed during the occurrence of the PM_{2.5} pollution episodes. Moreover, by analyzing the changes of PM_{2.5} and other air components with crop residue burning spots extracted from MODIS products, I concluded that crop residue burning greatly contributed to the pollution episodes in this region. In October and November, there were 19,790 crop residue burning spots in Northeastern China, which was much more than in other years. Primary aerosols from crop residue burning as well as secondary aerosols formed by special meteorological conditions and aerosol transportation significantly contributed to the severest episode near the 8th of November. Both the backward and forward trajectory models suggested that the pollutants from Heilongjiang Province exacerbated the pollution in Jilin and Liaoning Provinces during the third episode. Aerosol Optical Depth (AOD), Aerosol Absorption Optical Depth (AAOD), Ultraviolet Aerosol Index (UVAI) and CO from remote sensing and ground-measured datasets were compared; the results indicated that there was a significant correlation and spatial consistency between the two types of datasets, except for UVAI. This study proposes a comprehensive method that combines remote sensing datasets with ground-measured air quality and meteorology datasets to analyze and monitor pollution episodes.

Chapter 4: I used OCO-2 products and considered three factors that potentially affect CO₂ concentration in Indonesia: SST, forest fires and vegetation. From 2014 to 2016, CO₂ concentration in Indonesia showed a trend of increase, which is consistent with the global increase reported by GOSAT Project. As an archipelago country, the results indicate that SST has a direct effect on the CO₂ concentration in Indonesia. Their changing exhibit similar fluctuations, meanwhile, CO₂ concentration and SST also presented positive correlation. In 2015, the number of fire hotspots suddenly increased to 140,699, because of occurrence of the worst forest fire. Due to special geographic conditions, forest fires did not induce CO₂ concentration changes in Indonesia but CO₂ concentration in the corresponding islands showed a trend of increase. CO₂ concentration increased in Kalimantan during the occurrence of forest fire in September-October 2014, and CO₂ concentration increased in Kalimantan and Sumatra during the occurrence of forest fire in September-October 2015. Vegetation indices were stable and presented no correlation with CO₂ concentration. This study

demonstrated that OCO-2 is capable of monitoring CO₂ concentration at a regional scale; additionally, an effective method for using OCO-2 Level 2 products is proposed.

Chapter 5: The temporo-spatial changes in the CO₂ concentrations in Australia from June 2009 to December 2016 were analyzed using greenhouse gas monitoring satellites, GOSAT and OCO-2. In addition, meteorology, climate types and land cover were considered to characterize the changes in CO₂, precipitation and their mutual effects have been analyzed. The satellites both showed that the CO₂ concentration in Australia tended to increase. The spatial distribution of CO₂ in central Australia was always higher than that of other regions, and I assumed that the precipitation directly affected the spatial pattern of CO₂ in Australia. Combining the results with the Köppen-Geiger climate classification, the spatial distribution of CO₂ was found to be closely related to the various climate types. Precipitation, SST around the coastal region, vegetation cover and other factors were assumed to jointly affect the regional CO₂ concentration. Moreover, I found the abnormal SST in the 4 Niño zones would affect the precipitation in Australia, and there was a strong correlation between SST anomalies around the tropical equatorial Pacific and precipitation in Australia. According to the Niño-3 and Niño-3.4 indices, there were two ENSO events during the study period. One event was a La Niña around 2011, and the other one was an El Niño around 2015. The CO₂ increase rate decelerated and precipitation was higher in the period of the La Niña, while, CO₂ increase rate accelerated and precipitation was lower in the period of the El Niño. The abnormal SST in the equatorial Pacific during the ENSO events is assumed to lead to this phenomenon.

This thesis explored effective methods to extract daily crop residue burning spots and how to transfer OCO-2 Level 2 products into the spatial distribution of CO₂. Moreover, I integrated many different kinds of data resources to comprehensively analyze the effects of anthropogenic activities and climate change on our atmospheric environment. All these will help us to understand the mechanism of atmosphere changing, which is very important for us to take certain measures or make relative policies to improve our living environment. With more and more data resources are becoming available, such as Tansat and OCO-2 Level 3 products, in the future I will conduct more researches around the world and try to find the distinctive atmosphere characters for each region.

Chapter 1 Introduction to the issue and the case study

1.1 Introduction

The main objective of this research is to utilize the advantages of remote sensing and ground-measured datasets to analyze the effects of anthropogenic activities and climate change on atmospheric environment. For this study, biomass burning, greenhouse gas (GHG) increase, El Niño-Southern Oscillation (ENSO), natural disasters et al. have been considered as important factors to affect the atmospheric environment. The thesis structure has been introduced in this chapter: **i.** the research background and the case study; **ii.** the methods applied in this thesis and **iii.** the outline of the thesis.

1.2 Research background

1.2.1 The effect of anthropogenic activities on atmospheric environment

One of the undesired but partly unavoidable consequences of human activities is the pollution of the atmospheric environment (Dop, 1982). The adverse effects of air pollution are directly related to the ambient concentration. Scientific and political interest in atmospheric pollution, as well as attempts to control it, have expanded from local to regional to global scales. Acid deposition, ozone depletion, regional-scale haze, and global warming, unknown or little understood before 1970, are at the center of atmospheric research, domestic regulation, and international affairs.

Large-scale industrialization and urbanization, population inflow into large metropolitan centers located in complex topographic areas, and unfavorable meteorological conditions cause significant degradation of urban air quality. Because of the health effects associated with these conditions it is of great interest to characterize the status of air quality for several pollutants such as O₃, CO, SO₂, NO₂, particulate matter, etc.

Excess air pollution can cause airway inflammation, decrease lung function, exacerbate asthma and chronic obstructive pulmonary disease, and adversely affect cardiovascular morbidity (Liu et al., 2009). Children, the elderly and pregnant women are especially vulnerable to the adverse impacts of air pollution (Laumbach, 2010). The impact of individual air pollutants such as SO₂, NO₂, O₃, CO, fine particulate matters (PM), as well as their potential interactive effects on birth outcomes, have previously been reported. Prenatal exposure to SO₂ can lead to developmental and functional toxicities (Singh, 1989). NO₂ suppresses antioxidant defense systems of the human body (Tabacova et al., 1998). CO interferes with the delivery of oxygen to the fetus by shifting the oxygen dissociation curve to the left indicating displacement of

oxygen from haemoglobin (Longo, 1977). PM can be directly emitted (primary) or formed by the gas-to-particle conversion process (secondary) in the atmosphere (Zhang et al., 2012). Primary particles are directly emitted from sources such as biomass burning, combustion of fossil fuels, volcanic eruptions and wind-driven suspension of soil, mineral dust, sea salt and biological materials. However, secondary particles are formed in the atmosphere by gas-particle conversion processes such as nucleation, condensation and heterogeneous and multiphase chemical reactions (Hallquist et al., 2009). Additionally, fog and haze can concentrate aerosols in the near-surface, which results in enhanced air pollution and deteriorated air quality that causes significant harm to human health. Worldwide epidemiological studies show a consistent increase in cardiac and respiratory morbidity and mortality from exposure to particulate matter. PM is a key ingredient of polluted air and is estimated to kill more than 500,000 people each year. Emmanuel (2000) found that an increase in PM₁₀ levels in Singapore from 50 µg/m³ to 100 µg/m³ was significantly associated with increased upper respiratory tract illness, 19% for asthma and 26% for rhinitis.

Crude oil, coal and gas are still the main resources for world energy supply. The combustion of these fossil fuels in industries and transportation in particular has been a major source of pollution inducing health hazards. The world's energy market worth around 1.5 trillion dollars is still dominated by fossil fuels (Goldemberg, 2006). The World Energy Outlook (WEO) 2007 claims that energy generated from fossil fuels will remain the major source and is still expected to meet about 84% of energy demand in 2030. The emission of carbon monoxide gases from cars and trucks is the most commonly cited example, but not the only one. The combustion process also creates SO₂ and NO_x which are important precursors for the formation of secondary particles. These materials can cause bronchitis and pneumonia, decrease resistance to respiratory infections and irritate the lungs. Power plant and transportation-related activities are about equally responsible for NO₂ emissions. Fossil fuels consumption also produce byproducts that hang in the air and irritate the lungs, such as dust, soot and smoke.

Human evolution and the use of fire have gone hand in hand ever since the origin of our species in the savannas and woodlands of Africa. Scientific interest in the topic of biomass burning grew when early estimates of pyrogenic emissions suggested that for some atmospheric pollutants biomass burning could rival fossil fuel use as a source of atmospheric pollution (Seiler and Crutzen, 1980; Crutzen and Andreae, 1990). Biomass burning can be broadly defined as open or quasi-open combustion of any non-fossilized vegetative or organic fuel (Akagi et al., 2011). Examples range from open fires in forests, savannas, crop residues, semi-fossilized peatlands, etc. to biofuel burning (e.g. cooking fires, dung burning, charcoal or brick making, etc.). Savanna fires, domestic and industrial biofuel use, tropical forest fires, extratropical (mostly

boreal) forest fires, and crop residue burning are thought to account for the most global biomass consumption (Bond et al., 2004). Particles emitted and formed in biomass burning plumes have major direct and indirect effects on climate (Hobbs et al., 1997; Rosenfeld, 1999) and contribute to dense continental-scale haze layers that occupy much of the tropical boundary layer during the dry season (Andreae et al., 1988; Reid and Hobbs, 1998; Wofsy et al., 1992; Eck et al., 2003).

1.2.2 The effect of climate change on atmospheric environment

The most significant environmental issue of this century will likely be the increases in the atmospheric burden of radioactively important trace gases, or GHG (Feely et al., 1997). CO₂ and other GHG (e.g., water vapor, methane, ozone, chlorofluorocarbons, carbon monoxide and nitrous oxide) help reduce the back-radiation of heat from the earth to the stratosphere and space (Park et al., 2004). This phenomenon has a tight coupling to climate, in that it exerts significant controls on the temperature of the troposphere and the Earth's surface.

Carbon dioxide is the single most important trace constituent from the standpoint of global climate change, as its radiative impact is second only to that of H₂O (Ramanathan, 1987). Records generated both by proxy techniques and recovery of ancient air trapped in glacial ice show CO₂ abundance cycling between 200 ppm and 300 ppm as the climate cycled from glacial to interglacial conditions (Barnola et al., 1987; Genthon et al., 1987). Half a century ago, Charles David Keeling began his measurements of atmospheric greenhouse gases, at the South Pole and high on Mauna Loa volcano in the middle of the Pacific Ocean (Keeling, 1960; Harris, 2010). By 2011, Keeling's original two stations were expanded to a global network of almost 120 stations that are measuring atmospheric CO₂ and CH₄ concentrations (Manning, 2011).

Ozone changes will take place in response to increasing GHG concentrations in the earth's atmosphere (Shindell et al., 1998). These changes could have significant impacts on climate change and on the amount of harmful ultraviolet radiation reaching the earth's surface, since ozone plays a major role in atmospheric radiation and dynamics (Brasseur and Rudder, 1987). CO₂, coupled with the continued accumulation of other greenhouse gases in the atmosphere, is expected to cause the average temperature for last decade of twenty-first century rising 4.0 °C (2.4–6.4 °C), if the high economic growth is achieved by recognizing fossil fuel as the important source of energy (Solomon et al., 2014). These temperature changes will have an impact on ozone chemistry in the stratosphere, which will feed back on temperature, since ozone itself is an absorbing gas. Changes in stratospheric ozone will also alter the radiation field at lower levels, affecting dynamics and chemistry down into the troposphere.

Carbon is exchanged among the atmosphere, oceans, terrestrial biosphere, and sediments and sedimentary rocks, the latter two more slowly than the other reservoirs. During the preindustrial period, when the carbon cycle can be assumed to be in balance, 98.1% of the CO₂ resided in the oceans; only 1.9% in the atmosphere. Because of the massive emission of CO₂ into the atmosphere during the industrial period, it is predicted that the ultimate fate of anthropogenic CO₂ added to the atmosphere is that only 80 to 85% will be absorbed by the oceans, with 15 to 20% remaining in the atmosphere. Only about 42% of the CO₂ emitted since 1800 has dissolved in the oceans (Seinfeld and Pandis, 2016). Therefore, changes in SST could significantly affect the CO₂ concentration of the Earth.

ENSO exhibits the greatest influence on the interannual variability of the global climate (Webster et al., 1998). The ENSO process arises due to an interaction of the equatorial sea temperature with the atmosphere and influences climate variation across much of the world (Bjerknes, 1966; Ropelewski and Halpert, 1987). Changes in the equatorial Pacific sea temperatures and atmospheric pressures precede seasonal climate variation in other regions by one to 12 months. The warming phase is known as El Niño and the cooling phase as La Niña. Southern Oscillation is the accompanying atmospheric component, coupled with the sea temperature change: El Niño is accompanied with high, and La Niña with low air surface pressure in the tropical western Pacific. The two periods last several months each (typically occurring every few years) and their effects vary in intensity. The intensity and frequency of El Niño and La Niña events are known to have varied in recent decades (Wang and An, 2001), as well as in the more distant past (Tudhope et al., 2001). These changes appear to be connected to shifts in climate, raising the possibility that ENSO might undergo discernible changes in response to anthropogenically driven warming.

1.3 Case study

1.3.1 Air pollution in China

As the world's biggest developing countries, China has experienced nationwide severe haze pollution, with fine PM recently reaching unprecedentedly high levels across many cities. An understanding of the PM formation mechanism is critical in the development of efficient mediation policies to minimize its regional and global impacts (Guo et al., 2014). Haze is defined as a weather phenomenon in which atmospheric visibility is less than 10 km and results from dense layers of aerosol particles, such as acidic chemicals, organics, black carbon (BC), and fly ash as well as dust accumulated in the air, and has a lower relative humidity than fog (Tao et al., 2012). Fig. 1.1 shows the land cover types in China.

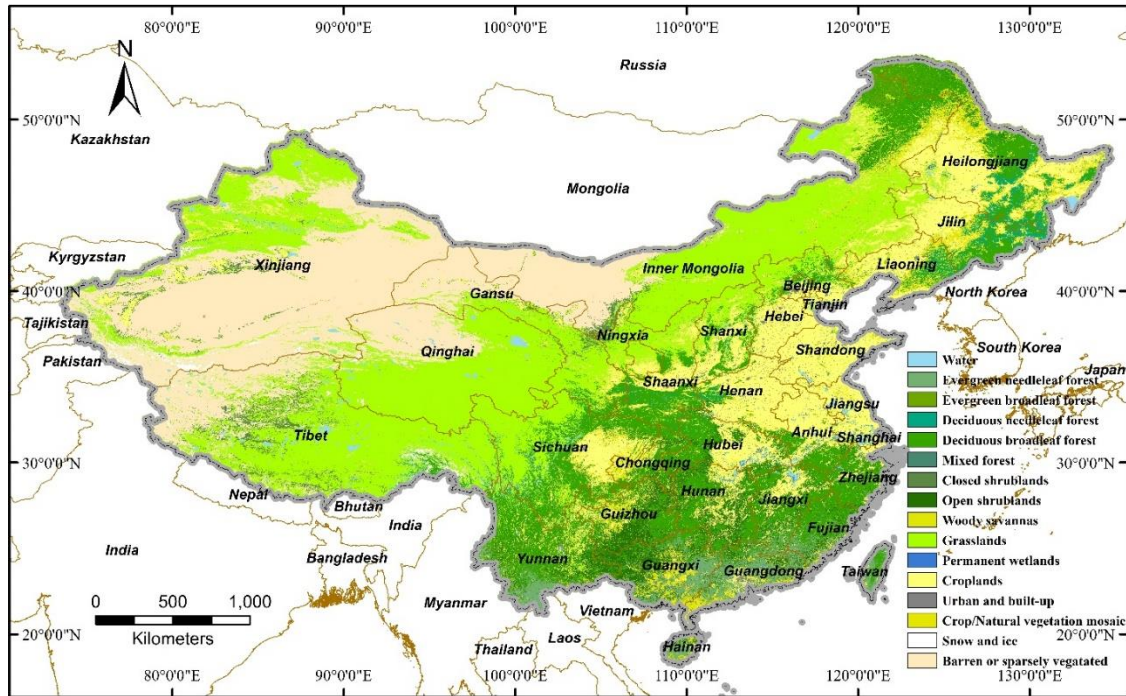


Figure 1.1 Land cover types in China from MCD12Q1 products.

During the 10th Five Year Plan (FYP, 2001–2005) period, China maintained 9.48% annual average growth rate of the national economy. The primary energy consumption increased by 62% from 1.38 G tons of standard coal equivalent (tce) in 2000 to 2.24 G tce in 2005 (Wang et al., 2010). The Chinese government implemented several new policies and measures during the 10th and 11th FYP to control environmental pollution. These relative polices were made to decrease GHG emission and maintain rapid growth in the economy and energy demand. Despite economy progress, several goals of the environment protection 10th FYP were not achieved. In 2012, China adopted their own Ambient Air Quality Standard, and began to develop a national Air Reporting System that now has been expanded to every prefectural-level city. These automated stations report hourly concentration for each air component via the internet, and focus on six components: PM_{2.5}, PM₁₀, SO₂, NO₂, O₃ and CO.

Research conducted in Beijing, China shows that about 47% of people have hypertension, which is defined by systolic blood pressure greater than 140 mm Hg and diastolic blood pressure greater than 90 mm Hg (Xu et al., 2008). Human exposure, animal experiments and epidemiological studies have illustrated that particulate air pollution potentially raises blood pressure (Brook, 2005), even in healthy individuals (Urch et al., 2005). For the haze pollution of China, too many researchers have focused on economically developed regions, such as the North China Plain, the Pearl River Delta and the Yangtze River Delta, whereas there has much less research on Northeastern China (Liaoning, Jilin, and Heilongjiang Provinces). Although the

increase rate of Northeastern China's economy for the past 10 years was in the lowest among all the provinces and the population in Northeastern China had a negative growth trend, its air quality deterioration was similar to or even worse than that of the economically booming regions. Interestingly, the air quality in the heating season sharply contrasts with that in the non-heating season in Northeast China. In November 2015, severe air pollution occurred in Northeast China and the maximum concentration of hourly PM_{2.5} greatly exceeded 1,000 µg/m³ during that period. For example, on 8th November 2015 the hourly PM_{2.5} concentration reached 1,326 µg/m³ in the city of Shenyang, where authorities said visibility would be as low as 500 meters in some places (Zhang et al., 2017). Theoretically, there should be good air quality in Northeast China. In contrast, that air pollution episode in Northeast China was much worse than in other regions and for the first time the air pollution in this region became a hot topic.

1.3.2 Biomass burning in Indonesia

Forest lands of Indonesia represent about 74% of the total land area. During 1950-1990 this area has been constantly reduced at a certain rate per year for both logging and forest conversion for other purposes, such as farming activities. One of the consequences of such changes is the release of carbon stored in the biomass as well as in the soil due to burning, oxidation and decay of organic matter. The land-use change, to some extent, offers a possible CO₂ sink, although, temporarily and can not compensate for the release of CO₂ during the same period. So there will be an imbalance caused by these anthropogenic activities. Primary forests are the largest above-ground carbon sink in the world and peatlands are the largest reservoirs of soil carbon. Indonesia's primary low land forests have long been threatened by human activities, such as deforestation and forest degradation (Curran et al., 2004; Hansen et al., 2009). Easy access to low land forest has made primary forests a target for logging and the subsequent conversion to higher value land uses. Wetland forests in Indonesia have historically remained largely intact (Murdiyarso et al., 2010). However, during the past two decades the conversion of wetland forests, including peatlands, to agro-industrial land uses has increased (Stibig et al., 2014).

The Southeastern of Asia is an important area of biomass burning because total biomass burning in Asia is estimated to be one of the largest biomass burning sources in the world (Seiler and Cruzen, 1980). In the Southeastern Asia, a thick haze pollution episode was reported in 1994 when the El Niño even occurred. The burning of biomass as a method to clear and fertilize soil is conducted in Indonesia every year by local farmers and forestry companies. The extensive destruction of rain forest across the Southeastern Asia and New Guinea region during the severe 1997-1998 El Niño event clearly demonstrated the vulnerability of large areas of rain forest to fire. Indonesia

biomass burning in 1997 was assumed to make up 15-40% of the annual global carbon emissions from fossil fuel burning (Page et al., 2002).

Dry conditions caused by the 2015 El Niño event made that approximately 2.6 million hectares of land were estimated to burn from June to October in Indonesia. The fires, many occurred on carbon-rich peatlands, exposed thousands of people across Southeastern Asia to severe haze pollution episode and significantly increased Indonesia's annual GHG emissions. The 2015 Southeastern Asian haze episode was an air pollution crisis affecting several neighbor countries in Southeastern Asia, including Brunei, Indonesia, Malaysia, Singapore, Thailand, Vietnam, Cambodia and the Philippines. The haze pollution episode affected Indonesia from at least late June, to the end of October, turning into an international problem for other neighbor countries in September.

1.3.3 Climate change in Australia

Australia, due to its size and isolation, is often considered as the “island continent” and is sometimes thought to be the world's largest island. The climate of Australia is significantly influenced by ocean currents, including the Indian Ocean Dipole and the ENSO, which is correlated with periodic drought, and the seasonal tropical low-pressure system that produces cyclones in northern Australia. These factors cause precipitation to change remarkably from year to year. For the climate types, most of the Northern part of the country has a tropical, predominantly summer-rainfall (monsoon). The south-west corner of the country has a Mediterranean climate. The south-east ranges from oceanic to humid subtropical. The interior is arid to semi-arid.

Australia's continental average temperature has increased by approximately 0.8 °C since 1910 (Collins, 2000). Most of this rise occurred after 1950, with 1998 being the warmest year, and the 1990s and 1980s being the warmest and second warmest decades, respectively. These tendencies are consistent with those measured globally. Since 1951, average temperatures have risen 0.1-0.2 °C per decade over most of Australia, with the greatest warming inland, particularly in Queensland and the Southern half of Western Australia, although some cooling has occurred in Southern Queensland and New South Wales. The recent warming has been greatest in winter and spring (Hulme and Sheard, 1999). Australian precipitation has increased slightly over the past century, and more so in summer than winter (Collins and Della-Marta, 1999; Hennessy et al., 1999). Higher Australian precipitation since 1910 is linked to increases in both heavy rainfall events and the number of rain days, with some regional exceptions (Haylock and Nicholls, 2000). On average, the number of wet-season days has increased by approximately 10%. The ENSO events have a strong influence on climate and sea level variability in many parts of Australia. Since the 1970s, El Niño

events have apparently increased and La Niña events decreased. In addition to possible changes in the frequency of ENSO, the relationship between ENSO, annual temperature and precipitation also changed in the early 1970s (Nicholls et al., 1996).

1.4 Aims and data resource

The main objective of this research is to investigate the effects of anthropogenic activities and climate change on atmospheric environment. This requires various information to explore the features of changing atmosphere and understand the mechanism of the changing process. To achieve this objective, remote sensing data combining with meteorological data and ground-measured data have been used to identify air pollution, climate change, biomass burning, crop residue burning, et al. The more specific objectives are outlined below:

- i. To analyze spatial distribution of crop residue burning and PM_{2.5} change in China.
- ii. To examine the spatial distribution and formation conditions of severe haze pollution in Northeastern China.
- iii. To analyze CO₂ concentration changes and their influencing factors in Indonesia.
- iv. To investigate the effects of climate and ENSO on the temporo-spatial changes of CO₂ and precipitation in Australia

In this study, mainly four kinds of data resources have been used, greenhouse gas monitoring satellites, other remote sensing datasets, meteorology data and ground-measured data.

1.4.1 Greenhouse gas monitoring satellites

The Greenhouse Gases Observing Satellite (GOSAT) was successfully launched from Japan on 23rd January, 2009. It is a special spacecraft that is used to measure the concentrations of carbon dioxide and methane, the two major greenhouse gases, from space (Yoshida et al. 2010). After the launch failure of the Orbiting Carbon Observatory (OCO) in 2009 (Crisp et al., 2004), the National Aeronautics and Space Administration (NASA) authorized the development of OCO-2, which successfully launched on 2nd July, 2014 (Frankenberg et al., 2014). These two satellites have different advantages; therefore, they will be able to provide sufficient data and information to ascertain the distribution of greenhouse gases and enhance the scientific understanding of concentration changes of CO₂.

Compared with OCO-2, GOSAT has a higher temporal resolution; it returns to the same location in 3-day periods and utilizes 44 orbits to cover the whole Earth (Basu et al., 2013). Thermal And Near-infrared Sensor for carbon Observation (TANSO)

Fourier Transform Spectrometer (FTS) Short-wavelength infrared (SWIR) Level 2 products Level 3 products are derived from the TANSO-FTS SWIR Level 2 products in a month by using the spatial statistical method to estimate the column averaged mixing ratio of GHG for the rectangular area with 2.5 degrees of latitude and longitude in a month. There are two kinds of FTS SWIR L3 products: GOSAT TANSO-FTS SWIR Level 3 global CO₂ column-averaged mixing ratio and GOSAT TANSO-FTS SWIR Level 3 global CH₄ column-averaged mixing ratio. These quantities, called X_{CO_2} and X_{CH_4} by members of the atmospheric carbon science community, quantify the average concentrations of CO₂ and CH₄, respectively, in a column of dry air extending from the Earth's surface to the top of the atmosphere (Satio et al., 2012). GOSAT SWIR Level 3 products are available from June, 2009, and the products from that month to December 2016 were all collected.

OCO-2 has a longer cycle (16 days) to return to the same location. It uses 233 orbits to cover the Earth, which means that it has a higher spatial resolution (Taylor et al., 2015). GOSAT can provide data for two kinds of greenhouse gas (X_{CO_2} and X_{CH_4}), whereas OCO-2 only provides data for the CO₂ column-averaged dry air mole fraction (X_{CO_2}). Estimates of X_{CO_2} are derived by taking the ratio of the column integrated number densities of carbon dioxide and molecular oxygen along the optical path from the Sun to the surface footprint and the instrument and then multiplying these results by the column-averaged oxygen concentration (Kawasaki et al., 2012). These carbon dioxide and oxygen number densities are estimated from high-resolution spectra of reflected sunlight, collected by the Observatory's instrument at wavelengths (colors) within the 0.765 nanometer molecular oxygen A band and two carbon dioxide bands centered at wavelengths near 1.61 microns and 2.06 microns. OCO-2 Level 2 standard products are available from 6th September, 2014, and the products from that date to December 2016 were all collected. OCO-2 Level 2 products are full orbits or fractions of orbits of geographically located estimates of X_{CO_2} and several atmospheric and geophysical properties that are collected during each spacecraft orbit.

1.4.2 Other remote sensing datasets

MODerate Resolution Imaging Spectroradiometer (MODIS) is an optical sensor on board Terra (launched on 24th April, 2000) and Aqua (launched on 12th July, 2002), NASA's earth observing satellites. They are designed to provide measurements in large-scale global dynamics including changes in Earth's cloud cover, radiation budget and processes occurring in the oceans, on land, and in the lower atmosphere. The series of MODIS products provide sufficient information about our earth, which include the condition of our land cover, vegetation cover, atmosphere, ocean, and so on.

MOD14A1 Thermal Anomalies/Fire products of the MODIS were collected to obtain the fire data. MODIS Thermal Anomalies/Fire products are primarily derived from MODIS bands at 4 and 11 micrometer radiances (Roy et al., 2002). The fire detection strategy is based on absolute detection of a fire (when the fire strength is sufficient to detect) and on detection relative to its background (to account for variability of the surface temperature and reflection by sunlight). The land cover data used in this study were also from MODIS. The MCD12Q1 product provides data characterizing five global land cover classification systems (Cai et al., 2014). The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP) (Loveland and Belward, 1997), which includes 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes. Global MODIS vegetation indices are designed to provide consistent spatial and temporal comparisons of vegetation conditions (Kim et al., 2014). Blue, red, and near-infrared reflectance, centred at 469 nm, 645 nm and 858 nm, respectively, are used to determine the MODIS daily vegetation indices (Lin et al. 2012). Due to vegetation indices' simplicity, ease of application, and widespread familiarity, these indices have a wide range of usages. We can acquire two important vegetation indices from MODIS, the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). The aerosol properties are derived by the inversion of the MODIS-observed reflectance using pre-computed radiative transfer look-up tables based on aerosol models (Remer et al., 2005). There are three MODIS Level 3 Atmosphere Products, each covering a different temporal scale: Daily, 8-Day, and Monthly. Each of these Level 3 products contains statistics derived from over 100 science parameters from the Level 2 Atmosphere products: aerosol, precipitable water, cloud, and atmospheric profiles.

The Ozone Monitoring Instrument (OMI) is on board the NASA Aura. OMI can distinguish between aerosol types, such as smoke, dust, and sulfates, and can measure cloud pressure and coverage, which provide data to derive tropospheric ozone. The OMI project is a cooperation between the Netherlands Agency for Aerospace Programmes (NIVR), the Finnish Meteorological Institute (FMI) and the NASA. The OMI Aerosol Absorption Optical Depth (AAOD), the non-scattering part of the Aerosol Optical Depth (AOD), is an atmospheric column measurement of absorbing aerosol particles, i.e., absorbing carbon and mineral dust (Koch et al., 2009). As an

important product for aerosol study, the Aura OMI level-2 near-UV Aerosol data product 'OMAERUV' derives extinction AOD, single scattering albedo and AAOD at the top of the atmosphere (Ahn et al., 2007). The OMAERUV retrieval algorithm is particularly sensitive to carbonaceous and mineral aerosols. The daily product (OMTO3D.003) from OMI has been used to obtain Ultraviolet Aerosol Index (UVAI) data. The OMI instrument can distinguish between aerosol types, such as smoke, dust, and sulfates, and measures cloud pressure and coverage, which provides data to derive tropospheric ozone (Liu et al., 2009).

MOPITT (Measurements of Pollution in the Troposphere) is a payload scientific instrument launched into Earth orbit by NASA on board the Terra satellite in 1999. It is assigned to monitor changes in pollution patterns and its effect in the lower atmosphere of the Earth. The instrument was funded by the Space Science Division of the Canadian Space Agency. MOPITT includes nadir-viewing channels for monitoring both carbon monoxide and methane and operated from March 2000. MOPITT measures the Earth with a pixel size of $22 \text{ km} \times 22 \text{ km}$ and provides the first continuous global measurements of CO in the troposphere (Emmons et al., 2004). I used Version 5 Level 3 products, which include CO concentrations, averaging kernels and error co-variances at 10 pressure levels. Level 3 products are available as gridded daily-mean and monthly-mean files. Data averaging is performed on a one-degree latitude/longitude grid. This product provides two types of CO concentration, total column concentration and surface concentration. To be consistent with the ground measurement, only the surface data ($<900 \text{ hpa}$) were used to infer CO variations. Retrieved CO total columns were calculated by integrating the retrieved mixing ratio profile, where each retrieval level corresponded to a uniformly-weighted layer immediately above that level (Deeter et al, 2007). Both the daily and monthly CO MOPITT products were used in this study.

1.4.3 Meteorology data

In this study, the global meteorology data were obtained from National Oceanic and Atmospheric Administration (NOAA). NOAA is an American scientific agency within the United States Department of Commerce that focuses on the conditions of the oceans and the atmosphere. From daily weather forecasts, severe storm warnings, and climate monitoring to fisheries management, coastal restoration and supporting marine

commerce. NOAA's dedicated scientists use cutting-edge research and high-tech instrumentation to provide citizens, planners, emergency managers and other decision makers with reliable information they need when they need it. Science at NOAA is the systematic study of the structure and behavior of the ocean, atmosphere, and related ecosystems; integration of research and analysis; observations and monitoring; and environmental modeling.

Optimum Interpolation Sea Surface Temperature (OISST) from NOAA was used in this study to analyze with the changes of CO₂ and ENSO episodes. The OISST uses both in situ and satellite-derived SST data to produce a weekly and monthly analysis (Yoshimi et al., 2006). The in situ SST data are obtained from the U.S. National Meteorological Center (NMC) file of surface marine observation. These data consist of all ship and buoy observations that are available to NMC. The satellite observations were obtained from the Advanced Very High Resolution Radiometer (AVHRR) onboard a polar orbiting satellite of NOAA (Reynolds and Smith, 1994). Bias adjustments of satellite and ship observation (referenced to buoys) were conducted to compensate for the platform differences and sensor biases (Reynolds and Marsico, 1993). NOAA's PRECipitation REConstruction over Land (PREC/L) was used in this study to analyze the change of precipitation during ENSO episodes and the relationship between precipitation and GHGs. The global analyses are defined by the interpolation of gauge observations over land (PREC/L) and the EOF (Empirical Orthogonal Function) reconstruction of historical observations over oceans (PREC/O). Gauge observations are collected from more than 17,000 stations in the Global Historical Climatology Network (GHCN) and the Climate Anomaly Monitoring System (CAMS) datasets. The OI (Optimum Interpolation) technique of Gandin was used to assimilate the observations. The mean distribution and annual cycle of precipitation observed in the PREC/L showed good agreement with those in several published gauge-based datasets (Maeda et al., 2013).

1.4.4 Ground-measured air quality data

PM_{2.5}, as the most important indicator of haze pollution, began to be monitored in China from 2012 and only available in important regions such as Beijing, Tianjin, the Yangtze River Delta Region, the Pearl River Delta Region and provincial capitals. In 2015, monitoring was extended to every prefecture-level city, and these data provide

sufficient support for the study of PM_{2.5} (EMSC, 2012). The ground-measurement data used in this study mainly included two parts: air quality data and meteorology data. Daily air quality data included PM_{2.5}, PM₁₀, SO₂, NO₂, CO and O₃, which were obtained from China's National Environmental Monitoring Center (CNEMC, 2015). China's Environmental Protection Conference of 2012 first mentioned and emphasized monitoring PM and ozone across the country. After acquiring the daily air quality data from China's National Environmental Monitoring Center, the data were combined with the geographic coordinates of each city in Northeastern China. Then, using the platform of Geographic Information System (GIS), a database of ground-measurement data was established and, finally, the ordinary Kriging interpolation method was chosen to obtain the distribution map of different air components, which can directly reveal the spatial characteristics. Meteorology data is the daily temperature in Northeastern China, which is used to analyze the formation condition of severe haze pollution in this region.

1.5 Thesis contents

This thesis consists of six chapters, covering four main topics: an introduction of the thesis (Chapter 1), the effect of anthropogenic activities on atmospheric environment (Chapter 2 and 3), the effect of climate change on atmospheric environment (Chapter 4 and 5), and final conclusions (Chapter 6). The schematic framework for this research is shown in Fig. 1.2.

In Chapter 2, with China as the study area, the datasets from MODIS have been used to derive daily crop residue burning spots from 2014 to 2015. After vectorization of crop residue burning pixels and with the use of fishnet, burning density distribution maps were eventually completed. Meanwhile, the daily air quality data from 150 cities in 2014 and 285 cities in 2015 were used to obtain daily and monthly PM_{2.5} distribution maps with the Kriging interpolation. The aim of this study is to characterize the spatial distribution and seasonal pattern of crop residue burning and PM_{2.5} concentration in China. The relationship between crop residue burning and PM_{2.5} has been analyzed to reveal the severe air pollution caused by the activities of farmers. The annual activities of crop residue burning have been divided into three periods, crop residue burning in spring before ploughing, crop residue burning in summer after the harvest of winter wheat and crop residue burning in autumn-winter after the harvest of corn and rice.

In Chapter 3, the PM_{2.5} pollution in Northeastern China was highlighted. In November 2015, for the first time the severe air pollution episode in this region became

a hot topic. The objective of this study is to analyze the spatial distribution and formation condition of severe haze pollution by ground-measured and remote sensing datasets. Northeastern China is made up of three provinces, Heilongjiang, Jilin and Liaoning province. In this section, the intensity of each pollution episode, air components and aerosol condition have been separately analyzed for each province. AOD, AAOD, UVAI and CO from remote sensing and ground-measured datasets were also compared to investigate whether remote sensing datasets can replace ground-measured datasets if the ground monitoring is unavailable. This section proposes a comprehensive method that combines remote sensing datasets with ground-measured air quality and meteorology datasets to analyze and monitor pollution episodes.

For Chapter 4, the datasets from OCO-2 have been used and three factors have been considered that potentially affect CO₂ concentration in Indonesia: sea surface temperature (SST), forest fires and vegetation. Because of the lower spatial resolution of GOSAT, a large proportion of the research using this satellite is applied on a global or continental, rather than a regional scale. In this study, Indonesia, because of its special geological condition, was selected as the study region to testify whether OCO-2 can be used to analyze the change of CO₂ concentration on a regional scale. The level 3 products of OCO-2 have not been released, therefore, we cannot directly obtain the spatial distribution of CO₂ concentration. Another aim of this section is proposing an effective method to present spatial distribution of CO₂ in Indonesia from OCO-2 Level 2 products.

The objectives of Chapter 5 were analyzing temporo-spatial changes in the CO₂ concentrations in Australia from June 2009 to December 2016 using greenhouse gas monitoring satellites. In addition, meteorology, climate types and land cover were considered to characterize the changes in CO₂, precipitation and their mutual effects have been analyzed. The relationship between CO₂ distribution and precipitation in Australia has been specifically analyzed. By combining the results with the Köppen-Geiger climate classification, SST around the coastal region, vegetation cover and other factors have been considered to affect the regional CO₂ concentration. Moreover, climate of Australia is significantly affected by ocean current, the abnormal changes of precipitation and CO₂ increase during the ENSO events have been investigated in this section. The CO₂ concentration from GOSAT and OCO-2 were also compared.

In Chapter 6, the new findings and innovative methods proposed in this study are summarized. This chapter illustrates the final conclusions of this thesis. I also make a comment on the advantages and disadvantages of this study. Finally, how conducting

future research is proposed and I believe the content of this study will provide sufficient support for future work.

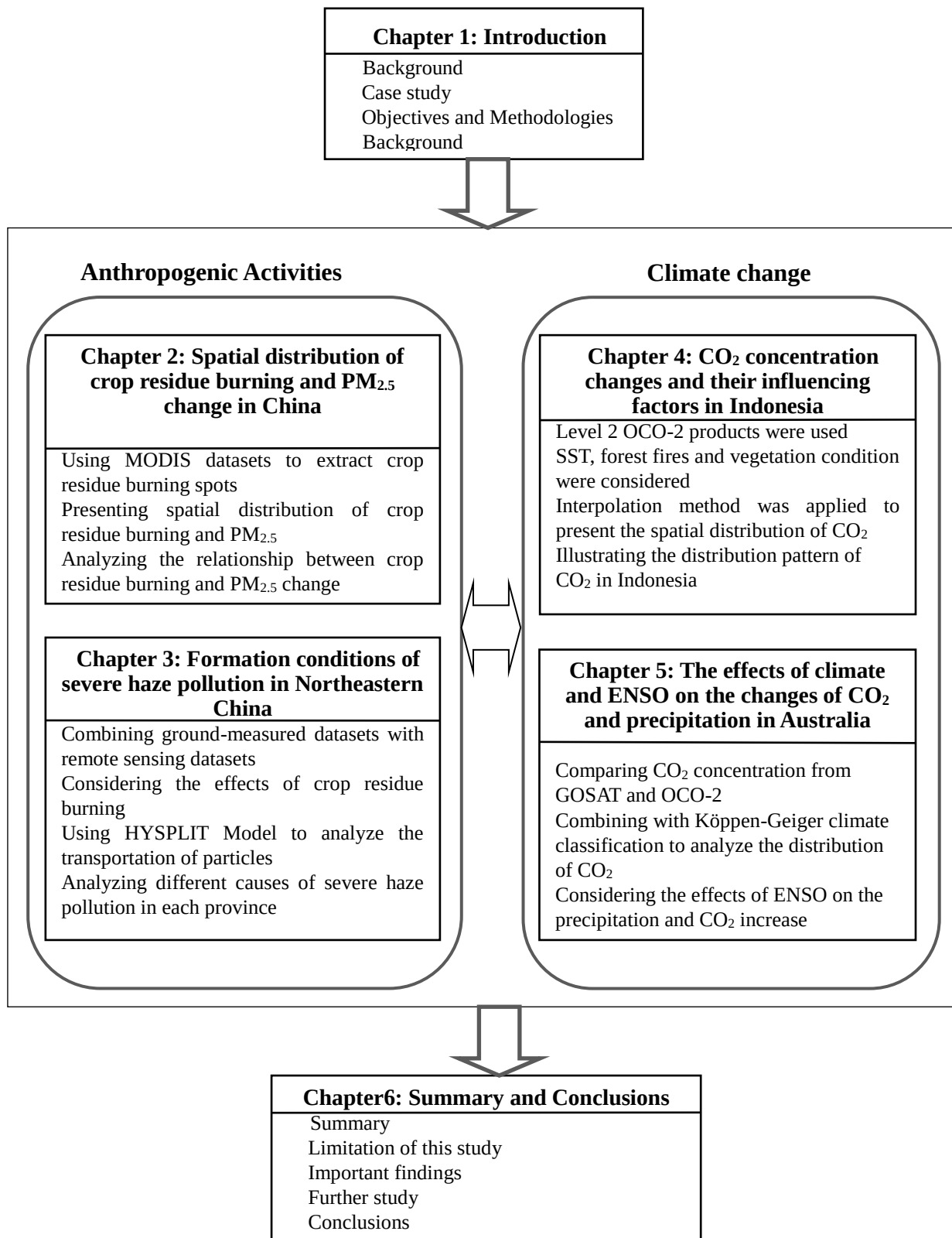


Figure 1.2 A schematic flow of the research organization.

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Chapter 2 Study on spatial distribution of crop residue burning and PM_{2.5} change in China

2.1 Introduction

Crop residue consists of materials left over from the production of crops, including the straw (or stalks) of rice, wheat, maize, sugarcane, and cereal (Lal, 2005). How to reuse crop residue effectively at a low cost is always a disturbing problem for crop planting (Smil, 1999). In developed countries, through technological progress and innovation, the comprehensive use of crop residue has been achieved in a variety of ways. For example, in 24 agricultural states in the United States, approximately 45 million tons of wheat crop residue have been collected to make fodder, arts & crafts, and used as insulation for house construction that is a popular commercial product (Lei et al., 2007). Straw fibers, when compresses under high temperature, bond together without any adhesive. For structural applications, the strawboard is then laminated between oriented-strand board to form a stress-skin panel (Glaser and Van Dyne, 1997). In addition, the U.S. government has paid more attention to biomass energy since the mid-1990s to mitigate global climate change (Wise et. al., 2014). Crop residue is used to generate electricity in Denmark, which not only increases income for local farmers but also cuts power plant costs (Nguyen et al., 2013). In Canada and Japan, most of the crop residue is shattered directly and returned to the farmland as fertilizer (Wang, 2010). In developing countries, effective methods of crop residue reuse are also a challenge for the government. Some innovative methods, such as using crop residue to generate methane or industrial raw materials and to raise edible mushrooms, have been implemented in China (An et al, 2004). However, because of the high cost, low agricultural product price and lack of certain technologies, the comprehensive use of crop residue is very hard to generalize across the country. According to estimates, from 1995 to 2005, China produced some 630 million tons of crop residue per year, one-third of which remained unused and most of which was burnt directly in the field (Liu et al., 2008; Wang et al., 2013). The burning of crop residue emits carbon dioxide, carbon monoxide, non-methane-hydrocarbons, nitric oxide, nitrous oxide and atmospheric particles (Hayashi et al., 2014). Open crop residue burning has caused great concern recently for its significant emissions of black carbon and organic carbon (Kharol et al., 2012; Hsu et al., 2009). These emissions can result in severe degradation of regional air quality (Crounse et al., 2009) and increasing respiratory disease morbidity (Arbex and Brage, 2007).

Because of the different climatic conditions and farming modes in China, the burning of crop residue is known to be spatially and temporally inhomogeneous, requiring better characterization. While burning is dispersed across the country after harvest and lasts

for a short time, it is unrealistic to monitor the burning of crop residue on the ground. Satellite remote sensing, because of its synoptic and repetitive coverage, can supply information to characterize fires in terms of intensity, extent, spatial-temporal variations, and radioactive energy (Lentile et al., 2006). This would supply efficient data that could be used to analyze the spatial and temporal change of crop residue burning on a large scale (McCarty, 2011; Vadrevu et al., 2014).

As the largest developing country in the world, China suffers from severe air pollution, especially haze in recent decades (Madaniyazi et al., 2015). Haze is traditionally an atmospheric phenomenon where dust, smoke and other dry particles obscure the clarity of the sky (Zhang et al., 2015). Haze often occurs when dust and smoke particles accumulate in relatively dry air (Youngsin and Lim, 2014). When weather conditions block the dispersal of smoke and other pollutants, they concentrate and form a usually low-hanging shroud that impairs visibility and may become a respiratory health threat (Othman et al., 2013).

The causes of severe haze in China are still controversial. The rapid economic increase in past decades has led to a soaring consumption of fossil energy (Liu and Li, 2011). Additionally, non-point source pollutions of water and soil resources, crop residue burning, special climatic condition, land cover and topography in China are also presumed to be causes of haze. Developed countries such as the United States and England also suffer from haze due to past industrial development (Wang and Liu, 2014). However, the situation in China is different. Although the Chinese government has taken effective measures to save energy and reduce emissions (Zhou et al., 2012; Yang et al., 2013), the occurrence of haze still shows no declining trend. PM_{2.5}, fine particles with a diameter of 2.5 micrometers or less (Zheng et al., 2005), is the most important index by which to judge the severity of haze. PM_{2.5} in China began to be monitored in 2012 only in important regions, such as Beijing, Tianjin, the Yangtze River Delta Region, the Pearl River Delta Region and provincial capitals. In 2015, monitoring was extended to every prefecture-level city, and these data provide sufficient support for the study of PM_{2.5} (<http://dignitaries.china.com.cn/html/huanbao/3714.html>).

An adequate understanding of the relationship between crop residue burning and PM_{2.5} is a prerequisite for taking effective measures to decrease the occurrence of haze in developing countries. However, due to the lack of accurate time-series data and the fact that China only began monitoring PM_{2.5} in 2012, no research exists on the relationship between crop residue burning and PM_{2.5}. To fill this gap, the aims of this study were as follows: first, use MOD14A1 and MCD12Q1 products of MODIS to analyze the changes and distributions of crop residue burning in China in 2014 and 2015; second, use the Kriging method to analyze the spatial distribution of PM_{2.5} in

China in 2014 and 2015 based on daily air quality data from China's National Environmental Monitoring Center; and third, use the daily data of crop residue burning and PM_{2.5} to analyze their spatial and temporal relationships.

2.2 Data and methods

2.2.1 Data

2.2.1.1 MOD14A1 products

MODIS Thermal Anomalies/Fire products are primarily derived from MODIS bands at 4 and 11 micrometer radiance (<http://modis.gsfc.nasa.gov/data/dataproduct/mod14.php>). The fire detection strategy is based on absolute detection of a fire (when the fire strength is sufficient to detect) and on detection relative to its background (to account for variability of the surface temperature and reflection by sunlight). Numerous tests are employed to reject typical false alarm sources, such as sun glint or an unmasked coastline (Giglio et al., 2003).

MOD14A1 is produced every 8 days at a resolution of 1 kilometer as a gridded level-3 product in the Sinusoidal projection. This product is unique in that it has three dimensions: fire-mask (1D) and a maximum fire-radiative-power (2D) are provided for each day (3D) in the 8-day period. For example, the fire-mask contains eight, band-sequential (day) 1200 × 1200 images of fire data representing consecutive days of data collection. By separating the eight fire-masks, the daily Thermal Anomalies/Fire images can be obtained.

The area of China spans from 53°33' N to 3°52' N and from 73°40' E to 135°2' E, which includes 22 tiles of MODIS products. The tile numbers are h25v03, h26v03, h23v04, h24v04, h25v04, h26v04, h27v04, h23v05, h24v05, h25v05, h26v05, h27v05, h28v05, h25v06, h26v06, h27v06, h28v06, h29v06, h28v07, h29v07, h28v08 and h29v08. MOD14A1 products for China from 2014 and 2015 were obtained from NASA's LAADS Web (<https://ladsweb.nascom.nasa.gov/data/search.html>).

2.2.1.2 MCD12Q1 products

The MODIS Land Cover Type product provides data characterizing five global land cover classification systems (Cai et al., 2014). In addition, it provides a land cover type assessment and quality-control information. The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP) (Loveland et al., 1997), which includes 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes. In this study Class 12 (Croplands) from the primary land cover scheme was used to extract crop

residue burning spots. The latest MCD12Q1, the land cover from 2013, was also obtained from NASA's LAADS Web.

2.2.1.3 *PM_{2.5} data*

Daily air quality data—including PM_{2.5}, PM₁₀, AQI and quality grade—were obtained from China's National Environmental Monitoring Center (<http://www.cnemc.cn/>). China's Environmental Protection Conference of 2012 first mentioned and emphasized monitoring PM_{2.5} and ozone across the country. By 2015, PM_{2.5} monitoring has been extended to every prefecture-level city. In this study, daily PM_{2.5} data were collected from 150 cities in 2014 and 285 cities in 2015 to analyze the PM_{2.5} spatial distribution change and explore the relationship between crop residue burning and PM_{2.5} change. The PM_{2.5} monitor cities cover all the provinces and are mainly concentrated in China's east, which suffers from severe air pollution.

2.2.1.4 *GIS data*

The temporal resolution of both crop residue burning and PM_{2.5} are well qualified at daily levels. To perform a specific analysis, it is necessary to calculate the crop residue burning spots and PM_{2.5} on a provincial level. Therefore, GIS data for China, such as the boundary and area of each province and the geographic coordinates of its cities, were used in this study. The GIS data were from the newest version (November 2015) of GADM database, which is a spatial database of the location of the world's administrative areas (or administrative boundaries) for use in GIS and similar software. Administrative areas in this database are countries and lower level subdivisions such as provinces, cities, counties, and so on. GADM describes where these administrative areas are, and for each area it provides some attributes, such as the name and variant names (<http://www.gadm.org/country>).

2.2.2 *Methods*

2.2.2.1 *Process for obtaining crop residue burning data*

MOD14A1 was used for two main reasons: to obtain the distribution map for crop residue burning and to compile the statistics for daily and monthly crop residue burning at the provincial level. First, after collecting MOD14A1 images from 2014 and 2015 in China, we obtained daily Thermal Anomalies/Fire images by separating the eight fire-masks. Second, the cropland area of MCD12Q1 was used to clip Thermal Anomalies/Fire images to obtain the daily crop residue burning spots. Afterwards, the daily crop residue burning spots were combined with the monthly crop residue burning spots and these spots were vectorized separately. Finally, a fishnet of squares measuring 0.5°×0.5° was created to cover all of China, and, by joining the crop residue burning spots with this fishnet, the daily and monthly distribution maps showing crop residue

burning were finally obtained. In the meantime, by joining the crop residue burning spots with the GIS data for China, the statistics for crop residue burning spots on a provincial scale were created (Fig. 2.1). The resolution of MOD14A1 products is $1\text{km}\times 1\text{km}$, and each pixel after the vectorization was regarded as a crop residue burning spot. All the procedures above were conducted on ERDAS, ArcGIS and ModisTool platforms.

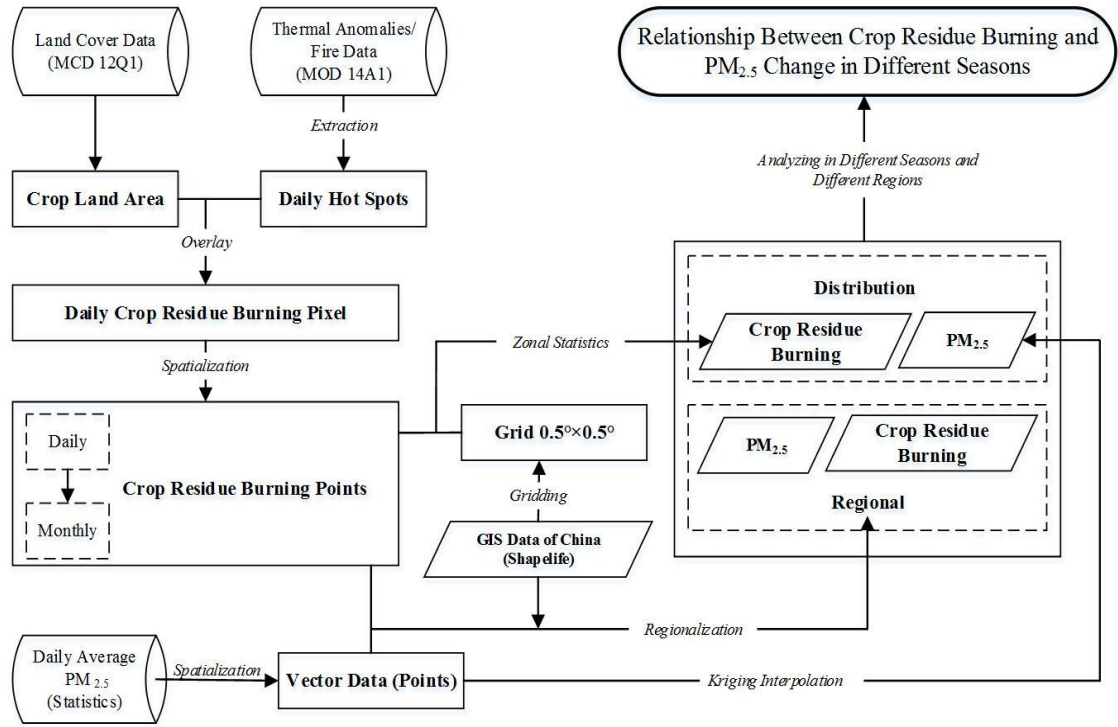


Figure 2.1 Flow chart of obtaining crop residue burning data and $\text{PM}_{2.5}$ data.

2.2.2.2 Process for obtaining $\text{PM}_{2.5}$ data

After acquiring the daily average $\text{PM}_{2.5}$ data from China's National Environmental Monitoring Center, the data were combined with the geographic coordinates of each city. Then, the $\text{PM}_{2.5}$ data for 150 cities in 2014 and 285 cities in 2015 were converted into vector data (point shapefile), which are more suitable for mapping the $\text{PM}_{2.5}$ distribution. For the 150 cities in 2014, the minimum distance between each other is 30.52 km, maximum distance is 3,803.48 km and average distance is 1,195.16 km. For the 285 cities in 2015, the minimum distance between each other is 22.39 km, maximum distance is 4,574.63 km and average distance is 1,368.42 km. Finally, the ordinary Kriging interpolation method and the daily $\text{PM}_{2.5}$ data for 150 cities in 2014 and 285 cities in 2015 was used to obtain the $\text{PM}_{2.5}$ distribution map of China (Fig. 2.1). The Kriging interpolation method is an important geostatic method based on the use of a variogram (Guo et al., 2013). A variogram is a geostatistical technique that can be used

to examine the spatial continuity of a regionalized variable and how this continuity changes as a function of distance and direction. Under suitable assumptions on the priors, Kriging gives the best linear unbiased prediction of the intermediate values. By using the Geostatistical Analyst on the ArcGIS platform, we can obtain the parameters (range, nugget and sill) of experimental semivariogram to perform the interpolation. In this section, the Kriging interpolation method is only used to present the spatial distribution characteristics of PM_{2.5} and the regional and period PM_{2.5} data are calculated with the daily average concentration from monitoring station.

After all of the processes described above, two sets of data can be mainly acquired, one is spatial distribution maps of crop residue burning and PM_{2.5} concentration, the other one is regional statistic data of crop residue burning spots and PM_{2.5} concentration. Then, the temporal and spatial distribution characteristics of crop residue burning and PM_{2.5} concentration were illustrated on a national scale. Furthermore, China's middle-east and northeast would be regarded as representative region to analyze the relationship between crop residue burning and PM_{2.5} change and the different attributes in four seasons are also revealed.

2.3 Results

2.3.1 Monthly changes in crop residue burning in China

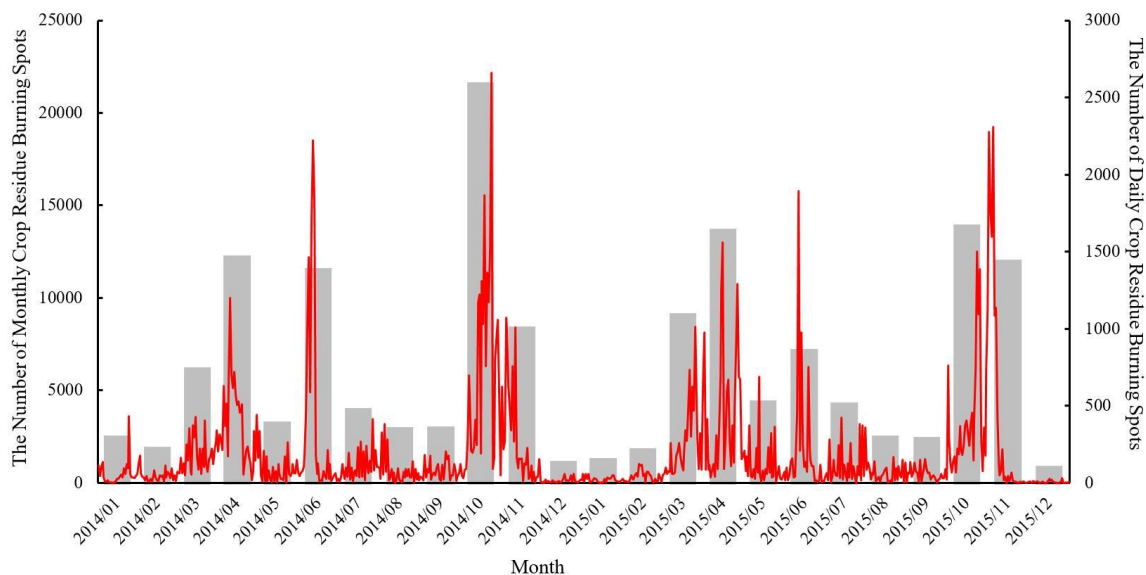


Figure 2.2 The daily (red line) and monthly (gray column) number of crop residue burning spots in China.

The daily and monthly number of number of crop residue burning spots in 2014 and 2015 were extracted from MODIS products. Table 2.1 shows that there were 71,237 and 66,051 crop residue burning spots in 2014 and 2015, respectively. Crop residue burning spots accounted for 52.08% and 56.47% of all the hot spots from MODIS in 2014 and

2015. Meanwhile, the ratios between crop residue burning spots and all hot spots in June, October and November were much higher than that in other months. As Fig. 2.2 and Table 2.1 shows, the number of spots in October was the highest of the whole year. Meanwhile, the number of monthly crop residue burning spots showed a similar change tendency in the two years studied. The monthly and daily crop residue burning spots were mainly concentrated in 3 periods: from March to April, in July and from October to November. On 23th October, 2014 and 4th November, 2015, the number of crop residue burning spots was 2,661 and 2,310, respectively, the highest daily totals for the two years. These days corresponded with China's autumn harvest. The second most intensive time for crop residue burning in 2014 and 2015 was on 11th June, which corresponded the summer harvest time in China.

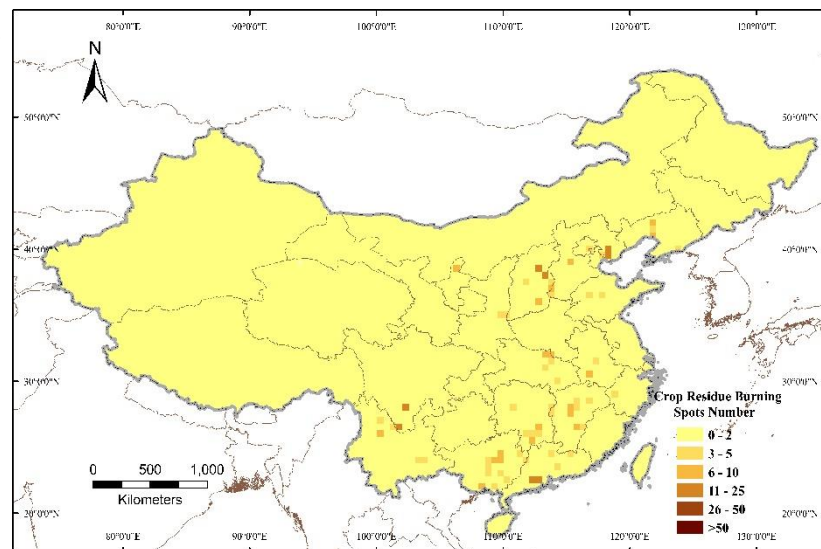
Table 2.1 Statistic of crop residue burning spots and all hot spots from MOD14A1 in China, China's middle-east and China's northeast.

Year	Month	Whole China			China's middle-east			China's northeast		
		Crop residue burning spots	All hot spots	Ration (%)	Crop residue burning spots	All hot spots	Ration (%)	Crop residue burning spots	All hot spots	Ration (%)
2014	Jan.	1886	16194	11.65	440	941	46.76	68	85	80.00
	Feb.	1288	5723	22.51	42	102	41.18	523	679	77.03
	Mar.	5560	14639	37.98	938	1454	64.51	2679	3781	70.85
	Apr.	11628	22735	51.15	1201	1751	68.59	7890	11470	68.79
	May.	2631	6453	40.77	1522	1913	79.56	239	501	47.70
	Jun.	10912	13216	82.57	10338	10849	95.29	155	462	33.55
	Jul.	3370	6404	52.62	1811	2291	79.05	169	532	31.77
	Aug.	2324	4752	48.91	1173	1503	78.04	267	793	33.67
	Sep.	2391	5473	43.69	342	489	69.94	691	1297	53.28
	Oct.	20965	26282	79.77	1338	1573	85.06	17411	19296	90.23
	Nov.	7767	10637	73.02	355	467	76.02	6563	7150	91.79
	Dec.	515	4266	12.07	131	234	55.98	61	75	81.33
	Sum	71237	136774	52.08	19631	23567	83.30	36716	46121	79.61
2015	Jan.	654	7402	8.84	123	258	47.67	33	51	64.71
	Feb.	1187	5823	20.38	175	306	57.19	453	618	73.30
	Mar.	8511	15216	55.93	781	1062	73.54	5166	6237	82.83
	Apr.	13075	23541	55.54	788	1070	73.64	9751	12737	76.56

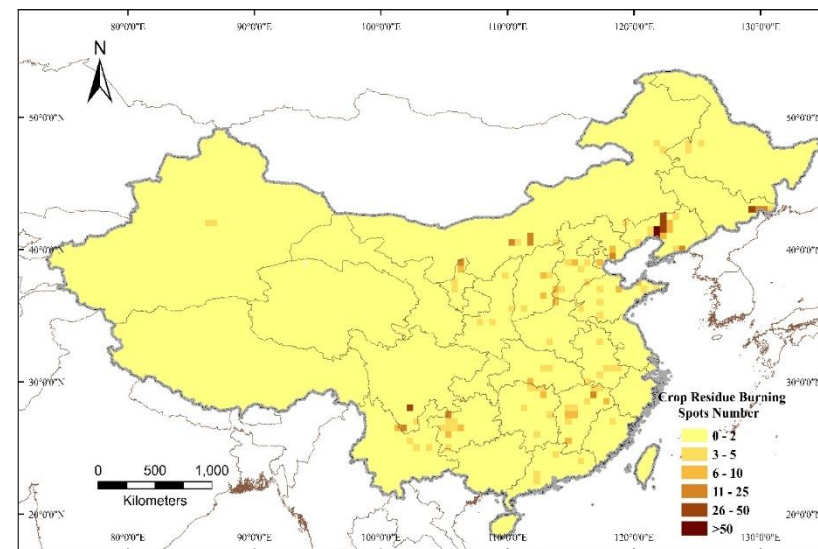
Year	Month	Whole China			China's middle-east			China's northeast		
		Crop residue burning spots	All hot spots	Ration	Crop residue burning spots	All hot spots	Ration	Crop residue burning spots	All hot spots	Ration
				(%)			(%)			(%)
2015	May.	3787	7436	50.93	2238	2735	81.83	507	1082	46.86
	Jun.	6555	8821	74.31	5777	6223	92.83	184	547	33.64
	Jul.	3652	6566	55.62	2329	2829	82.33	197	607	32.45
	Aug.	1885	4473	42.14	884	1269	69.66	164	476	34.45
	Sep.	1802	4085	44.11	422	560	75.36	653	1410	46.31
	Oct.	13293	18997	69.97	2019	2274	88.79	9176	11396	80.52
	Nov.	11397	13709	83.14	106	155	68.39	10614	11845	89.61
	Dec.	253	900	28.11	105	135	77.78	63	79	79.75
	Sum	66051	116969	56.47	15747	18876	83.42	36961	47085	78.50

To understand the spatial characteristics of crop residue burning, the monthly distribution maps have been used (Fig. 2.3). In March and April, burning spots are mainly distributed in China's north, especially the northeast because of straw burning before spring ploughing (Fig. 2.3). During this period, local farmers burn the straw left on the farmland as fertilizer to make the spring ploughing easier. The burning spots even show a transfer trend to more northerly regions from March to April. This is consistent with spring ploughing times in China's northeast. The fire points in June are mainly distributed in the Henan, Shandong, Anhui, Jiangsu and Hebei provinces, which are China's wheat planting areas (Fang et al., 2014). In June, after the wheat harvest, a large proportion of wheat straw is burnt directly on the farmland. According to the report from China's Ministry of Environmental Protection (<http://www.zhb.gov.cn/>), crop residue burning spots in June 2015 decreased by 45.35% compared with those in 2014. Meanwhile, the results of this study demonstrated a 39.93% decrease in June 2015, conforming to the official report. In October, crop residue burning spots rose to 20,965 in 2014 and 13,293 in 2015. This sudden increase was caused by autumn harvest. In October, the spots are mainly concentrated in China's northeast, and this is consistent with harvest times for corn, soybean and rice in China's north (Fig. 2.3). In November, the number of crop residue burning spots showed a distinct decrease, but in China's northeast, crop residue burning was still ongoing. This is because the high latitudes result in a later harvest time in this region than in other places. In December, the number of crop residue burning spots decreased to the lowest rates in the whole year.

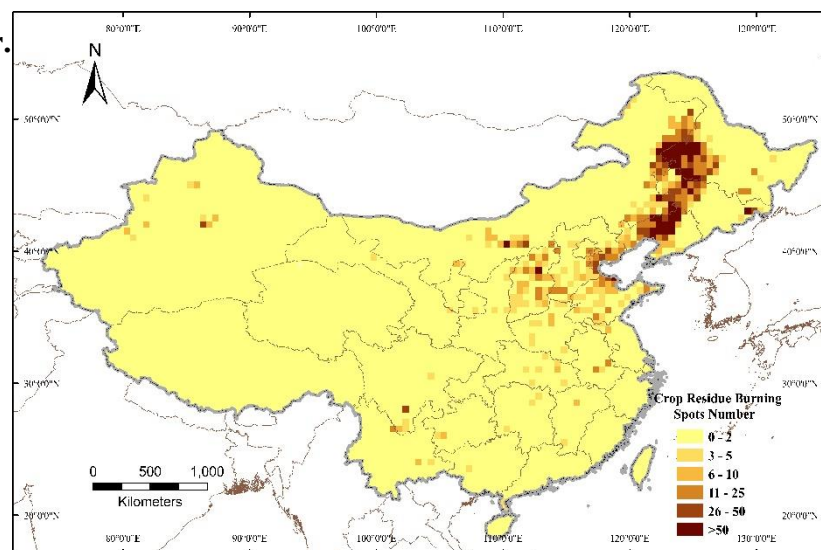
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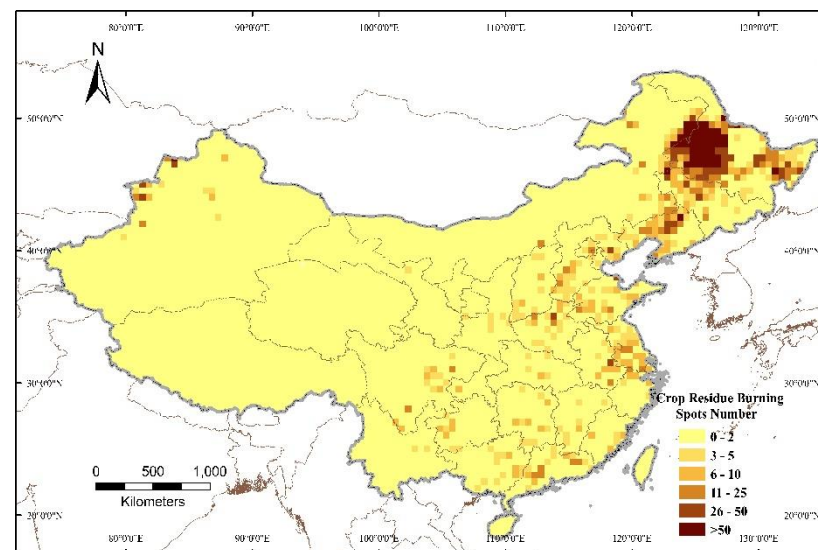
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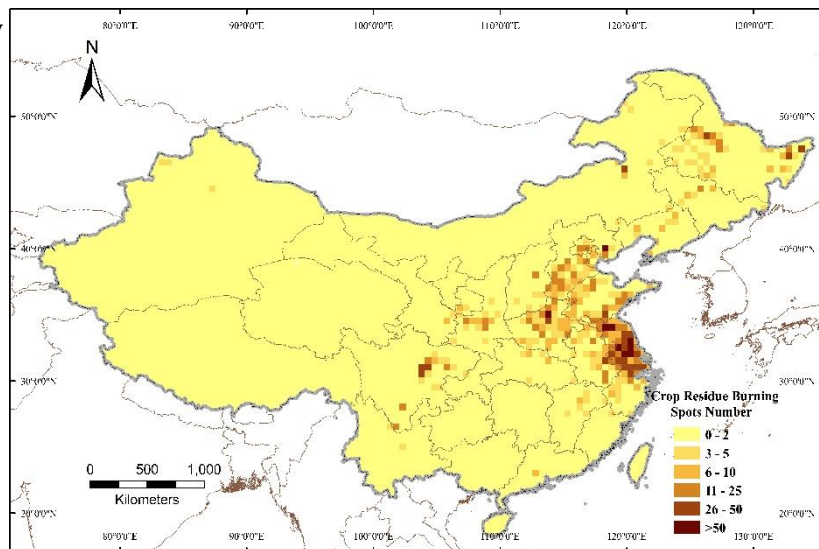
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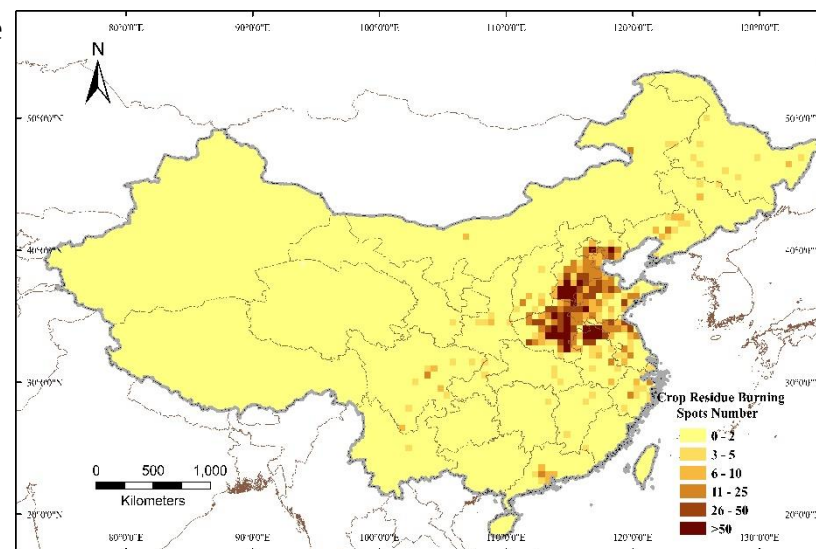
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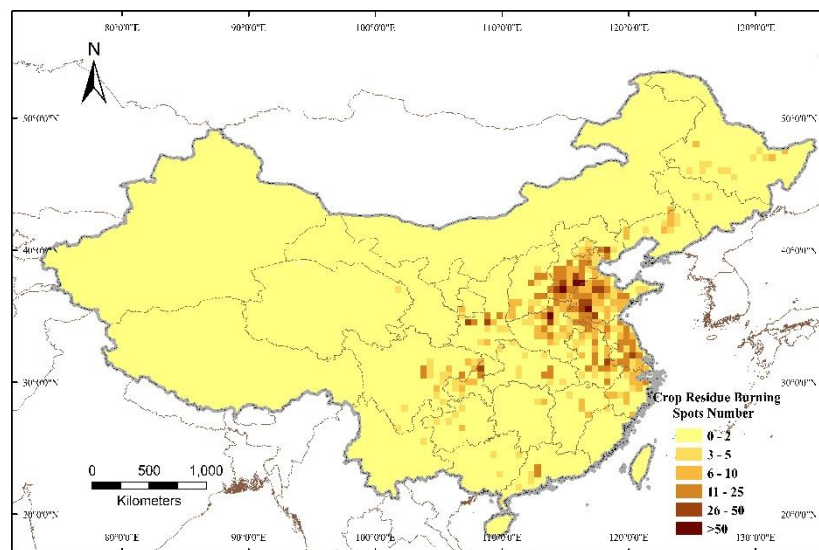
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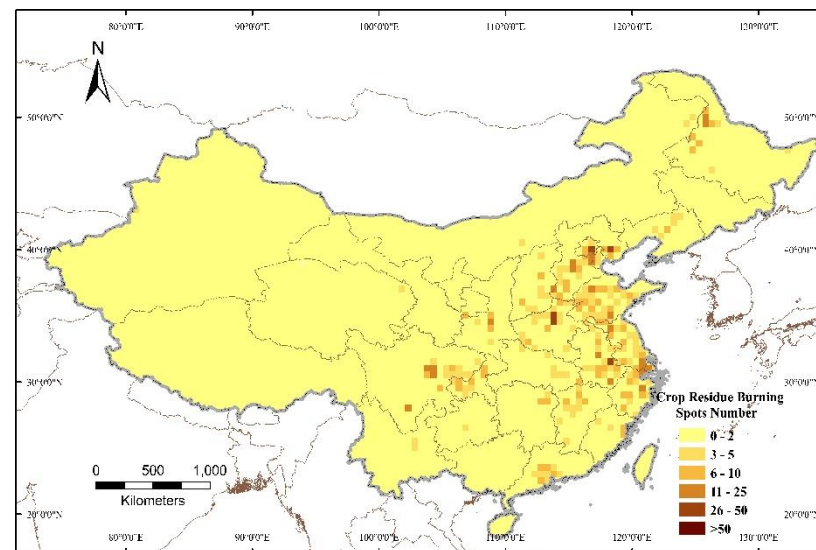
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Aug.



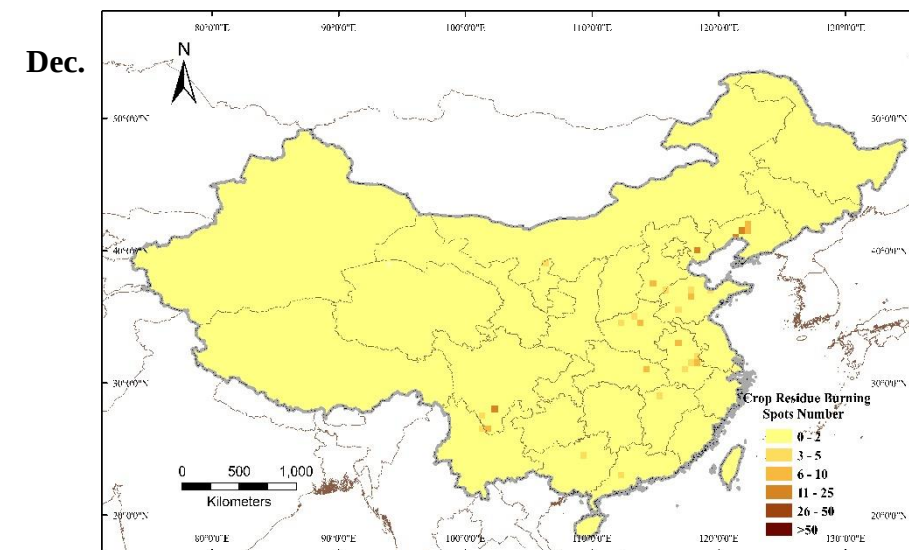
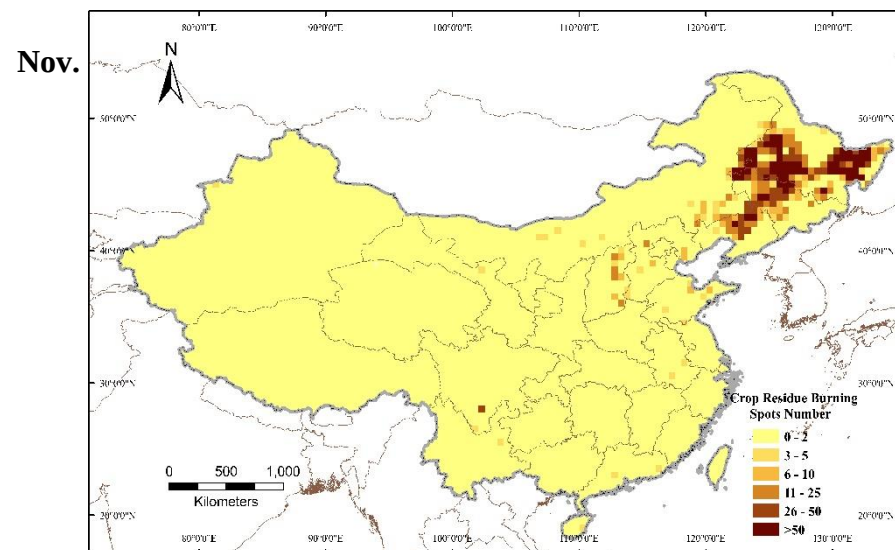
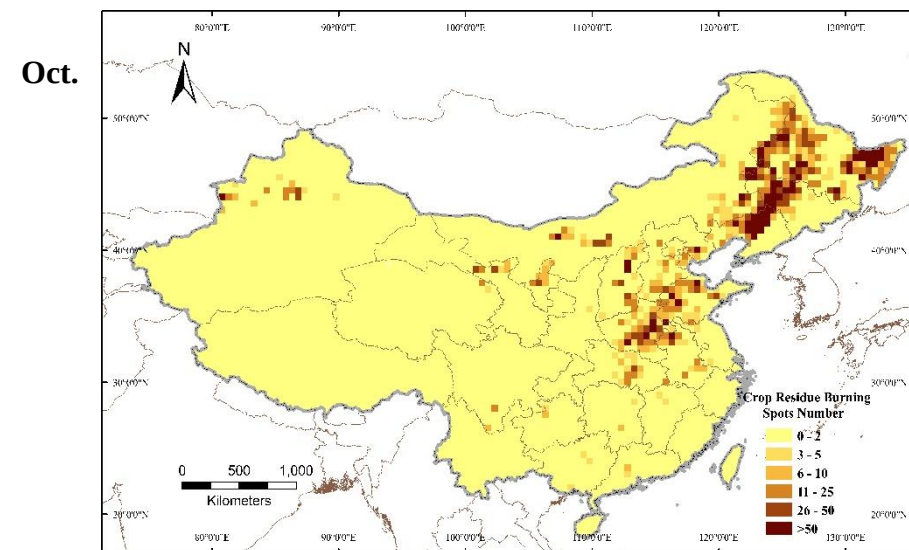
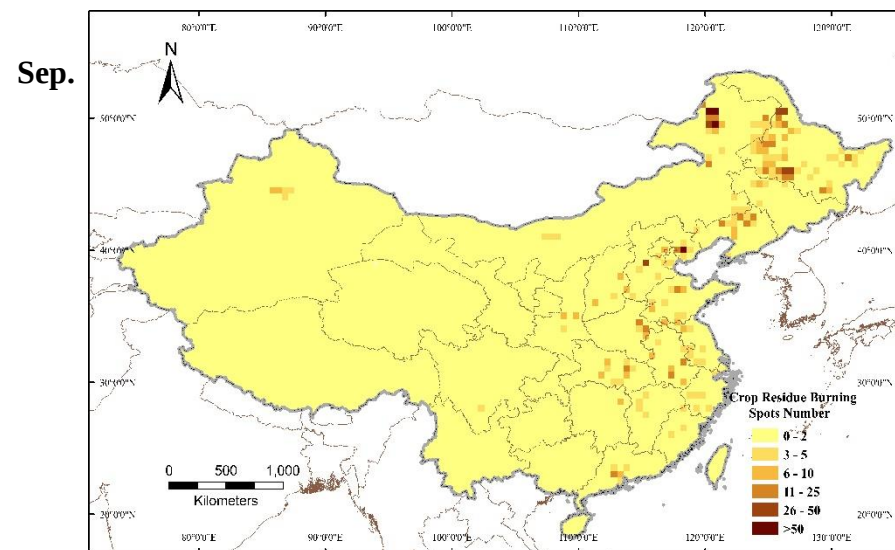


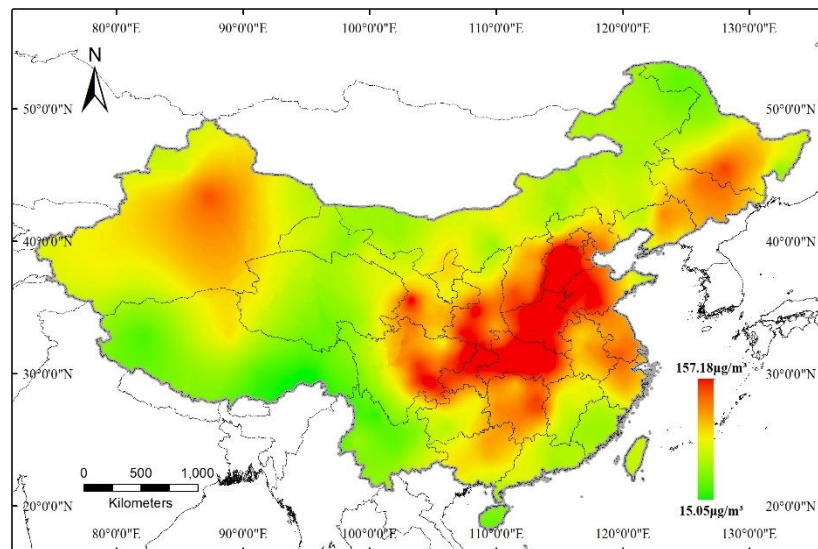
Figure 2.3 The monthly spatial distribution of crop residue burning spots in 2015, China.

2.3.2 Monthly PM_{2.5} changes in China

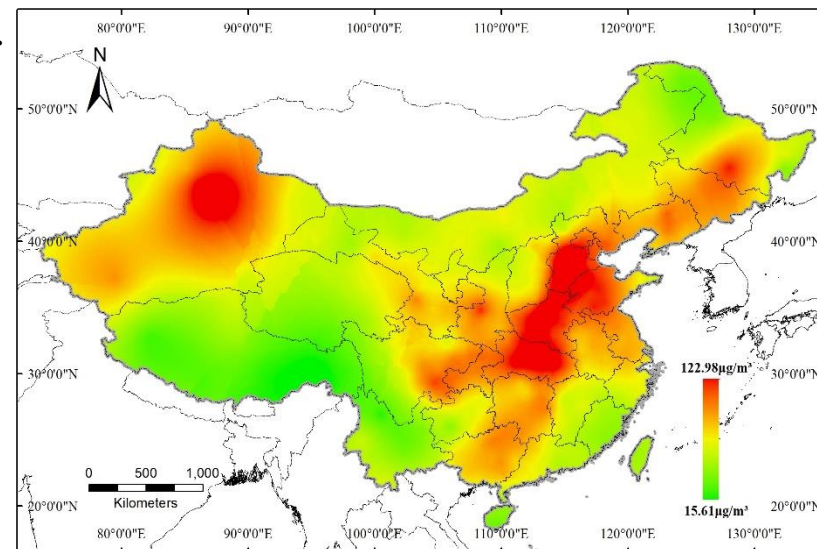
PM_{2.5} is an important indicator of air quality, and reducing PM_{2.5} effectively is key to decreasing the occurrence of haze in China. However, there is hardly any research about PM_{2.5} changes in China because of the shortage of time-series PM_{2.5} data. In this study, daily air quality data from China's National Environmental Monitoring Center were used to study temporal and spatial changes in PM_{2.5} in China. The data show that PM_{2.5} is always higher in winter than in other seasons (Fig. 2.4). In January the average PM_{2.5} was the highest of the year. After January, PM_{2.5} declined for 9 consecutive months and finally reached in September, making it the month with the lowest PM_{2.5} concentration of the year. After September, PM_{2.5} grew continuously until the end of the year. The monthly PM_{2.5} value was always lower in 2015 than in 2014 and the average PM_{2.5} in 2015 was 54.03 $\mu\text{g}/\text{m}^3$, a decrease of 11.15% when compared with 2014. This result is in accordance with Greenpeace's report.

The PM_{2.5} distribution map shows that PM_{2.5} in China's east is always higher than in China's west (Fig. 2.4). Dense population, cities, and rapid industrial development in China's east are the main causes of higher PM_{2.5}. The distribution shows that PM_{2.5} in the west of the Xinjiang Uygur Autonomous Region is also higher than in other regions. That is related to poor surface conditions and low vegetation cover, causing dusty weather to be more likely to occur (Qian et al., 2007). Meanwhile, Taklimakan Desert is also located in the Xinjiang Uygur Autonomous Region (Dong et al., 2004). The result also shows that PM_{2.5} in China's north is always higher than in China's south. Because China's north is far away from the ocean, dry climate and serious desertification, dusty weather is more common in this region. Moreover, most of China's energy resources and processing are distributed in its north. Mining, transportation and processing will produce massive dust and airborne particles. Coal-fired heating in the winter in China's north also exacerbates the increase of PM_{2.5}.

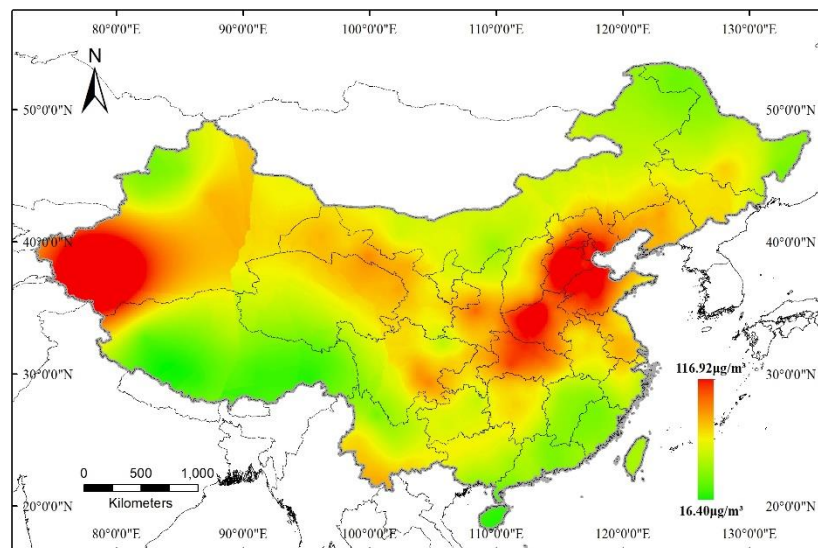
Jan.



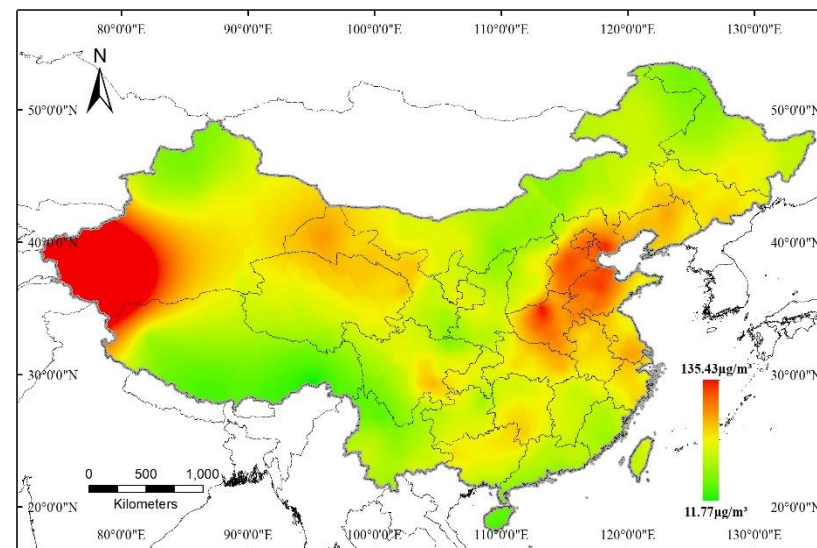
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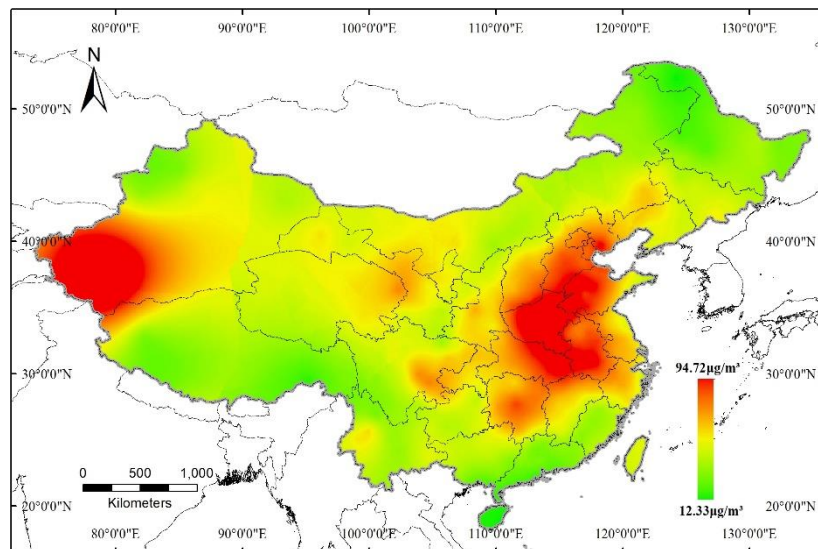
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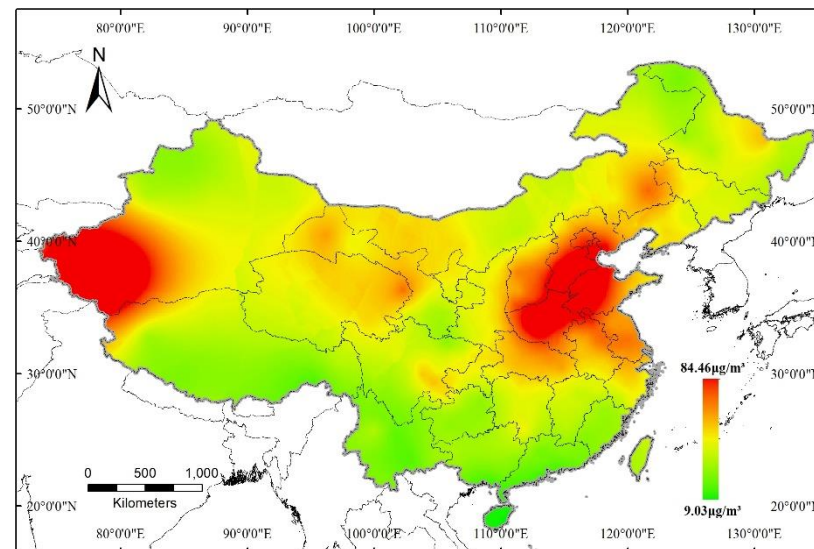
Apr.



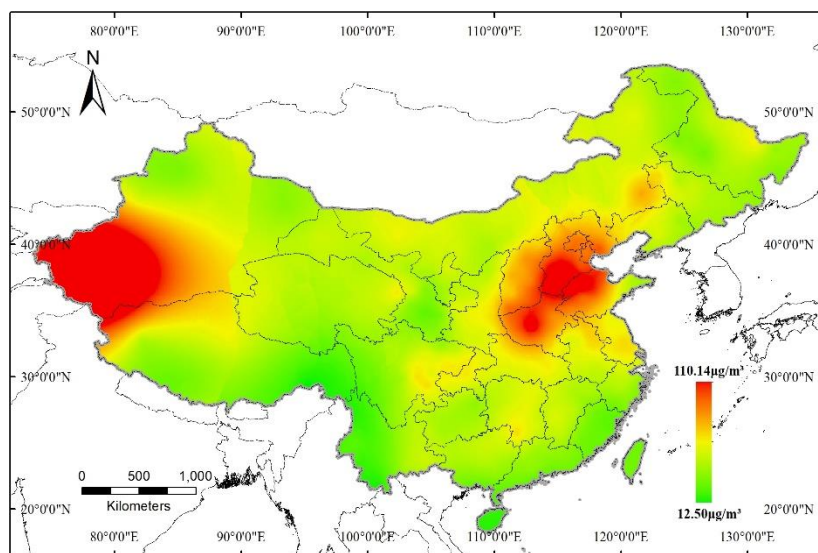
May



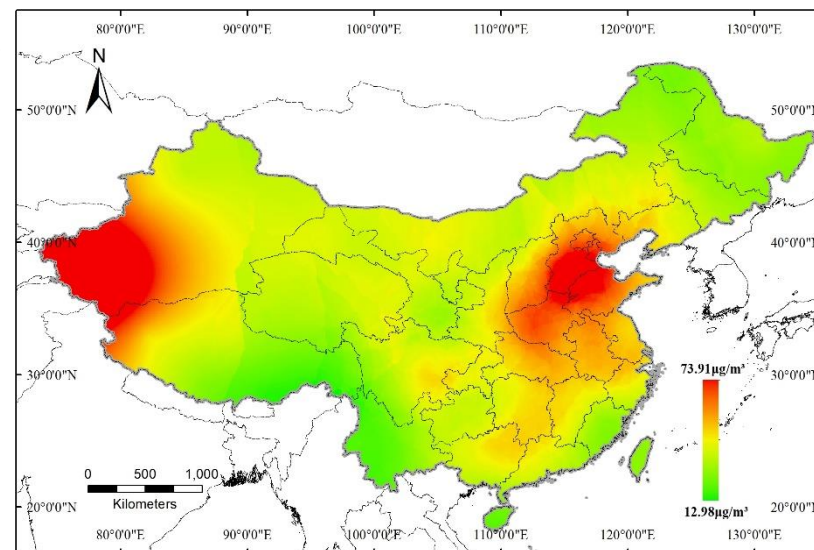
June



July



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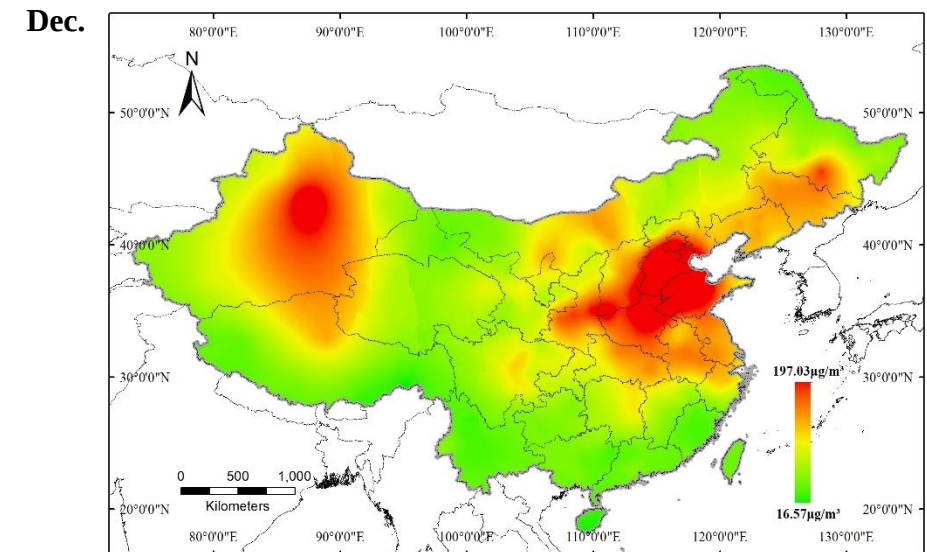
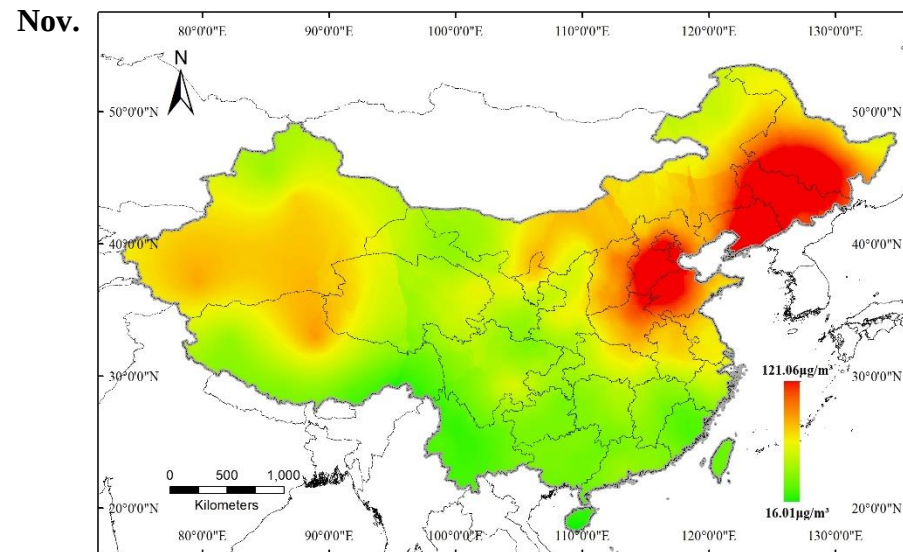
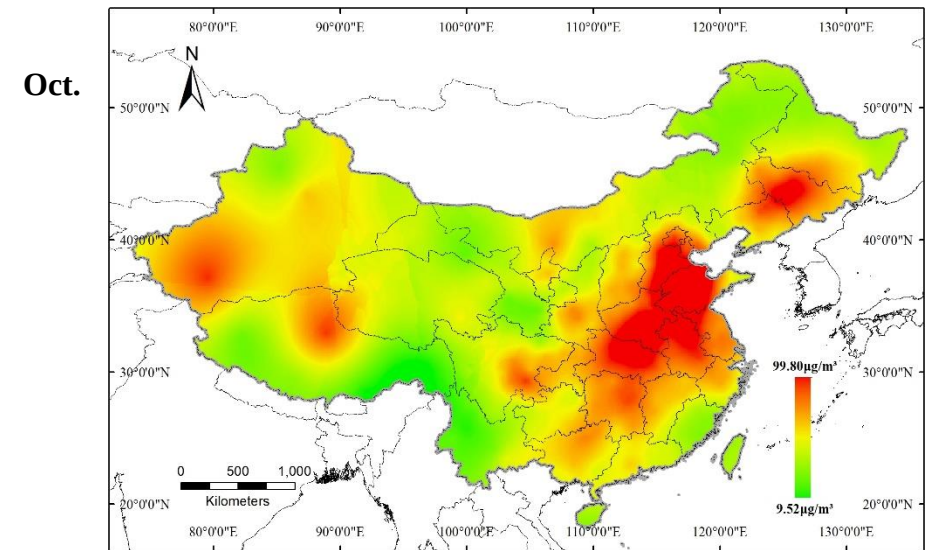
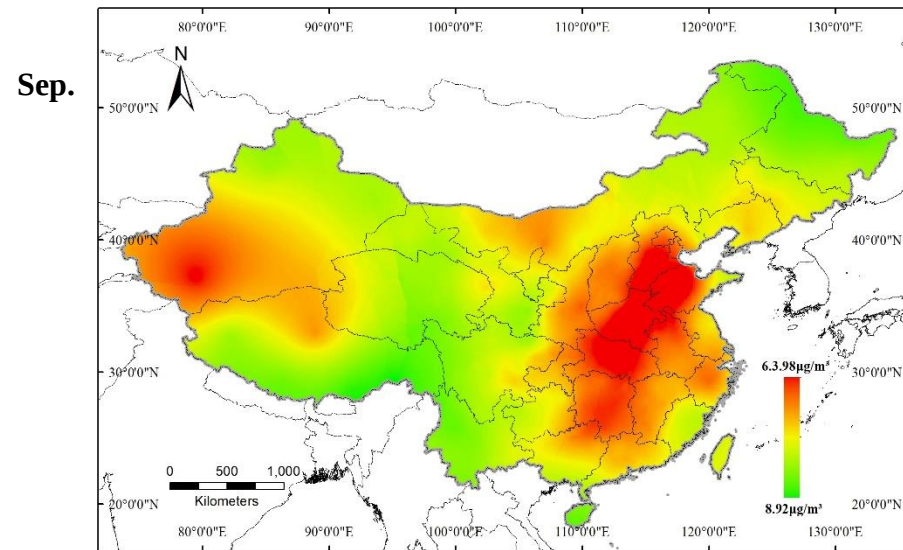
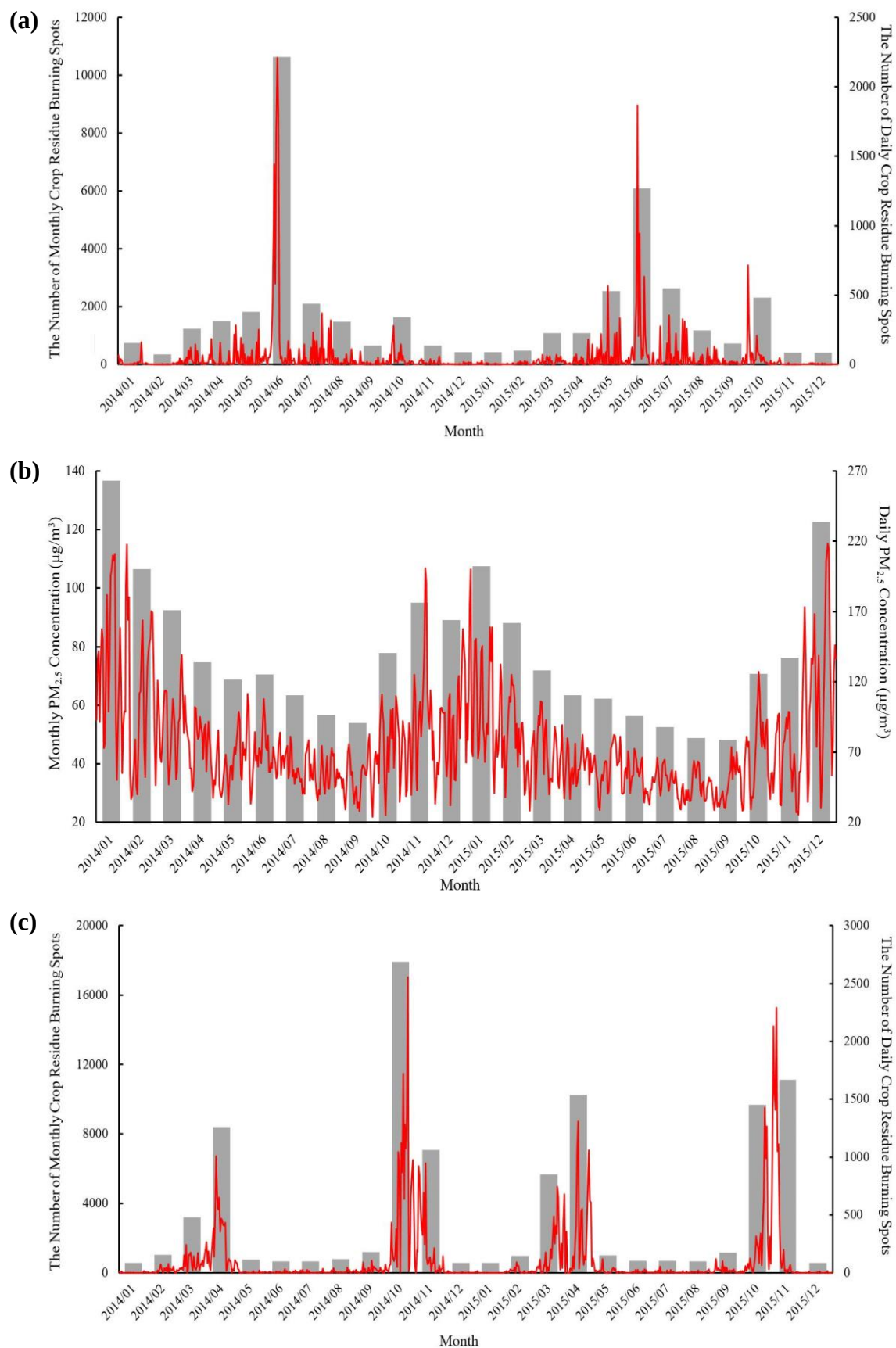


Figure 2.4 The monthly spatial distribution of PM_{2.5} in 2015, China.

2.3.3 The relationship between PM_{2.5} and crop residue burning

2.3.3.1 The relationship between PM_{2.5} and crop residue burning in spring



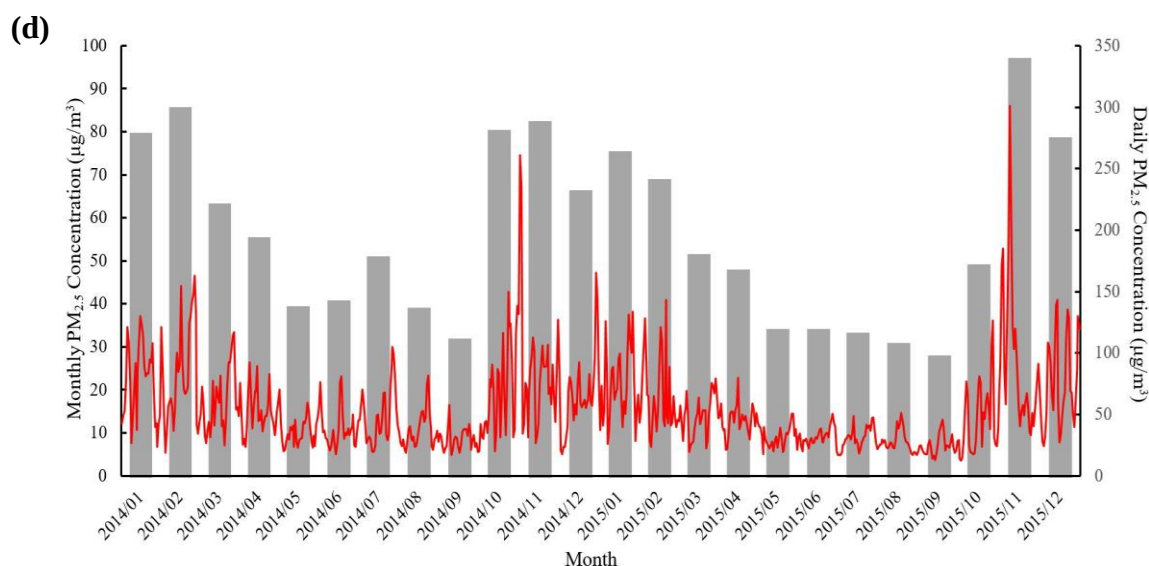
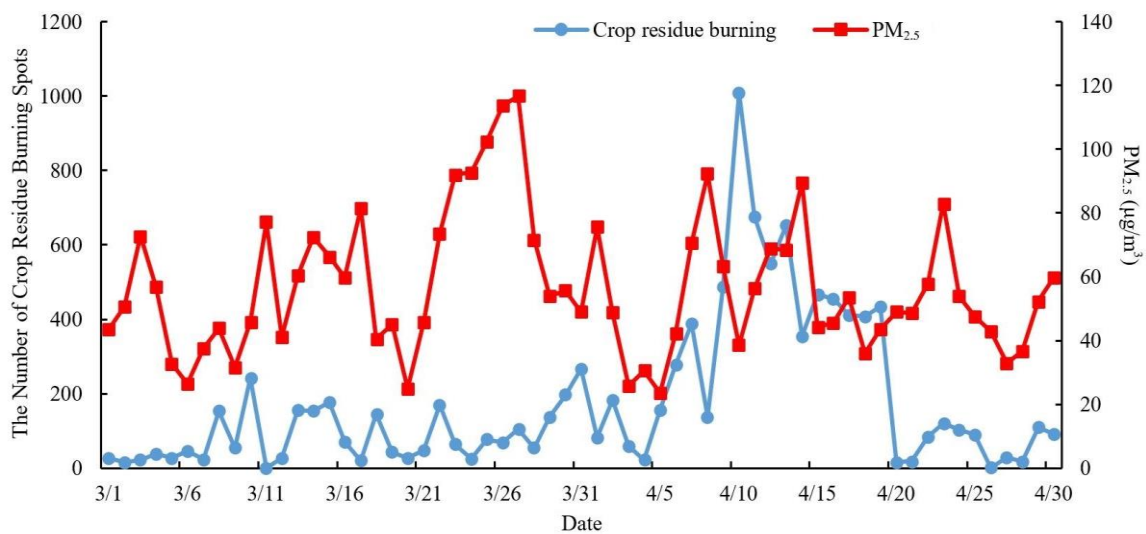


Figure 2.5 The daily (red line) and monthly (gray column) data of crop residue burning spots in China's middle-east (a) and China's northeast (c) and PM_{2.5} concentration in China's middle-east (b) and China's northeast (d).

Crop residue burning in the spring is mainly concentrated in China's northeast in March and April before spring ploughing. Heilongjiang Province, Jilin Province and Liaoning Province, all located in China's northeast, account for 61.46% in 2014 and 69.10% in 2015 of burning spots from the whole country in these two month. Fig. 2.5 also demonstrates there are two significant crop residue burning period in northeast China, one is from March to April and the other one is from October to November. Therefore, these three provinces are regarded as the study region in this section. Fig. 2.6 shows that, the crop residue burning is more concentrated in April than that in March and the crop residue burning spots of 3 provinces reached its highest point on 10th April, 2014, and 15th April, 2015, with numbers of 1,308 and 1,009, respectively. The burning time in spring was dispersive and PM_{2.5} change trend was random. Unlike the crop residue burning in summer and autumn-winter, crop residue burning and PM_{2.5} present different tendency and PM_{2.5} did not show a notable increase after the burning of crop residue. Table 2.3 also demonstrates that the crop residue burning in these three provinces did not induce PM_{2.5} concentration increase in certain period and it shows a stable decrease that is consistent with that of other provinces. Meanwhile, comparing the data in 2015 with 2014 (Table 2.2), the number of crop residue burning spots in both March and April rise evidently, with 92.83% increase in March and 23.59% increase in April. On the contrary, the concentration of PM_{2.5} in March declined 19.25%, from 60.58 µg/m³ to 48.92 µg/m³, and for April, it declined 14.02%, from 52.70 µg/m³ to 45.31 µg/m³, which is even more intense than the annual PM_{2.5} decrease (11.15%). Therefore, when comparing the spring residue burning data and PM_{2.5} data from 2014 and 2015, we can conclude the change in crop residue burning spots did not cause an evident change in PM_{2.5} that is also different from the results of crop residue burning in

summer and autumn-winter. Furthermore, through analyzing the daily data of crop residue burning spots and $PM_{2.5}$, no correlation between crop residue burning and $PM_{2.5}$ was found on the same day or from several days later and the $PM_{2.5}$ did not present a rising tendency during the crop residue burning (Table 2.3). Regarding spatial distribution, even though most of the crop residue burning spots in March and April is distributed in China's northeast, the $PM_{2.5}$ concentration was very low in this region. In these two months, crop residue burning and $PM_{2.5}$ showed no spatial consistency.

(a)



(b)

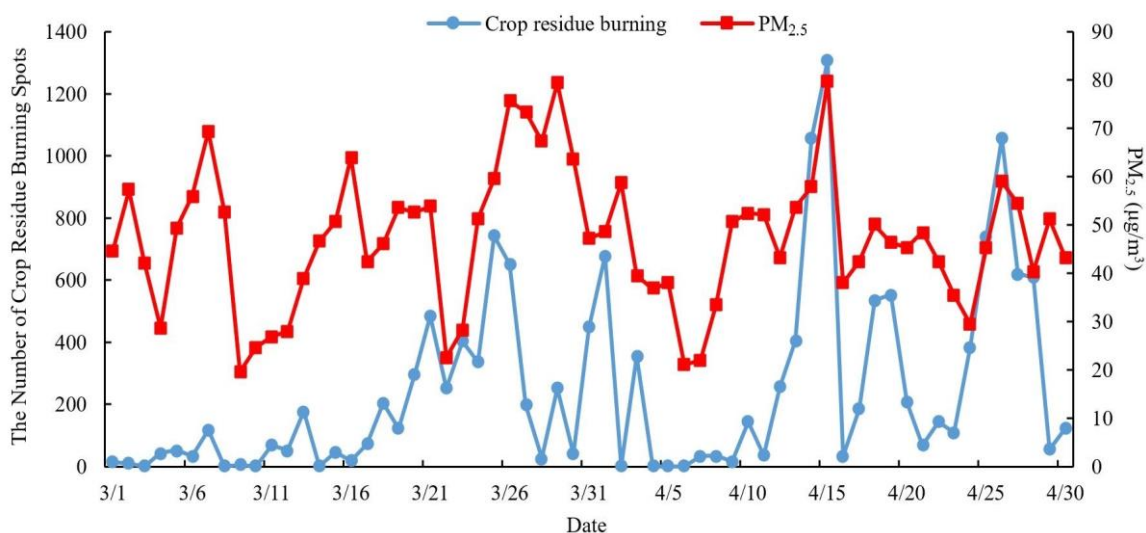


Figure 2.6 The number of crop residue burning spots and $PM_{2.5}$ of China's northeast in March and April: 2014(a); 2015(b).

On the daily-level, period-level (Table 2.3), year-level (Table 2.2) and spatial distribution, all the results indicated that the crop residue burning in spring cannot cause a notable change of PM_{2.5} that was totally different from the final results of summer and autumn-winter. As mentioned above, since the crop residue burning in these two month was before the spring ploughing and the other two were after the harvest of crops, the amount of biomass burnt in spring was much less than in summer and autumn-winter. However, there were large numbers of crop residue burning spots in spring, a large proportion of the crop residue had already been burned in last autumn-winter. Meanwhile, the crop residue burning time in spring was more scattered than the other two which would reduce its effects on PM_{2.5} change.

Table 2.2 Comparing change tendency of crop residue burning spots and PM_{2.5} concentration between 2014 and 2015.

Month	Crop residue burning			PM _{2.5} (μg/m ³)		
	2014	2015	Change ration (%)	2014	2015	Change ration (%)
March	2679	5166	92.83	60.58	48.92	-19.25
April	7890	9751	23.59	52.70	45.31	-14.02
June	10338	5777	-44.12	67.43	53.06	-21.31
October	17411	9176	-47.30	77.74	46.48	-40.21
November	6563	10614	61.72	79.81	94.38	18.26

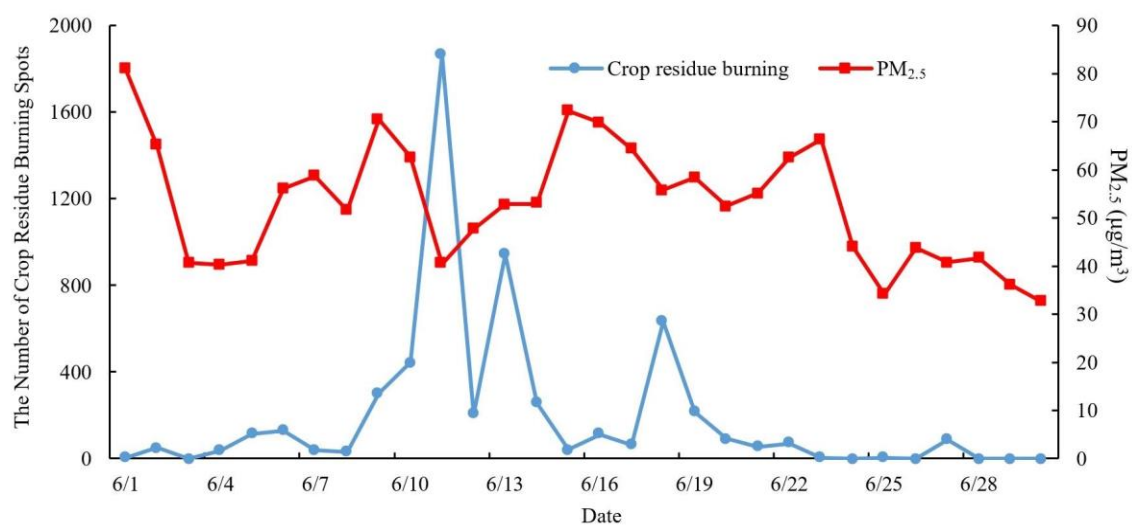
For March, April, October and November, the study region is the three provinces in China's northeast; for June, the study region is the five provinces in China's middle-east.

2.3.3.2 The relationship between PM_{2.5} and crop residue burning in summer

Crop residue burning in the summer is mainly concentrated in China's middle-east in early June, after the winter wheat harvest. As China's wheat production region, Henan, Shandong, Anhui, Jiangsu and Hebei provinces are all located in China's middle-east, and these five provinces account for a large proportion of crop residue burning spots in June. Crop residue burning spots in these five provinces in June constituted 94.74% of all spots in China in 2014 and 88.13% in 2015. Therefore, these five provinces are regarded as the study region for this part of the study. Fig. 2.5 shows that in this region the crop residue burning of June was much higher than other month and the daily number also reached peak during this period. Meanwhile, Table 2.1 indicates that in China's middle-east the rations between crop residue burning and all hot spots in this month were even over 90%, which were also the highest of the whole year. To the PM_{2.5} concentration (Fig. 2.5), the month change trend was almost the same as that of the whole China. But in June 2014 the concentration was little higher than last month that is different from the whole China. The daily data (Fig. 2.7) shows that crop residue

burning and $PM_{2.5}$ present similar change tendency, but the change in $PM_{2.5}$ is delayed by approximately 4 days. Crop residue burning in the summer lasts for approximately 1 week: for 2014 that was from 5th to 14th June, and for 2015, that was from 9th to 15th June. Crop residue burning in these 5 provinces reached its highest point on 11th June for both years, with the number of spots registering at 2,210 in 2014 and 1,866 in 2015. After the peak of crop residue burning, $PM_{2.5}$ started to show a growth trend and finally reached its highest point 4 days later in China's middle-east. $PM_{2.5}$ reached its highest point on June 15 of both years, with values of $116.76 \mu\text{g}/\text{m}^3$ in 2014 and $86.70 \mu\text{g}/\text{m}^3$ in 2015, showing a decrease of $30.06 \mu\text{g}/\text{m}^3$ between the years. Moreover, when compared with 2014, the annual decrease of $PM_{2.5}$ in 2015 was 11.15%. Meanwhile, $PM_{2.5}$ in June in these 5 provinces decreased 21.31% from $67.43 \mu\text{g}/\text{m}^3$ in 2014 to $53.06 \mu\text{g}/\text{m}^3$ in 2015 (Table 2.2), a more intensive decrease than the annual decrease. Table 2.2 also shows that crop residue burning spots in June 2015 presented a 44.12% decrease from previous year. Therefore, this finding indicates the decrease in crop residue burning is consistent with the decline in $PM_{2.5}$ in June, the summer harvest month. And the efforts of local government to reduce crop residue burning and improve air quality have achieved remarkable results. Meanwhile, Table 2.3 demonstrates that the crop residue burning in these five provinces induced $PM_{2.5}$ concentration increase during crop burning time, after that $PM_{2.5}$ concentration presented a steep fall that is totally different from the result of other provinces which showed a stable decline during this period. In June 2015, as the crop residue burning spots dropped from previous year, the $PM_{2.5}$ concentration increase in burning time was not so evident.

(a)



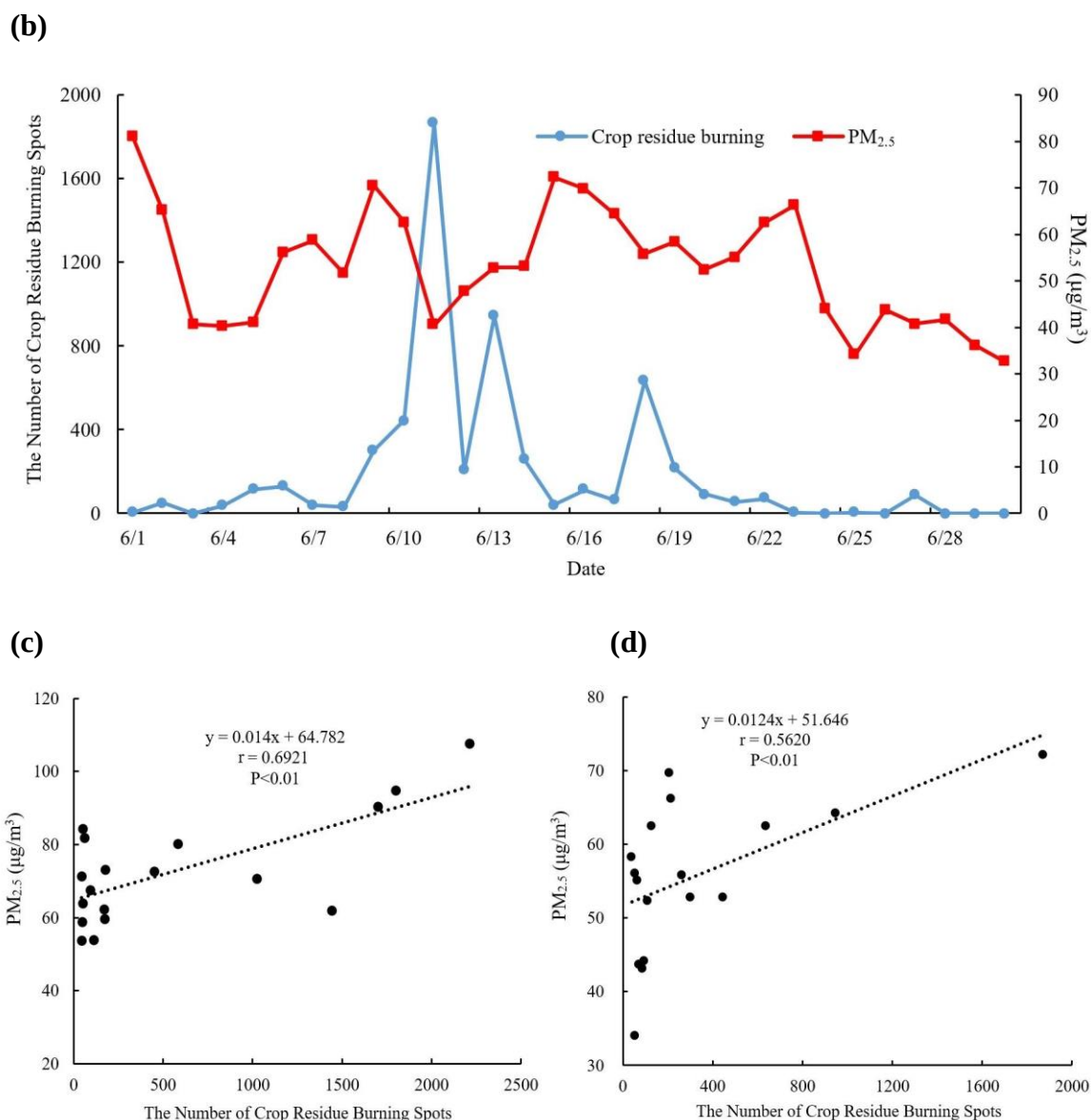


Figure 2.7 The number of crop residue burning spots and $PM_{2.5}$ of China's middle-east in June: 2014(a); 2015(b). And the correlation between the number of crop residue burning spots and $PM_{2.5}$ measured 4 days later: June 2014(c); June 2015(d).

In these five provinces with an area of 759,400 km², crop residue burning cannot induce an instantaneous increase in $PM_{2.5}$. Therefore, there is no correlation between crop residue burning and $PM_{2.5}$ on the same day. In 2014 and 2015, the crop residue burning in other provinces (excluding the five provinces in China's middle-east and three provinces in China's northeast) was not severe and the average daily crop residue burning spots in these provinces would be regarded as the baseline in the daily analysis, the number of which was 38.68. If the number of average daily crop residue burning spots is below 38.68, it would be ignored, because the crop residue burning in these days is not significant. the correlation between the number of crop residue burning spots and the $PM_{2.5}$ concentration from several days later was analyzed and the final results (Fig.

2.7) shows that the correlation coefficient between crop residue burning and PM_{2.5} from 4 days later is considerably higher with an r of 0.6921 ($P < 0.01$) in 2014 and 0.5620 ($P < 0.01$) in 2015. Furthermore, Fig. 2.7 also demonstrates that crop residue burning and PM_{2.5} are positively correlated. Regarding spatial distribution, Fig. 2.8 shows that crop residue burning was distributed mainly in the middle–east of China in June, and PM_{2.5} concentration was also high in these regions. In June 2015, crop residue burning and PM_{2.5} showed higher spatial consistency, except in the west of the Xinjiang Uygur Autonomous Region. High PM_{2.5} in Xinjiang is caused by its special landscape, as described earlier. In June 2014, crop residue burning was much more intensive than it was 2015. Therefore, Fig. 2.8 indicates that crop residue burning caused high PM_{2.5} not only in and but also around those areas in this year, such as Hubei and Hunan. In summer, China’s east is influenced by southeast monsoon, which is from ocean to continent, but impeded by Taihang Mountains, Qinling Mountains, Yunnan-Gzuihou Plateau and hilly region of Southeastern China, the PM_{2.5} from crop residue burning can only concentrate in North China Plain and Yangtze Plain. Areas west of the Xinjiang Uygur Autonomous Region did not present high PM_{2.5} in 2014 because at that time there was no PM_{2.5} detection data in that area.

Table 2.3 PM_{2.5} concentration change trend (before, during and after crop residue. burning) in study region and other provinces.

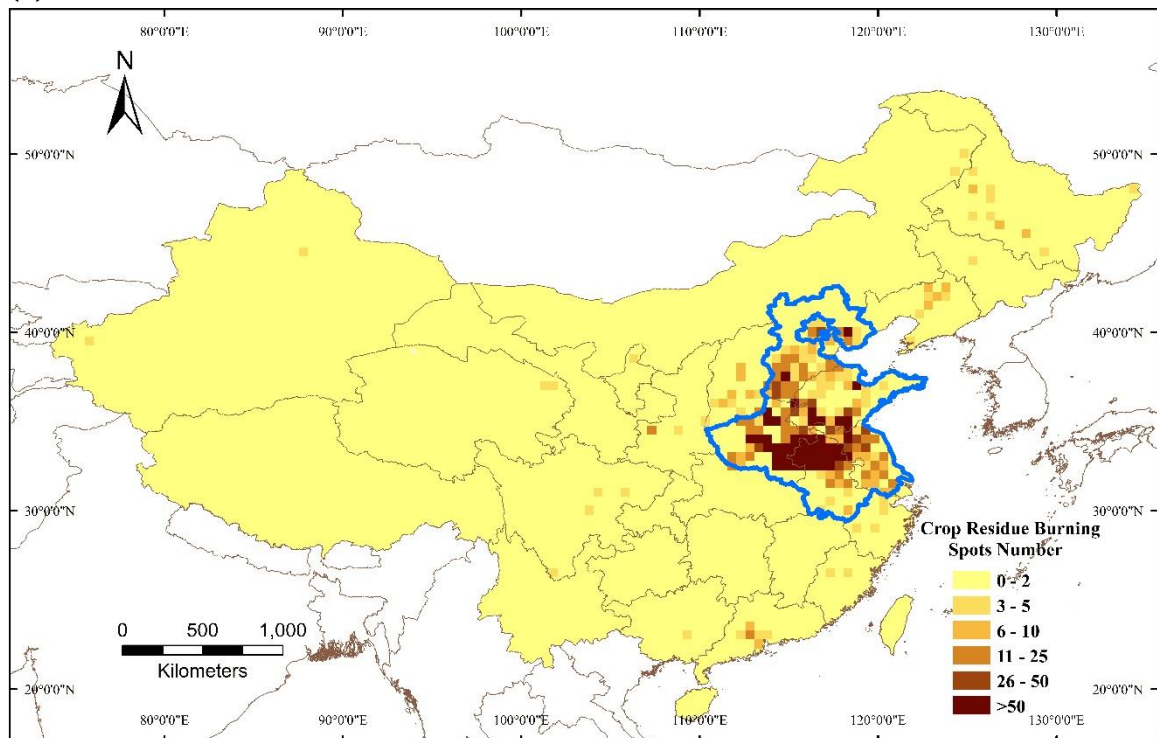
Year	Area	Spring ($\mu\text{g}/\text{m}^3$)			Summer ($\mu\text{g}/\text{m}^3$)			Autumn-winter ($\mu\text{g}/\text{m}^3$)		
	<i>Period</i>	3/15-4/04	4/05-4/25	4/26-5/16	5/21-6/04	6/05-6/19	6/20-7/04	9/06-10/11	10/12-11/16	11/17-12/22
2014	Study region	65.03	55.99	36.45	70.48	76.42	64.44	37.30	84.58	64.43
	Other provinces	68.05	58.85	46.52	44.59	42.99	32.38	48.09	61.71	68.43
	<i>Period</i>	3/20-4/11	4/12-5/04	5/05-5/27	5/28-6/08	6/09-6/20	6/21-7/02	9/26-10/20	10/21-11/14	11/15-12/09
2015	Study region	49.07	45.06	31.30	58.00	58.34	45.33	36.85	102.90	58.17
	Other provinces	46.32	45.73	43.29	30.38	29.48	28.81	46.49	48.71	52.77

The study region in spring and autumn-winter is China’s northeast and in summer is China’s middle-east. Because the PM_{2.5} presented a hysteresis change, after the concentrated crop residue burning time five more days would be considered as crop residue burning period. The number of the days before, during and after crop residue burning is the same.

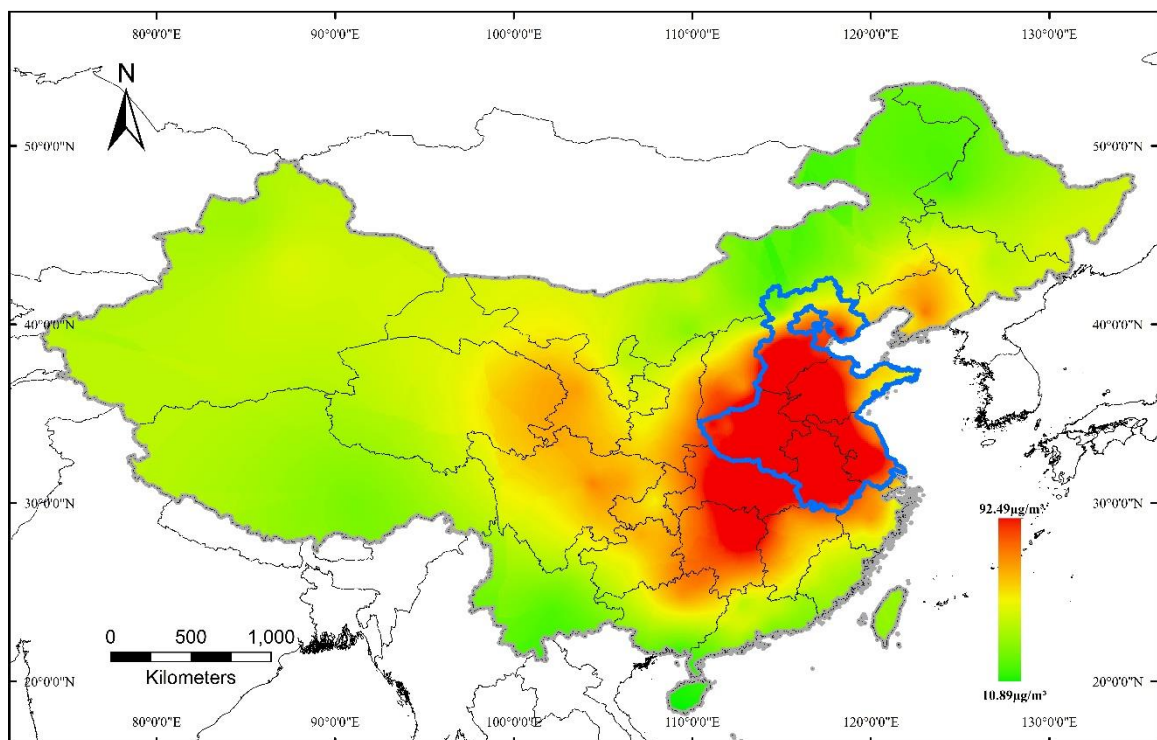
Overall, on the daily-level (Fig. 2.7), period-level (Table 2.3), year-level (Table 2.2) and spatial distribution (Fig. 2.8), all the results indicated that the crop residue burning of summer can induce PM_{2.5} increase in China’s middle-east. Although summer crop residue burning dramatically declined in 2015, the quantity is still large. For better

air quality, the government needs to continue taking effective measures to reduce crop residue burning.

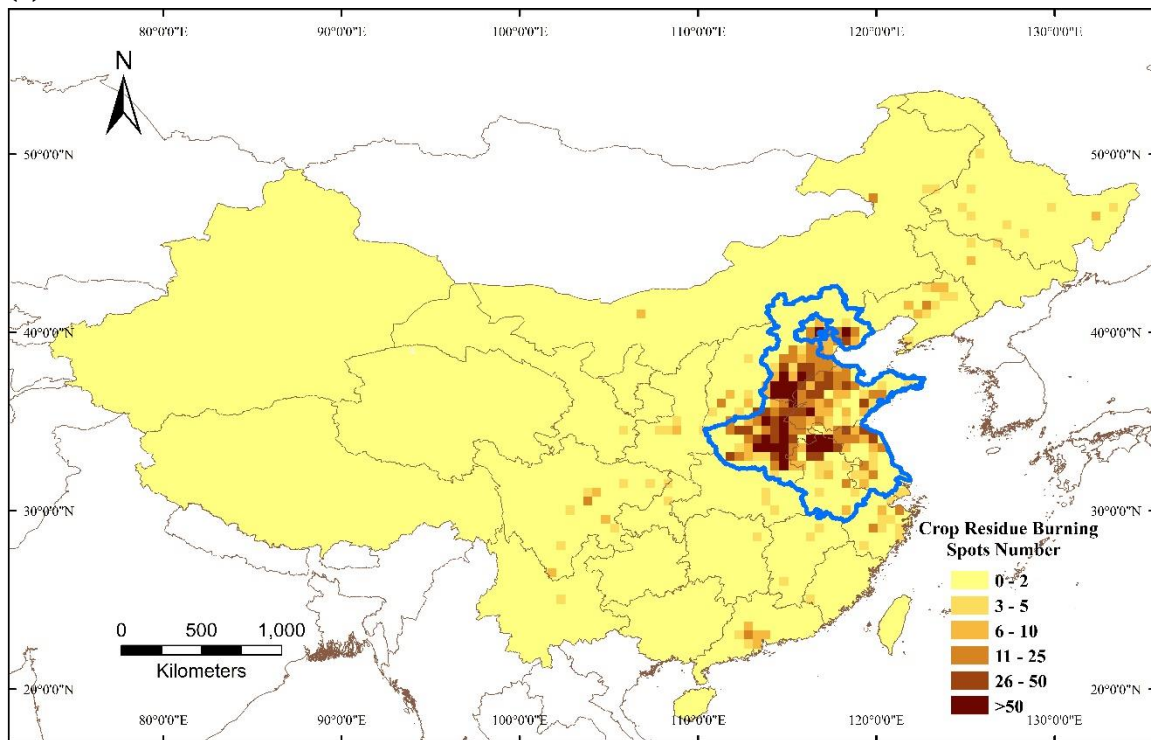
(a)



(b)



(c)



(d)

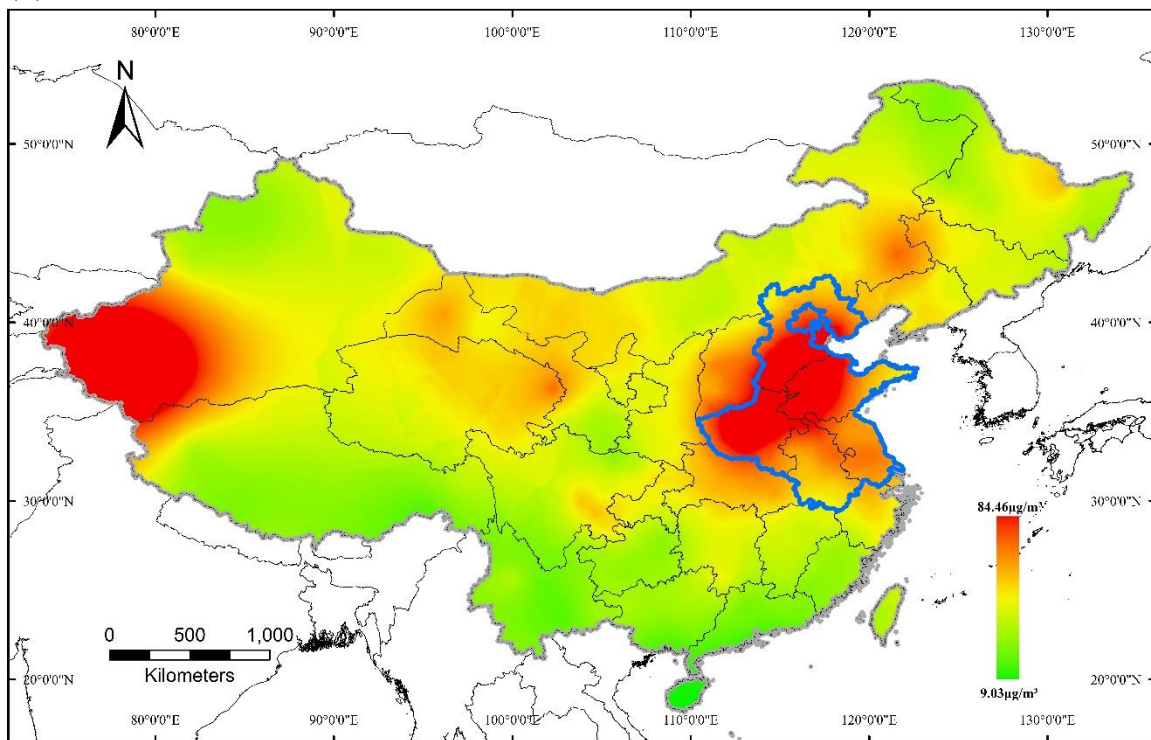


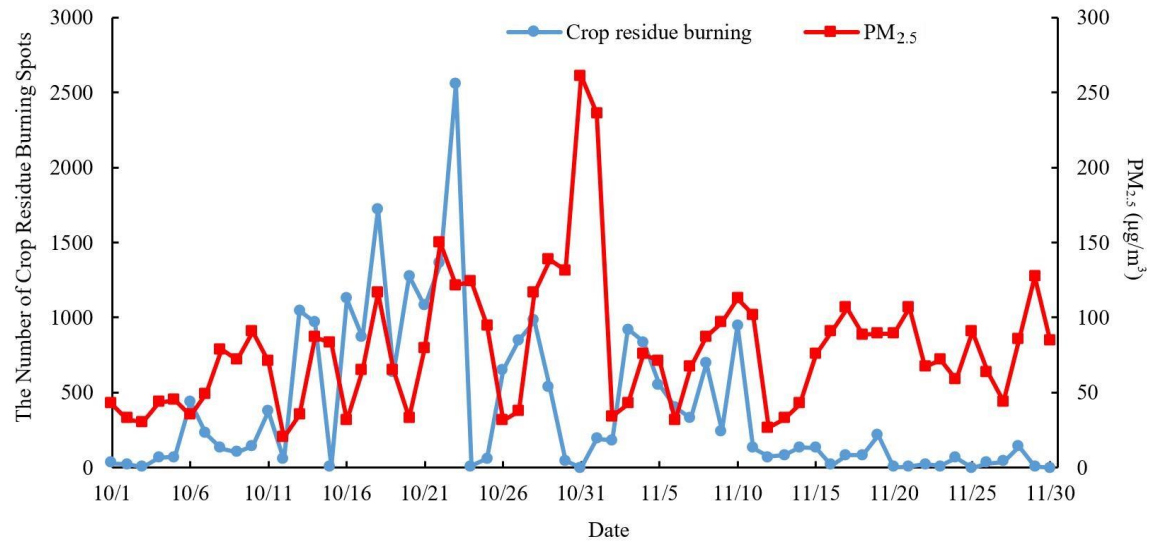
Figure 2.8 Spatial distribution of crop residue burning and PM_{2.5} in China in June (blue line is the boundary of the five provinces in China's middle-east): crop residue burning in June 2014(a); crop residue burning in June 2015(c); PM_{2.5} distribution in June 2014(b); PM_{2.5} distribution in June 2015(d).

2.3.3.3 The relationship between PM_{2.5} and crop residue burning in autumn-winter

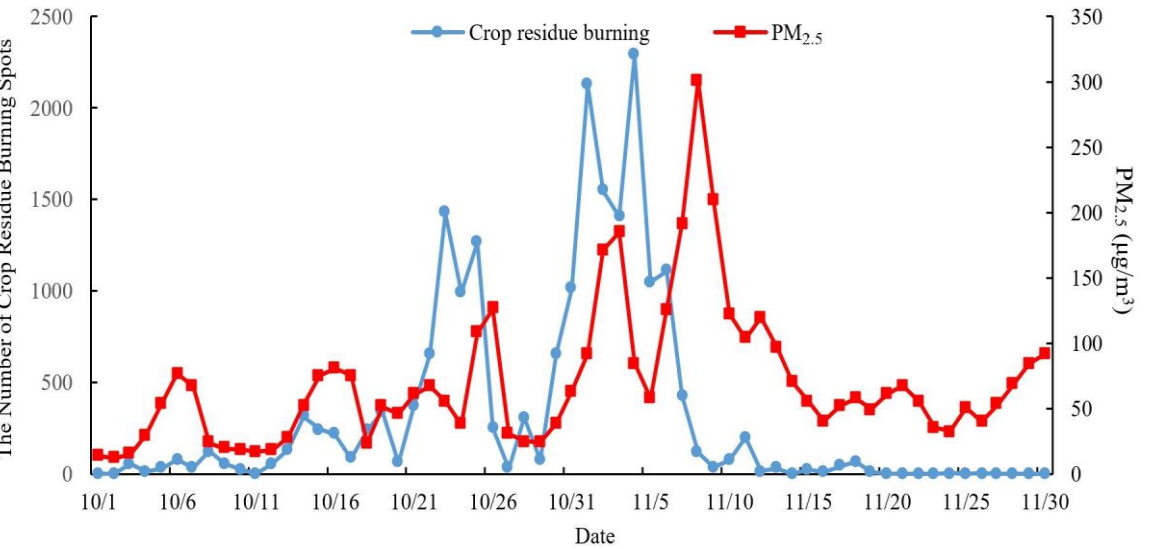
Autumn crop residue burning is mainly concentrated in China's northeast from late October to early November after the harvest of corn, rice and soybean. Heilongjiang Province, Jilin Province and Liaoning Province, as China's main grain producing areas, are all located in China's northeast. According to the statistics, the autumn-winter crop residue burning spots in these three province account for 83.44% in 2014 and 80.15% in 2015 of burning spots from the whole country. Therefore, these three provinces are regarded as the study region in this section. Fig. 2.5 shows that in this region the crop residue burning of October and November was much higher than other months and the daily number also reached peak during this period. Meanwhile, Table 2.1 indicates that in China's northeast the rations between crop residue burning and all hot spots in these months were around 90%, which were also the highest of the whole year in this region. To the PM_{2.5} concentration (Fig. 2.5), the month change trend was almost the same as that of the whole China. Fig. 2.9 shows that crop residue burning and PM_{2.5} present almost the same change tendency, with PM_{2.5} delayed by several days, in accordance with the result of crop residue burning in summer. While summer crop residue burning lasts only for one week, autumn crop residue burning lasts for a longer time, approximately 1 month. In 2014, autumn crop residue burning occurred from 12th October–11th November. In 2015, autumn crop residue burning was more concentrated, happening from 21st October–9th November. Fig. 2.9 shows that crop residue burning in these 3 provinces reached its highest point on 23rd October, 2014, and 4th November, 2015, with numbers of 2,555 and 2,291, respectively. Several days later, after the peak of crop residue burning, PM_{2.5} also reached its highest point, 249.06 $\mu\text{g}/\text{m}^3$ on 31st October, 2014 and 298.40 $\mu\text{g}/\text{m}^3$ on 8th November, 2015, an increase of 49.34 $\mu\text{g}/\text{m}^3$ within a year. Table 2.2 shows that in October crop residue burning spots in these 3 provinces decreased from 17,411 in 2014 to 9,176 in 2015, a proportion of 47.30%. At the same time, PM_{2.5} in October in these 3 provinces also showed a 40.21% decline from 77.74 $\mu\text{g}/\text{m}^3$ in 2014 to 46.48 $\mu\text{g}/\text{m}^3$ in 2015, while the annual decrease of PM_{2.5} in all of China was only 11.15%. In November, crop residue burning spots in these 3 provinces increased from 6,563 in 2014 to 10,614 in 2015, or 61.72%. Although the annual PM_{2.5} of China decreased by 11.15%, PM_{2.5} in November in these 3 provinces increased 18.26% from 79.81 $\mu\text{g}/\text{m}^3$ in 2014 to 94.38 $\mu\text{g}/\text{m}^3$ in 2015. Therefore, when comparing the summer residue burning data and PM_{2.5} data from 2014 and 2015, we can conclude in summer and autumn-winter the change in crop residue burning spots caused an evident change in PM_{2.5}. Meanwhile, Table 2.3 also demonstrates that during the crop residue burning time, PM_{2.5} concentration in these three provinces rose dramatically, for 2014 it increased from 37.30 $\mu\text{g}/\text{m}^3$ to 84.58 $\mu\text{g}/\text{m}^3$ and for 2015 it increased from 36.85 $\mu\text{g}/\text{m}^3$ to 102.90 $\mu\text{g}/\text{m}^3$, which was more intense than other provinces. After that PM_{2.5}

concentration in this region presented a steep fall, while other provinces showed a stable increase during this period. These results have indicated that during the crop residue burning, the $PM_{2.5}$ in autumn-winter presented a more evident increase than that in summer. This can be explained from three aspects. Firstly, in summer the burnt crop residue was mainly from wheat stalk, while, in autumn-winter the corn stalk took a large proportion of crop residue burning. Obviously, the biomass from corn stalk is much larger than that from wheat stalk, which means more $PM_{2.5}$ release. Secondly, in autumn-winter, because of the special weather condition, thermal inversion layer is much easier to form that impede the vertical movement of air convection. This causes the pollutant near the surface, such as $PM_{2.5}$, cannot diffuse in a short time. Thirdly, except crop residue burning, there are more sources increasing the concentration of $PM_{2.5}$ in autumn- winter, including greater fossil energy consumption.

(a)



(b)



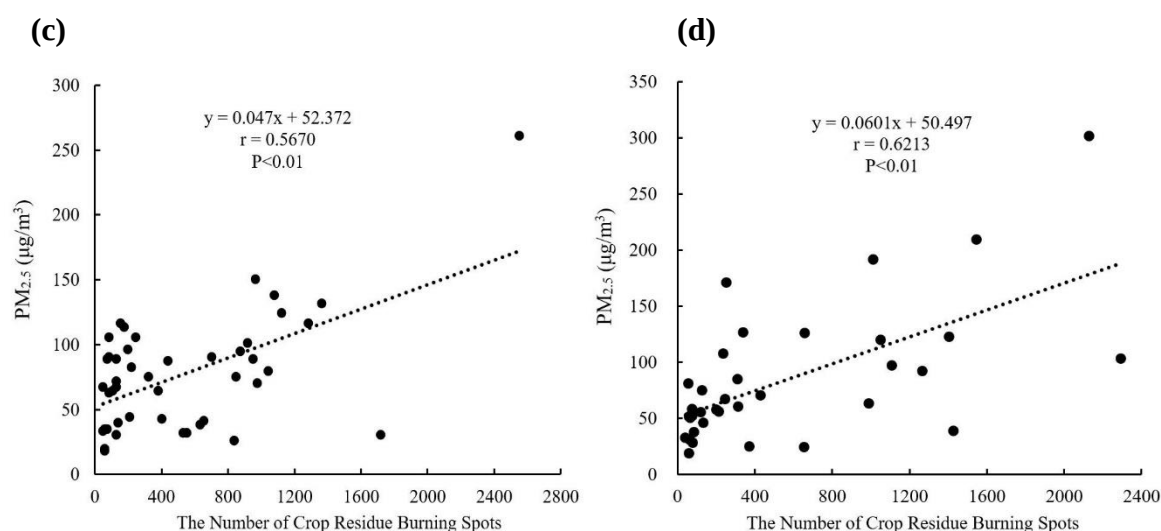
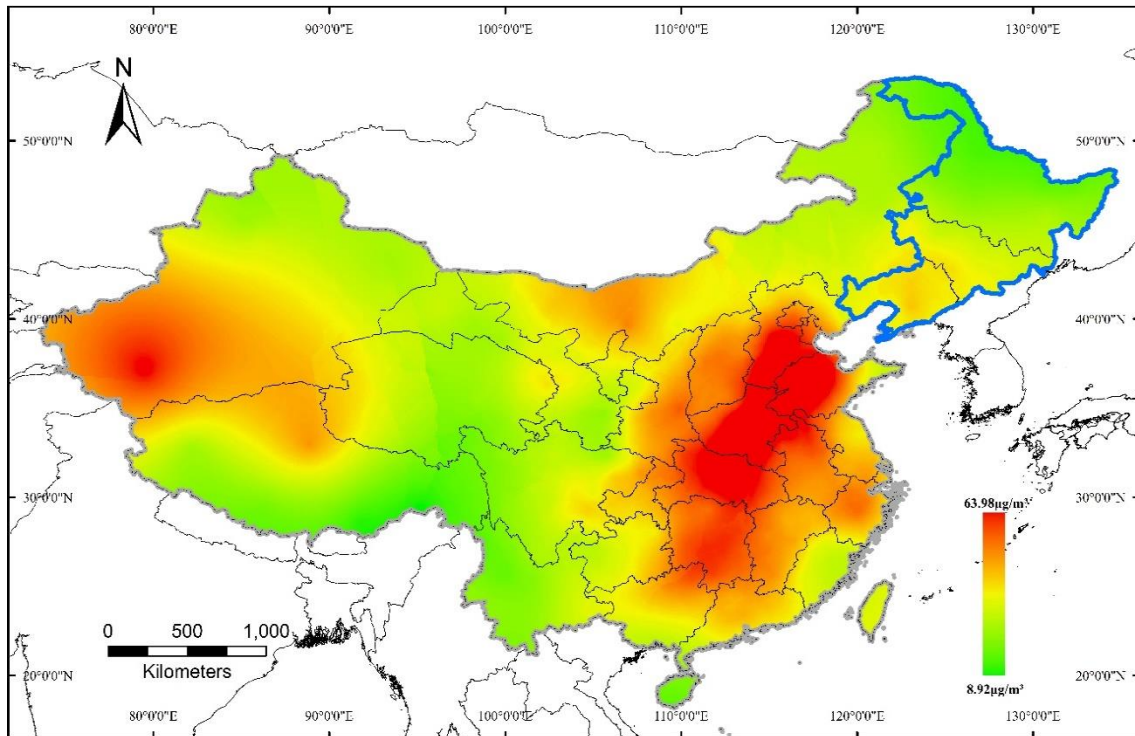


Figure 2.9 The number of crop residue burning spots and $PM_{2.5}$ in China's northeast in October and November: 2014(a); 2015(b). And the correlation in China's northeast between the number of autumn crop residue burning spots and $PM_{2.5}$ from 8 days later in October and November 2014(c) and 7 days later in October and November 2015(d).

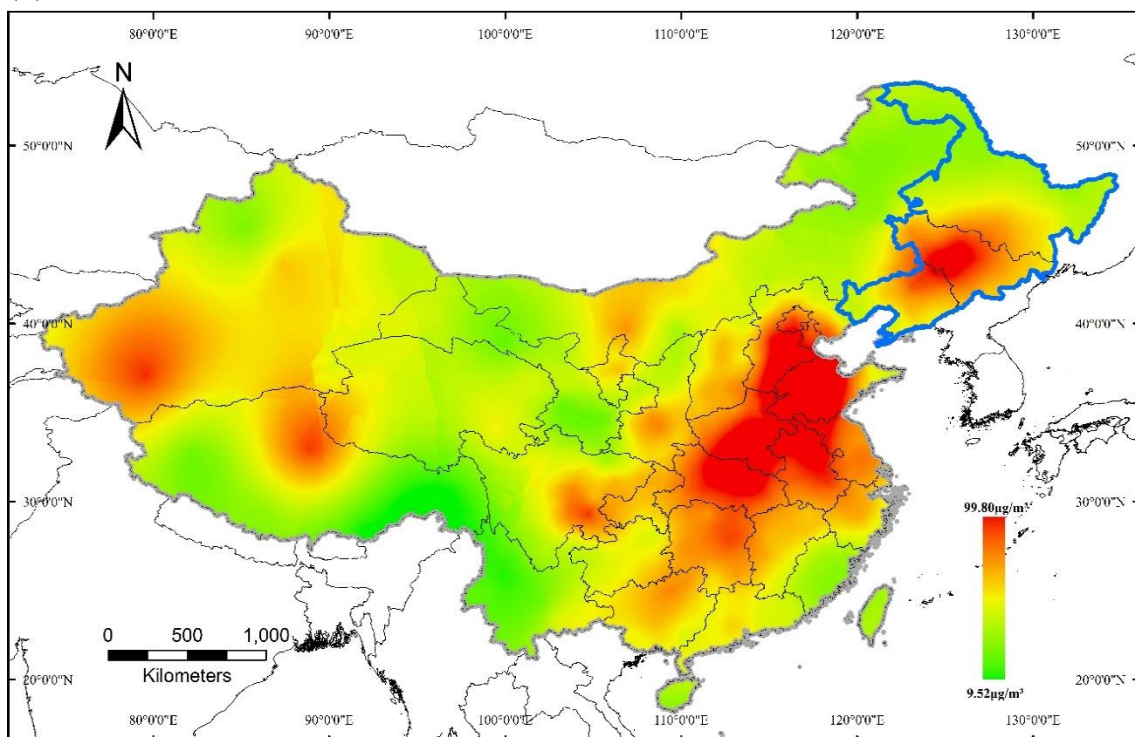
Because of the large area in China's northeast, there is no correlation between autumn crop residue burning and $PM_{2.5}$ on the same day, similar to summer crop residue burning. As mentioned before, if the number of average daily crop residue burning spots is below 38.68, it would be ignored in the daily analysis. The correlation between the number of crop residue burning spots was analyzed and the $PM_{2.5}$ concentration from several days later and the final results (Fig. 2.9) shows that the correlation coefficient between 2014 autumn crop residue burning and $PM_{2.5}$ from 8 days later is much higher, with r of 0.5670 ($P < 0.01$). In 2015, the r between autumn crop residue burning and $PM_{2.5}$ from 7 days later was 0.6213 ($P < 0.01$). Compared with summer crop residue burning, the correlation coefficient of autumn crop residue burning is lower because crop residue burning in summer was only concentrated for one week. However, the crop residue burning time in autumn is more scattered and can last for approximately one month. Even the correlation coefficient of autumn-winter crop residue burning in 2015 is higher than it was in 2014, again because of the more concentrated burning time in 2015. Additionally, the causes of $PM_{2.5}$ change in autumn and winter are more complex than in summer. Fig. 2.9 also demonstrates that crop residue burning and $PM_{2.5}$ are positively correlated. In summer, crop residue burning shows a higher correlation with $PM_{2.5}$ from 4 days later, while in autumn, crop residue burning demonstrates a higher correlation with $PM_{2.5}$ from approximately 1 week later. The superposition of many factors cause this longer hysteresis in autumn-winter. As mentioned above, the formation of thermal inversion layer reduces the height of atmospheric convective boundary layer, which inhibits the vertical diffusion of pollutants. Meanwhile, without the disturbance of strong cold air during this period, the continued weak or static wind weather impedes

horizontal diffusion of pollutants. These two reasons have provided sufficient conditions for pollutant accumulation. Therefore, the $\text{PM}_{2.5}$ from crop residue burning cannot diffuse in a short time. Meantime, $\text{PM}_{2.5}$ from other sources, such as vehicle exhaust and coal-fired heating, adding the $\text{PM}_{2.5}$ from crop residue burning gradually accumulate and finally reach the peak several days later.

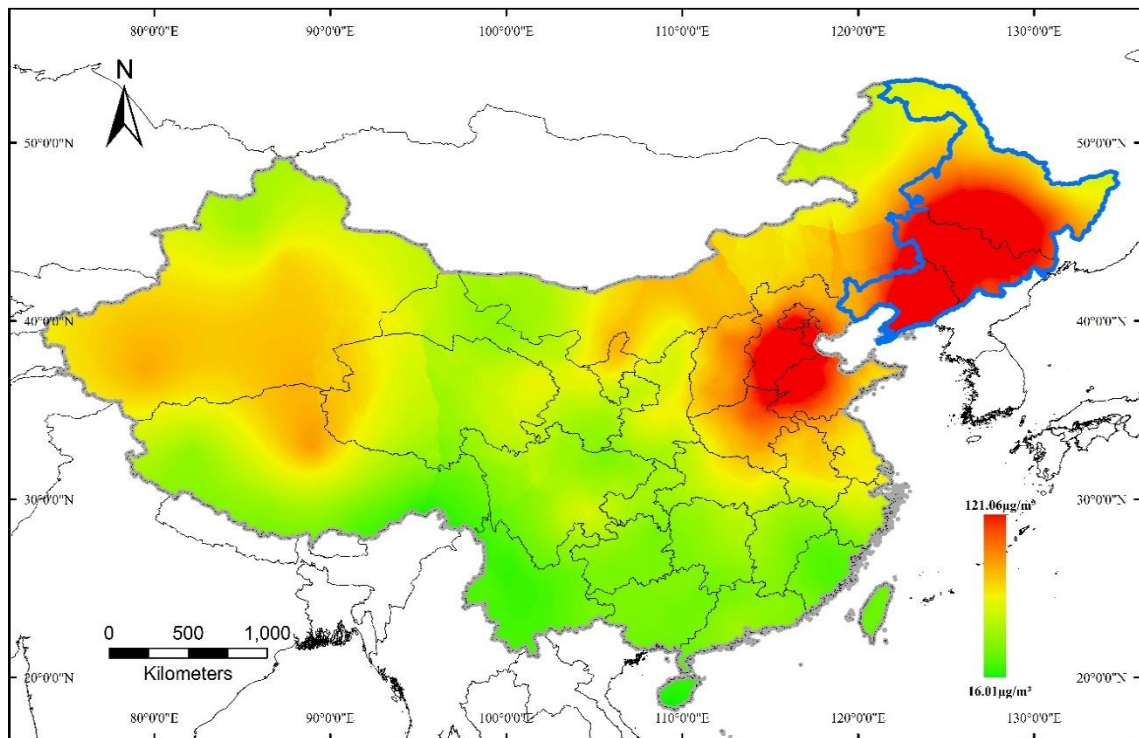
(a)



(b)



(c)



(d)

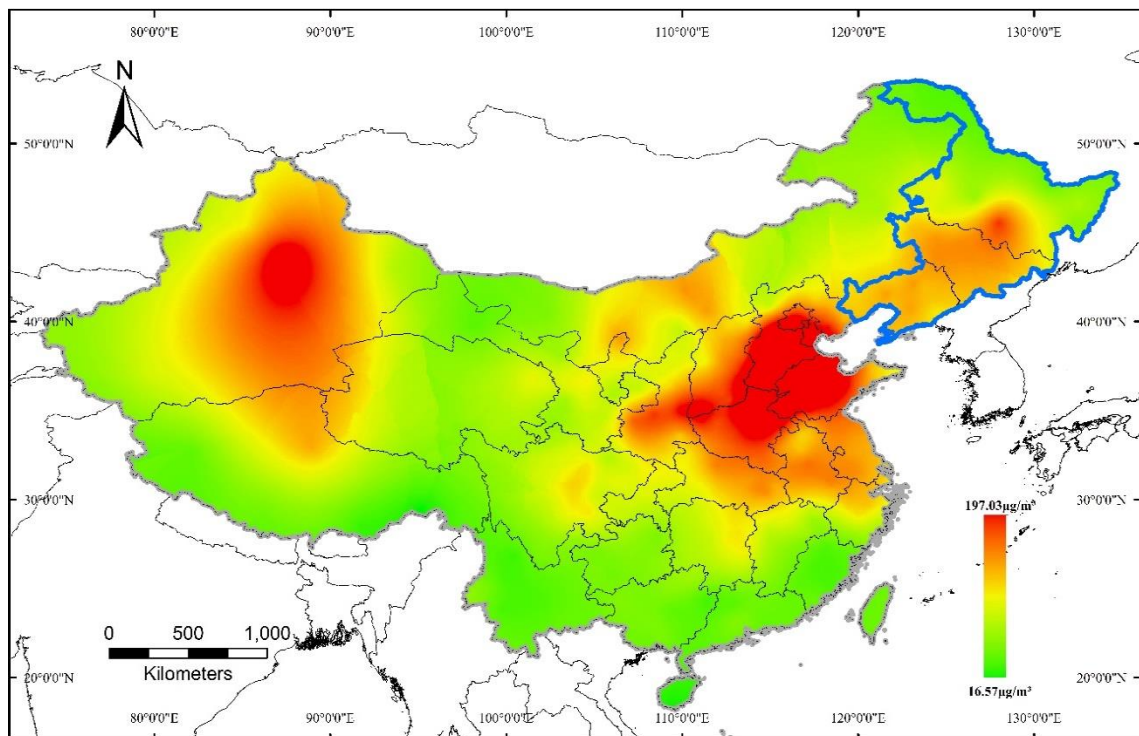
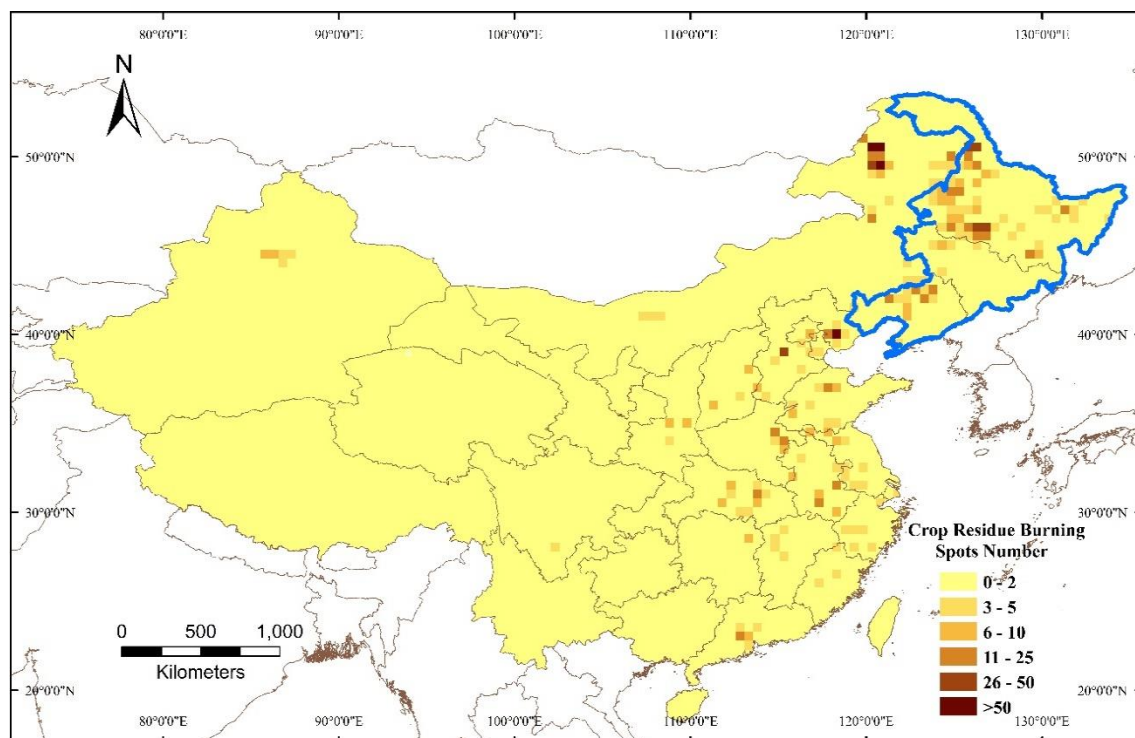


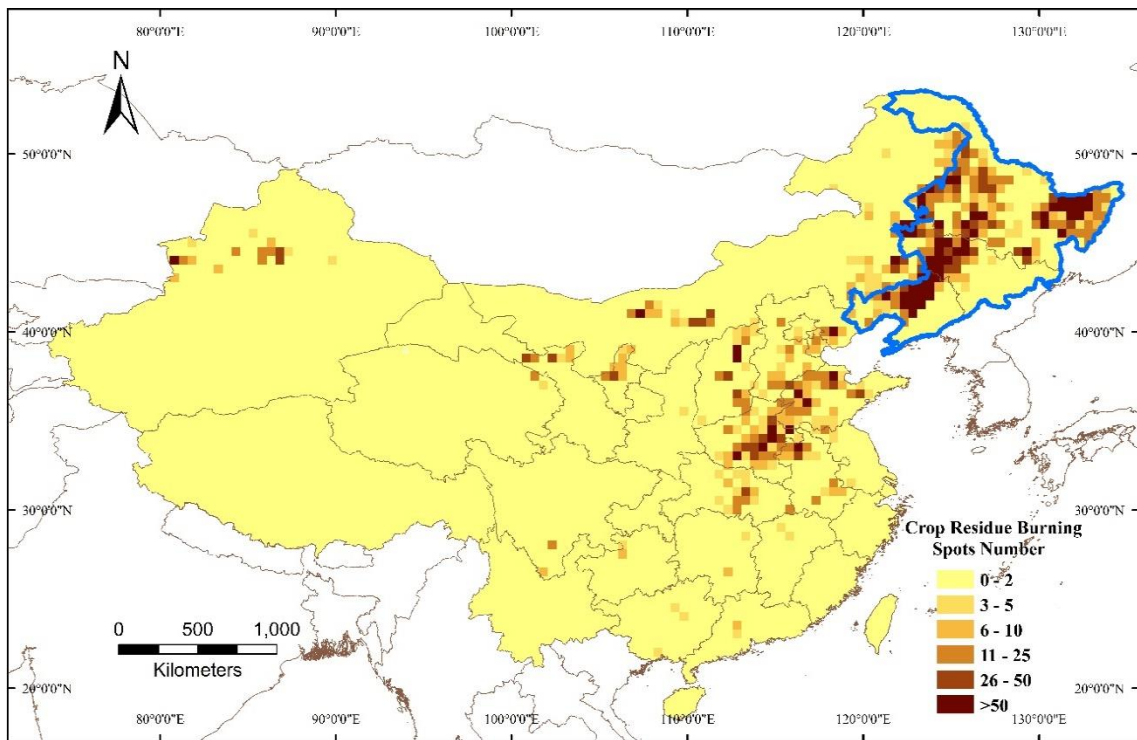
Figure 2.10 Spatial distribution of PM_{2.5} from September to December in 2015: September (a); October (b); November (c); December (d) (blue line is the boundary of the 3 provinces in China's northeast).

As shown in Fig. 2.10, the $PM_{2.5}$ of China's northeast in September is much lower than in other regions, where it is only $29.18 \mu\text{g}/\text{m}^3$ in 2014 and $25.33 \mu\text{g}/\text{m}^3$ in 2015, and the average $PM_{2.5}$ for China in September is $39.73 \mu\text{g}/\text{m}^3$ in 2014 and $36.39 \mu\text{g}/\text{m}^3$ in 2015. Fig. 2.10 demonstrates that in October, the $PM_{2.5}$ in China's northeast shows an increasing trend, and the $PM_{2.5}$ rises to $77.74 \mu\text{g}/\text{m}^3$ in 2014 and $46.48 \mu\text{g}/\text{m}^3$ in 2015. Compared with September, the speed of $PM_{2.5}$ increase in China's northeast is much faster than in other regions, especially in 2014. Meanwhile, Fig. 2.11 shows that autumn crop residue burning has started in October and is mainly concentrated in China's northeast. In November, $PM_{2.5}$ remains elevated in China's northeast, at $79.81 \mu\text{g}/\text{m}^3$ in 2014 and $94.38 \mu\text{g}/\text{m}^3$ in 2015, which is much higher than average $PM_{2.5}$ in China in this month. At the same time, Fig. 2.11 shows crop residue burning is still ongoing in China's northeast. In December, average $PM_{2.5}$ across the country is increasing. By contrast, there is hardly any crop residue burning in this month, and $PM_{2.5}$ in China's northeast decreased to $63.73 \mu\text{g}/\text{m}^3$ in 2014 and $76.05 \mu\text{g}/\text{m}^3$ in 2015. From September to December, the change in $PM_{2.5}$ in China's northeast is consistent with crop residue burning in this area. Furthermore, crop residue burning and $PM_{2.5}$ show high spatial consistency in this area.

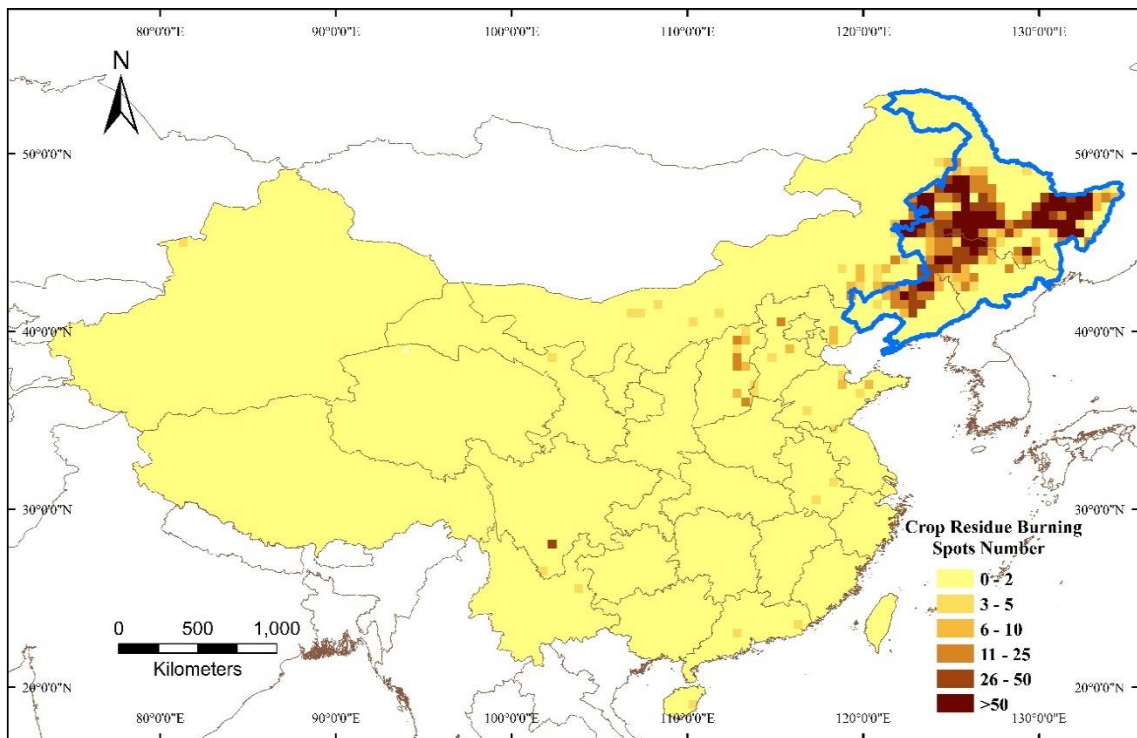
(a)



(b)



(c)



(d)

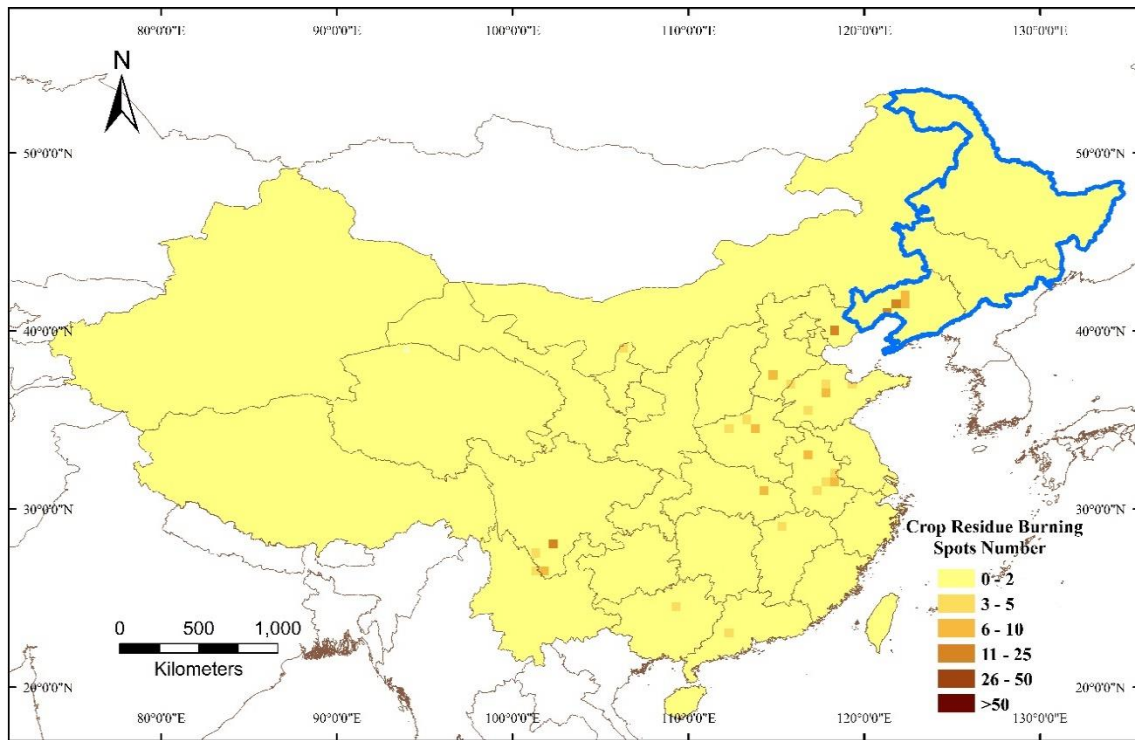


Figure 2.11 Spatial distribution of crop residue burning from September to December in 2015: September (a); October (b); November (c); December (d) (blue line is the boundary of the 3 provinces in China's northeast).

Therefore, on the daily-level (Fig. 2.9), period-level (Table 2.3), year-level (Table 2.2) and spatial distribution (Fig. 2.10), all the results indicated that the crop residue burning in autumn-winter can cause a rise in $PM_{2.5}$. Compared with summer crop residue burning in China's middle-east, $PM_{2.5}$ increase of autumn-winter crop residue burning in China's northeast is more obvious.

2.4 Conclusions and discussions

For China and other developing countries, it is important to understand the features and relationships between crop residue burning and $PM_{2.5}$. In this study, I used MODIS products to extract the daily and monthly crop residue burning in China from 2014 to 2015, and spatial distribution was also analyzed. Meanwhile, daily air quality data were used to map the spatial distribution of $PM_{2.5}$ concentration. Finally, relationships between crop residue burning and $PM_{2.5}$ were specifically analyzed in different seasons. The main findings are listed below.

First, the spatial distribution of crop residue burning presents strong seasonal patterns in China. In summer, it mainly concentrates in China's middle-east, and in spring and autumn-winter it mainly concentrates in China's northeast. These patterns are closely related to local farming activities.

Second, PM_{2.5} is always higher in winter than in other seasons, and the average PM_{2.5} of 2015 decreased 11.15% compared with the previous year. Regarding PM_{2.5} spatial distribution, PM_{2.5} in China's east and north is higher than in China's west and south because of different anthropogenic activities, climate and landscape.

Third, crop residue burning is close related to PM_{2.5} change in summer, China's middle-east and autumn-winter, China's northeast, they showed a spatial consistency during these two periods. But the crop residue burning in spring does not cause a notable change in PM_{2.5}. In autumn-winter, crop residue burning can effectively induce the PM_{2.5} increase in China's northeast, and it is more obvious than summer crop residue burning because of the special weather condition, different crop residue and other sources of PM_{2.5}.

In this study, because of the high-temporal-resolution of MODIS, we can obtain the daily number of crop residue burning spots to judge the intensity of crop residue burning. But the spatial resolution of MOD14A1 is only 1 kilometer. For each pixel of crop residue burning, it only means there is crop residue burning within the 1 km² area and it does not represent the entire 1 km² area burned. If we using the area of corresponded pixel to represent the crop residue burning area the result would likely be overestimated. Therefore, in this study we cannot acquire the accurate area of crop residue burning, which is also an important index to assess the intensity of crop residue burning and the emissions. Given current satellite data characteristics, it would be hard to achieve high-spatial-resolution and high-temporal-resolution at the same time. Another important index to assess the intensity of crop residue burning is the amount of burnt biomass and the result of crop residue burning in spring have proved only the number of crop residue burning spots cannot represent the intensity of crop residue burning. Regarding the number of crop residue burning spots, some anthropogenic activities may slightly affect the final results. For example, in rural China, most of the cemeteries are dispersed on the farmland and Chinese have the tradition to show their respect to dead people by burn joss paper and paper making stuff. Addition to that, some people directly burn household garbage in the farmland. All these maybe falsely regarded as crop residue burning. But it would not impact the accuracy of the whole results, because it is individual activity and last for a short time which is not so easy for the satellite to capture these points. From Fig. 2.5, the number of crop residue burning spots present different change pattern in China's middle-east and China's northeast. For China's middle-east, the crop residue burning in June is the highest of the whole year and for China's northeast, the crop residue burning in March-April and October-November is much higher than other months. The results conform to the actual situation on these two regions, which prove the final results are adequately accurate.

The results about the monthly spatial distribution of crop residue burning on the whole China furtherly confirm this point.

To the PM_{2.5}, a variety of factors can increase its concentration. Only crop residue burning was taken into consideration in this study. For future work, more factors need to be considered to understand fully PM_{2.5} change, such as vehicle emissions, coal consumption, construction dust, etc. Although annual PM_{2.5} in China has decreased from 2014 to 2015, PM_{2.5} is still higher than standards set by WHO (World Health Organization). Therefore, to reduce PM_{2.5} emissions and control crop residue burning, China's national and local governments need to take more measures to promote the comprehensive use of crop residue.

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Chapter 3 Comprehensive analysis of the spatial distribution and formation conditions of severe haze pollution in Northeastern China by ground-measured and remote sensing datasets

3.1 Introduction

Haze is defined as a weather phenomenon in which atmospheric visibility is less than 10 km and results from dense layers of aerosol particles, such as acidic chemicals, organics, black carbon (BC), and fly ash as well as dust accumulated in the air, and has a lower relative humidity than fog (Tao et al., 2012). As the world's second largest economy, China has experienced severe haze pollution, with fine particulate matter (PM) recently reaching unprecedentedly high levels across many cities. An understanding of the PM formation mechanism is critical in the development of efficient mitigation policies to minimize its regional to global impacts (Guo et al., 2014). Aerosols can be directly emitted (primary) or formed by the gas-to-particle conversion process (secondary) in the atmosphere (Seinfeld and Pandis, 2006; Zhang et al., 2012). Primary aerosols are directly emitted from sources such as biomass burning, combustion of fossil fuels, volcanic eruptions and wind-driven suspension of soil, mineral dust, sea salt and biological materials. However, secondary aerosols are formed in the atmosphere by gas-particle conversion processes such as nucleation, condensation and heterogeneous and multiphase chemical reactions (Hallquist et al., 2009). Additionally, fog and haze can concentrate aerosols in the near-surface, which results in enhanced air pollution and deteriorated air quality that causes significant harm to human health. Emmanuel (2000) found that an increase in PM₁₀ levels in Singapore from 50 $\mu\text{g}/\text{m}^3$ to 100 $\mu\text{g}/\text{m}^3$ was significantly associated with increased upper respiratory tract illness, 19% for asthma and 26% for rhinitis.

PM_{2.5}, as the most important indicator of haze pollution, began to be monitored in China from 2012 and only in important regions such as Beijing, Tianjin, the Yangtze River Delta Region, the Pearl River Delta Region and provincial capitals. In 2015, monitoring was extended to every prefecture-level city, and these data provide sufficient support for the study of PM_{2.5} (EMSC, 2012). With the development of remote sensing technology, satellite measurement is becoming one of the most effective approaches to the high spatio-temporal resolution monitoring of atmospheric pollution distribution. Air pollution remote sensing was begun in the 1970s of the twentieth century when K. Templemeyer, O. Ey (1974) and F. R. Benjamin et al. (1978) estimated the state of air pollution based on the change of reflectance and the mistiness of ground objects on air photos. Currently, the A-Train satellites (Aqua, Aura, PARASOL, and CALIPSO) provide an unprecedented opportunity to simultaneously observe haze clouds from

numerous perspectives (Hsu et al., 2006; Omar et al., 2009; Tanré et al., 2011; Torres et al., 2007).

The formation mechanisms that lead to severe haze episodes with exceedingly high PM_{2.5} levels in China remain highly uncertain, and the abundance and chemical constituents of PM_{2.5} vary considerably depending on the complex interplay between meteorology, pollution sources, and atmospheric chemical processes (Sun et al., 2014; Zhang et al., 2013; Wu et al., 2007). For the haze pollution of China, too many researchers have focused on economically developed regions, such as the North China Plain, the Pearl River Delta and the Yangtze River Delta, whereas there has much less research on Northeast China (Liaoning, Jilin, and Heilongjiang Provinces). Although the increase rate of Northeast China's economy for the past 10 years was in the lowest among all the provinces and the population in Northeast China had a negative growth trend, its air quality deterioration was similar to or even worse than that of the economically booming regions. Interestingly, the air quality in the heating season sharply contrasts with that in the non-heating season in Northeast China. In November 2015, severe air pollution occurred in Northeast China and the maximum concentration of hourly PM_{2.5} greatly exceeded 1,000 µg/m³ during that period. For example, on 8 November 2015 the hourly PM_{2.5} concentration reached 1,326 µg/m³ in the city of Shenyang, where authorities said visibility would be as low as 500 meters in some places (Zhang et al., 2017). Theoretically, there should be good air quality in Northeast China. In contrast, that air pollution episode in Northeast China was much worse than in other regions and for the first time the air pollution in this region became a hot topic. Attention to this region overtook even China's capital Beijing, which is renowned for severe haze pollution. By integrating the advantages of remote sensing data with ground-measurement data, this study aimed to find the causes of haze pollution in Northeastern China and analyze the changes of air composition and atmosphere indexes during the occurrence of haze pollution episodes. Remote sensing technology was used to track the burning of crop residues, which was assumed to be the cause of haze pollution in Northeastern China. Moreover, meteorological data were considered to illustrate the conditions conducive to such severe haze pollution, and the Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT) was adopted to analyze the transport and dispersion of pollution particles. To reveal the causes of haze pollution in different regions of Northeastern China, haze pollution was separately analyzed for Heilongjiang, Jilin and Liaoning Provinces.

3.2 Data resources and methods

3.2.1 Ground-measurement data

The ground-measurement data used in this study mainly included two parts: air quality data and meteorological data. Daily air quality data included PM_{2.5}, PM₁₀, SO₂, NO₂, CO and O₃, which were obtained from China's National Environmental Monitoring Center (CNEMC, 2015). China's Environmental Protection Conference of 2012 first mentioned and emphasized monitoring PM and ozone across the country. By 2015, PM and O₃ monitoring had been extended to every prefecture-level city. In this study, daily air quality data were collected from 36 cities in Northeastern China, including 13 prefecture-level cities of Heilongjiang Province, 9 prefecture-level cities of Jilin Province and 14 prefecture-level cities of Liaoning Province. Daily meteorology data included lowest temperature, highest temperature, weather, wind direction and wind force.

After acquiring the daily air quality data from China's National Environmental Monitoring Center, the data were combined with the geographic coordinates of each city in Northeastern China. Then, using the platform of Geographic Information System (GIS), a database of ground-measurement data was established and, finally, the ordinary Kriging interpolation method was chosen to obtain the distribution map of different air components, which can directly reveal the spatial characteristics. The Kriging interpolation method is an important geostatic method based on the use of a variogram (Guo et al., 2013). A variogram is a geostatistical technique that can be used to examine the spatial continuity of a regionalized variable and how this continuity changes as a function of distance and direction.

3.2.2 Aerosol Optical Depth (AOD)

Satellite remote sensing can be used to assess PM_{2.5} air quality for areas where surface PM_{2.5} monitors are not available (Di Nicolantonio et al., 2009; Engel-Cox et al., 2004; Gupta and Christopher, 2008). The most applicable satellite-retrieved product for estimating PM_{2.5} concentrations is aerosol optical depth (AOD), which measures the light extinction by aerosol scattering and absorption in the atmospheric column. The higher the AOD value, the more aerosols are within a column, and thus visibility within that column is lower. The aerosol properties are derived by the inversion of the MODIS-observed reflectance using pre-computed radiative transfer look-up tables based on aerosol models (Remer et al., 2005). There are three MODIS Level 3 Atmosphere Products, each covering a different temporal scale: Daily, 8-Day, and Monthly. Each of these Level 3 products contains statistics derived from over 100 science parameters from the Level 2 Atmosphere products: Aerosol, Precipitable

Water, Cloud, and Atmospheric Profiles. For this study, the monthly AOD products (MYD08_M3) and daily AOD products (MYD08_D3) were used to characterize the spatial and temporal variations of aerosol properties during the occurrence of haze pollution.

3.2.3 Aerosol Absorption Optical Depth (AAOD)

The OMI (Ozone Monitoring Instrument) AAOD, the non-scattering part of the AOD, is an atmospheric column measurement of absorbing aerosol particles, i.e., absorbing carbon and mineral dust (Koch et al., 2009). As an important product for aerosol study, the Aura OMI level-2 near-UV Aerosol data product 'OMAERUV' derives extinction AOD, single scattering albedo and AAOD at the top of the atmosphere (Ahn et al., 2007). The OMAERUV retrieval algorithm is particularly sensitive to carbonaceous and mineral aerosols. It assumes that the column aerosol load can be represented by one of three types of aerosols (carbonaceous aerosol from biomass burning, desert dust, and weakly absorbing sulfate-based aerosols) and uses a set of aerosol models to account for their presence. Because of the large sensitivity of OMI near-UV observations to particle absorption, AAOD is the most reliable quantitative OMAERUV aerosol parameter, especially over land. In this study, the AAOD daily product at 500 nm (OMAERUVd.003) was used.

3.2.4 Carbon monoxide from MOPITT

Combined with ground measurements, the MOPITT CO datasets were used to characterize the spatial variation of CO during the occurrence of haze pollution. The MOPITT remote sensing instrument, which was developed to quantify and track the movement of pollution in the troposphere, was launched aboard the Earth Observing System (EOS) Terra satellite in December 1999 (Deeter et al., 2003). MOPITT includes nadir-viewing channels for monitoring both carbon monoxide and methane and became operational in March 2000. MOPITT measures the Earth with a pixel size of 22 km × 22 km and provides the first continuous global measurements of CO in the troposphere (Emmons et al., 2004). I used Version 5 Level 3 products, which include CO concentrations, averaging kernels and error co-variances at 10 pressure levels. Level 3 products are available as gridded daily-mean and monthly-mean files. Data averaging is performed on a one-degree latitude/longitude grid. This product provides two types of CO concentration, total column concentration and surface concentration. To be consistent with the ground measurement, only the surface data (<900 hpa) were used to infer CO variations. Retrieved CO total columns were calculated by integrating the retrieved mixing ratio profile, where each retrieval level corresponded to a uniformly-weighted layer immediately above that level (Deeter et al, 2007). Both the daily and monthly CO MOPITT products were used in this study.

3.2.5 UV Aerosol Index (UVAI)

UVAI is an index that detects the presence of UV-absorbing aerosols such as dust and soot (Vadrevu et al., 2014). UVAI is based on a spectral contrast method in a UV region where the ozone absorption is very small. It is the difference between the observations and model calculations of absorbing and non-absorbing spectral radiance ratios. The daily product (OMTO3D.003) from OMI has been used to obtain UVAI data. The OMI instrument can distinguish between aerosol types, such as smoke, dust, and sulfates, and measures cloud pressure and coverage, which provides data to derive tropospheric ozone (Liu et al., 2009). The instrument is a contribution of the Netherlands's Agency for Aerospace Programs (NIVR) in collaboration with the Finnish Meteorological Institute (FMI) to the Aura mission (Carn et al., 2007). Positive values of UVAI generally represent absorbing aerosols (dust and smoke), whereas small or negative values represent non-absorbing aerosols (sulfate, sea-salt) and clouds.

3.2.6 Fire spots

Fires that occur either naturally or ignited by humans strongly affect the atmospheric composition and thermal balance on both global and regional scales by providing major sources of GHGs and aerosols (Konovalov et al., 2014). The impact of fires on the carbon cycle can become especially important in the face of continuing climate change because global warming is expected to change fire regimes and may accelerate the accumulation of carbon dioxide, methane, and ozone precursors in the atmosphere, thus leading to further warming (Bond-Lamberty et al., 2007). MOD14A1 Thermal Anomalies/Fire products of the MODerate-resolution Imaging Spectrometer (MODIS) were collected to obtain the fire data over Northeastern China. MODIS Thermal Anomalies/Fire products are primarily derived from MODIS bands at 4 and 11 micrometer radiances (Roy et al., 2002). The fire detection strategy is based on absolute detection of a fire (when the fire strength is sufficient to detect) and on detection relative to its background (to account for variability of the surface temperature and reflection by sunlight). Numerous tests are employed to reject typical false alarm sources, such as sun glint or an unmasked coastline (Giglio et al., 2003). MOD14A1 is produced every 8 days at a resolution of 1 kilometer as a gridded level-3 product in the Sinusoidal projection. The daily Thermal Anomalies/Fire images can be obtained by separating the eight fire-masks.

3.2.7 Land cover type

Crop residue burning is assumed to be one of the main reasons for the severe haze pollution in Northeastern China. Although crop residue burning is dispersed across the country after harvest and lasts for a short time, it is unrealistic to monitor the burning of

crop residue on the ground. With remote sensing technology, we could combine the active fire spots, extracted from MOD14A1, with land cover types to obtain the crop residue burning spots. To be consistent with the source of fire data, the land cover data used in this study were also from MODIS. The MCD12Q1 product provides data characterizing five global land cover classification systems (Cai et al., 2014). The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP) (Loveland and Belward, 1997), which includes 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes. Class 12 (Croplands) from the primary land cover scheme was used to clip Thermal Anomalies/Fire images (MOD14A1) to obtain crop residue burning spots, and each pixel of the final result was regarded as one crop residue burning spot.

3.2.8 HYSPLIT model

The National Oceanic and Atmospheric Administration (NOAA) Air Resources Laboratory's (ARL) Hybrid Single Particle Lagrangian Integrated Trajectory model (HYSPLIT) (Draxler and Hess 1998) is a complete system for computing simple air parcel trajectories as well as complex transport, dispersion, chemical transformation, and deposition simulations. One of the most common model applications is a back-trajectory analysis to determine the origin of air masses and establish source–receptor relationships (Fleming et al., 2012). HYSPLIT has also been used in a variety of simulations describing the atmospheric transport, dispersion, and deposition of pollutants and hazardous materials. In this study, the HYSPLIT model was used to analyze the dispersion of pollutants emitted from crop residue burning and find the origin of haze pollution.

3.3 Results

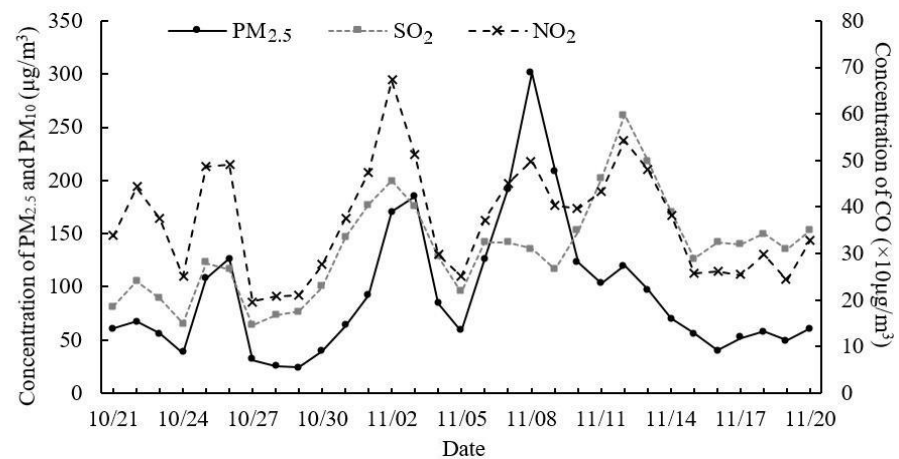
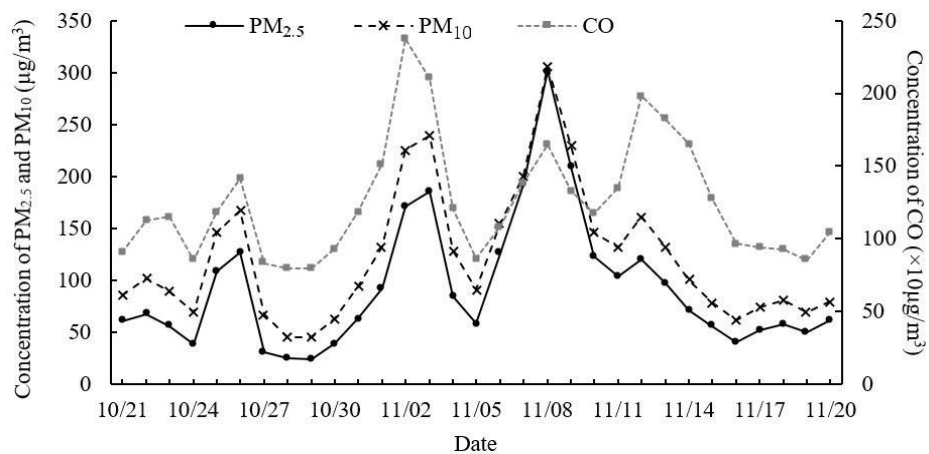
3.3.1 Air composition change from ground measurement

In China, the daily average concentration of $PM_{2.5}$ exceeded $75 \mu g/m^3$, which could be regarded as pollution and is approximately twice that of the US EPA (United States Environmental Protection Agency) standard of $35 \mu g/m^3$ (Huang et al., 2014). According to the standard, Fig. 3.1a shows that there were 3 pollution episodes in Northeastern China from 21st October to 20th November. The first episode was from 25th October to 26th October, when $PM_{2.5}$ concentration reached $126.45 \mu g/m^3$; the second was from 1st November to 4th November, with $PM_{2.5}$ concentration reaching $185.06 \mu g/m^3$ on 3rd November; and the last episode was from 6th November to 13th November, with $PM_{2.5}$ concentration reaching $301.27 \mu g/m^3$ on 8th November. Since $PM_{2.5}$ monitoring began, this was the first time three severe $PM_{2.5}$ pollution episodes

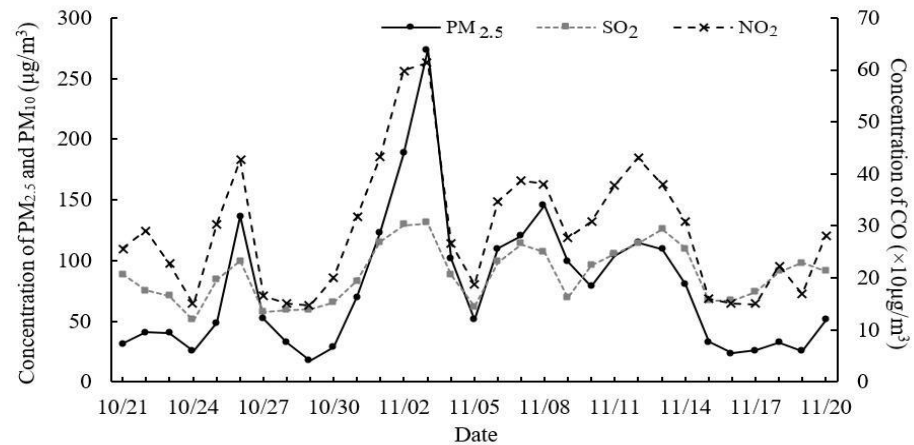
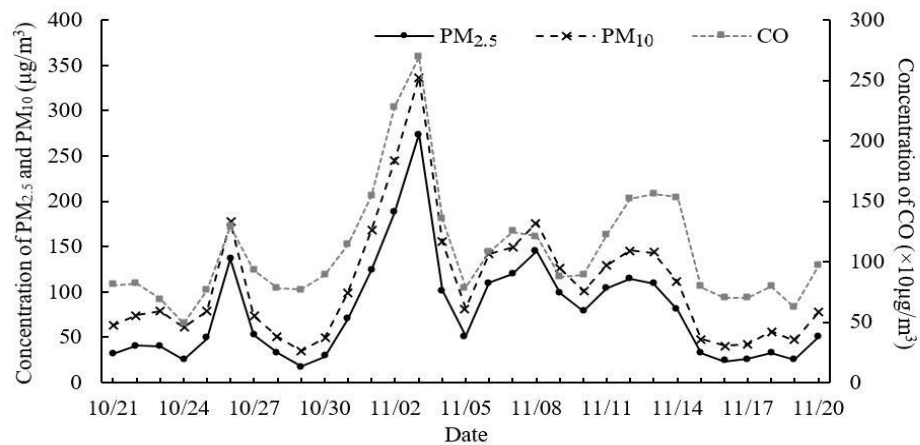
occurred within a month, and the third episode was the worst ever recorded in Northeastern China. The daily average concentration of $\text{PM}_{2.5}$ in 14 prefecture-level cities of Northeastern China exceeded $300 \mu\text{g}/\text{m}^3$ on 8th November, the value in Shenyang reached $848 \mu\text{g}/\text{m}^3$, and in Anshan, Liaoning and Tieling the values exceeded $600 \mu\text{g}/\text{m}^3$. Fig. 3.1a shows that PM_{10} presented almost the same fluctuation as $\text{PM}_{2.5}$ and that the value of PM_{10} was always higher than $\text{PM}_{2.5}$; on 8th November PM_{10} reached $305.88 \mu\text{g}/\text{m}^3$, which was the highest value during this period. For CO, the change tendency was slightly different from $\text{PM}_{2.5}$ and PM_{10} but also presented high values during the occurrence of the three $\text{PM}_{2.5}$ pollution episodes. The concentration of CO on 2nd November (the second $\text{PM}_{2.5}$ pollution episode) reached the highest point at $2,375.15 \mu\text{g}/\text{m}^3$ and in 12th November reached the second peak at $1,980.61 \mu\text{g}/\text{m}^3$, whereas the daily average concentration of CO on 8th November was only $1,646.36 \mu\text{g}/\text{m}^3$. For NO_2 , the change tendency was similar to CO; on 2nd November it also reached the highest value at $67.21 \mu\text{g}/\text{m}^3$ and on 12th November reached a second peak at $59.85 \mu\text{g}/\text{m}^3$. The change of SO_2 concentration presented a change tendency different from other components. The concentration of SO_2 on 12th November was the highest, $59.85 \mu\text{g}/\text{m}^3$. During the third $\text{PM}_{2.5}$ pollution episode, SO_2 even showed a decreasing trend, from $32.30 \mu\text{g}/\text{m}^3$ on 6th November to $26.70 \mu\text{g}/\text{m}^3$ on 9th November, which was the intense period of $\text{PM}_{2.5}$ pollution. The changes of atmospheric components for three provinces in Northeastern China were elaborated as follows.

Fig. 3.1b shows that there were also three $\text{PM}_{2.5}$ pollution episodes in Heilongjiang Province and that the second one, from 1st to 4th November, was the most severe. Daily average concentration of $\text{PM}_{2.5}$ reached $273.83 \mu\text{g}/\text{m}^3$ on 3rd November (the second pollution episode), the concentration of Harbin reached $650 \mu\text{g}/\text{m}^3$ and the concentration of Qitaihe was above $400 \mu\text{g}/\text{m}^3$. Daily average concentrations of CO and NO_2 had almost the same fluctuations as PM and on 4th November achieved their highest values of $2,691.67 \mu\text{g}/\text{m}^3$ and $61.33 \mu\text{g}/\text{m}^3$, respectively. Although SO_2 reached its peak in the second $\text{PM}_{2.5}$ pollution episode, the amplification was not as obvious as that of CO and NO_2 and in 4th November reached $30.50 \mu\text{g}/\text{m}^3$. Table 3.1 indicates that, except for O_3 , there were high correlations between $\text{PM}_{2.5}$ and the other components in Heilongjiang Province. The correlation coefficients of $\text{PM}_{2.5}$ - PM_{10} , $\text{PM}_{2.5}$ -CO and $\text{PM}_{2.5}$ - NO_2 were higher than 0.90, and even the lowest correlation coefficient of $\text{PM}_{2.5}$ - SO_2 reached 0.78. We also found that the correlation coefficient in Heilongjiang was much higher than in the other two provinces, Jilin and Liaoning Provinces.

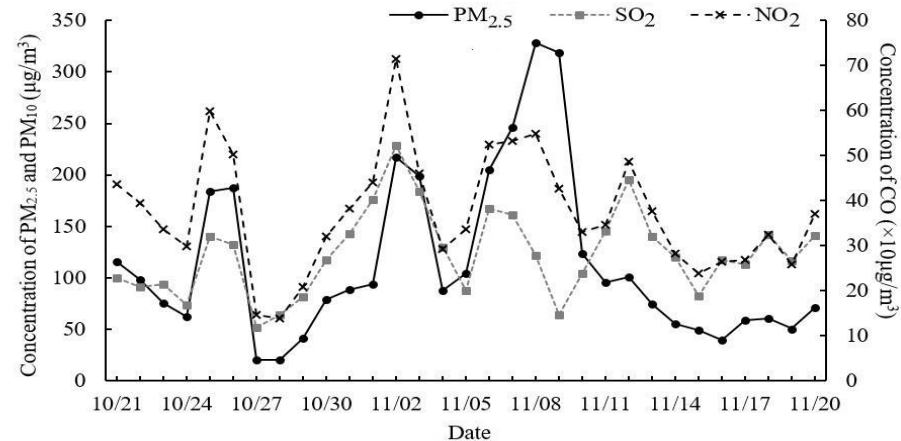
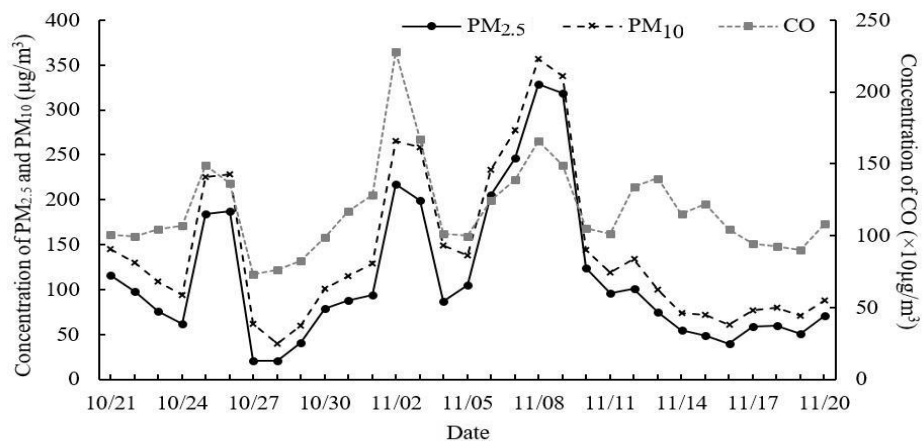
(a)



(b)



(c)



(d)

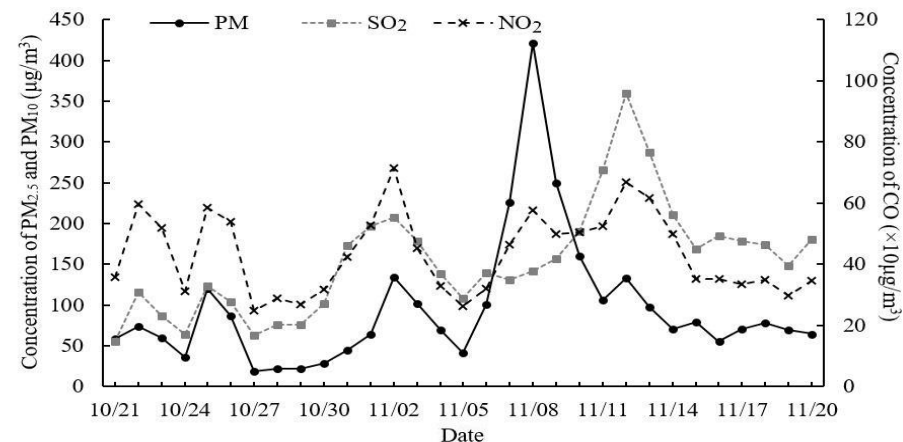
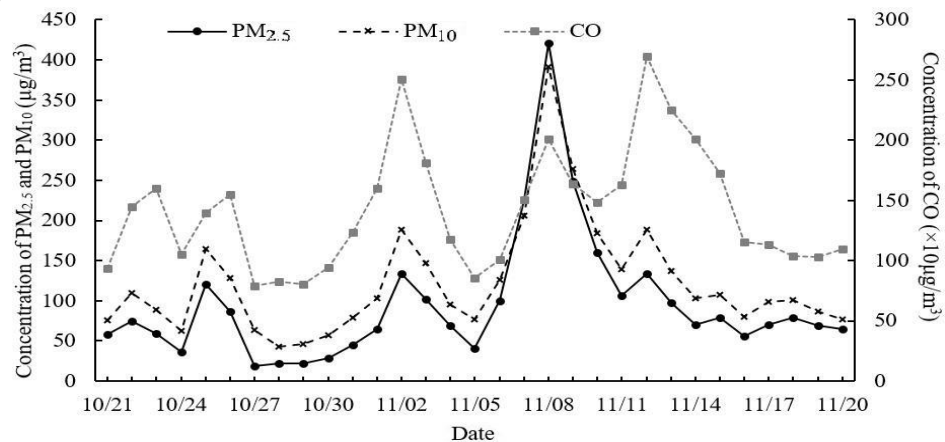


Figure 3.1 Daily average concentration of $PM_{2.5}$ and other components from 21st October to 20th November: Northeastern China (a); Heilongjiang Province (b); Jilin Province (c); Liaoning Province (d).

Table 3.1 Correlation coefficient between PM_{2.5} and other components from 20th October to 20th November in Northeastern China.

Provinces	PM _{2.5} and PM ₁₀	PM _{2.5} and CO	PM _{2.5} and NO ₂	PM _{2.5} and SO ₂	PM _{2.5} and O ₃
Heilongjiang	0.99	0.92	0.93	0.78	0.26
Jilin	0.99	0.74	0.78	0.33	0.09
Liaoning	0.98	0.5	0.51	0.23	0.07

For Jilin Province, there were also three PM_{2.5} pollution episodes; the third one was the severest from 5th to 12th November. Daily average concentration of PM_{2.5} reached 328.71 µg/m³ on 8th November, and the concentrations for Siping and Songyuan reached 562 µg/m³ and 537 µg/m³, respectively. Unlike the other two provinces, the three PM_{2.5} pollution episodes in Jilin were intense. For the first episode, the concentration of PM_{2.5} reached 187.57 µg/m³ on 26th October; for the second one, PM_{2.5} reached 217.14 µg/m³ on 2nd November. Instead of reaching the highest points in the third PM_{2.5} pollution episode, CO, NO₂ and SO₂ during the second PM_{2.5} pollution episode were higher than other episodes; on 2nd November they reached 2277.14 µg/m³, 71.43 µg/m³ and 52.29 µg/m³, respectively. During the third PM_{2.5} pollution episode, CO and NO₂ concentration increased to a peak on 8th November, whereas SO₂ concentration showed a decreasing trend from 6th to 9th November when the most intense PM_{2.5} pollution occurred. Table 3.1 indicates that, except for PM_{2.5}-PM₁₀, the correlation between PM_{2.5} and other components in Jilin Province was not as high as in Heilongjiang Province. The correlation coefficients *r* of PM_{2.5}-CO and PM_{2.5}-NO₂ were approximately 0.75, and the correlation coefficient of PM_{2.5}-SO₂ was only 0.33.

Fig. 3.1c indicates that for Liaoning Province the third PM_{2.5} pollution episode from 6th to 13th November was much more severe than the others (on 8th November the daily average concentration of PM_{2.5} reached the astonishing level of 421.14 µg/m³) and that in 9 prefecture-level cities the concentration was higher than 300 µg/m³. On 12th November, the daily average concentration of CO and SO₂ reached their highest levels of 2695.00 µg/m³ and 96.00 µg/m³, respectively, whereas the daily average concentration of PM_{2.5} was only 133.64 µg/m³. As in Jilin Province, the SO₂ concentration also maintained a relatively low level from 6th to 9th November when the most intense PM_{2.5} pollution occurred. The daily average concentration of NO₂ on 2nd November was the highest and corresponded to the second PM_{2.5} pollution episode. Table 3.1 shows that the correlation coefficient between PM_{2.5} and other air components was much lower than for the other two provinces; the correlation coefficient of PM_{2.5}-SO₂ was only 0.23.

3.3.2 Crop residue burning and air component changes

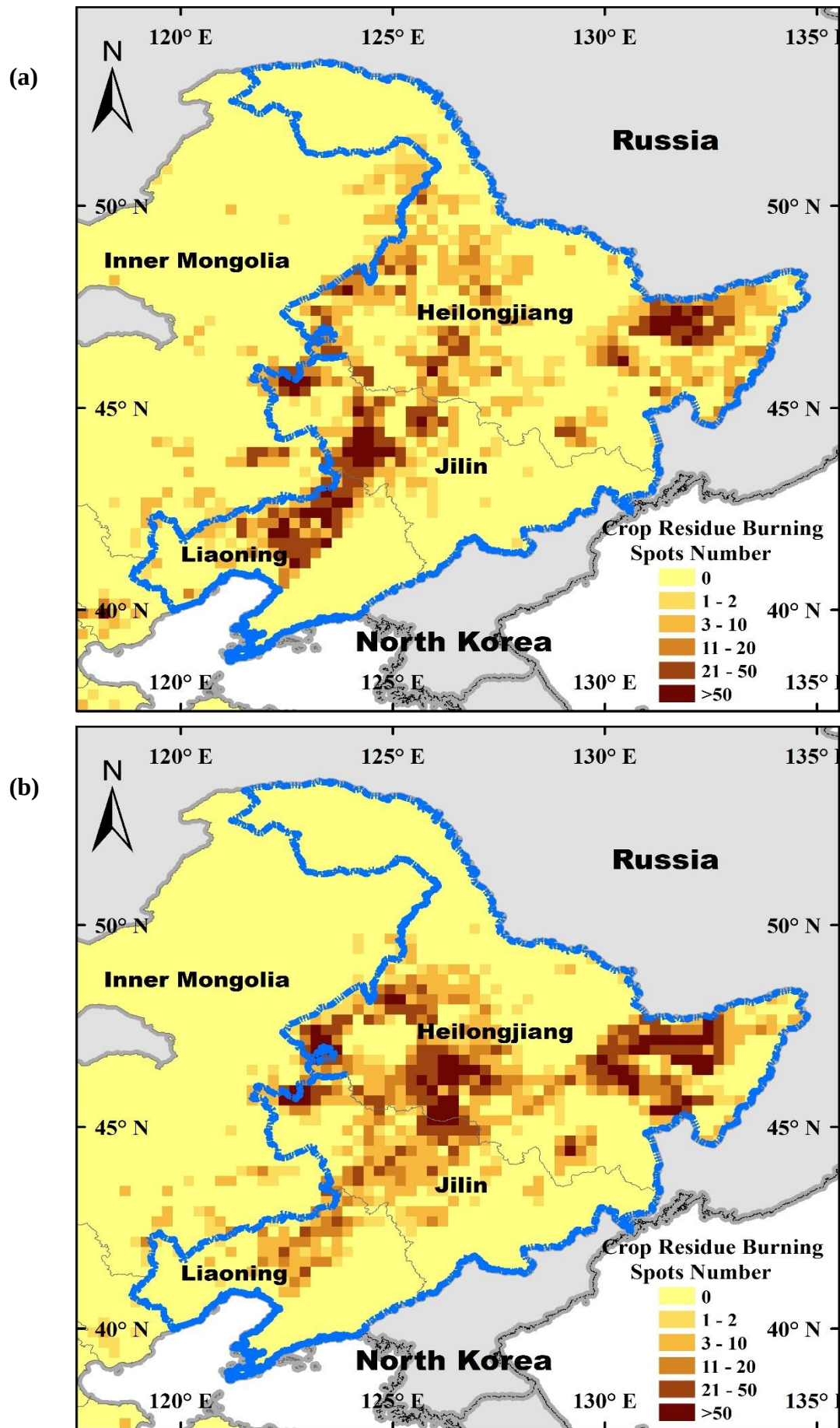
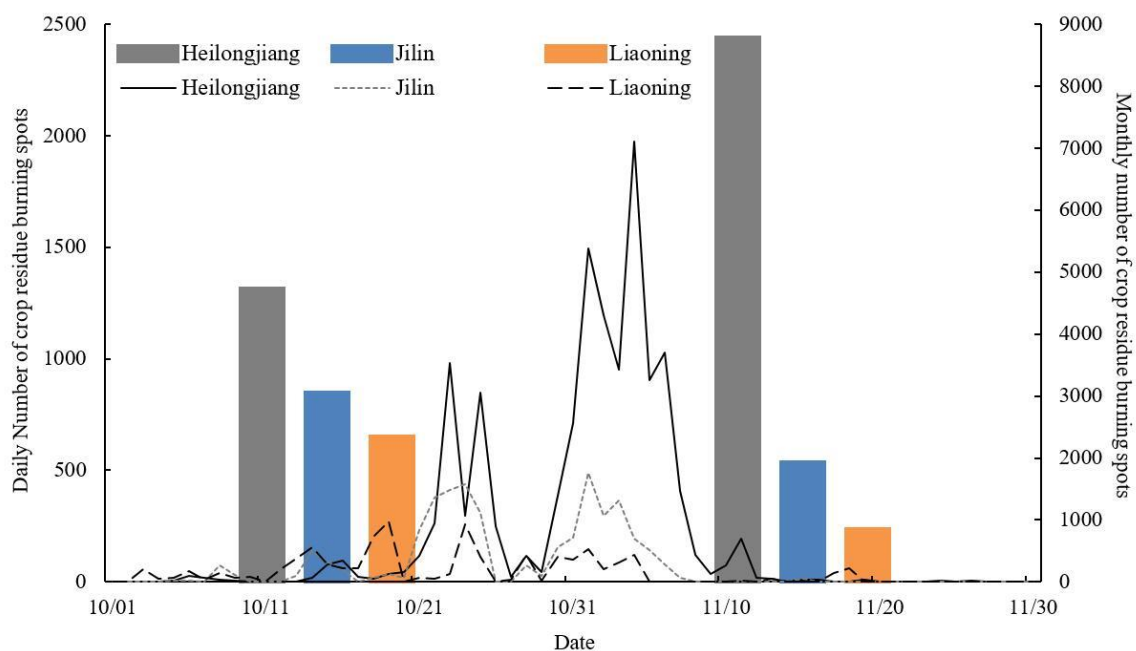


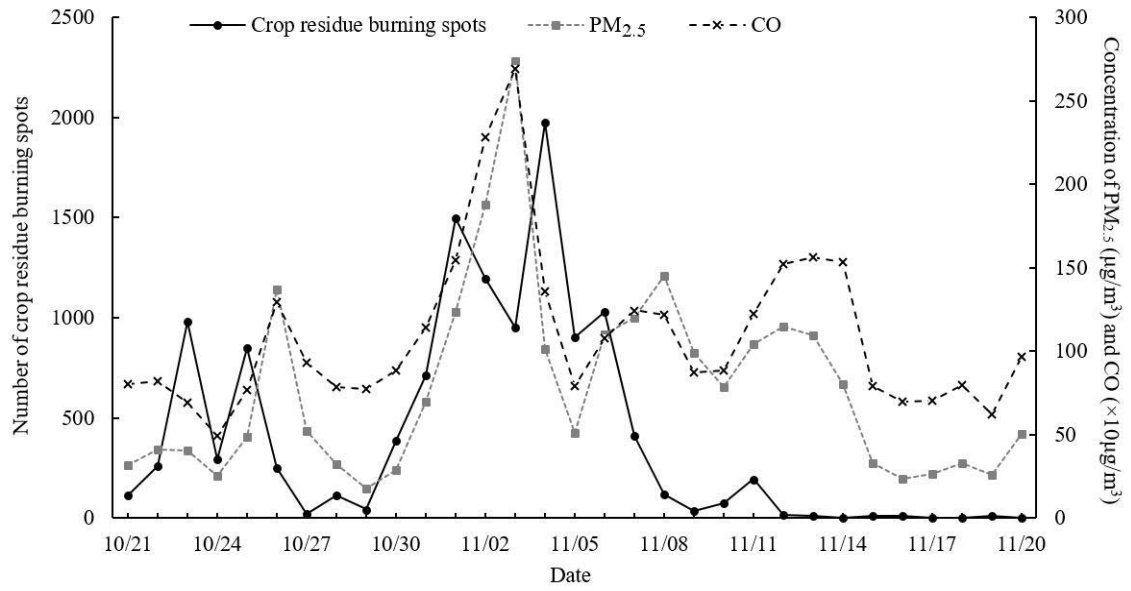
Figure 3.2 Spatial distribution of crop residue burning spots in Northeastern China: October (a); November (b).

According to estimates, China produced some 630 million tons of crop residues per year from 1995 to 2005, one-third of which remained unused and most of which was burnt directly in the field (Liu et al., 2008; Wang et al., 2013). The spatial distribution of crop residue burning presents strong seasonal patterns in China. In summer, it mainly concentrates in China's middle-east after the harvest of winter wheat. The last time of crop residue burning in summer is relatively short and the meteorological conditions in this season do not promote severe haze pollution. In autumn, crop residue burning is mainly distributed in Northeastern China after the harvest of corn and rice. The results showed that in October 2015 there were 9,176 crop residue burning spots in Northeastern China that accounted for 69.02 % of all the crop residue burning in China; crop residue burning in North China Plain also accounted for a large proportion. For each province, there were 4,415 crop residue burning spots in Heilongjiang, 2,735 in Jilin and 2,026 in Liaoning (Fig. 3.3a). With respect to spatial distribution, crop residue burning in this month mainly occurred in western Liaoning and Jilin Provinces and Northeastern Heilongjiang Province (Fig. 3.2). In November 2015 there were 10,614 crop residue burning spots in Northeastern China, which accounted for 93.13% of all the crop residue burning in China. From October to November, crop residue burning spots in Heilongjiang rose sharply to 8,463, whereas in Liaoning and Jilin Province the spots decreased to 541 and 1,610, respectively (Fig 3.3a). In this month crop residue burning was concentrated in the south and northeast parts of Heilongjiang Province.

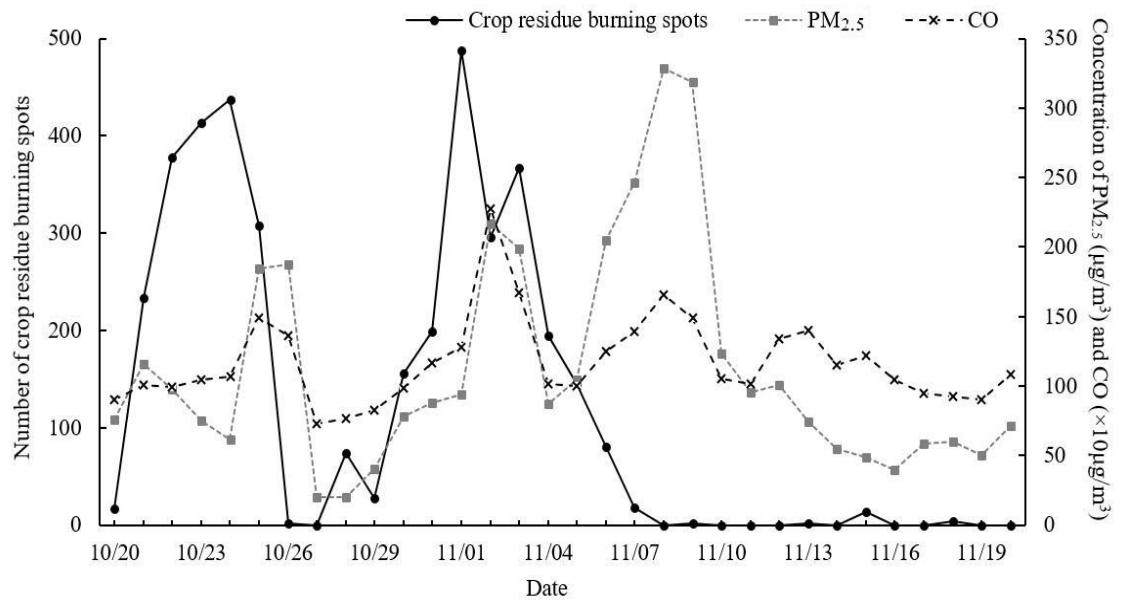
(a)



(b)



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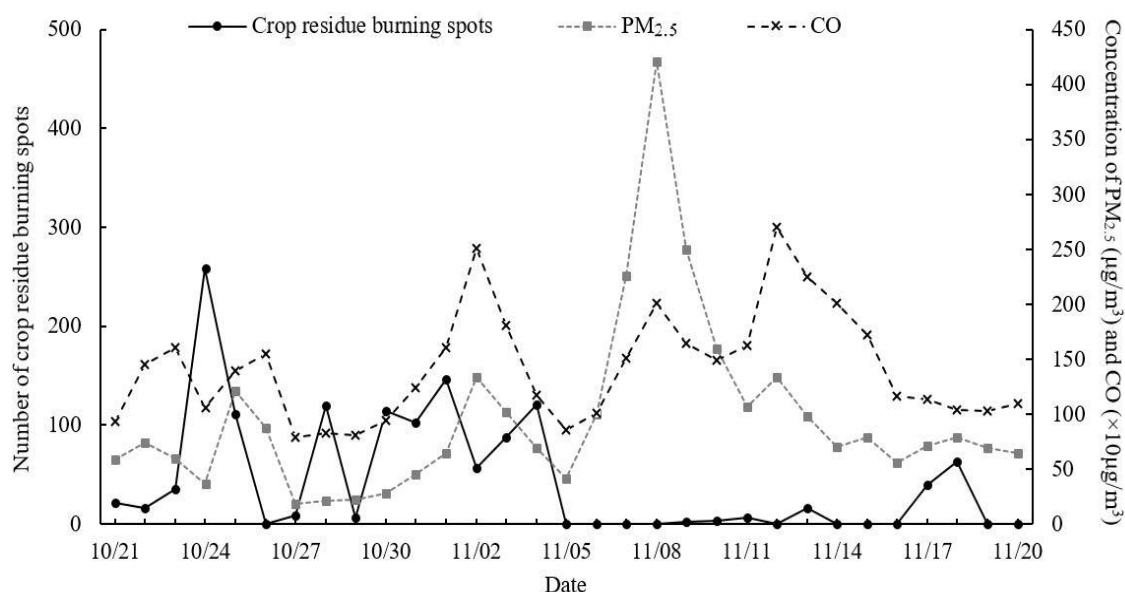


Figure 3.3 The number of crop residue burning spots in the three provinces (a) and the change of PM_{2.5} and CO during crop residue burning: Heilongjiang Province (b); Jilin Province (c); Liaoning Province (d).

Fig 3.3b shows that there were two periods for crop residue burning in Heilongjiang Province, the first from 22nd to 26th October and the second from 30th October to 7th November. The second period was not only longer but also much more intense; on 6th November the daily number reached 1,975, more than twice that of the first burning period. During the first burning period, the daily average concentrations of PM_{2.5}, CO and NO₂ reached their peaks on 26th October, with values of 126.45 $\mu\text{g}/\text{m}^3$, 1,291.67 $\mu\text{g}/\text{m}^3$ and 49.06 $\mu\text{g}/\text{m}^3$, respectively. For the second burning period, the daily average concentrations of PM_{2.5}, CO and NO₂ rose sharply and reached their peaks on 3rd November, with concentrations of 273.83 $\mu\text{g}/\text{m}^3$, 2691.67 $\mu\text{g}/\text{m}^3$ and 61.33 $\mu\text{g}/\text{m}^3$, respectively. The concentrations of PM_{2.5} and CO were also more than twice that of the first burning period. Although, the concentration of SO₂ showed an increasing trend during the two period of crop residue burning, it was not as obvious as other components.

There were two periods for crop residue burning in Jilin Province, the first from 21th to 26th October and the second from 30th October to 6th November (Fig 3.3c). Differently than Heilongjiang Province, the intensities of the two periods for crop residue burning were almost the same; the first peak reached 437 on 24th October and the second one reached 488 on 1st November. Moreover, the concentrations of PM_{2.5}, CO and NO₂ showed an increasing trend during the two burning periods and the increase ratio of the second one was slightly higher than that of the first one. After the crop residue burning, the concentration of PM_{2.5} in Jilin province reached its highest

point on 9th November (the third pollution episode); we can thus infer that this severe haze pollution was not induced by the local crop residue burning. Additionally, the concentrations of other components maintained a relatively low level during the third haze pollution episode; therefore, the PM transported from other regions and secondary aerosols are assumed to have contributed to this severe haze pollution.

The crop residue burning times in Liaoning Provinces were dispersive and lasted from 24th October to 4th November. Moreover, the intensity was much weaker than in the other two provinces, and the highest daily number of burning spots was only 258 on 24th October. Fig. 3.3d indicates that there were two peaks in the daily average concentration of PM_{2.5} during crop residue burning: the first one was 139.36 $\mu\text{g}/\text{m}^3$ on 25th October and the second one was 133.93 $\mu\text{g}/\text{m}^3$ on 2nd November, which was much lower than the corresponding PM_{2.5} concentrations in Jilin and Heilongjiang Province. As was the case for Jilin Province, the concentration of PM_{2.5} soared to 421.14 $\mu\text{g}/\text{m}^3$ in 8th November after crop residue burning, and the concentration of other components maintained a relatively low level during this PM_{2.5} pollution episode. Moreover, the correlation coefficient between PM_{2.5} and other air components was the lowest among the three provinces. PM of this episode was assumed to be mainly from transported pollutants or secondary aerosols.

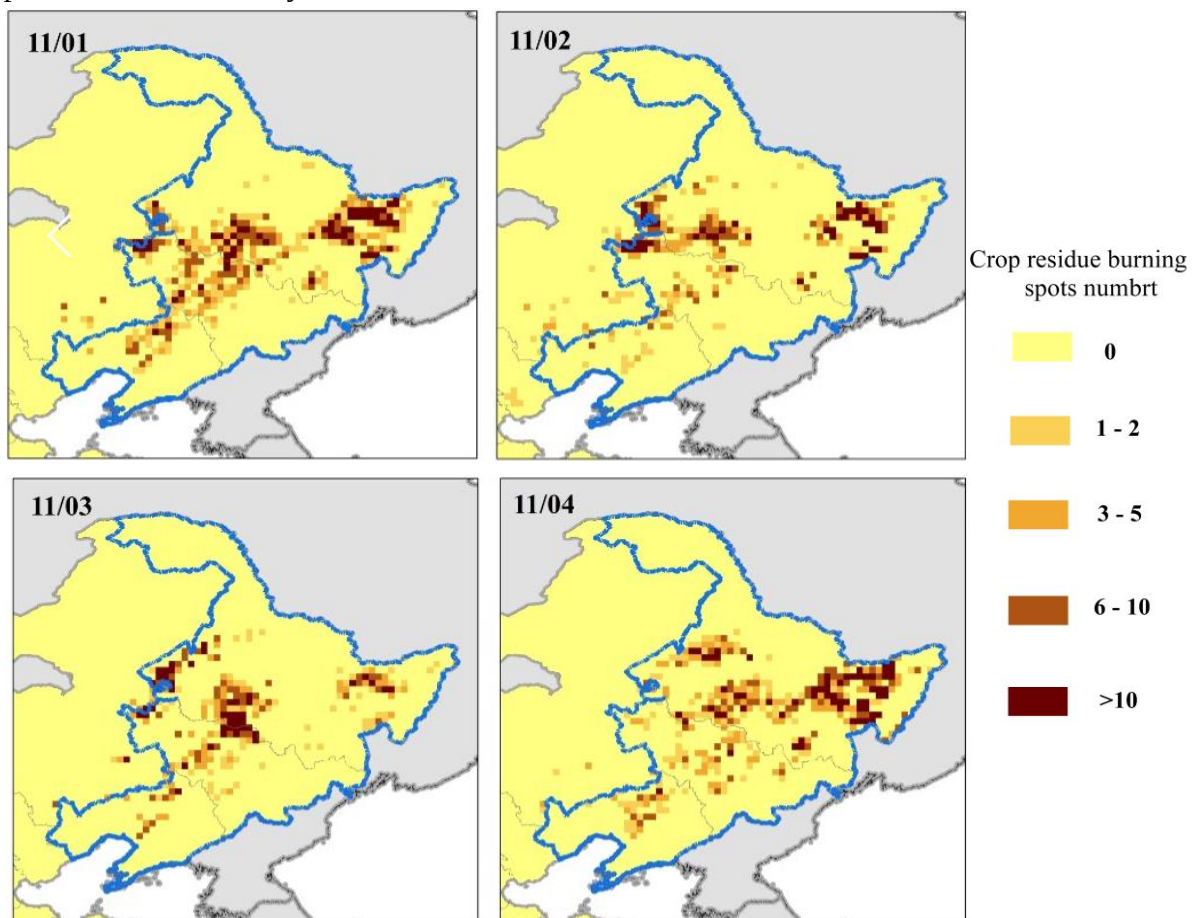
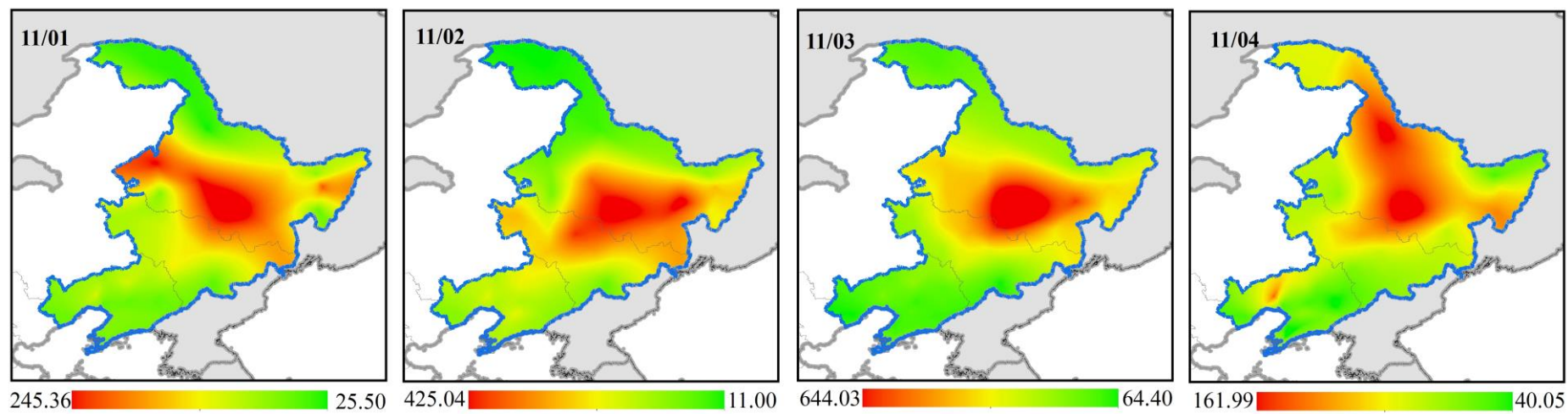
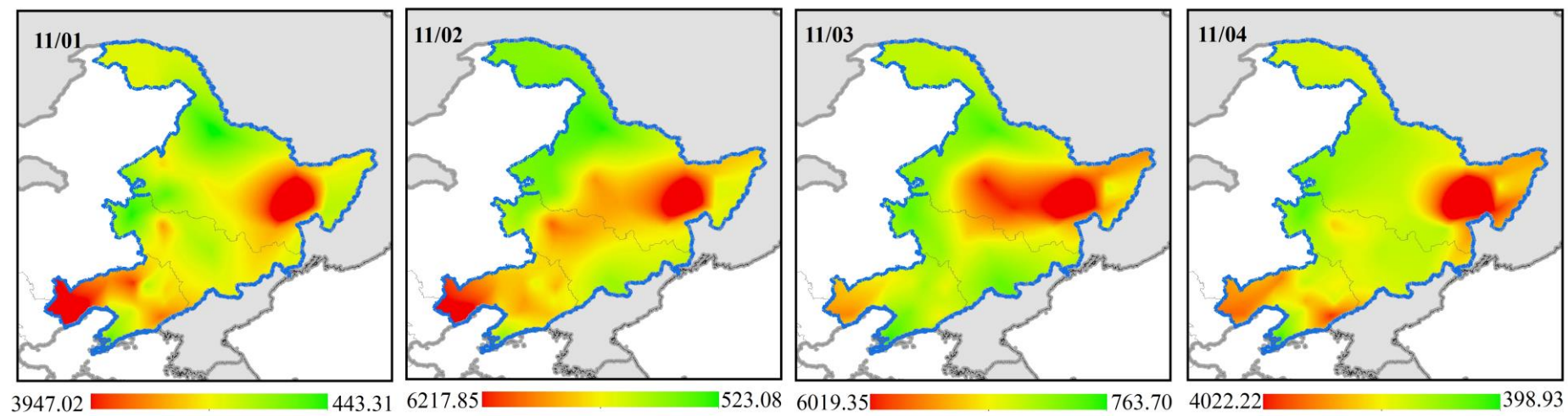


Figure 3.4 The daily spatial distribution of crop residue burning spots from 1st to 4th November.

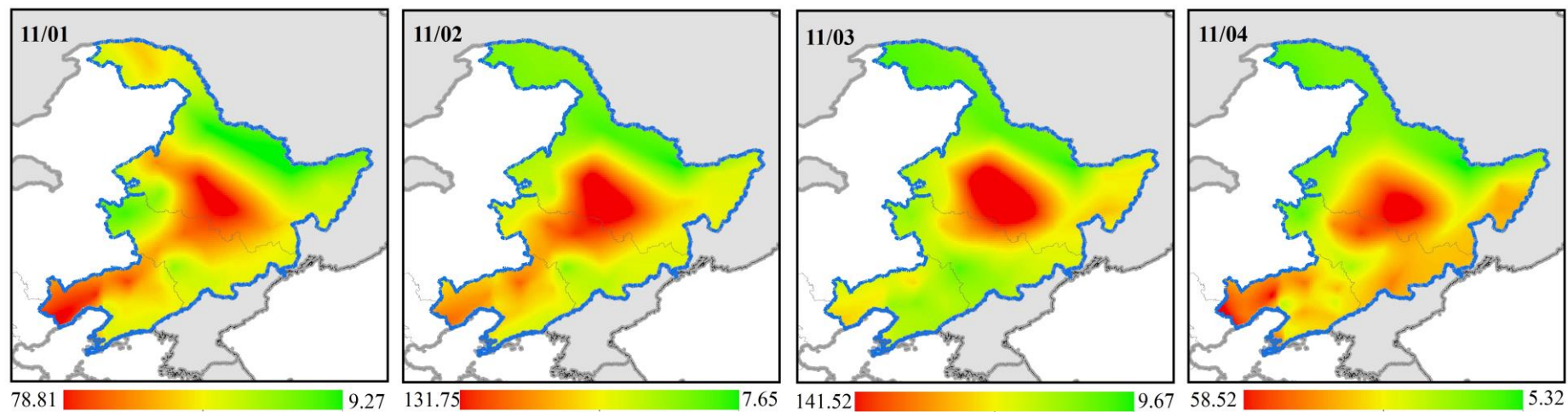
(a)



(b)



(c)



(d)

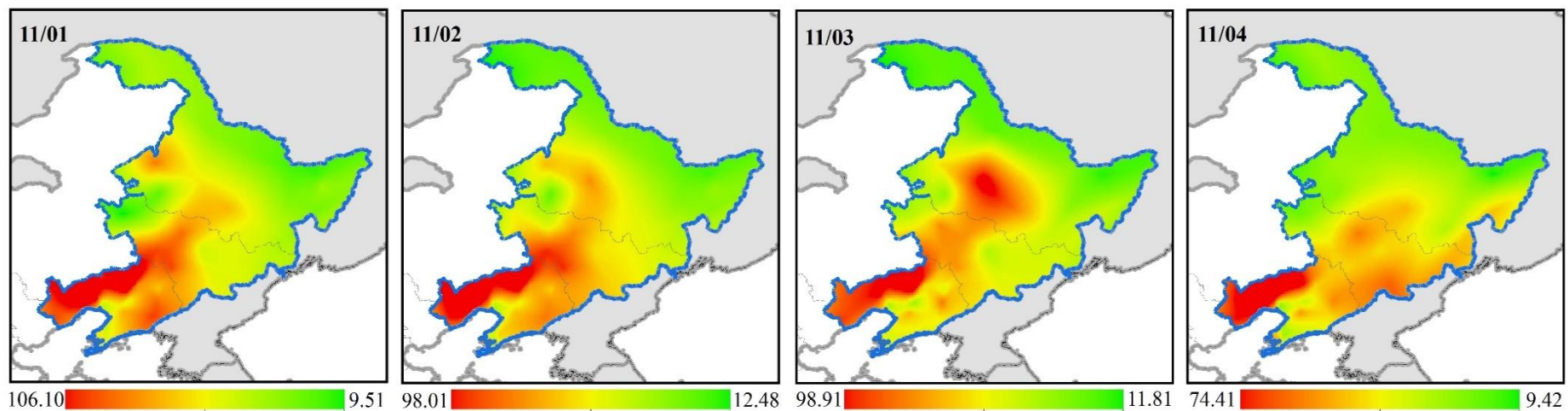


Figure 3.5 The daily spatial distribution of air compositions in Northeastern China from 1st to 4th November: PM_{2.5} concentration (a); CO concentration (b); NO₂ concentration (c); SO₂ concentration (d). Unit: $\mu\text{g}/\text{m}^3$.

The daily number of crop residue burnings in 1st and 4th November exceeded 2,000 in Northeastern China and the number was approximately 1,500 in 2nd and 3rd November, which can be regarded as the most intense period for crop residue burning. Therefore, this period was chosen to analyze the spatial distribution of crop residue burning and air components. Fig. 3.4 shows that the burning spots were mainly concentrated in Northeastern Heilongjiang Province and west of the junction region between Heilongjiang and Jilin Province. There were also some disperse crop residue burnings in Liaoning Province but the number was very limited. For PM_{2.5}, the daily average concentration from 1st to 3rd November in south Heilongjiang was always higher than in other regions and on 4th November the concentration in all of Heilongjiang Province was higher than in the other two Provinces (Fig. 3.5a). The concentration of CO in northeast Heilong was much higher during these four days; on 3rd November the concentration in Qitaihe City reached 6,040 µg/m³ and in Harbin, Jiamusi and Suihua the concentrations also exceeded 3,000 µg/m³ (Fig. 3.5b). As was the case with PM_{2.5}, the concentration of NO₂ was always higher in the junction region between Heilongjiang and Jilin Province, and on 2nd and 3rd November the daily average concentration in Harbin and Suihua exceeded 120 µg/m³ (Fig. 3.5c). The spatial distribution of SO₂ was totally different from that of PM_{2.5}, CO and NO₂, and the concentration in west Liaoning Province was the highest during this period (Fig. 3.5d). In fact, the yearly concentration of these air components in Heilongjiang Province was much lower than in Liaoning and Jilin provinces; it even maintained the lowest level among all provinces in China. Table 3.2 also indicates that from September to December 2015 the monthly concentrations of these air components in Heilongjiang were the lowest in Northeastern China. Moreover, combined with the spatial distribution of crop residue burning, we found there were certain spatial consistencies between crop residue burning and PM_{2.5}, CO, NO₂. The burning of crop residues emits carbon dioxide, carbon monoxide, non-methane hydrocarbons, nitric oxide, nitrogen oxide and atmospheric particles (Hayashi et al., 2014). Therefore, I infer that crop residue burning caused the abnormal high concentrations of PM_{2.5}, CO and NO₂ in Heilongjiang Province from 1st to 4th November. The low SO₂ concentration in Heilongjiang during these four days also proves that this PM_{2.5} pollution episode was not caused by fossil fuel consumption and that crop residue burning made a great contribution to this episode.

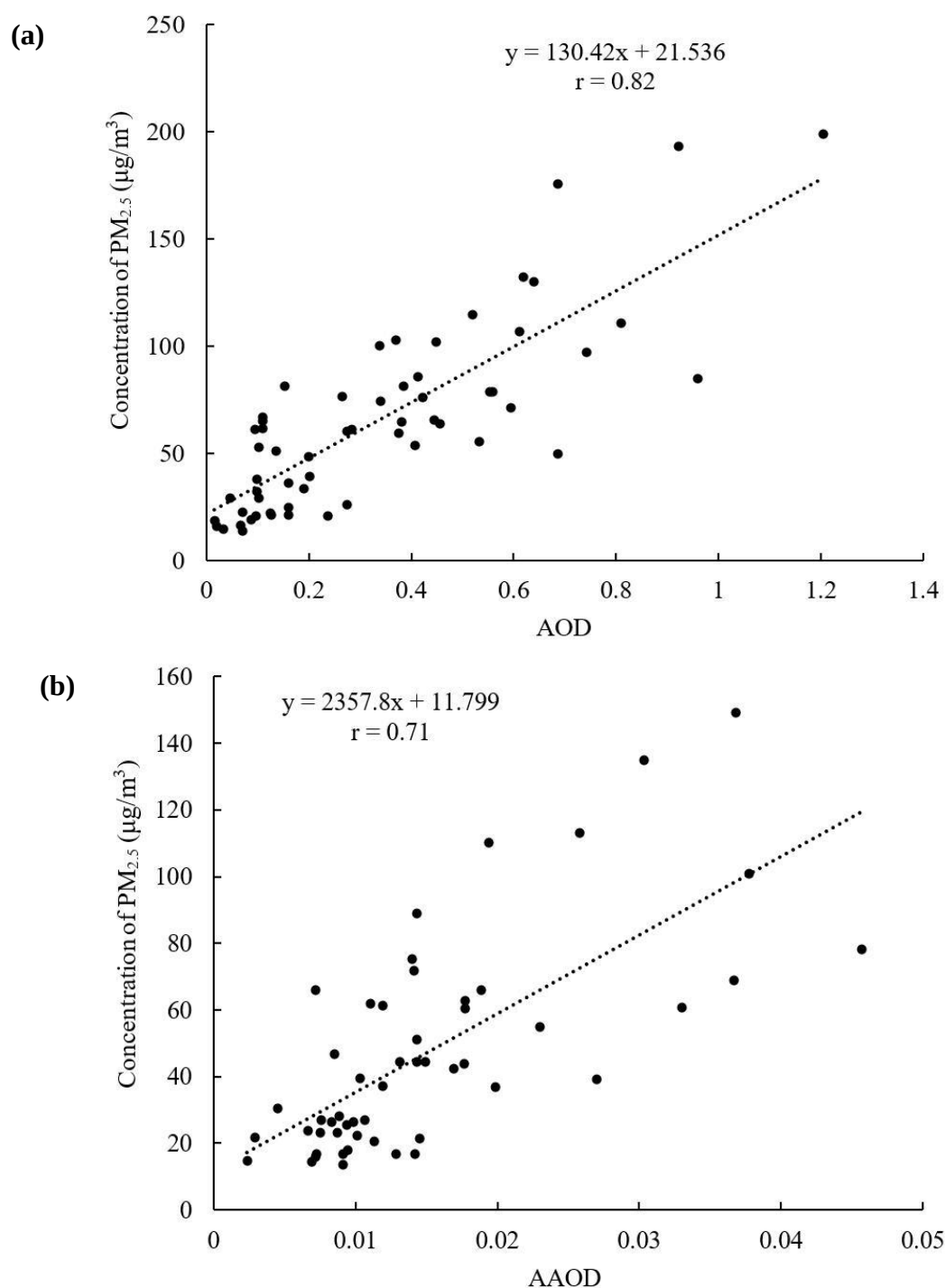
Table 3.2 Monthly concentrations of ground-measured air components from September to December in Northeastern China (unit: $\mu\text{g}/\text{m}^3$).

Compositions	Provinces	Month			
		September	October	November	December
PM _{2.5}	Heilongjiang	17.27	35.76	78.78	54.63
	Jilin	28.87	64.43	107.41	94.74
	Liaoning	30.47	46.68	101.23	85.08
PM ₁₀	Heilongjiang	39.70	61.96	107.14	78.77
	Jilin	54.78	95.47	135.16	120.79
	Liaoning	57.87	61.96	125.71	114.77
CO	Heilongjiang	559.81	759.11	1111.58	1277.85
	Jilin	787.67	965.48	1195.1	1328.76
	Liaoning	905.67	1044.42	1472.45	1712.88
NO ₂	Heilongjiang	17.68	21.42	29.00	32.59
	Jilin	26.43	31.47	37.89	42.95
	Liaoning	30.47	34.73	42.41	44.26
SO ₂	Heilongjiang	9.12	14.06	23.34	34.88
	Jilin	10.95	17.42	36.44	60.86
	Liaoning	17.55	21.17	55.72	77.37
O ₃	Heilongjiang	41.24	45.53	35.54	32.07
	Jilin	46.80	46.96	36.56	31.24
	Liaoning	64.30	54.71	37.69	28.68

By comparing the ground-measured data with the number of crop residue burning spots and analyzing the spatial distribution, I concluded that the primary particles directly emitted from crop residue burning were one of the important causes of the first

and the second PM_{2.5} pollution episodes in Northeastern China. From 31st October to 6th November, the daily number of crop residue burning spots consecutively exceeded 1,000; Heilongjiang contributed 78.34% of the total number, Jilin 16.79% and Liaoning only 4.87%. Meanwhile, the second PM_{2.5} pollution episode occurred during this intense crop residue burning period; the daily average concentration of PM_{2.5} reached an extraordinary 273.83 µg/m³ in Heilongjiang (the severest of the three episodes), 217.14µg/m³ in Jilin and only 133.93 µg/m³ in Liaoning.

3.3.3 Air components and air index changes from remote sensing



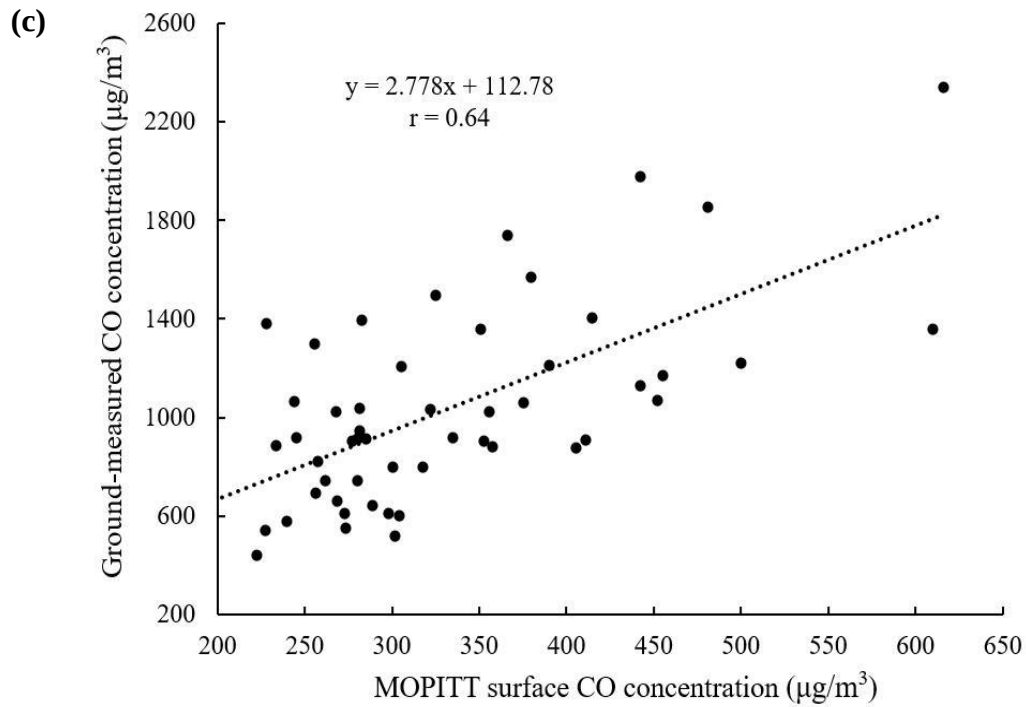
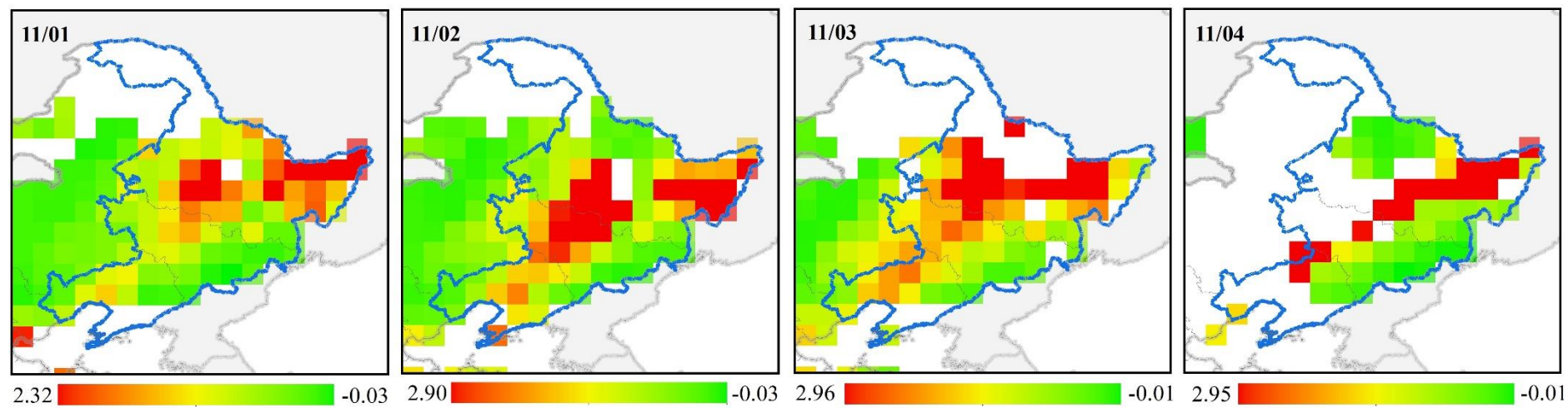


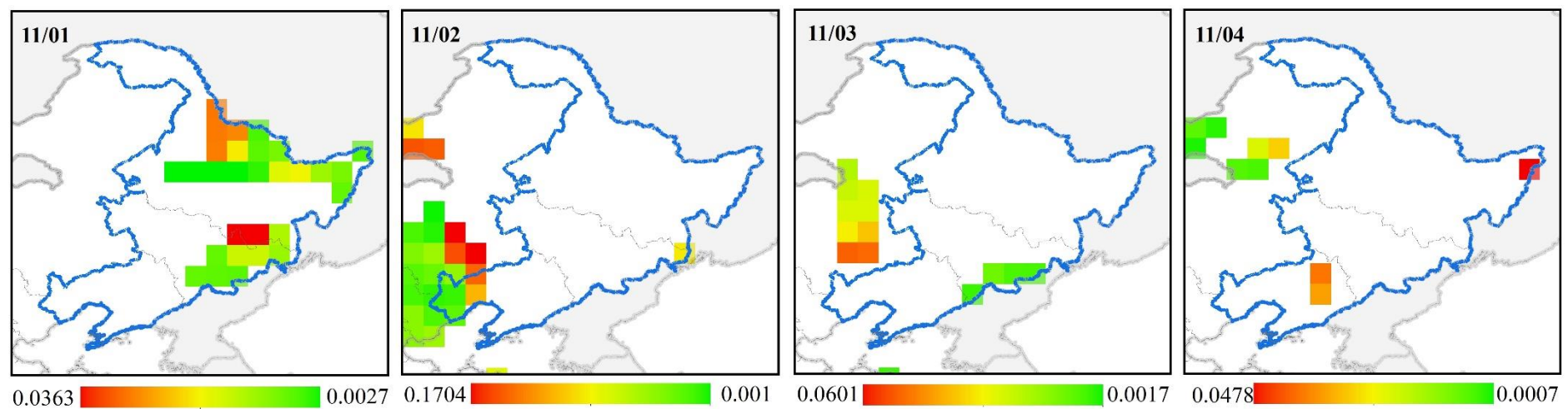
Figure 3.6 The correlation between remote sensing and ground-measured datasets in October and November 2015: Aerosol Optical Depth (AOD) and ground-measured $\text{PM}_{2.5}$ (a); Aerosol Absorption Optical Depth (AAOD) and ground-measured $\text{PM}_{2.5}$ (b); surface CO and ground-measured CO (c).

It is hard for remote sensing technology to simultaneously achieve both high spatial resolution and high temporal resolution. In this study, the daily data of AOD (MODIS), AAOD (OMI), UVAI (OMI), and CO surface concentration (MOPITT) and monthly data of AOD (MODIS) and CO surface concentration (MOPITT) were used to analyze aerosol index changes and air components in Northeastern China. Moreover, the results of remote sensing were compared with ground measurements. The remote sensing data mentioned above were global coverage data that could not cover the entire region of Northeastern China every day; sometimes there was even no data from this region. Therefore, to be consistent with remote sensing data and produce more accurate results, I only determined the statistics of ground measurement of the region covered by daily and monthly remote sensing data.

(a)



(b)



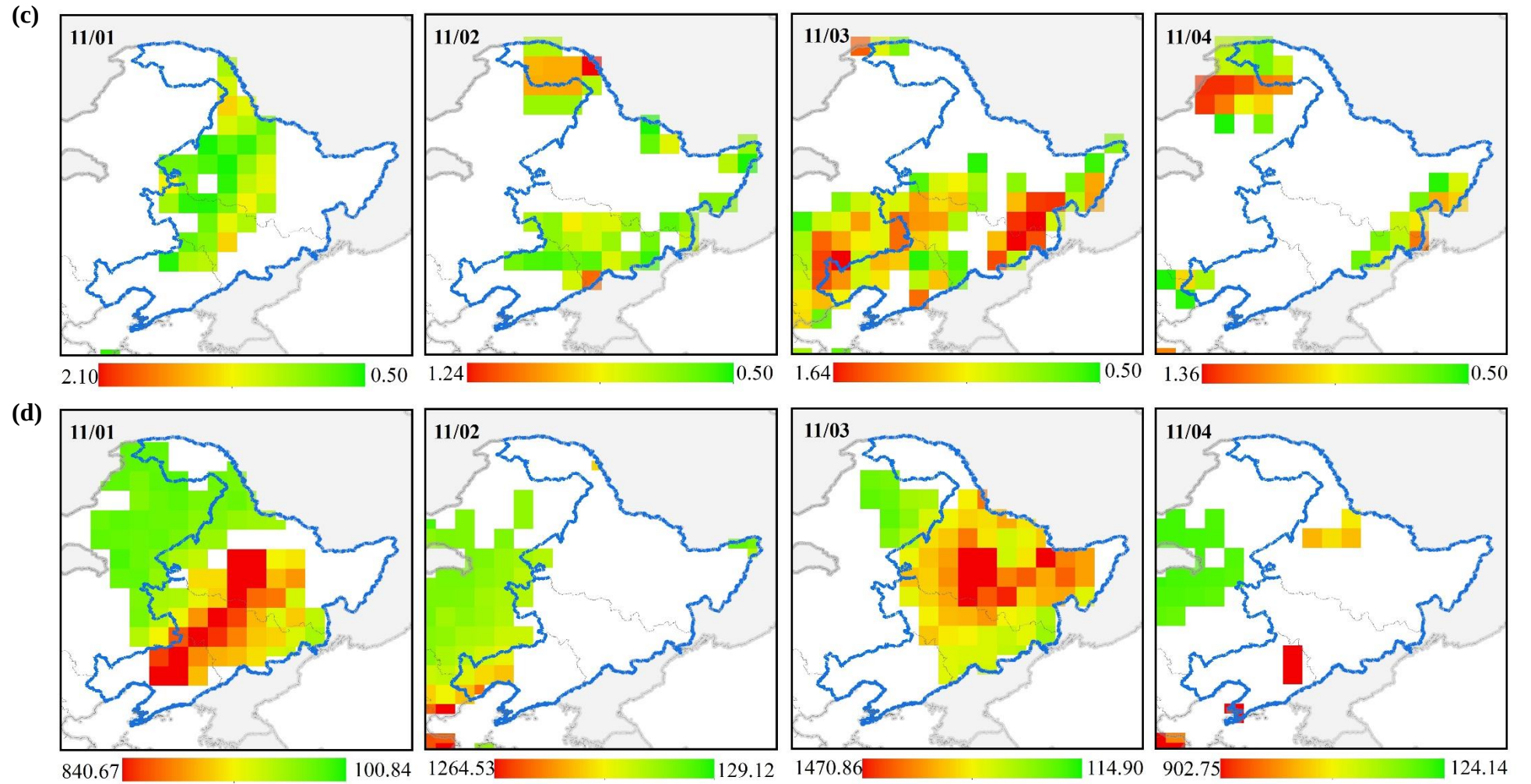


Figure 3.7 The daily aerosol indicators and CO concentration from remote sensing datasets from 1st to 4th December: AOD (a); AAOD (b); Ultraviolet Aerosol Index (UVAI) (c); surface CO concentration (d) in $\mu\text{g}/\text{m}^3$.

As an important indicator of visibility, AOD was compared with ground-measured PM_{2.5}. For the daily MYD08 product from October to December, there were no intersections between remote sensing images and ground-measured data in the two days of 26th October and 16th November. Fig. 3.6a indicates that the correlation was highly significant between the two daily datasets, with a correlation coefficient r of 0.82. In the last section we discussed the spatial distribution of crop residue burning and air components from 1st to 4th November; therefore, the daily remote sensing data for those 4 days were also selected to compare the spatial distribution in Fig. 3.7. The results show that there were high AOD values in Northeastern China, especially in northeast Heilongjiang and the junction region of Jilin and Heilongjiang Province that also corresponded to the intense crop residue burning area (Fig. 3.7a). The spatial distribution of AOD was consistent with ground-measured PM_{2.5}; they especially presented high spatial consistency on November 2nd and 3rd. The monthly MYD08 product revealed that the AOD suddenly increased from 0.1884 in October to 0.5100 in November, and ground-measured PM_{2.5} also rose sharply from 46.75 $\mu\text{g}/\text{m}^3$ in October to 95.48 $\mu\text{g}/\text{m}^3$ in November (Table 3.3). In the following month, AOD decreased from 0.5100 to 0.4267 and PM_{2.5} correspondingly decreased from 95.48 $\mu\text{g}/\text{m}^3$ to 81.32 $\mu\text{g}/\text{m}^3$, whereas PM_{2.5} in other part of China showed an increasing trend.

Another important aerosol indicator, AAOD, was also compared with ground-measured PM_{2.5}. Fig. 3.7b shows that there was very little AAOD data covering Northeastern China from 1st to 4th November. On 1st November, the AAOD values of two pixels in the junction area of Heilongjiang and Jilin province were higher than in other regions, and the AAOD value of one pixel in northeast Heilongjiang was higher on the 4th. Although we could not analyze the spatial consistency between AAOD and ground-measured PM_{2.5} on these 4 days, Fig. 3.6b indicates that there was high significance between daily AAOD and ground-measured PM_{2.5} in October and November, with a correlation coefficient r of 0.71. In those two months, there was no intersection between remote sensing images and ground-measured data for 9 days: 10th, 31st October and 8th, 9th, 13th, 16th, 27th, 29th, and 30th November. During the four days, the UVAI was always low in Northeastern China, and I found UVAI in the junction region of Jilin and Heilongjiang Province to be higher than in the other regions only on 3rd November. Comparing the daily UVAI and ground-measured PM_{2.5}, the results indicate that there was no correlation between these two datasets in October and November. However, the ten-day average UVAI from 1st to 10th November was 0.7751, and the ten-day average UVAIs before the 1st and after the 10th of November were 0.7062 and 0.7253, respectively. As was previously mentioned, two severe PM_{2.5} pollution episodes occurred in Northeastern China during the ten days, and the corresponding ten-day average of ground-measured PM_{2.5} was 161.72 $\mu\text{g}/\text{m}^3$ (not the

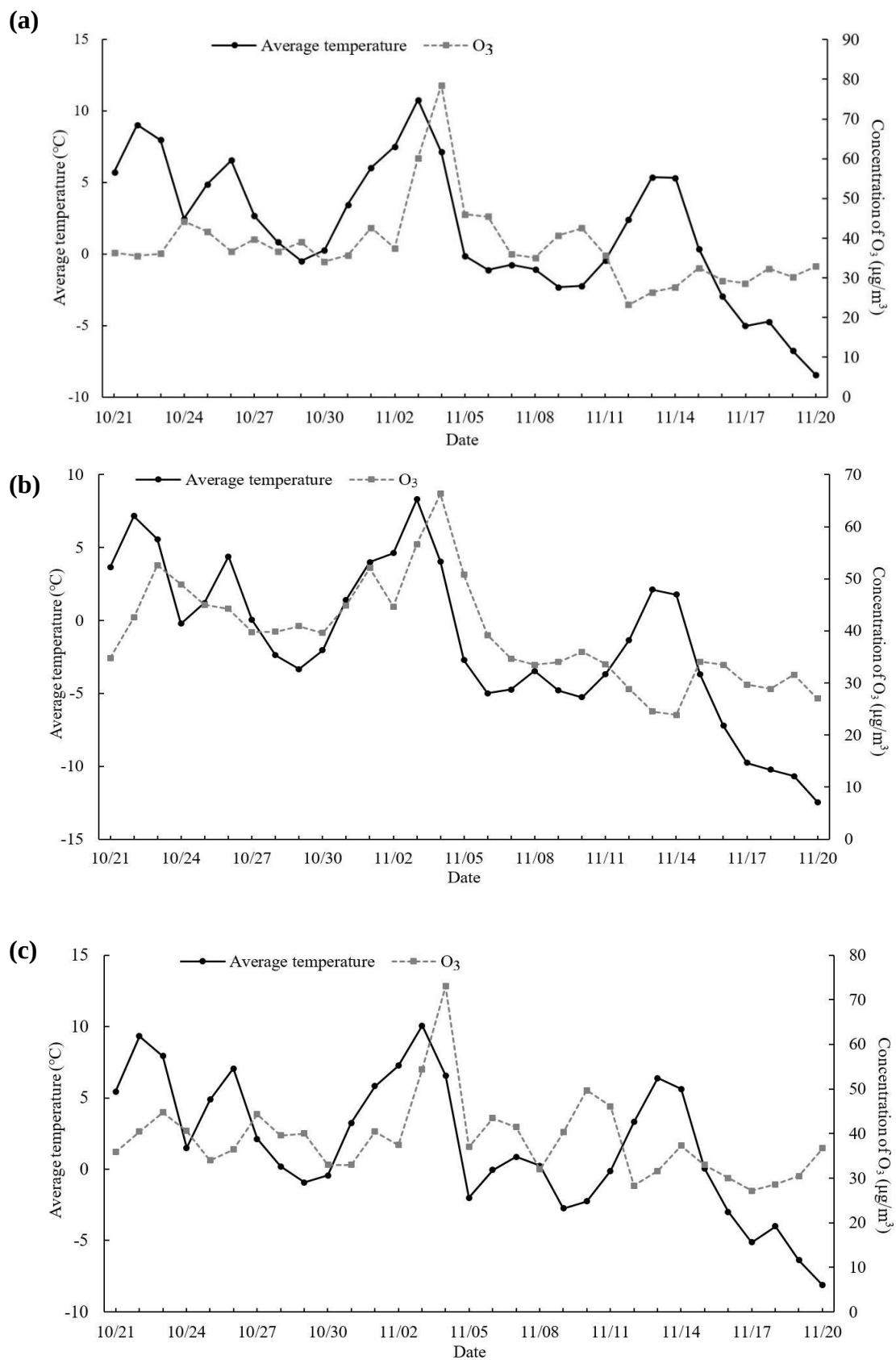
entire region of Northeastern China but the daily UVAI image-covered area); before the 1st and after the 10th of November the average PM_{2.5} was 57.57 $\mu\text{g}/\text{m}^3$ and 68.49 $\mu\text{g}/\text{m}^3$, respectively. I inferred that although the UV-absorbing aerosol was not the main composition of PM_{2.5} in Northeastern China, the increase of UV-absorbing aerosol could still be observed during the two severe PM_{2.5} pollution episodes.

Table 3.3 Monthly AOD and CO surface concentration and ground-measured PM_{2.5} and CO.

Datasets	Month			
	September	October	November	December
MODIS AOD	0.1297	0.1884	0.5100	0.4267
PM _{2.5} ($\mu\text{g}/\text{m}^3$)	25.33	46.75	95.48	81.32
MOPITT CO ($\mu\text{g}/\text{m}^3$)	321.41	334.14	350.85	407.16
CO ($\mu\text{g}/\text{m}^3$)	754.87	923.93	1253.2	1451.44

The daily CO MOPITT data revealed that the concentrations in Northeastern China on 1st and 3th November were higher than in the other parts and that the spatial distribution was basically consistent with the ground-measured CO concentration. On 3rd November they both showed especially-high CO concentration in the north part of Heilongjiang Province (Fig. 3.7d). However, on 2nd and 4th November, the CO MOPITT data were not sufficient to analyze the spatial distribution in Northeastern China. Fig. 3.6c indicates that there was high significance between daily CO and ground-measured CO in October and November, with a correlation coefficient r of 0.64. In these two months, there were no intersections between CO MOPITT and ground-measured data for 10 days: 3rd, 10th, and 17th October and 2nd, 4th, 7th, 9th, 14th, 18th, and 27th November. For the monthly MOPITT products, CO concentration consecutively increased from 321.41 $\mu\text{g}/\text{m}^3$ in September to 407.16 $\mu\text{g}/\text{m}^3$ in December, and ground-measured CO presented the same change tendency of increase from 754.87 $\mu\text{g}/\text{m}^3$ in September to 1451.44 $\mu\text{g}/\text{m}^3$ in December. Both the daily and monthly data showed that the ground-measured CO concentration was much higher than the result from MOPITT and that ground-measured CO concentration was almost two times larger. I assume that this was because most CO monitoring sites nationwide were in high-traffic urban areas, where the corresponded CO concentration is much higher than other areas.

3.3.4 Meteorological conditions and transportation of PM



(d)

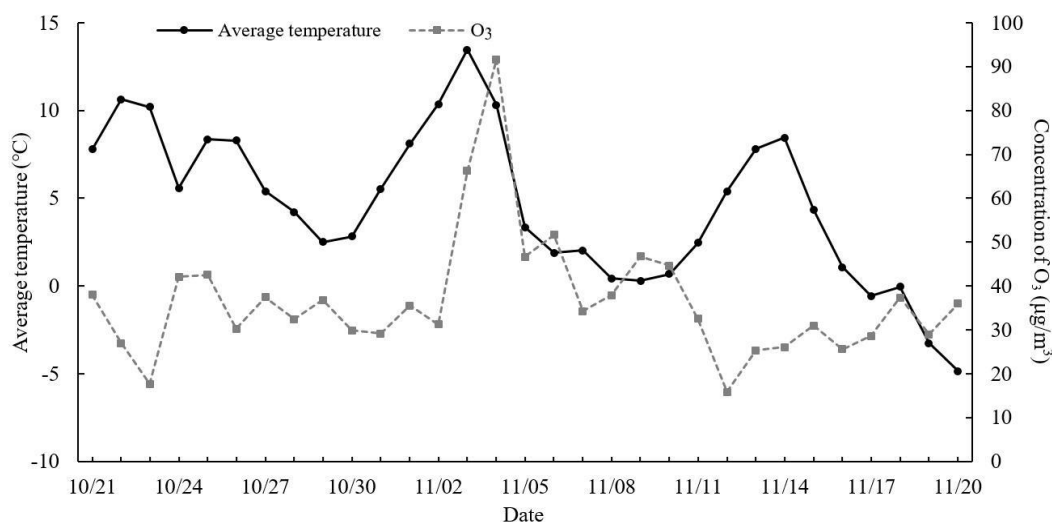
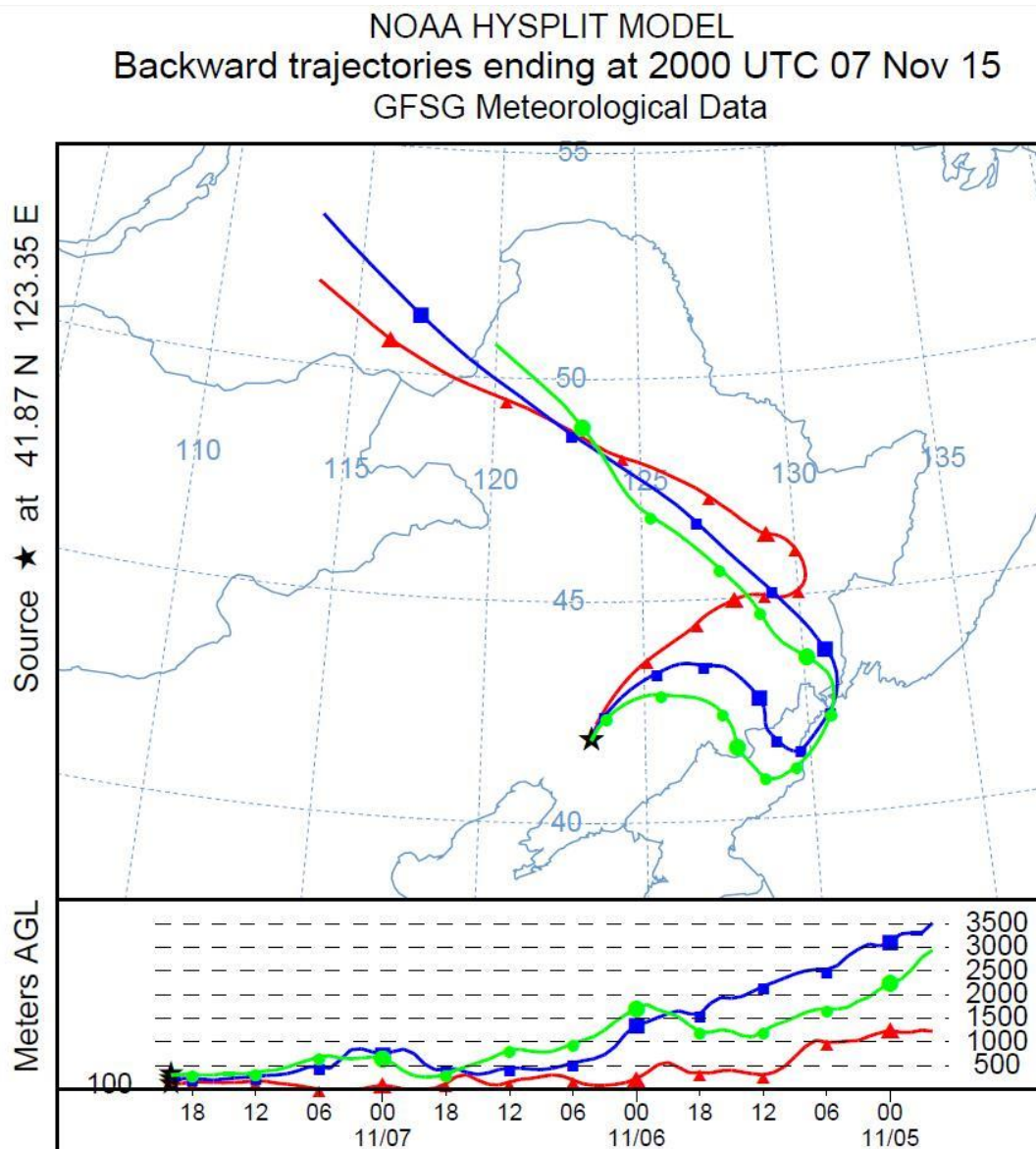


Figure 3.8 Daily average temperature and O₃ concentration in Northeastern China: Northeastern China (a); Heilongjiang Province (b); Jilin Province (c); Liaoning Province (d).

Fog, haze and dust episodes are closely associated with certain large-scale circulation patterns (Wang et al., 2014). An analysis of the evolution of atmospheric circulation via the meteorological background can advance the understanding of the formation of haze, fog and dust. According to the meteorological data, the average temperature in Northeastern China showed an abnormal increase from -0.45°C on 29th October to 10.77°C on 3rd November, and the monthly average temperature on October 2015 was only 8.33°C (Fig. 3.8a). This meteorological condition accelerates photochemical reaction in the troposphere. Additionally, Fig. 6.1 shows that the NO₂ and SO₂ concentrations peaked on 2nd November and provided sufficient precursors for the formation of O₃, secondary organic aerosol (SOA) and secondary inorganic aerosol (SIA). The ground-measured data revealed that the concentration of O₃ rose sharply from $34.09\text{ }\mu\text{g/m}^3$ on 30th October to $78.48\text{ }\mu\text{g/m}^3$ on 4th November, which also proved that the photochemical reaction was intense during this period. For the three provinces, the O₃ concentration in Heilongjiang, Jilin and Liaoning Provinces rose from $39.58\text{ }\mu\text{g/m}^3$ to $66.33\text{ }\mu\text{g/m}^3$, from $33.00\text{ }\mu\text{g/m}^3$ to $73.00\text{ }\mu\text{g/m}^3$ and from $29.21\text{ }\mu\text{g/m}^3$ to $91.64\text{ }\mu\text{g/m}^3$, respectively (Fig. 3.8b, c and d). The formation of O₃ always produces a variety of oxidants and secondary pollutants (e.g., organic oxygenates; oxidized organic and inorganic nitrogen compounds). Moreover, Iinuma et al. (2013) found a newly identified ozone-driven SOA production chain that dramatically increases SOA formation. Therefore, I assume that masses of secondary aerosols were formed in Northeastern China during this period by photochemical reaction and that photochemical reaction in Liaoning was the most intense and in Heilongjiang was the least intense.

(a)



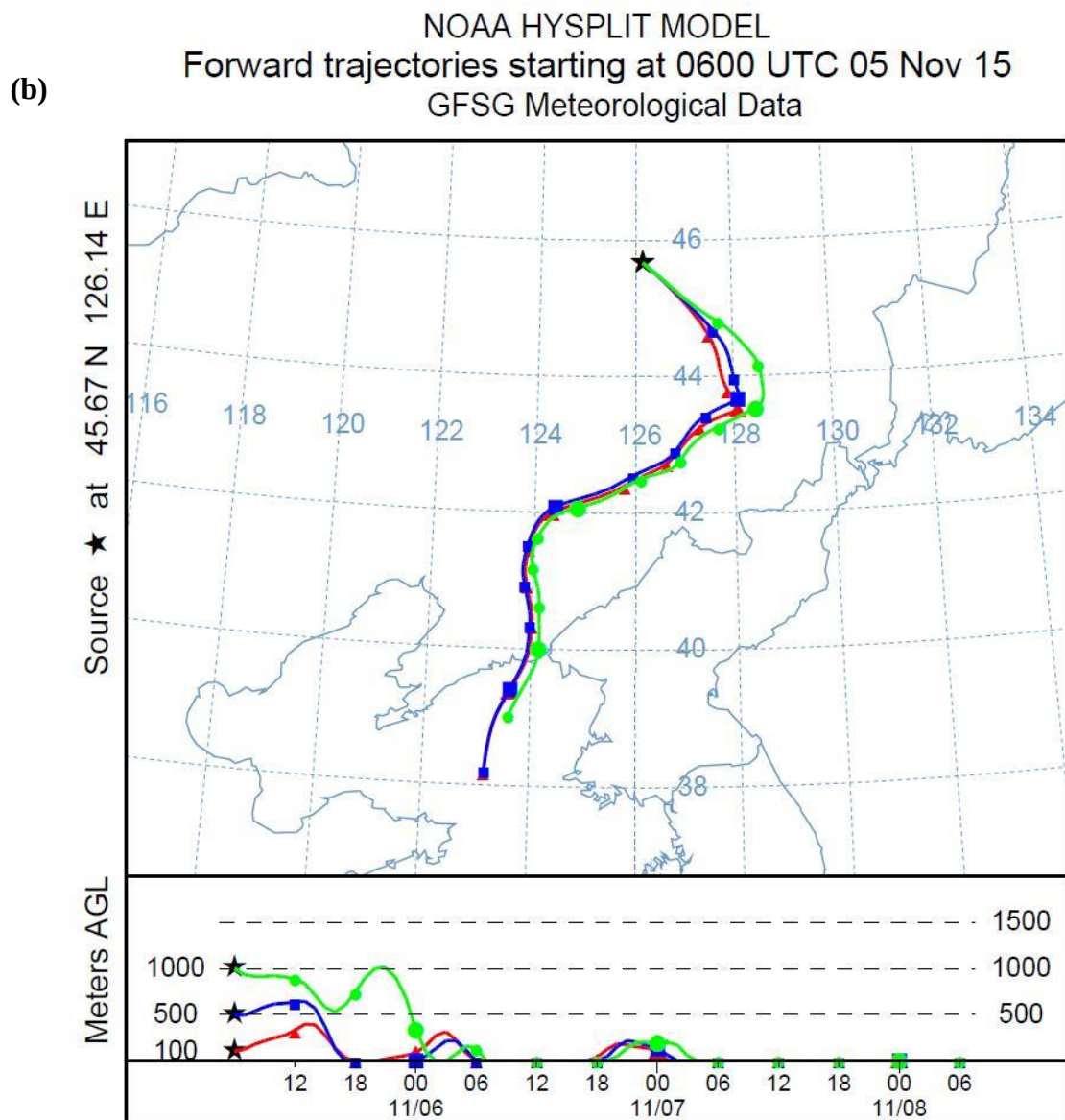


Figure 3.9 Backward trajectories of the HYSPLIT model showing the origin of pollutants in Shenyang (a) and the transportation forward trajectories showing the transportation of pollutants from crop residue burning in Heilongjiang Province (b).

From 4th November, the Siberian cold current swept Northeastern China and local temperatures dramatically decreased from 10.77°C to -1.11°C on 6th November. This cold current would transport pollutants from north to south. Moreover, Liaoning started central heating from 1st November, which increased fossil fuel consumption and exacerbated PM_{2.5} pollution in this region. On 8th November, the daily average concentration in Shenyang, the capital of Liaoning Province, reached 848 $\mu\text{g}/\text{m}^3$ and hourly PM_{2.5} concentration reached 1,326 $\mu\text{g}/\text{m}^3$. The backward trajectories of the HYSPLIT model were used to trace the origin of PM in this city. The results showed that the air masses at 100 m, 200 m and 300 m altitudes were mainly transported from the northwest, the direction of Siberia (Fig. 3.9a). As the cold current became weak, the

air mass finally settled out and fell toward the surface in Shenyang. The transportation routine passed through southern Heilongjiang Province and the results suggests that intense crop residue burning was still ongoing during this period, when every day there were approximately 1,000 crop residue burning spots in this region. I inferred that this cold current had transported the air pollutants from crop residue burning to Jilin and Liaoning province. To further prove this inference, I used the forward trajectories to model the transportation of the pollutants. The intense crop residue burning region was selected as the star point. The results showed that from 5th to 8th November the air mass at 100-m, 500-m and 1,000-m altitudes moved southward and fell toward the surface in Jilin and Liaoning province (Fig. 3.9b). Primary aerosols from crop residue burning and fossil fuel consumption and the secondary aerosols formed before this cold current had been totally transported from Heilongjiang to Jilin and Liaoning Province. As mentioned above, the photochemical reaction in Liaoning was assumed to have been more intense than in other provinces, which means that more secondary aerosols were formed in this region. Additionally, the suddenly decreased temperature could form a thermal inversion layer that would reduce the height of the atmospheric convective boundary layer, which would inhibit the vertical diffusion of pollutants and provide conditions for pollutant accumulation. Fig. 3.9b also suggests that after the sedimentation the air mass was always at an altitude below 100 m from 6th to 8th November.

From meteorological conditions and transportation simulation, all the results explained why the third PM_{2.5} pollution episode (near 8th November) in Heilongjiang was much weaker than in the other two provinces and why the third pollution episode in Jilin and Liaoning province, especially Liaoning Province, was much stronger than the first and second episodes.

3.4 Discussion

The severe haze episode in November 2015 first stimulated attention to the PM pollution in Northeastern China. By analyzing three PM_{2.5} pollution episodes by ground-measured and remote sensing data, I found that the causes of high PM in each province and each episode were totally different. Heilongjiang Province is located in the extreme north of China and borders on Russia. In the winter the prevailing wind is south forward and there is no heavily populated, urbanized and industrialized area upwind of Heilongjiang Province. Therefore, local pollutants make a great contribution to PM concentration. As was previously mentioned, aerosols mainly included primary aerosols and secondary aerosols. There was significant correlation between PM and the other air components in Heilongjiang Province; in particular, the correlation coefficient of daily PM_{2.5}-CO and PM_{2.5}-NO₂ was higher than 0.90. Therefore, I further inferred that

primary aerosols were the main contributors of PM_{2.5} in Heilongjiang Province during the study period. At the end of October and the beginning of November 2015, severe crop residue burning occurred in Northeastern China and the spots were mainly distributed in northeast Heilongjiang and the junction region between Jilin and Heilongjiang Province. I found that the daily average PM_{2.5}, CO and NO₂ concentrations showed high spatial consistency with crop residue burning during the intense burning period. Additionally, since the crop residue burning emitted a large amount of CO, NO₂ and atmospheric particles, their concentrations in Heilongjiang Province also reached their highest point during the second pollution episode. Therefore, I concluded that the crop residue burning induced the severe PM_{2.5} pollution in Heilongjiang Province.

Liaoning Province is located in the south part of Northeastern China. Adjacent to the China North Plain, the populated, industrialized and the severest air polluted region in China, and downwind of Heilongjiang and Jilin Provinces, the transportation of pollutants from these regions would directly affect local PM_{2.5} concentration. The correlation coefficient of PM_{2.5} concentration with other components in Liaoning Province was the lowest among the three provinces, which also proved that except for local primary aerosols, transportation or secondary aerosols had a significant impact on local PM_{2.5} concentration. In section 3.2, I concluded that primary aerosols from crop residue burning were one of the important causes of the first and second pollution episodes. The results indicated that crop residue burning in Liaoning was much weaker than in other provinces; therefore, the first and second pollution episodes were not as severe as the pollution episodes in Heilongjiang and Jilin, and the third pollution episode in Liaoning was much more severe, caused by the special meteorological conditions that accelerated the formation of secondary aerosols and the transportation of pollutants from Heilongjiang and Jilin Province.

Jilin Province is located between Heilongjiang and Liaoning province. Table 3.2 shows that the concentrations of CO, NO₂, SO₂ and O₃ in Liaoning Province were always the highest, whereas, theoretically, PM_{2.5} concentration in Liaoning should have been the highest. However, PM_{2.5} concentration in Jilin Province was the highest. I assume that this was caused by the special geographical condition that the pollutant transportation from Heilongjiang Province in the winter would affect local PM_{2.5} concentration. Moreover, unlike Liaoning, Jilin is not a coastal province that would exacerbate the accumulation of pollutants. Although crop residue burning in Jilin is not as intense as in Heilongjiang, there are still massive burning spots in this province. Because it is located downwind, in the third episode the pollutants from crop residue burning in Heilongjiang caused the sudden increase of PM_{2.5} concentration in Jilin Province, which explains why both the three pollution episodes in Jilin were intense.

Central heating was always thought to be one of the main causes of severe PM_{2.5} pollution in Northeastern China; Heilongjiang starts central heating in approximately the first half month of October, Jilin starts at approximately the second half month of October and Liaoning starts at approximately the first half month of November. In recent years severe haze has always occurred in late October and early November in Northeastern China. In fact, compared with colder December and January, the fossil consumption during late October and early November was much less and the ground-measured data also indicated that the daily average concentration of CO, NO₂ and SO₂ in December and January was higher than the concentration in October and November. Table 3.2 shows that from November to December, the concentration of CO, NO₂ and SO₂ in the three provinces showed an increasing trend, whereas the PM_{2.5} concentration showed a decreasing trend. From the analysis of crop residue burning I concluded that intense crop residue burning makes a great contribution to the severe PM_{2.5} pollution episodes in Northeastern China in October and November (there is almost no crop residue burning in December). In 2016, the local government of Northeastern China made a great effort to reduce crop residue burning and, according to MOD14A1, the number of burning spots decreased from 9,176 to 3,264 in October and from 10,614 to 1,913 in November. Moreover, the PM_{2.5} concentration decreased from 46.48 μg/m³ to 38.52 μg/m³ in October and from 94.38 μg/m³ to 62.11 μg/m³ in November. For the daily average concentration of PM_{2.5} during the same period in 2016, none of the values exceeded 170 μg/m³, and the air quality was much better than in 2015.

In this study, ground-measured datasets and AOD, AAOD, UVAI and MOPITT CO concentrations were used to analyze the pollution episodes. The results indicated that AOD showed good correlation with ground-measured PM_{2.5}, that the spatial coverage was also better than the other products, and that there were no intersections between remote sensing images and ground-measure data for only two days. To be consistent with ground-measured data, the monthly AOD products found a significant increase in November. AAOD and MOPITT CO also showed significant correlations with ground-measured data; however, the spatial coverage was not as good as that of MODIS AOD. Moreover, MOPITT CO represented high concentrations in the crop residue burning region and showed a certain spatial consistency with ground-measured CO. Only daily UVAI showed no correlation with ground-measured data, although an increased value from 1st to 10th November was observed. Compared with the several-thousand surface temperature monitoring stations, the monitoring net of air quality is still too small, and in many developing countries, which are heavily air-polluted regions, there are no sufficient air quality monitoring stations. This study showed that if ground-measured data are not available, remote sensing datasets could

play an important role in air pollution studies. Ground-measured data only represent air quality in one spot, whereas remote sensing datasets can present the air conditions and distributions at a spatial level.

3.5 Conclusions

Satellite datasets were integrated with ground-measured datasets to analyze the PM_{2.5} pollution episodes in October and November 2015 in Northeastern China. The results indicated that multiple factors working together caused the severest PM_{2.5} pollution episode near the 8th of November. Primary aerosols came from crop residue burning, secondary aerosols formed by special meteorological conditions, and aerosol transportation significantly contributed to this episode. The three episodes in this study were associated with crop residue burning; therefore, I assume that reduction in crop residue burning is an effective measure to prevent severe PM_{2.5} in Northeastern China. Moreover, some special meteorological conditions in the alternate periods of winter and autumn could accelerate the formation of secondary aerosols and exacerbate the accumulation of aerosols. Therefore, I suggest that reduction in secondary aerosol precursors (NO_x, SO₂ and NH₃) can also help achieve PM_{2.5} reduction targets. This study showed that there are significant correlations and spatial consistencies between remote sensing and ground-measured datasets. In many heavily-polluted countries where we cannot obtain ground-measured data, remote sensing data could replace them and will play an important role in the study of air pollution.

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Chapter 4 Analyzing CO₂ concentration changes and their influencing factors in Indonesia by OCO-2 and other remote sensing data

4.1 Introduction

The rate of change of atmospheric CO₂ reflects the balance between anthropogenic carbon emissions and the dynamics of a number of terrestrial and ocean processes that remove or emit CO₂ (Poulter et al., 2011; Canadell et al., 2007). Since the beginning of the industrial period in the late 18th century, humankind has emitted large amounts of CO₂ into the atmosphere, primarily in the form of fossil-fuel burning; additionally, land-use changes, such as deforestation, urbanization and desertification, are also an important factor that affect global CO₂ concentration (Lubowski et al., 2005; Stocker, Strassmann and Joos, 2010). The increase in CO₂ and possible concomitant climate change could affect the ecology of most living things, including production agriculture (Kimball et al. 1993). CO₂, as the most important greenhouse gas, coupled with the continued accumulation of other greenhouse gases in the atmosphere, is expected to cause the average world temperature for last decade of 21st century rising 4.0 °C (2.4 °C -6.4 °C) in the society where the high economic growth is achieved by recognizing fossil fuel as the important source of energy (Solomon et al., 2007). Therefore, monitoring the changes of CO₂ concentration on the earth is critical to relieving the global warming.

With the development of remote sensing technology, satellite measurement is becoming one of the most effective approaches to high spatio-temporal resolution monitoring of global greenhouse gas distribution (Oguma et al., 2011). In this study, two greenhouse gas monitoring satellites have been compared. One is the Greenhouse Gases Observing Satellite (GOSAT), which was launched successfully from Japan Aerospace eXploration Agency (JAXA) on 23rd January, 2009; it is a special spacecraft to measure the concentrations of carbon dioxide and methane, the two major greenhouse gases, from space (Yoshida et al., 2010). After the launch failure of the Orbiting Carbon Observatory (OCO) in 2009 (Crisp et al., 2004), the National Aeronautics and Space Administration (NASA) authorized the development of OCO-2, which was successfully launched on July 2, 2014 (Frankenberg et al., 2014). Because these two satellites have different advantages, they will be able to provide sufficient data and information to ascertain the distribution of greenhouse gases and enhance scientific understanding of concentration changes of CO₂. GOSAT returns to the same location in 3-day periods and utilizes 44 orbits to cover the whole Earth (Basu et al., 2013). We can obtain the results of CO₂ and CH₄ column-averaged dry air mole fraction (X_{CO_2} and X_{CH_4}) from the GOSAT project. Although, OCO-2 has a longer cycle, 16 days, to return to the same location, it uses 233 orbits to cover the Earth (Taylor et al., 2015). Comparing with

GOSAT which can provide data of two kinds of greenhouse gas (CO_2 and CH_4), OCO-2 only provides data of CO_2 column-averaged dry air mole fraction (X_{CO_2}). Because of the lower spatial resolution, a large proportion of the research using GOSAT is applied on a global or continental, rather than a regional, scale (Prasad et al., 2014; Guo et al., 2013). However, since OCO-2 data are only available in recent years, there is almost no research about using OCO-2 to analyse the change of CO_2 concentration. Therefore, whether the greenhouse gas monitoring satellite is suitable for regional studies remains unknown. The advantage of the greater number of Earth orbits by OCO-2 will be used to apply the research on a regional scale. Indonesia is the world's largest island country, with more than seventeen thousand islands (Salazar, 2014). In addition, a devastating forest fire occurred in Indonesia in 2015, which represents a significant source of carbon emitted to the atmosphere. Hence, Indonesia is selected as the study area and CO_2 concentration changes during the period of the forest fire have been analysed specifically. In this study, three important factors that affect CO_2 concentration have been considered: Sea Surface Temperature (SST), fires and vegetation. The objective of this study is to fill in the gap that no research exists on using the greenhouse gas monitoring satellite to analyse CO_2 concentration changes on a regional scale and investigate the relationships between CO_2 concentration changes and other environment factors.

4.2 Data and methodology

4.2.1 Datasets

4.2.1.1 CO_2 concentration data

Both GOSAT and OCO-2 can provide CO_2 concentration data. The primary product delivered by the two satellites consist of spatially resolved estimates of the column-averaged dry air mole fraction. This quantity, called X_{CO_2} by members of the atmospheric carbon science community, quantifies the average concentration of carbon dioxide in a column of dry air extending from the Earth's surface to the top of the atmosphere (Satio et al., 2012). Estimates of X_{CO_2} are derived by taking the ratio of the column integrated number densities of carbon dioxide and molecular oxygen along the optical path between the Sun, the surface footprint, and the instrument, and then multiplying these results by the column-averaged oxygen concentration (Kawasaki et al., 2012). These carbon dioxide and oxygen number densities are estimated from high-resolution spectra of reflected sunlight, collected by the Observatory's instruments at wavelengths (colors) within the 0.765 nanometer molecular oxygen A band and two carbon dioxide bands centered at wavelengths near 1.61 and 2.06 microns (OCO-2 Data Product User's Guide, 2015).

In this section, both Thermal And Near-infrared Sensor for carbon Observation (TANSO) Fourier Transform Spectrometer (FTS) Short-wavelength infrared (SWIR) Level 2 products of GOSAT and Level 2 standard products of OCO-2 over Indonesia were collected. GOSAT data were found to be not feasible to perform research on Indonesia because there are few data to cover the country, and even we cannot obtain the annual CO₂ distribution of Indonesia. While, Level 2 standard products of OCO-2 provide sufficient data to cover Indonesia. Therefore, only OCO-2 data were eventually used in this study. OCO-2 Level 2 standard products are available from September 6th, 2014, and the products from that date to December 2016 have all been collected.

4.2.1.2 Sea Surface Temperature data

Fossil fuel combustion and other human activities are now emitting almost 40 billion tons of CO₂ into the atmosphere every year (Crisp, 2014). Atmospheric CO₂ measurements indicate that less than half of the CO₂ is accumulating in the atmosphere (Siegenthaler and Sarmiento, 2009). The remainder is apparently being absorbed by CO₂ sinks in the ocean and the terrestrial biosphere (Quéré et al., 2009). Since the ocean represents an important carbon sink (Landschützer et al., 2014), changes in sea surface temperature could significantly affect the CO₂ concentration of the Earth, especially as related to an island country, such as Indonesia. Therefore, Optimum Interpolation Sea Surface Temperature (OISST) from the National Oceanic and Atmospheric Administration (NOAA) has been used in this study. The OISST uses both in situ and satellite-derived SST data to produce a weekly and monthly analysis (Yoshimi et al. 2006). The in situ SST data are obtained from the U.S. National Meteorological Center (NMC) file of surface marine observation. These data consist of all ship and buoy observations available to NMC. The satellite observations are obtained from the Advanced Very High Resolution Radiometer (AVHRR) onboard polar orbiting satellite of NOAA (Reynolds and Smith, 1994). Bias adjustments of satellite and ship observation (referenced to buoys) have been conducted to compensate for platform differences and sensor biases (Reynolds and Marsico, 1993).

4.2.1.3 Fire hotspots data

Wildfires occurring either naturally or ignited by humans strongly affect the atmospheric composition and thermal balance on both global and regional scales by providing major sources of greenhouse gases and aerosols (Konovalov et al., 2014). The impact of fires on the carbon cycle can become especially important in the face of continuing climate change, as global warming is expected to change fire regimes and may accelerate the accumulation of carbon dioxide, methane, and ozone precursors in the atmosphere, thus leading to further warming (Bond-Lamberty et al., 2007).

To obtain the wildfire data in Indonesia, MOD14A1, Thermal Anomalies/Fire products of MODerate-resolution Imaging Spectrometer (MODIS) have been collected. MODIS Thermal Anomalies/Fire products are primarily derived from MODIS bands at 4 and 11 micrometer radiances (Justice et al., 2002). The fire detection strategy is based on absolute detection of a fire (when the fire strength is sufficient to detect) and on detection relative to its background (to account for variability of the surface temperature and reflection by sunlight). Numerous tests are employed to reject typical false alarm sources, such as sun glint or an unmasked coastline (Giglio et al., 2003). MOD14A1 is produced every 8 days at a resolution of 1 kilometer as a gridded level-3 product in the Sinusoidal projection. This product is unique in that it has three dimensions: fire-mask (1D) and a maximum fire-radiative-power (2D) are provided for each day (3D) in the 8-day period. For example, the fire-mask contains eight, band sequential (day) 1200 × 1200 images of fire data representing consecutive days of data collection. By separating the eight bands of fire-masks, we were able to attain the daily Thermal Anomalies/Fire images.

4.2.1.4 Vegetation data

Plant respiration is an environmentally sensitive component of the ecosystem carbon balance, and net ecosystem carbon flux will change as the balance between photosynthesis and respiration changes (Ryan et al., 1991). While photosynthesis and respiration respond differently to the environment, climate change may alter the balance between them, finally affecting carbon allocation within ecosystems and net carbon flux. Numerous experiments have recorded that plants generally exhibit faster growth when the CO₂ around their leaves is increased (Kimball et al., 1993). Therefore, MOD13A3 has been used to obtain the vegetation data. Global MODIS vegetation indices are designed to provide consistent spatial and temporal comparisons of vegetation conditions (Kim et al., 2014). Blue, red, and near-infrared reflectance, centred at 469 nm, 645 nm, and 858 nm, respectively, are used to determine the MODIS daily vegetation indices (Lin et al. 2012). Due to vegetation indices' simplicity, ease of application, and widespread familiarity, these indices have a wide range of usages. We can acquire two important vegetation indices from MODIS, the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). Compared with NDVI, EVI minimizes canopy background variations and maintains sensitivity over dense vegetation conditions (Fensholt and Sandholt 2005). The following equations are used to calculate NDVI and EVI:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

$$EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + 6.0\rho_{RED} - 7.5\rho_{BLUE} + 1} \quad (2)$$

where ρ_{NIR} , ρ_{RED} and ρ_{BLUE} is the reflectance of near infrared, red and blue, respectively. Global MOD13A3 data are provided monthly at 1-kilometer spatial resolution as a gridded level-3 product in the Sinusoidal projection.

4.2.1.5 Other data

To conduct a specific analysis and understand the distribution features of CO₂, Geographic Information System (GIS) data for Indonesia was used. The GIS data were from the newest version of the Global ADMinistrative areas (GADM), which is a spatial database of the location of the world's administrative areas (or administrative boundaries) for use in GIS and similar software. Indonesia is an island country, and, according to the geographic position, Indonesia has been divided into 6 main parts: Sumatra, Kalimantan, Java, Sulawesi, New Guinea and other islands. Meanwhile, the land cover of Indonesia was also used to characterize fire types. As Table 4.1(Land Process Distributed Active Archive Center listed on its website: lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1) shown, MCD12Q1 is a MODIS Land Cover Type product and it provides data characterizing five global land cover classification systems (Cai et al., 2014). In addition, it provides a land cover type assessment and quality-control information. The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP) (Loveland and Belward, 1997), which includes 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes.

Table 4.1 Land cover types description of MCD12Q1.

Class	IGBP	UMD	LAI/fPAR	NPP	PFT
1	Water	Water	Water	Water	Water
2	Evergreen Needleleaf forest	Evergreen Needleleaf forest	Grasses/Cereal crops	Evergreen Needleleaf vegetation	Evergreen Needleleaf trees
3	Evergreen Broadleaf forest	Evergreen Broadleaf forest	Shrubs	Evergreen Broadleaf vegetation	Evergreen Broadleaf trees
4	Deciduous Needleleaf forest	Deciduous Needleleaf forest	Broadleaf crops	Deciduous Needleleaf vegetation	Deciduous Needleleaf trees
5	Deciduous Broadleaf forest	Deciduous Broadleaf forest	Savanna	Deciduous Broadleaf vegetation	Deciduous Broadleaf trees
6	Mixed forest	Mixed forest	Evergreen Broadleaf forest	Annual Broadleaf vegetation	Shrub
7	Closed shrublands	Closed shrublands	Deciduous Broadleaf forest	Annual grass vegetation	Grass
8	Open shrublands	Open shrublands	Evergreen Needleleaf forest	Non-vegetated land	Cereal crops
9	Woody savannas	Woody savannas	Deciduous Needleleaf forest	Urban	Broad-leaf crops
10	Savannas	Savannas	Non-vegetated		Urban and built-up
11	Grasslands	Grasslands	Urban		Snow and ice
12	Permanent wetlands	Croplands			Barren or sparse vegetation
13	Croplands	Urban and built-up			
14	Urban and built-up	Barren or sparsely vegetated			
15	Cropland/Natural vegetation mosaic				
16	Snow and ice				
17	Barren or sparsely vegetated				

4.2.2 Methodology

OCO-2 Level 2 products are full orbits or fractions of orbits of geographically located estimates of the column-averaged dry air mole fraction of carbon dioxide and several atmospheric and geophysical properties collected during each spacecraft orbit. All the Level 2 products are stored in HDF5 form, which is a unique technology suite that makes possible the management of extremely large and complex data collections (Manduchi, 2010). Level 2 products cannot be used directly in the GIS platform; therefore, a database has been built to extract useful information from the original HDF5 products, such as X_{CO_2} , retrieval latitude, retrieval longitude, and retrieval time. Then, the related information has been converted into a point shapefile, which can be directly used in the ArcGIS platform. To perform the distribution of CO_2 , natural neighbour interpolation has been applied to obtain the distribution map. Natural neighbour interpolation is a method of spatial interpolation, developed by Robin Sibson (Sibson 1981). The method is based on the Voronoi tessellation of a discrete set of spatial points (Viironen et al., 2012). In this section, the interpolation is only used to present the spatial distribution characteristics of CO_2 and the regional and period CO_2 concentrations are calculated with the original values from OCO-2 Level 2 products.

Global SST from NOAA covers all areas of the earth; even the land area is included. To make results more accurate, the land area has to be removed by using a land-sea mask. Indonesia lies between latitudes $11^\circ S$ and $6^\circ N$ and longitudes $95^\circ E$ and $141^\circ E$ (Fig. 4.3). According to this boundary of the country, two rectangles have been created in the ArcGIS platform. Fig. 4.3 shows the first one marked with red dash line (SST1) is extended 5° of Indonesia ($16^\circ S - 11^\circ N$, $90^\circ E - 146^\circ E$), the other one marked with black dash line (SST2) is extended 10° ($21^\circ S - 16^\circ N$, $85^\circ E - 151^\circ E$). Then, the rectangles have been used to clip SST around Indonesia and eventually obtain the monthly average SST in this area.

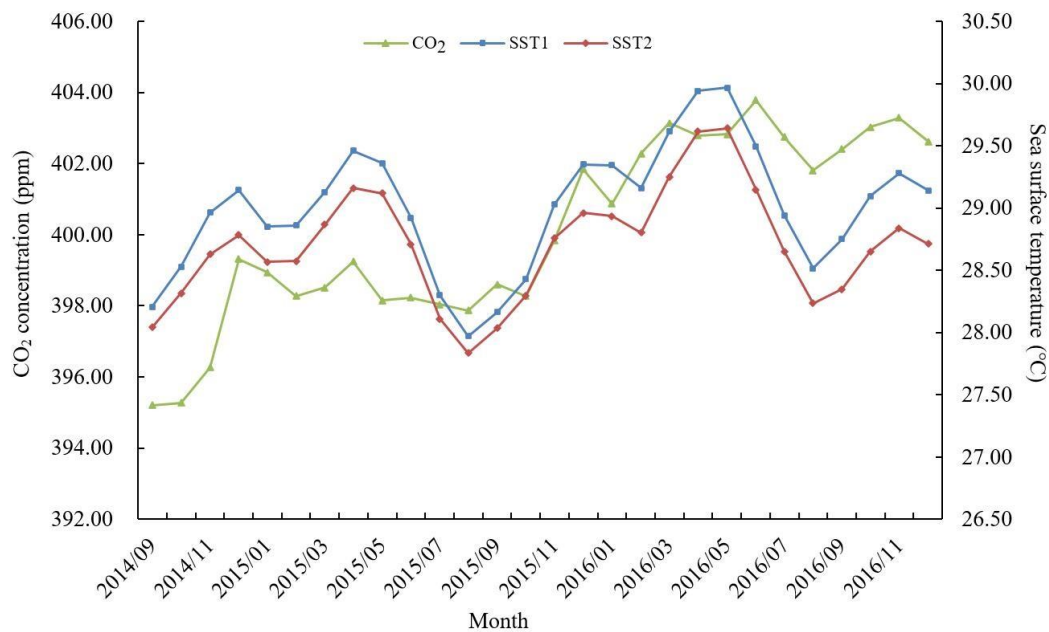
After collecting MOD14A1 images from 2014 and 2015 in Indonesia, daily Thermal Anomalies/Fire images were obtained by separating the eight fire-masks. Then, the daily fire hotspots were extracted from these images and we also acquired monthly fire hotspots using the raster calculator in the ArcGIS platform. Afterwards, the daily and monthly hotspots were vectorized separately. Finally, a fishnet of squares measuring $0.2^\circ \times 0.2^\circ$ was created to cover all of Indonesia, and, by joining the crop residue burning spots with this fishnet, finally the daily and monthly distribution maps were obtained. In the meantime, by joining the fire hotspots with the GIS data and land cover for Indonesia, statistics for hotspots in different regions and land covers were calculated.

Vegetation data MOD13A3 was used for two main reasons: first, to analyse the relationship between CO₂ concentrations and vegetation indices and, second, to observe how the vegetation indices changed when wildfires occurred in Indonesia. The NDVI and EVI indices can be directly extracted from MOD13A3 and the indices were also combined with the GIS data of Indonesia to perform the specific analysis and statistics.

4.3 Results and discussion

4.3.1 SST and CO₂ concentration

(a)



(b)

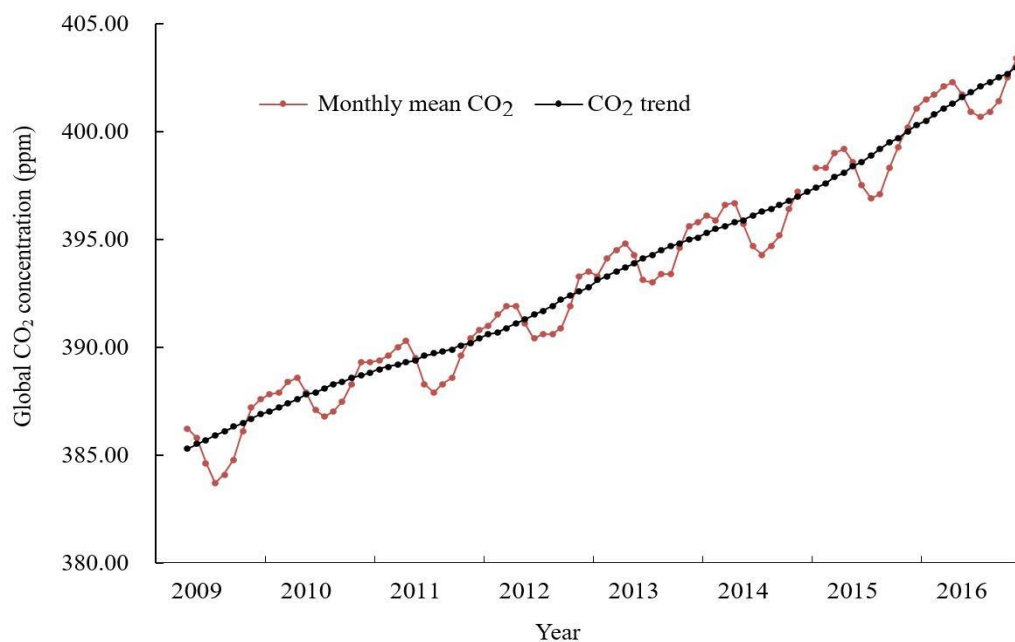


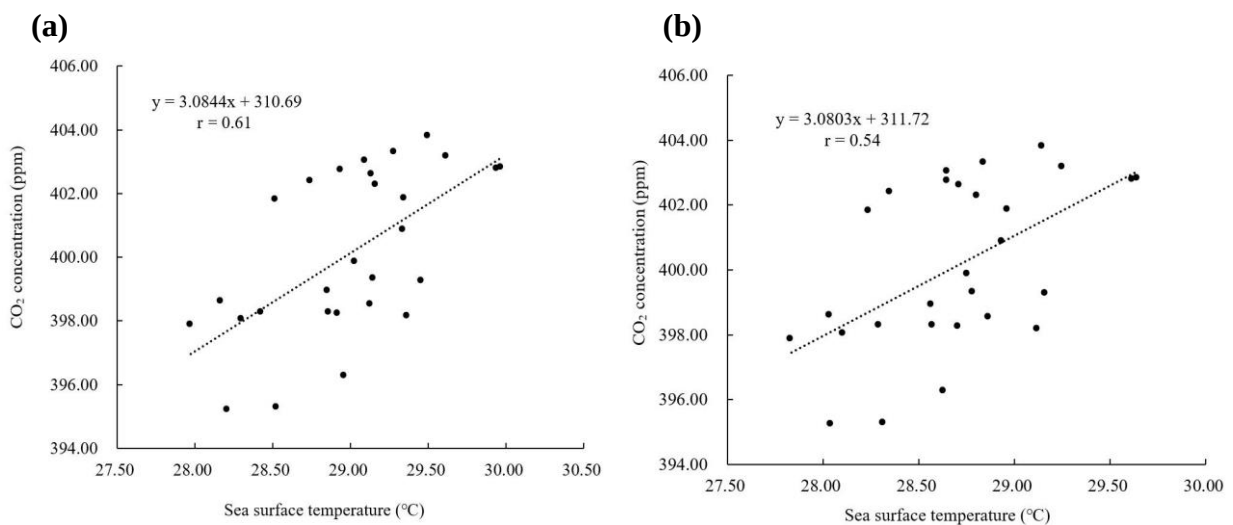
Figure 4.1 Monthly CO₂ concentration and SST1, SST2 of Indonesia (a); monthly CO₂ concentration and CO₂ trend on the earth from GOSAT data (b).

The average CO₂ concentration of Indonesia in 2014 (only September to December because OCO-2 Level 2 products are available from September, 2014), 2015 (whole year) and 2016 (whole year) was 396.5 ppm, 398.8 ppm and 402.6 ppm, respectively. SST1 (16°S - 11°N, 90°E-146°E) of corresponding period was 28.71°C, 28.82°C and 29.27 °C, respectively. While, SST2 (21°S - 16°N, 85°E-151°E) was 28.44°C, 28.58°C and 28.90 °C, separately. Fig. 4.1a indicates that CO₂ concentration and SST1, SST2 exhibit almost identical fluctuations during the study period. SST1 is always higher than SST2 because it is closer to the equator. In August, SST is the annually lowest and CO₂ concentration of this month is also much lower. By comparing the CO₂ concentration during the period September-to-December in 2014, 2015 and 2016, we observed that the CO₂ concentration increased dramatically from 396.5 ppm (2014) to 399.6 ppm (2015) and 402.8 ppm (2016) in Indonesia; that finding is consistent with the discoveries of global increase from GOSAT project (Fig. 4.1b). From 2009 to 2016, global CO₂ have been growing from 385.2 ppm to 401.5 ppm according to the data of this project. For the same period from September to December in 2014, 2015 and 2016, GOSAT revealed an increase from 395.9 ppm (2014) to 398.7 ppm (2015) and 402.1 ppm (2016) on the global scale, which is closer to the increase of CO₂ concentration in Indonesia.

Table 4.2 Monthly CO₂ concentration in six different parts.

Month	CO ₂ Concentration (ppm)					
	Sumatra	Sulawesi	New Guinea	Java	Kalimantan	Others
2014/09	395.6	395.3	396.5	394.7	394.9	395.2
2014/10	395.1	395.2	396.0	393.8	396.3	395.0
2014/11	398.5	395.6	396.3	394.3	397.8	395.3
2014/12	398.6	399.7	399.8	398.3	400.6	397.1
2015/01	401.0	397.3	399.1	396.9	400.4	396.6
2015/02	398.5	397.1	399.5	397.2	400.1	397.6
2015/03	399.5	397.8	398.6	396.7	398.8	398.3
2015/04	399.3	398.4	399.1	397.0	400.4	398.5
2015/05	398.6	396.7	397.8	397.5	399.1	397.9
2015/06	398.9	396.2	398.5	397.7	398.9	397.4
2015/07	398.4	398.6	398.6	397.3	397.8	398.0

Month	CO ₂ Concentration (ppm)					
	Sumatra	Sulawesi	New Guinea	Java	Kalimantan	Others
2015/08	399.1	397.7	398.2	396.7	398.4	398.3
2015/09	399.5	398.5	398.6	398.0	398.9	398.8
2015/10	400.4	397.6	397.2	397.8	399.8	398.6
2015/11	400.6	399.4	401.1	399.6	401.1	399.2
2015/12	404.1	400.8	403.1	401.7	403.4	401.1
2016/01	402.0	400.4	400.2	401.3	403.0	398.4
2016/02	403.5	401.0	402.2	401.6	402.5	399.6
2016/03	403.2	403.5	405.6	401.2	403.1	403.1
2016/04	403.9	402.6	403.5	403.0	404.2	400.5
2016/05	404.0	401.4	403.3	400.7	405.0	401.0
2016/06	404.3	403.6	402.4	403.0	404.2	402.3
2016/07	403.8	401.7	400.2	400.7	403.8	401.7
2016/08	405.1	400.0	401.6	402.3	402.7	400.8
2016/09	402.8	403.1	403.3	401.4	403.8	401.1
2016/10	402.8	405.0	402.3	404.1	404.0	402.4
2016/11	404.1	403.5	406.4	401.0	401.5	401.6
2016/12	402.3	398.1	406.6	402.9	404.9	401.6



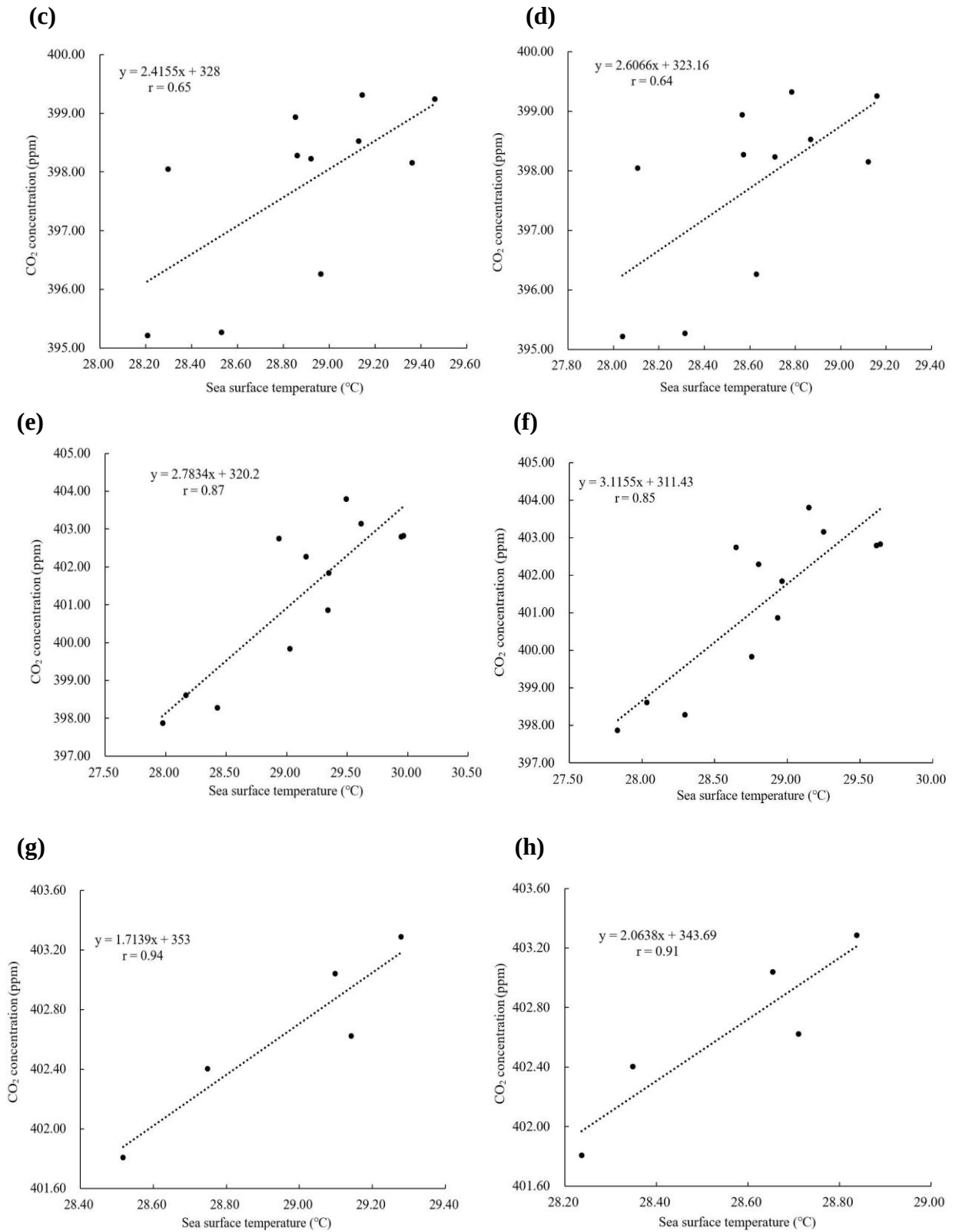
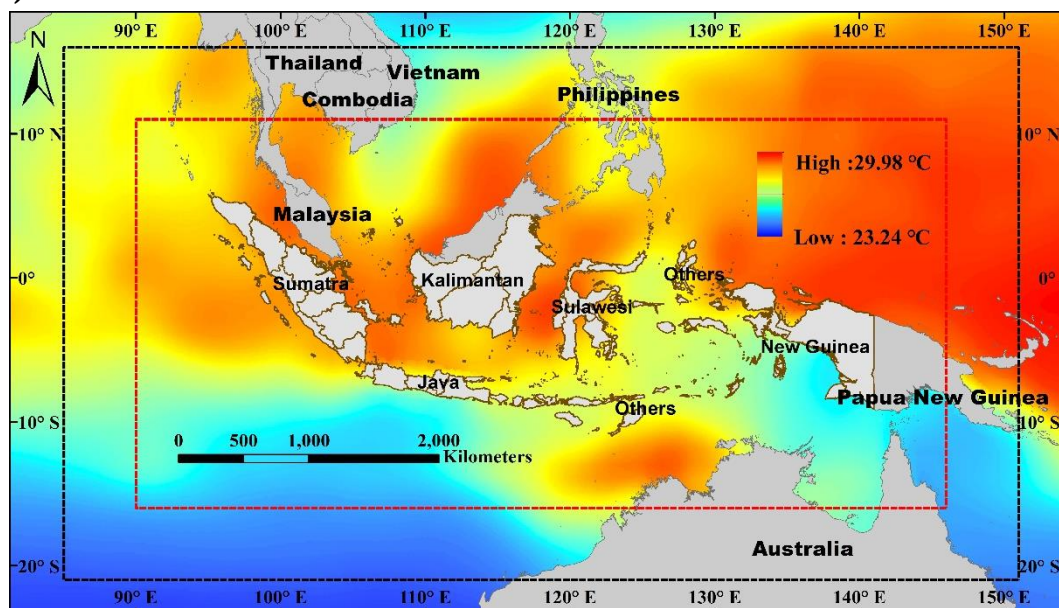


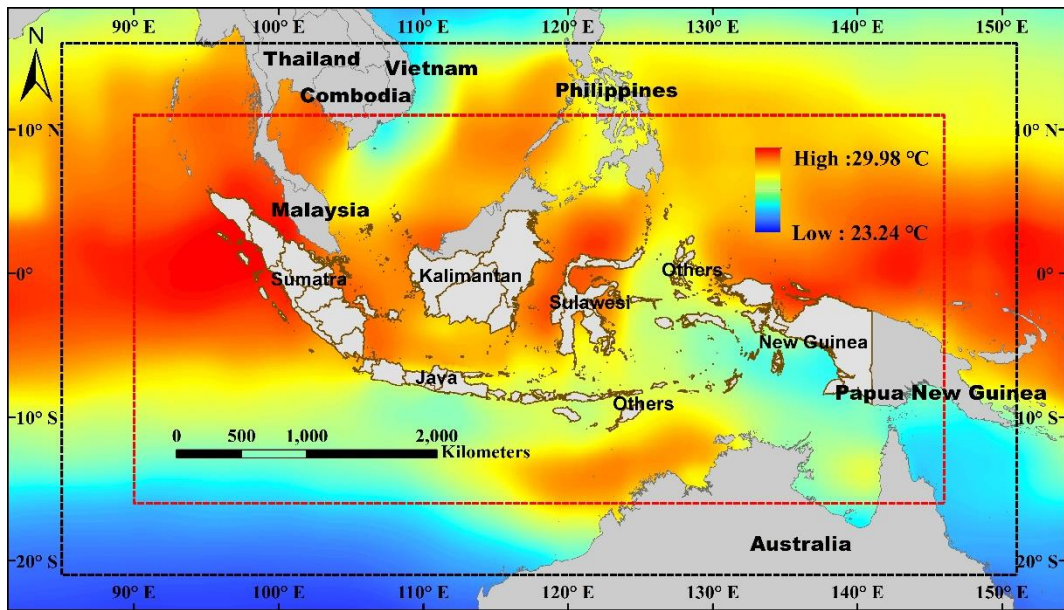
Figure 4.2 The correlation between CO₂ concentrations and Sea Surface Temperature (SST) in Indonesia: 2014.09-2016.12, with SST1 (a); 2014.09-2016.12, with SST2 (b); 2014.09-2015.07, with SST1 (c); 2014.09-2015.07, with SST2 (d); 2015.08 to 2016.07, with SST1 (e); 2015.08 to 2016.07, with SST2 (f); 2016.08 to 2016.12, with SST1 (g); 2016.08 to 2016.12, with SST2 (h).

Meanwhile, SST1, SST2 and global SST during the period September-to -December also show a trend of increase from 2014 to 2016. SST1 increased from 28.71 °C (2014) to 28.74 °C (2015) and 29.07 °C (2016); SST2 increased from 28.44 °C (2014) to 28.51 °C (2015) and 28.64 °C (2016); global SST increased from 13.76 °C (2014) to 13.90 °C (2015) and 13.95 °C (2016). In Fig. 4.2, correlation analysis have been conducted between CO₂ concentration and SST1, SST2; the correlation coefficient r for the 30 months of this study is 0.61 for SST1 and 0.54 for SST2 (Fig. 4.2a and 2b). Although the monthly fluctuations and change trends in CO₂ concentration were relatively similar to SST, the annual increase of CO₂ concentration is much more obvious than the increase of SST which would affect the results of the correlation analysis and caused the correlation coefficient r to not be as high as expected. Both Fig. 4.1a and Fig. 4.1b shows that an intact annual cycle of the wave for the change of CO₂ concentration and SST is from August to next July. Therefore, to alleviate the effect of fast annual increase of CO₂ concentration, the study period has been divided into three parts in August 2015, 2016 and correlation analysis for each annual cycle has been separately conducted. From September 2014 to July 2015, the correlation coefficient r rose to 0.65 for SST1-CO₂ and 0.64 for SST2-CO₂ (Fig. 4.2c and 4.2d). From August 2015 to July 2016, the correlation coefficient r rose to 0.87 for SST1-CO₂ and 0.85 for SST2-CO₂ (Fig. 4.2e and 4.2f). From August 2016 to December 2016, the correlation coefficient r rose to 0.94 for SST1-CO₂ and 0.91 for SST2-CO₂ (Fig. 4.2g and 4.2h). The results show that all the correlations between CO₂ concentration and SST are positive and the correlations between CO₂ and SST1 are always higher than correlations between CO₂ and SST2 which indicate the SST of the inshore area would affect CO₂ concentration in Indonesia more than the SST of the offshore area.

(a)



(b)



(c)

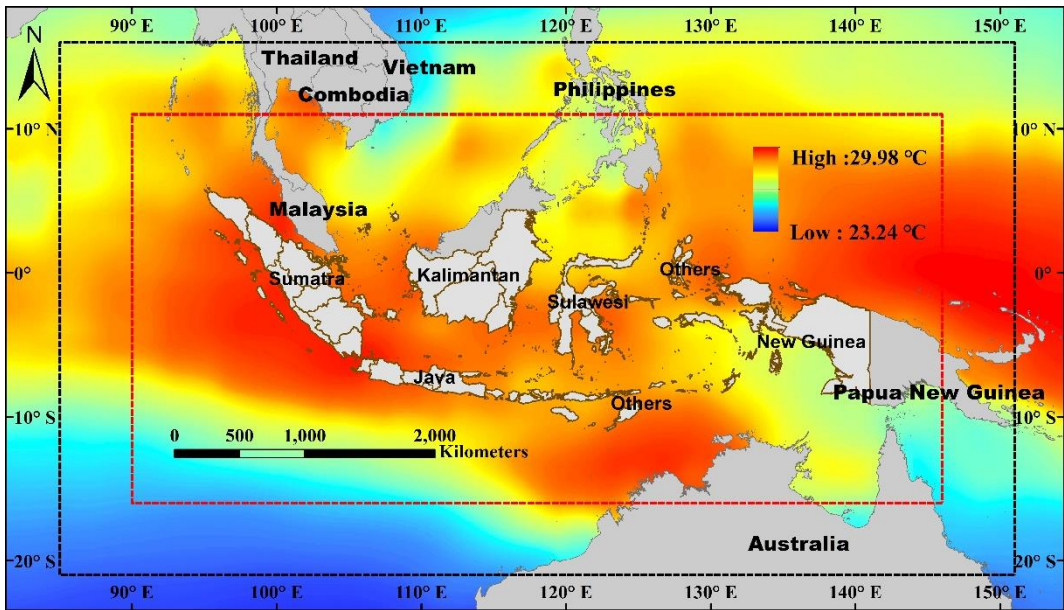


Figure 4.3 SST around Indonesia in September-December 2014 (a), 2015 all year (b) and 2016 all year (c). Red dash line is the boundary of SST1 and black dash line is the boundary of SST2.

Regarding the spatial distribution, Fig. 4.3 shows that the annual SST around Sumatra is always higher than other parts of Indonesia. Meanwhile, the average CO₂ concentration of Sumatra was 399.8 ppm in 2015 and 403.5 ppm in 2016, which was also the highest of the six parts (Table 4.2). For the data in Table 4.2, the boundaries of the six regions have been used as masks to obtain CO₂ concentration in these areas. By contrast, the average CO₂ concentration in Java was low, with only 397.8 ppm in 2015 and 401.7 ppm in 2016 (Table 4.2). Because Java is far away from the equator, Fig. 4.3 shows that the annual SST around Java is also low. The population of Indonesia

according to the 2010 national census was 237.64 million (Akbar, Wicaksono and Dachlan 2012). Fifty-eight percent of the population lives on the island of Java, the world's most populous island (Afsah and Vincent 2000). Theoretically, the CO₂ concentration in Java should be higher than other regions because of the dense population and active anthropogenic activities. The transportation sector, as one of the most important anthropogenic activities and prolific emitters of Greenhouse Gase (GHG), accounted for about 28 percent of U.S. GHG emissions (Morrow et al. 2010). All of the results indicate that the SST as an important factor has a significant impact on the CO₂ concentration in the archipelagic country of Indonesia. Moreover, its annual increase in CO₂ concentration is in accordance with the global concentration increase.

4.3.2 Fire hotspots and CO₂ concentration

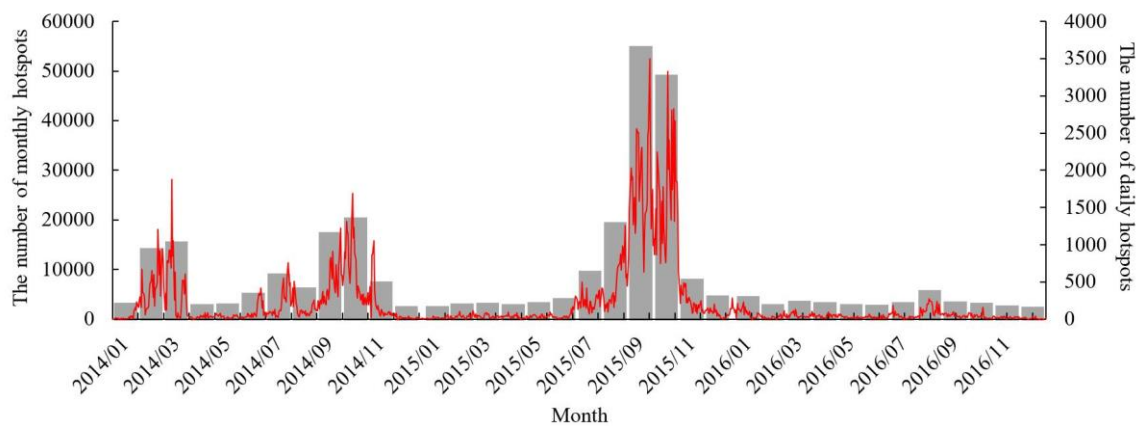


Figure 4.4 Daily (red line) and monthly (gray column) number of fire hotspots in Indonesia from 2014 to 2016.

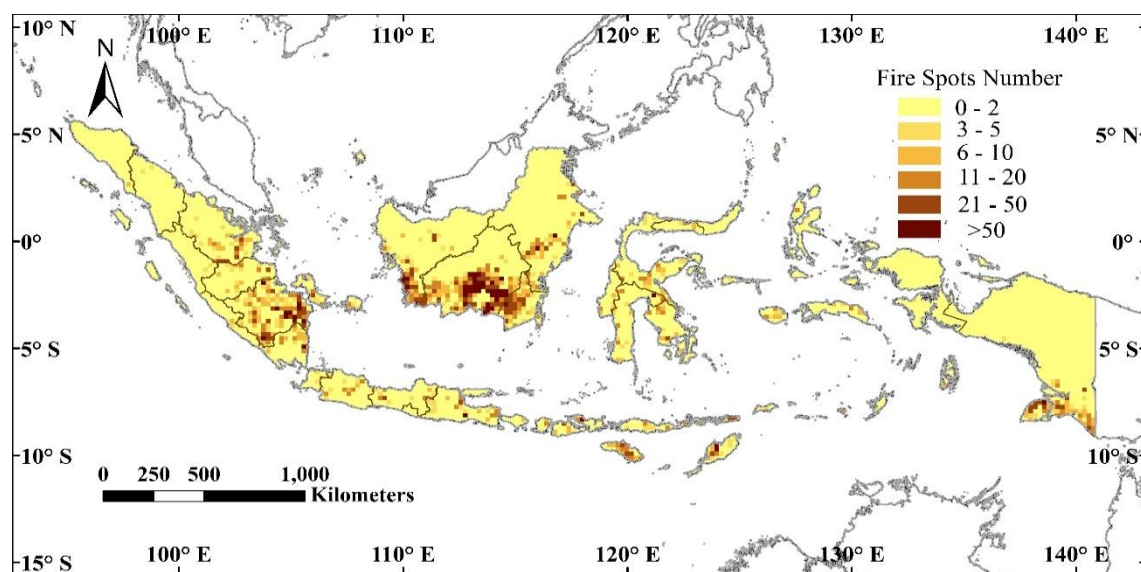
From Thermal Anomalies/Fire images, 83,083 fire hotspots were detected in Indonesia in 2014 and this number increased 69.35% to 140,699 in 2015. This sudden growth of fire hotspots was caused by the worst forest fire since 1997, burning approximately 261,000 hectares of forests and peatland. While, after devastating forest fire there were only 16,454 fire hotspots detected in 2016 that was much lower than the other two years. Fig. 4.4 shows that the number of hotspots was greatest in September 2015, at 52,903, and the second largest occurred in October 2015, at 47,094. The number of hotspots detectable in these two months account for 71.05% of all hotspots detected in 2015. On September 23, 2015, the number of hotspots was 3,497, the highest daily totals for the three years in the study period. According to Fig. 4.4, three main fires occurred in Indonesia, the first in February-March 2014, the second in September-October 2014 and the last one in September-October 2015. The daily and monthly number of fire hotspots in 2016 showed no evident fluctuation and they were always less than the other two years.

Table 4.3 Number of fire hotspots in different islands.

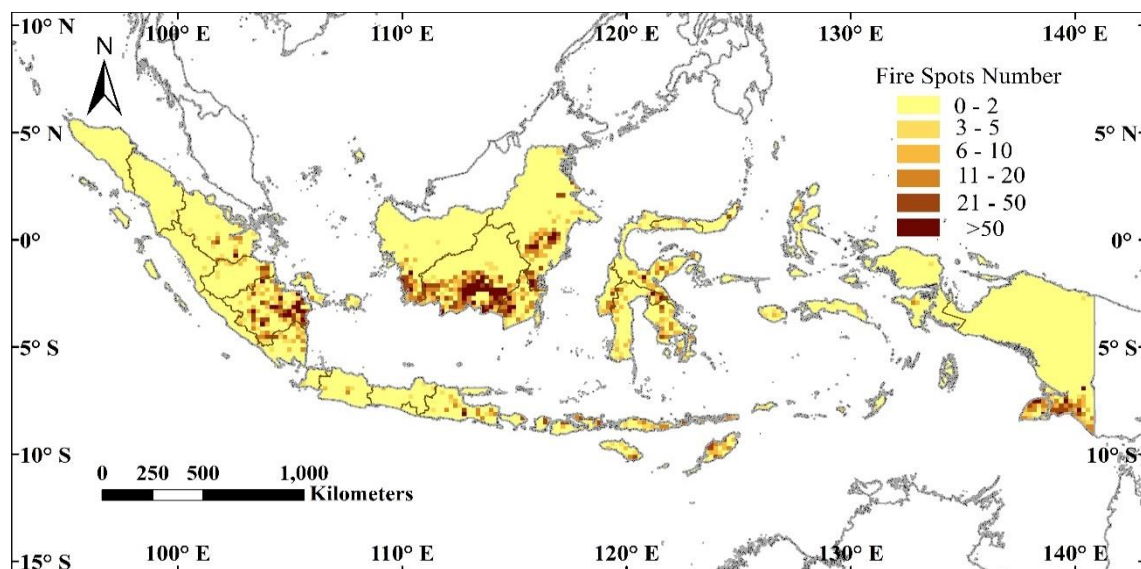
Islands	2014/02	2014/03	2014/09	2014/10	2015/09	2015/10
Sumatra	10475	12325	4110	4627	19914	16388
Sulawesi	98	165	822	1489	2509	3415
New Guinea	29	25	904	1452	2853	4680
Java	28	106	674	493	758	808
Kalimantan	1386	708	7400	8662	23923	18385
Others	174	205	1519	1590	2946	3418
Sum	12190	13534	15429	18313	52903	47094

In February -March 2014, Table 4.3 and results show that most of hotspots were distributed in Sumatra's middle-east portion (Riau). Fire hotspots in Sumatra accounted for 85.93% of all of the hotspots in February and 91.07% in March. In September-October 2014, Fig. 4.5a and 4.5b present most of the hotspots were distributed in the south of Kalimantan (Kalimantan Tengah). Fire hotspots in Kalimantan accounted for 47.96% of all hotspots in September and 47.30% in October. In September-October 2015, most of the hotspots were distributed in south of Kalimantan (Kalimantan Tengah) and southeast of Sumatra (Sumatera Selatan). Fire hotspots in these two islands accounted for 82.92% of all hotspots in September and 73.84% in October. Combining fire hotspots with the land cover of Indonesia, the results indicate that most of the hotspots were distributed in two land cover types, Evergreen Broadleaf Forest and Crop and Natural Vegetation Mosaic. In 2014, hotspots in Evergreen Broadleaf Forest accounted for 63.11% of all hotspots and 19.43% in Crop and Natural Vegetation Mosaic. In 2015, hotspots in Evergreen Broadleaf Forest accounted for 70.51% of all hotspots and in Crop and Natural Vegetation Mosaic accounted for 16.05%. In 2016, hotspots in Evergreen Broadleaf Forest accounted for 51.63% of all hotspots and in Crop and Natural Vegetation Mosaic accounted for 20.69%. This finding demonstrates that a large proportion of hotspots in Indonesia are from forest fire, while crop residue burning also accounts for a certain percentage of hotspots.

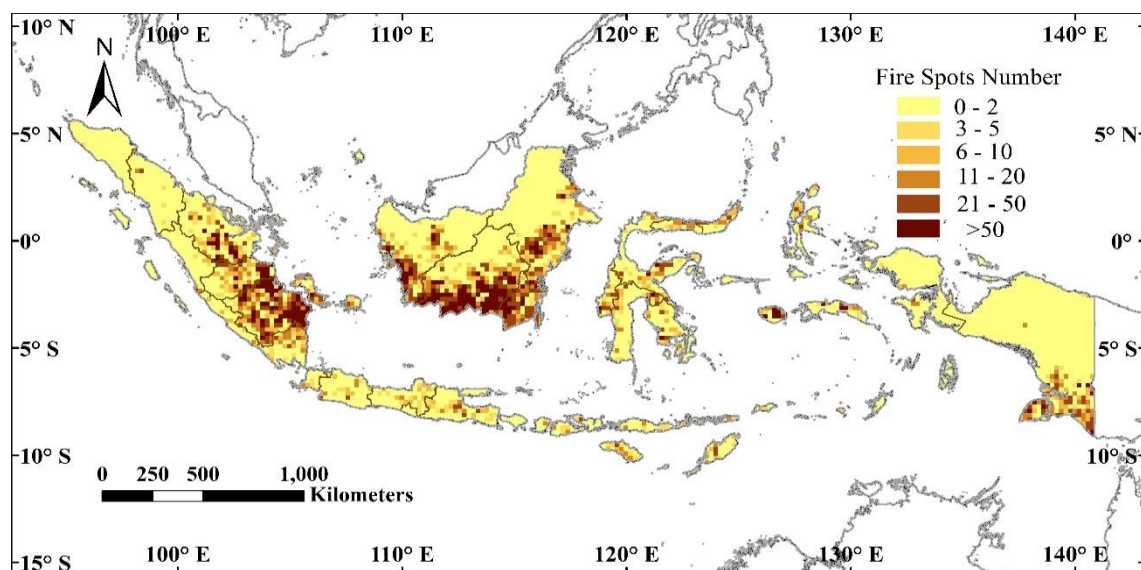
(a)



(b)



(c)



(d)

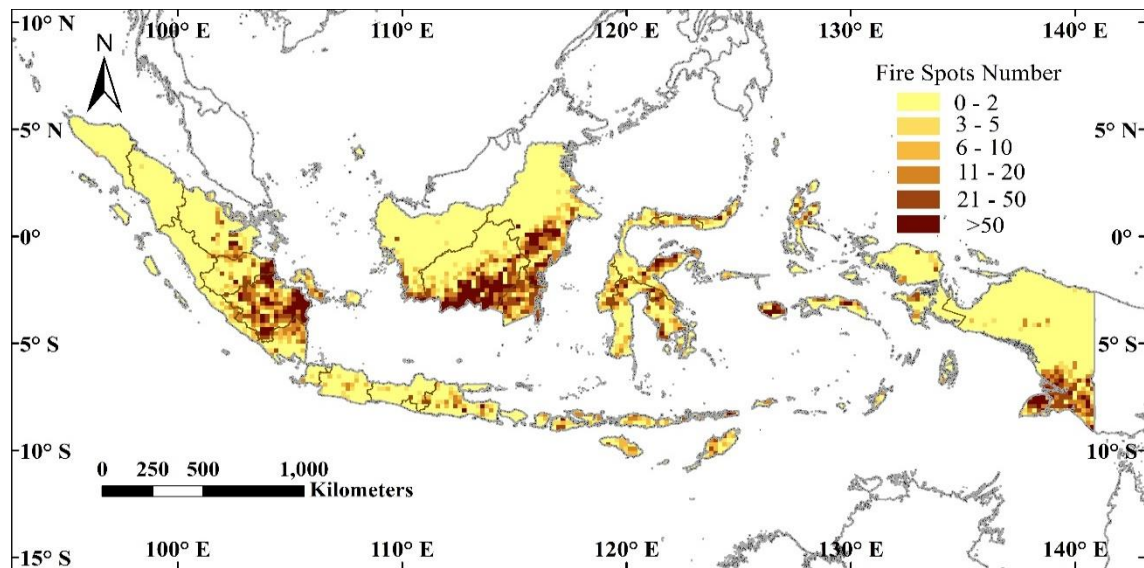
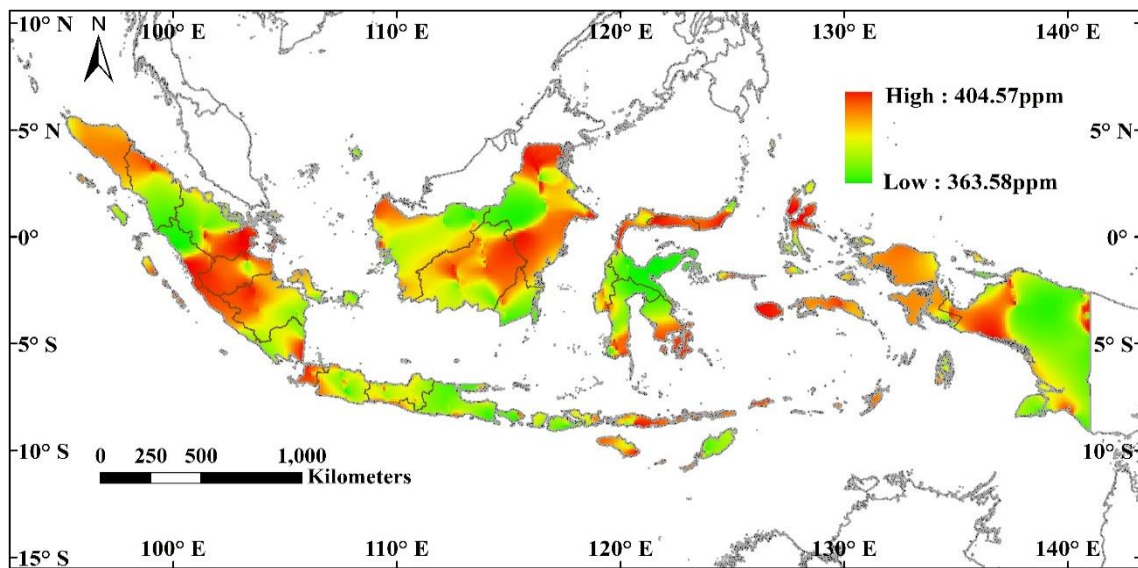


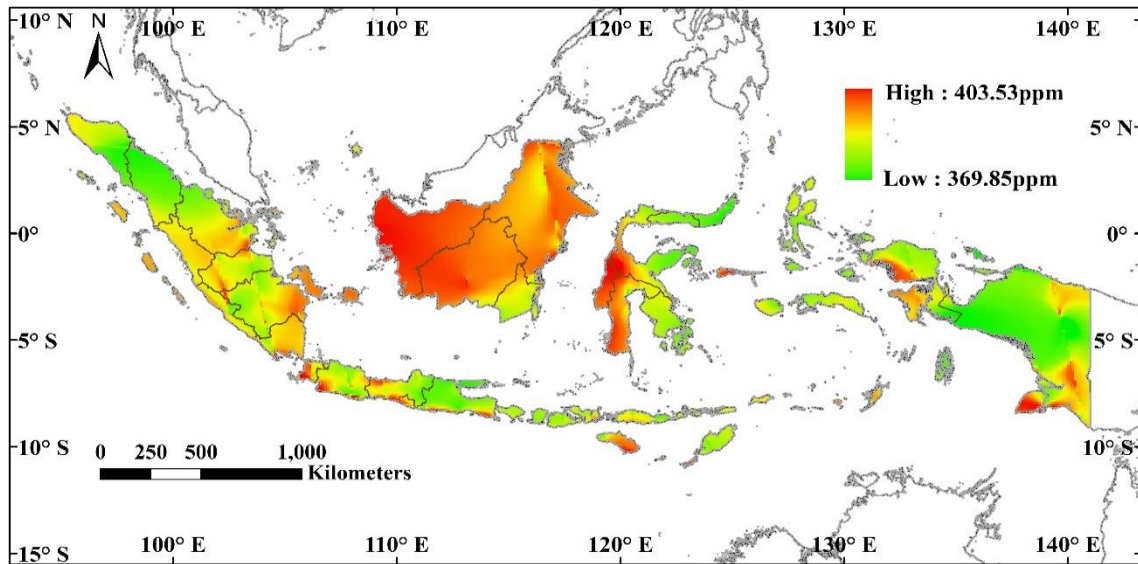
Figure 4.5 Spatial distribution of fire hotspots in Indonesia: September, 2014 (a); October, 2014 (b); September, 2015 (c); October, 2015 (d).

During the most severe forest fire in September and October 2015, the CO₂ concentration in Indonesia only exhibited an obvious rise in September. By contrast, in October it exhibits a sudden decline. Regarding the spatial distribution, Fig. 4.5 shows that in September and October the CO₂ concentration of Kalimantan and Sumatra was higher than in other areas. Meanwhile, via Fig. 4.5e, 4.5f and Fig. 4.6c, 4.6d, we found that hotspots and CO₂ concentration showed a higher spatial consistency. Although the average CO₂ concentration of Indonesia decreased from 398.6 ppm to 398.3 ppm in October 2015, the CO₂ concentration in Kalimantan and Sumatra increased dramatically in this month. In Kalimantan, CO₂ concentration increased from 399.5 ppm to 400.4 ppm and in Sumatra the CO₂ concentration increased from 398.9 ppm to 399.8 ppm (Table 4.2), which is totally different from the left four parts of Indonesia and the left four parts presented a trend of decrease. The still ongoing forest fire is assumed to be the main reason for the CO₂ concentration increase in Kalimantan and Sumatra in October 2015. Table 4.3 shows that in this month there were still 16,388 fire hotspots on Sumatra and 18,385 on Kalimantan.

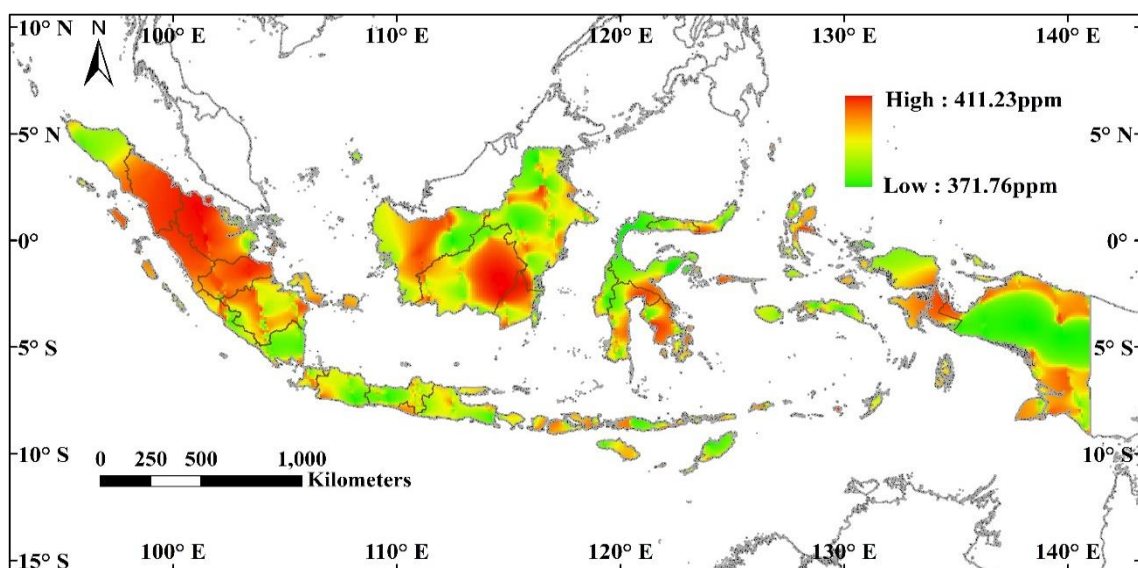
(a)



(b)



(c)



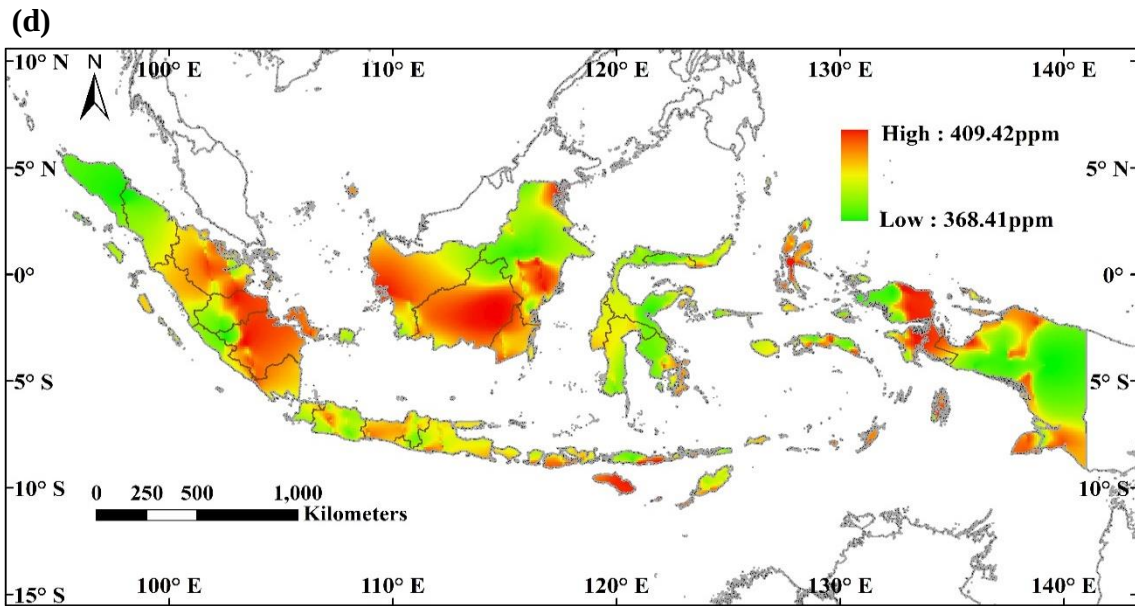


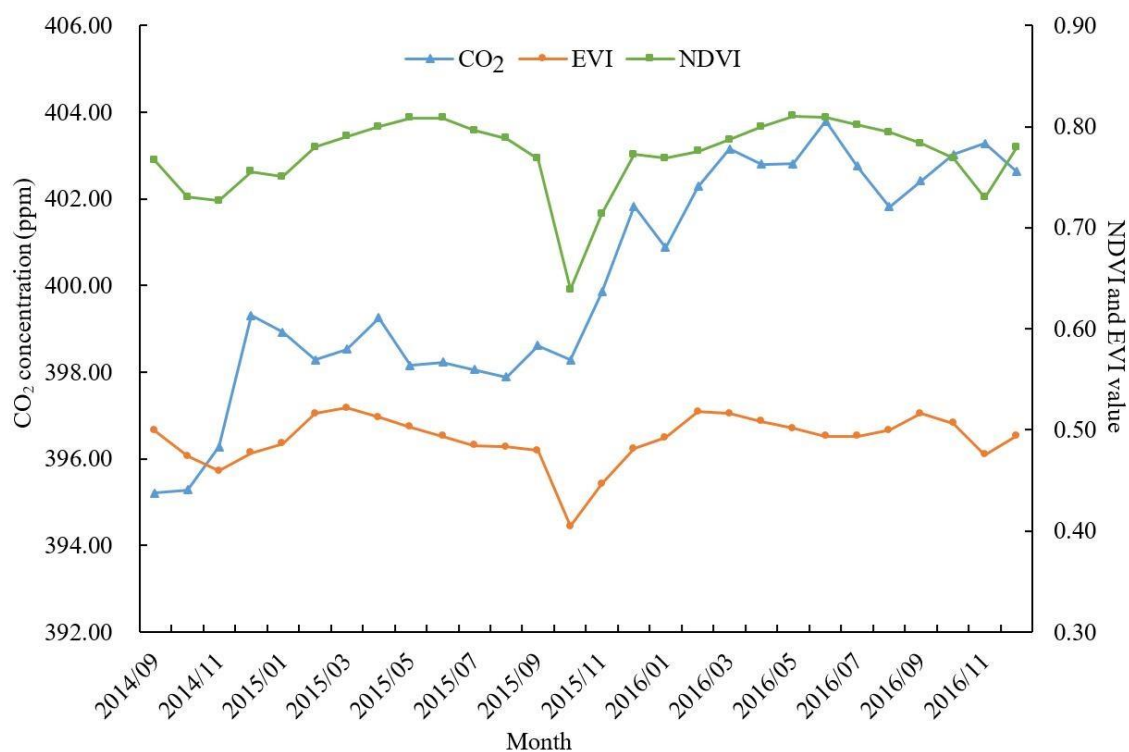
Figure 4.6 Spatial distribution of CO₂ concentration in Indonesia: September, 2014 (a); October, 2014 (b); September, 2015 (c); October, 2015 (d).

Since the CO₂ data after September 2014 are available, the CO₂ concentration change during the forest fires in September and October 2014 has also been analysed. Regarding the spatial distribution, the distribution map Fig. 4.6b shows that in October the CO₂ concentration in Kalimantan was much higher than in other areas. Unlike 2015, the CO₂ concentration in Indonesia did not exhibit a decreasing trend from September to October; instead, the concentration increased very slightly from 395.2 ppm to 395.3 ppm, while, the CO₂ concentration in Kalimantan rose steeply from 394.9 ppm to 396.3 ppm. By contrast, CO₂ concentration in the left five parts of Indonesia clearly decreased, including in Sumatra where it declined from 395.6 ppm to 395.1 ppm. As previously mentioned, hotspots were mainly distributed in Kalimantan during the forest fire in September-October 2014 and the CO₂ emissions from forest fires are regarded as an important factor in the CO₂ concentration increase in Kalimantan.

By analysing the CO₂ concentration change during the two forest fires in 2014 and 2015, I concluded that unlike SST, forest fires cannot induce an obvious CO₂ increase over the whole country because the six parts of Indonesia are separated by the ocean and their geographical locations are relatively independent. However, CO₂ concentration presented a trend of rise in corresponding islands during the occurrence of forest fire, and CO₂ concentration increased in Kalimantan during the forest fire in 2014 and CO₂ concentration increased on Kalimantan and Sumatra during the forest fire in 2015.

4.3.3 Vegetation and CO₂ concentration

(a)



(b)

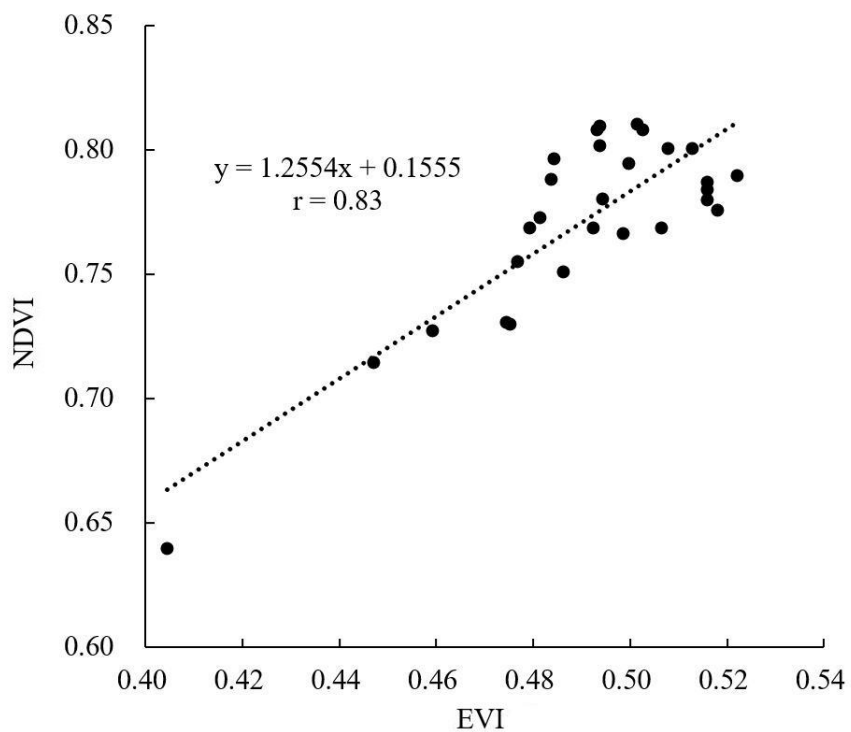
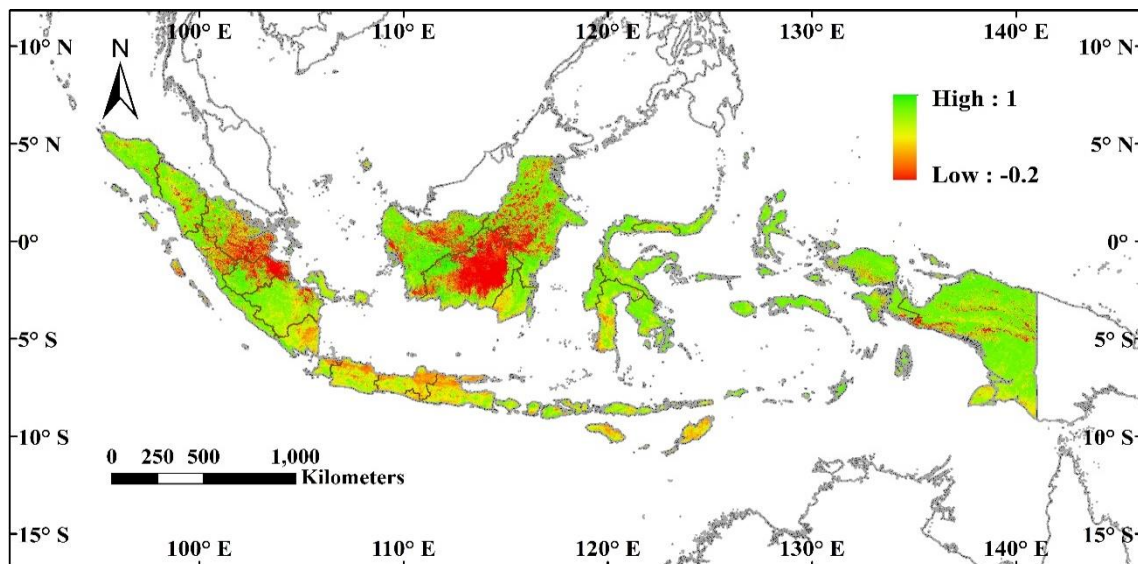


Figure 4.7 Monthly CO₂ concentration and vegetation indices, NDVI and EVI (a); correlation between NDVI and EVI (b).

The vegetation found in Indonesia is typical of the tropics and forests cover approximately 60% of the country. Fig. 4.7a shows that vegetation indices were very stable and smooth during the study period except in October 2015. Because of the high forest coverage rate, the average NDVI and EVI in 2014-2016 were relatively higher than in other countries, with values of 0.77 and 0.49, respectively. Fig. 4.7a shows that the wave of vegetation indices are entirely different from CO₂ concentration. Our analysis did not uncover any correlations between vegetation indices and CO₂ concentration; by contrast, the correlation coefficient r between NDVI and EVI is 0.83 (Fig. 4.7b). Guo et al. (2013) has found that in East Asia's arid and semi-arid regions, the correlation coefficient between annual CO₂ concentration and annual NDVI can reach up to 0.87. CO₂ concentration data of their research were obtained from Scanning Imaging Absorption spectroMeter for Atmospheric CHartographY (SCIAMACHY) and GOSAT. I assume that the following reasons explain why there is no correlation between vegetation indices and CO₂ concentration. Firstly, Indonesia is an archipelago country, and, hence, SST plays a crucial role in CO₂ concentration; second, the location of Indonesia is around the equator and there are not four distinctive seasons in this country. Lastly, the vegetation is mainly evergreen broadleaf and the vegetation indices of this kind vegetation are stable throughout the entire year. Unlike the vegetation cover on frigid zone and temperate zone, the photosynthesis and respiration of the vegetation in Indonesia are more steady all through the year.

(a)



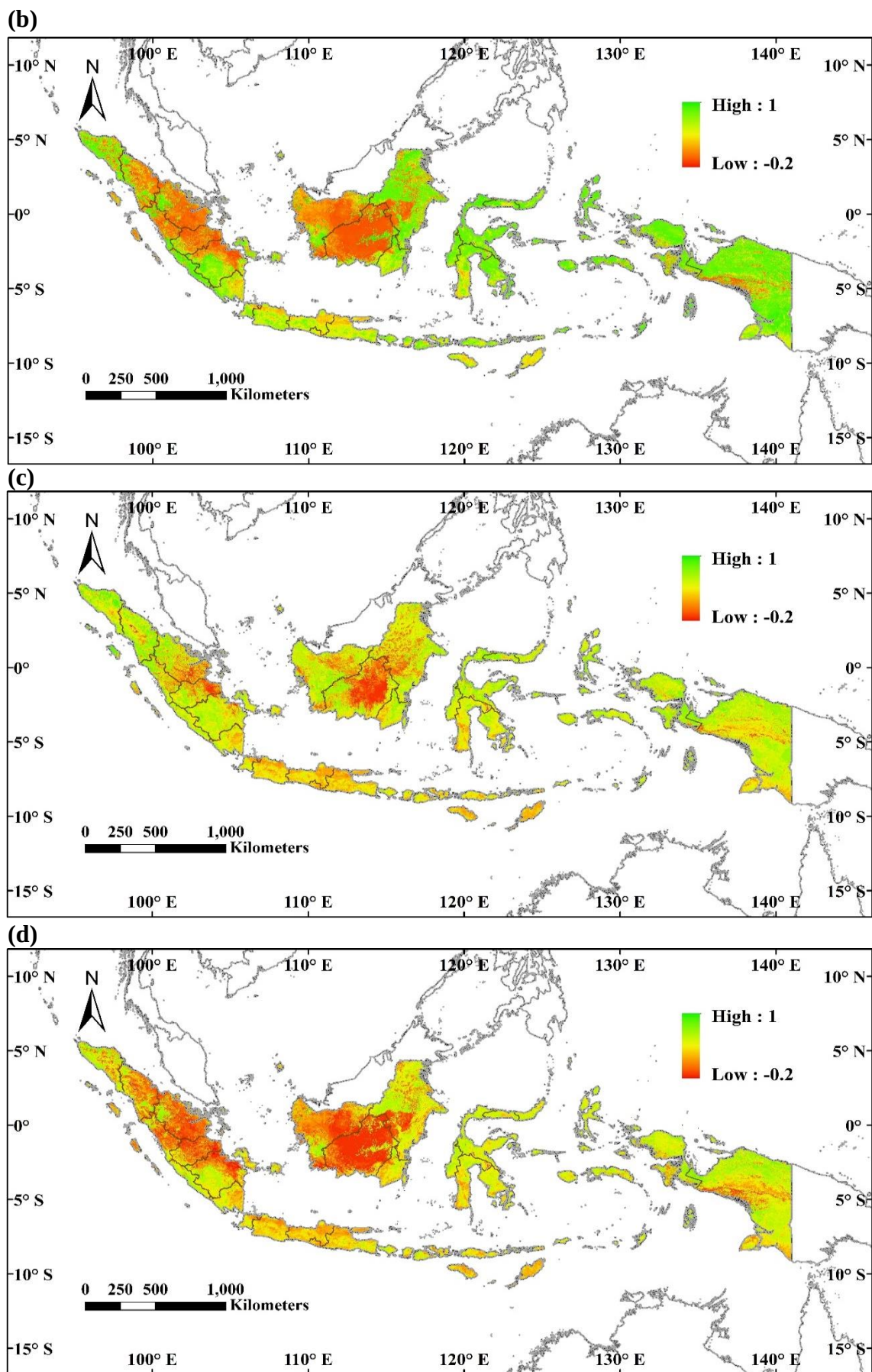


Figure 4.8 NDVI of Indonesia in September (a) and October (b) 2015; EVI of Indonesia in September (c) and October (d) 2015.

In October 2015, forest fire caused a sudden decrease of NDVI in Indonesia from 0.77 to 0.64 and a decrease of EVI from 0.48 to 0.40. Comparing the six parts of the country, NDVI and EVI in Kalimantan and Sumatra decreased even more clearly. NDVI decreased from 0.81 to 0.64 in Kalimantan and from 0.78 to 0.52 in Sumatra. EVI decreased from 0.50 to 0.40 in Kalimantan and from 0.50 to 0.35 in Sumatra. Fig. 4.8 also indicates that the forest fire induced a decline in vegetation indices in Kalimantan and Sumatra. Vegetation indices in the other four parts did not exhibit any abnormal changes, but the vegetation indices in Java was always lower, and the monthly fluctuations were more evident than on other islands. This finding is observed because some 60% of the country's cultivated land is in Java. The vegetation indices of farmland are much lower than in tropic forests and the farming activities could also affect the fluctuations of vegetation indices in Java.

4.4 Conclusions

CO₂ concentration changes in Indonesia from September 2014 to December 2016 have been analysed using OCO-2 Level 2 products. Via other remote sensing data, the relationship between CO₂ concentration changes and three influencing factors (SST, forest fire and vegetation) is also presented in this study. As an archipelago country, SST directly affects the CO₂ concentration in Indonesia and its effect is more crucial than the other factors. CO₂ concentration in Indonesia showed an annual increase that is consistent with the global increase discovered by GOSAT project (Fig. 4.1). At the same time, global SST and SST around Indonesia also show an increasing trend. Although the forest fires in September-October 2014 and 2015 did not induce an obvious rising of CO₂ over the whole country, both CO₂ concentration in corresponded islands show a trend of increases during the forest fires. CO₂ concentration increased in Kalimantan during the occurrence of forest fire in September-October 2014 and CO₂ concentration increased in Kalimantan and Sumatra during occurrence of forest fire in September-October 2015. MODIS hotspots also prove that forest fires in September-October 2014 were mainly distributed in Kalimantan and forest fires in September-October 2015 were primarily distributed in Kalimantan and Sumatra. The GHG emitted from forest fire is assumed to be an important source to lead to CO₂ increase in these regions. Since only two fires have been studied in this research and in the future more fire cases in Indonesia need to be analysed to obtain the final conclusion. The vegetation indices in Indonesia are stable and show no correlation with CO₂ changes because of the special geographic location, climate conditions and vegetation types in Indonesia. Meanwhile, the vegetation index declined rapidly during the devastating forest fire in September-October 2015. This study shows that unlike GOSAT, which provides limited data on Indonesia, OCO-2 can effectively facilitate CO₂ concentration research at a regional scale, such as Indonesia and even smaller

areas.

Meanwhile, this study also fills in the gap that no research exists on using greenhouse gas monitoring satellites to analyse CO₂ concentration changes at a regional scale. The results and influencing factors of this study are only applicable for island countries around the equator. Other studies should consider different factors according to the conditions in the study area. Before NASA releases OCO-2 Level 3 products (Global X_{CO2}), this study proposes an effective method to use Level 2 products (Orbit granules of geolocated X_{CO2} products) to analyse CO₂ concentration changes. The data of OCO-2 are only available from September, 2014 and CO₂ concentration changes are a long, slow and complicated process, therefore, I hope in the future more researches will be carried out by greenhouse gas monitoring satellites. And combining OCO-2 with GOSAT, greenhouse gas monitoring satellites will also become powerful tools to improve predictions of future atmospheric CO₂ increases and their impact on the Earth's climate.

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Chapter 5 Analyzing the effects of climate and ENSO on the temporo-spatial changes of CO₂ and precipitation in Australia by greenhouse gas monitoring satellites

5.1 Introduction

The most significant environmental issue of the this century will likely be the systematic changes in the earth's climate due to increases in the atmospheric burden of radioactively important trace gases, or greenhouse gas (GHG) (Feely et al., 1997). CO₂ and other GHG (e.g., water vapor, methane, ozone, chlorofluorocarbons, carbon monoxide and nitrous oxide) help reduce the back-radiation of heat from the earth to the stratosphere and space (Park et al., 2004). This phenomenon has a tight coupling to climate, in that it exerts significant controls on the temperature of the troposphere and the Earth's surface. CO₂, as the most important greenhouse gas, coupled with the continued accumulation of other greenhouse gases in the atmosphere, is expected to cause the average world temperature (over the last decade of the 21st century) to increase by 4.0°C (2.4 -6.4°C) in areas where the high economic growth is achieved by using fossil fuels as an important source of energy (Solomon et al., 2007). Most GHGs have substantial natural and human-made sources, and there are powerful natural mechanisms for removing them from the atmosphere. However, the continuing growth in atmospheric concentrations establishes that for each of the major greenhouse gases, more gas is being emitted than absorbed each year; that is, the natural absorption mechanisms are lagging behind.

Half a century ago, Charles David Keeling began his measurements of atmospheric greenhouse gases, at the South Pole and high on Mauna Loa volcano in the middle of the Pacific Ocean (Keeling, 1960; Harris, 2010). By 2011, Keeling's original two stations were expanded to a global network of almost 120 stations that are measuring atmospheric CO₂ and CH₄ concentrations (Manning, 2011). This monitoring network is very small. For example, compared to the several thousand surface temperature monitoring stations, there are large gaps in many parts of the world, such as Africa, Siberia, Asia, South America, and the tropics. These geographic gaps in the measurement network significantly hinder the scientific investigation and understanding of the carbon cycle and carbon-climate interactions. However, with the development of remote sensing technology, satellite measurement is becoming one of the most effective approaches for the high spatio-temporal resolution monitoring of global greenhouse gas distribution (Oguma et al., 2011).

Two greenhouse gas monitoring satellites were used in this study. The Greenhouse Gases Observing Satellite (GOSAT) was successfully launched from Japan on 23rd January, 2009. It is a special spacecraft that is used to measure the concentrations of

carbon dioxide and methane, the two major greenhouse gases, from space (Yoshida et al. 2010). After the launch failure of the Orbiting Carbon Observatory (OCO) in 2009 (Crisp et al., 2004), the National Aeronautics and Space Administration (NASA) authorized the development of OCO-2, which successfully launched on 2nd July, 2014 (Frankenberg et al., 2014). These two satellites have different advantages; therefore, they will be able to provide sufficient data and information to ascertain the distribution of greenhouse gases and enhance the scientific understanding of concentration changes of CO₂. Since GOSAT and OCO-2 have only recently become available, there is almost no research using both satellites to analyze the changes in CO₂ concentration.

Australia, due to its size and isolation, is often dubbed the “island continent” and is sometimes considered the world’s largest island (Ward, 2014). The climate of Australia is significantly influenced by ocean currents, including the Indian Ocean Dipole and the El Niño–Southern Oscillation (ENSO), which is correlated with periodic drought, and the seasonal tropical low-pressure system that produces cyclones in northern Australia (Pui et al., 2012). In this study, I analyzed the distribution characteristics and temporal changes of CO₂ from September 2009 to December 2016 in Australia. As previously mentioned, Australia is significantly influenced by ocean currents, and whether there are abnormal CO₂ changes during the ENSO episodes in Australia is still unknown. To specifically illustrate the spatial distribution of CO₂ and analyze the CO₂ changes during ENSO episodes, meteorological data, such as Sea Surface Temperature (SST) and precipitation, were considered. In addition, how ENSO affected the precipitation in Australia and the mutual effects between precipitation and CO₂ concentration was presented in this study. The CO₂ concentration of different climate types was specifically analyzed with the Köppen-Geiger climate classification and land cover types. The GOSAT and OCO-2 data were compared in this study to fill in the gap, where no research existed on using these two satellite to analyze CO₂ concentrations on a continental scale.

5.2 Datasets

5.2.1 GOSAT data

Compared with OCO-2, GOSAT has a higher temporal resolution; it returns to the same location in 3-day periods and utilizes 44 orbits to cover the whole Earth (Basu et al., 2013). Thermal And Near-infrared Sensor for carbon Observation (TANSO) Fourier Transform Spectrometer (FTS) Short-wavelength infrared (SWIR) Level 3 products are derived from the TANSO-FTS SWIR Level 2 products in a month by using the spatial statistical method to estimate the column averaged mixing ratio of GHGs for the rectangular area with 2.5 degrees of latitude and longitude in a month. There are two kinds of FTS SWIR L3: GOSAT TANSO-FTS SWIR Level 3 global CO₂ column-averaged mixing ratio and GOSAT TANSO-FTS SWIR Level 3 global CH₄

column-averaged mixing ratio. These quantities, called X_{CO_2} and X_{CH_4} by members of the atmospheric carbon science community, quantify the average concentrations of CO_2 and CH_4 , respectively, in a column of dry air extending from the Earth's surface to the top of the atmosphere (Satio et al., 2012). GOSAT SWIR Level 3 products are available from June, 2009, and the products from that month to December 2016 were all collected.

5.2.2 OCO-2 data

OCO-2 has a longer cycle (16 days) to return to the same location. It uses 233 orbits to cover the Earth, which means that it has a higher spatial resolution (Taylor et al., 2015). GOSAT can provide data for two kinds of greenhouse gas (X_{CO_2} and X_{CH_4}), whereas OCO-2 only provides data for the CO_2 column-averaged dry air mole fraction (X_{CO_2}). Estimates of X_{CO_2} are derived by taking the ratio of the column integrated number densities of carbon dioxide and molecular oxygen along the optical path from the Sun to the surface footprint and the instrument and then multiplying these results by the column-averaged oxygen concentration (Kawasaki et al., 2012). These carbon dioxide and oxygen number densities are estimated from high-resolution spectra of reflected sunlight, collected by the Observatory's instrument at wavelengths (colors) within the 0.765 nanometer molecular oxygen A band and two carbon dioxide bands centered at wavelengths near 1.61 microns and 2.06 microns. OCO-2 Level 2 standard products are available from September 6, 2014, and the products from that date to December 2016 were all collected. OCO-2 Level 2 products are full orbits or fractions of orbits of geographically located estimates of X_{CO_2} and several atmospheric and geophysical properties that are collected during each spacecraft orbit.

5.2.3 Sea Surface Temperature data

Since the ocean represents an important carbon sink (Landschützer et al., 2014), changes in SST could significantly affect the CO_2 concentration of the Earth. In addition, El Niño events are characterized by anomalous warming in the eastern equatorial Pacific Ocean. Therefore, Optimum Interpolation Sea Surface Temperature (OISST) from the National Oceanic and Atmospheric Administration (NOAA) was used in this study to analyze the changes of CO_2 during the ENSO episodes. The OISST uses both in situ and satellite-derived SST data to produce a weekly and monthly analysis (Yoshimi et al., 2006). The in situ SST data are obtained from the U.S. National Meteorological Center (NMC) file of surface marine observation. These data consist of all ship and buoy observations that are available to NMC. The satellite observations were obtained from the Advanced Very High Resolution Radiometer (AVHRR) onboard a polar orbiting satellite of NOAA (Reynolds and Smith, 1994). Bias adjustments of satellite and ship observation (referenced to buoys) were conducted to compensate for the platform differences and

sensor biases (Reynolds and Marsico, 1993). In this section, OISST monthly data from December 1981 (first month of this data) to December 2016 were collected.

5.2.4 Precipitation data

NOAA's PRECipitation REConstruction over Land (PREC/L) was used in this study to analyze the change of precipitation during ENSO episodes and the relationship between precipitation and GHGs. The global analyses are defined by the interpolation of gauge observations over land (PREC/L) and the EOF (Empirical Orthogonal Function) reconstruction of historical observations over oceans (PREC/O). Gauge observations are collected from more than 17,000 stations in the Global Historical Climatology Network (GHCN) and the Climate Anomaly Monitoring System (CAMS) datasets. The OI (Optimum Interpolation) technique of Gandin was used to assimilate the observations. The mean distribution and annual cycle of precipitation observed in the PREC/L showed good agreement with those in several published gauge-based datasets (Maeda, Torres and Carmona-Moreno, 2013). All maps were stored using a landmask, as smoothing puts values well over the oceans. In this section, PREC/L data from January 1961 to December 2016 were collected.

5.2.5 Köppen-Geiger Climate classification

Köppen climate classification is one of the most widely used climate classification systems. It was first published by Russian German climatologist Wladimir Köppen in 1884 (Rubel and Kottek, 2011), with several later modifications by Köppen, notably in 1918 and 1936 (Köppen, 1918; Köppen, 1936). Later, the German climatologist Rudolf Geiger (1954, 1961) collaborated with Köppen on changes to the classification system, which is thus sometimes called the Köppen–Geiger climate classification system (Geiger, 1954; Geiger, 1961). Köppen was trained as a plant physiologist and realized that plants were indicators for many climatic elements. His effective classification was constructed on the basis of five vegetation groups determined by the French botanist De Candolle referring to the climate zones of the ancient Greeks (Sanderson, 1999). The five vegetation groups of Köppen distinguished among plants of the equatorial zone (A), the arid zone (B), the warm temperate zone (C), the snow zone (D) and the polar zone (E). A second letter in the classification considers the precipitation (e.g., Df for snow and fully humid), and a third letter considers the air temperature (e.g., Dfc for snow, fully humid with cool summer).

The world maps of the Köppen-Geiger climate classification used in this study were obtained from the Institute for Veterinary Public Health. This institute provides global data, world maps and computer animations of the updated Köppen-Geiger climate

classification published by Kottek et al. (2006), Rubel and Kottek (2010) and Rubel et al. (2017).

5.2.6 Other data

Geographic Information System (GIS) data for Australia were used to conduct a specific analysis and understand the distribution features of CO₂. The GIS data were from the newest version of the Global ADMinistrative areas (GADM), which is a spatial database of the location of the world's administrative areas (or administrative boundaries) for use in GIS and similar software. The land cover of Australia was also used to illustrate the relationship with GHGs and precipitation. MCD12Q1 is a MODIS Land Cover Type product, and it provides data that characterize five global land cover classification systems (Cai et al., 2014). In addition, it provides a land cover type assessment and quality-control information. The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP) (Loveland et al., 1997), which includes 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes.

5.3 Results

5.3.1 ENSO events from 2010 to 2016

The primary mode of tropical Pacific interannual SST variability is related to the ENSO phenomenon (Weare et al., 1976; Harrison and Larkin, 1998). The Japan Meteorological Agency (JMA) declares that an El Niño event has started when 5-month running means of the monthly SST Anomalies (SSTA) for the Niño-3 region are more than 0.5°C (0.90 °F) warmer for 6 consecutive months or longer (Historical El Niño and La Niña Events, <http://ds.data.jma.go.jp/tcc/tcc/products/elnino/ensoevents.html>). Trenberth (1997) indicated that El Niño can be said to occur if the 5-month running means of SSTA in the Niño-3.4 region (5°N–5°S, 120°–170°W) exceed 0.4°C for 6 months or longer. The position of the four Niño zones was shown in Fig. 5.1. In this section, I adapted these two widely used standards to determine ENSO episodes. For OISST, the temporal coverage of monthly SST lasted from December 1981 to the present. Therefore, the SST from 1982 to 2011 (30 years) was used as the mean data, and the monthly SST minus the means was considered the SSTA.

Fig. 5.2 shows that according to the Niño-3 index, the SSTA exceed +0.5°C from March 2015 to April 2016 (14 consecutive months). In November 2015, SSTA reached 2.75°C, which was the highest during this period. The SSTA for the Niño-3.4 index exceeded +0.4°C from September 2014 to April 2016 (20 consecutive months). In December 2015, the SSTA reached 2.68°C, which was the highest during this period. A La Niña event around 2010-2011 was also found. La Niña is a coupled ocean-atmosphere

phenomenon that is the counterpart of El Niño and is part of the broader ENSO climate pattern. During a period of La Niña, the SST across the equatorial Eastern Central Pacific Ocean is lower than normal. Fig. 5.2 shows that according to the Niño-3 index, the SSTA was below -0.5°C from June 2010 to March 2011 (10 consecutive months). In December 2010, the SSTA reached -1.47°C , which was the lowest during this period. The SST anomalies for the Niño-3.4 index were below -0.4°C from June 2010 to March 2012 (22 consecutive months). The SSTA reached -1.61°C in November 2010, which was the lowest during this period.

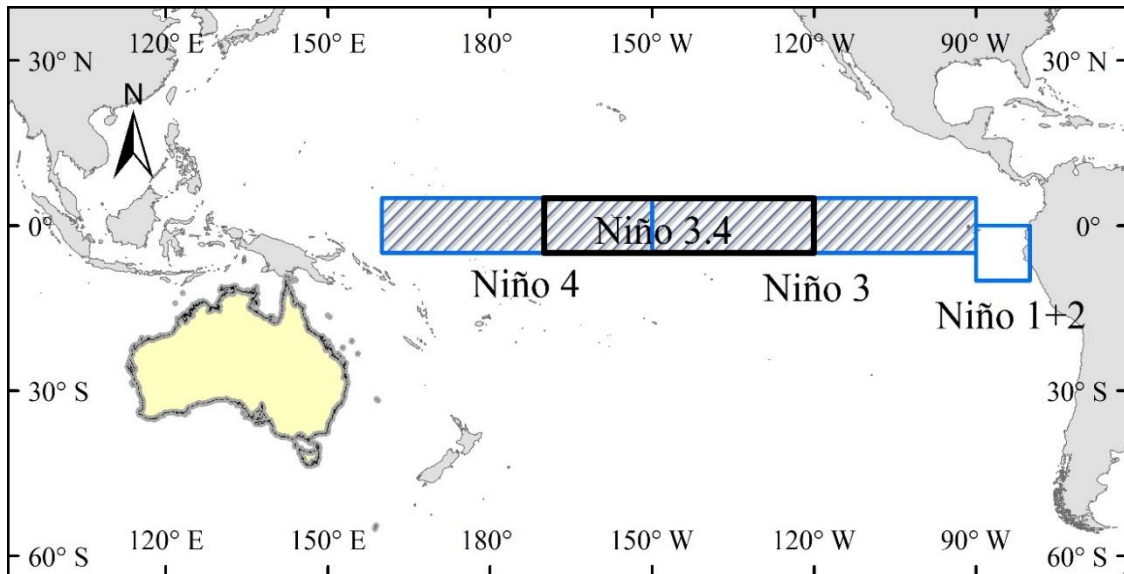


Figure 5.1 The position of 4 Niño zones: Niño 4, Niño 3.4, Niño 3, Niño 1+2.

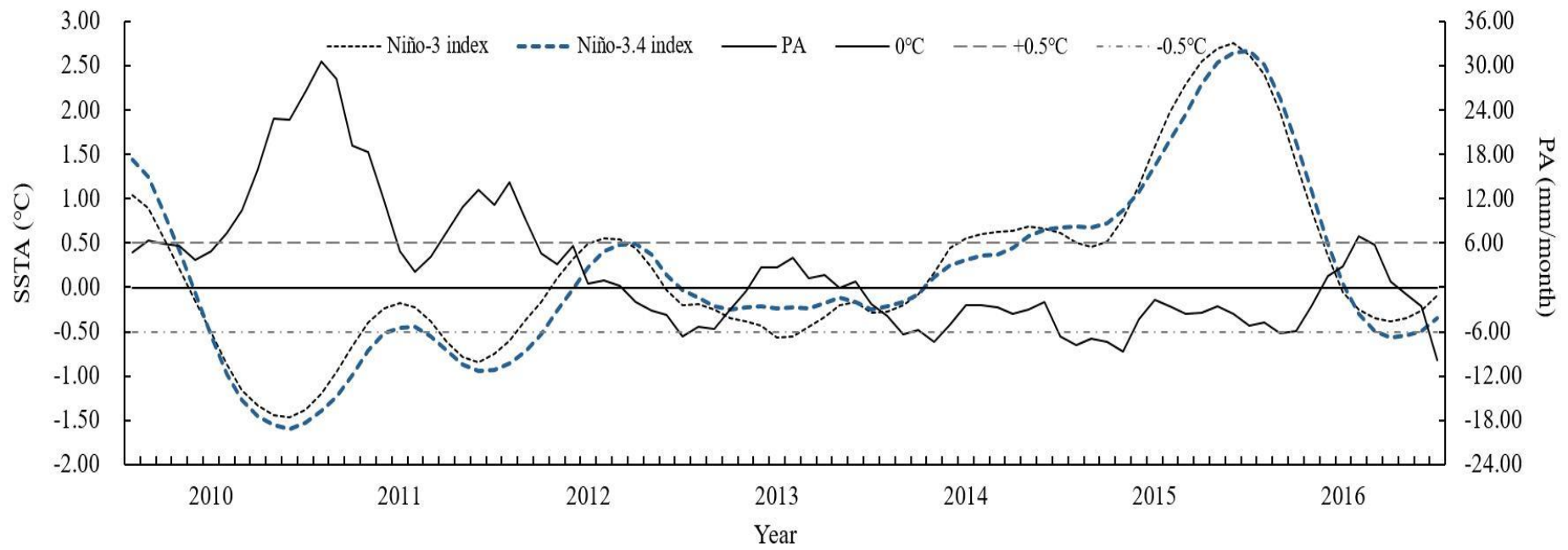


Figure 5.2 Niño-3 index, Niño-3.4 index and 5-month running means of PA in Australia.

The indicators both declared two ENSO events: one was around 2011 (La Niña), and the other one was around 2015 (El Niño). The ENSO events always lasted for a long time according to the Niño-3.4 index, particularly for the La Niña event around 2011, which was one year longer than the Niño-3 index. I assumed that the application of the threshold significantly affected the final result. If the threshold for Niño-3.4 index were $\pm 0.5^{\circ}\text{C}$, the ENSO events from the Niño-3 and Niño-3.4 indices would last for almost the same duration. The SSTA shows that the El Niño around 2015 is relatively more intense than the La Niña around 2011.

5.3.2 ENSO events and precipitation in Australia

Table 5.1 Monthly precipitation in Australia from 2010 to 2016.

Month	Year						
	2010	2011	2012	2013	2014	2015	2016
Jan.	87.07	98.77	103.69	84.81	95.12	94.11	84.30
Feb.	111.57	128.53	86.43	79.59	80.15	69.23	83.42
Mar.	69.32	101.83	89.30	65.03	50.15	51.87	59.67
Apr.	36.10	44.15	27.56	25.08	27.97	28.42	21.81
May.	28.12	26.12	24.73	35.75	22.23	25.14	29.05
Jun.	19.15	26.90	29.27	30.19	20.14	20.03	34.99
Jul.	31.65	26.12	22.76	22.78	18.36	17.48	26.70
Aug.	27.58	19.34	15.62	18.01	17.04	17.76	19.57
Sep.	35.37	16.53	16.72	18.14	14.46	10.82	29.23
Oct.	40.38	33.22	17.53	18.09	17.31	16.48	19.15
Nov.	60.34	57.20	31.27	45.18	28.54	34.27	23.54
Dec.	104.73	81.06	54.25	51.39	59.40	59.33	55.13
In total	651.36	659.75	519.12	494.04	450.88	444.94	486.57

Table 5.1 shows that the precipitation in Australia was mainly concentrated in the summer, and precipitation from December to the next February accounted for approximately 40% of the annual precipitation. The precipitation in winter was much lower than other seasons, and precipitation from June to August only accounted for approximately 15% of the annual precipitation. For the annual precipitation from 2010 to 2016, the value in 2011 was the highest, at 659.75 mm/year. By contrast, the precipitation in 2015 was only 444.94 mm/year, which was the lowest during the study

period. As previously mentioned, there were two ENSO events from 2010 to 2016: a La Nina around 2011 and an El Niño around 2015. Fig. 5.2 shows that the precipitation in central Australia was much lower than in other parts of Australia from 2011 to 2016. In 2010, the precipitation in west Australia was the lowest in the whole country. The precipitation in the north, east coastal region and Tasmania island was always much higher than other regions.

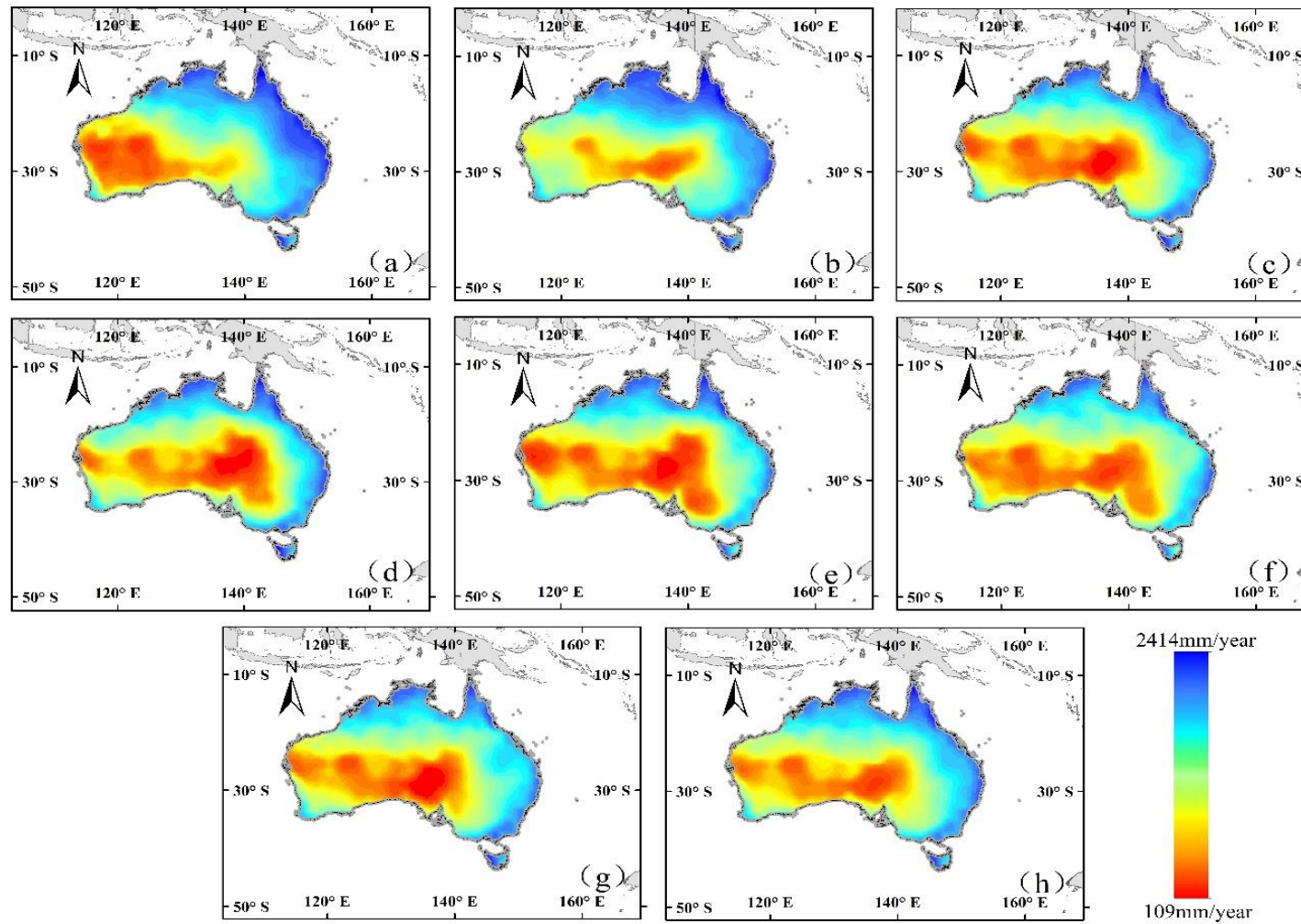
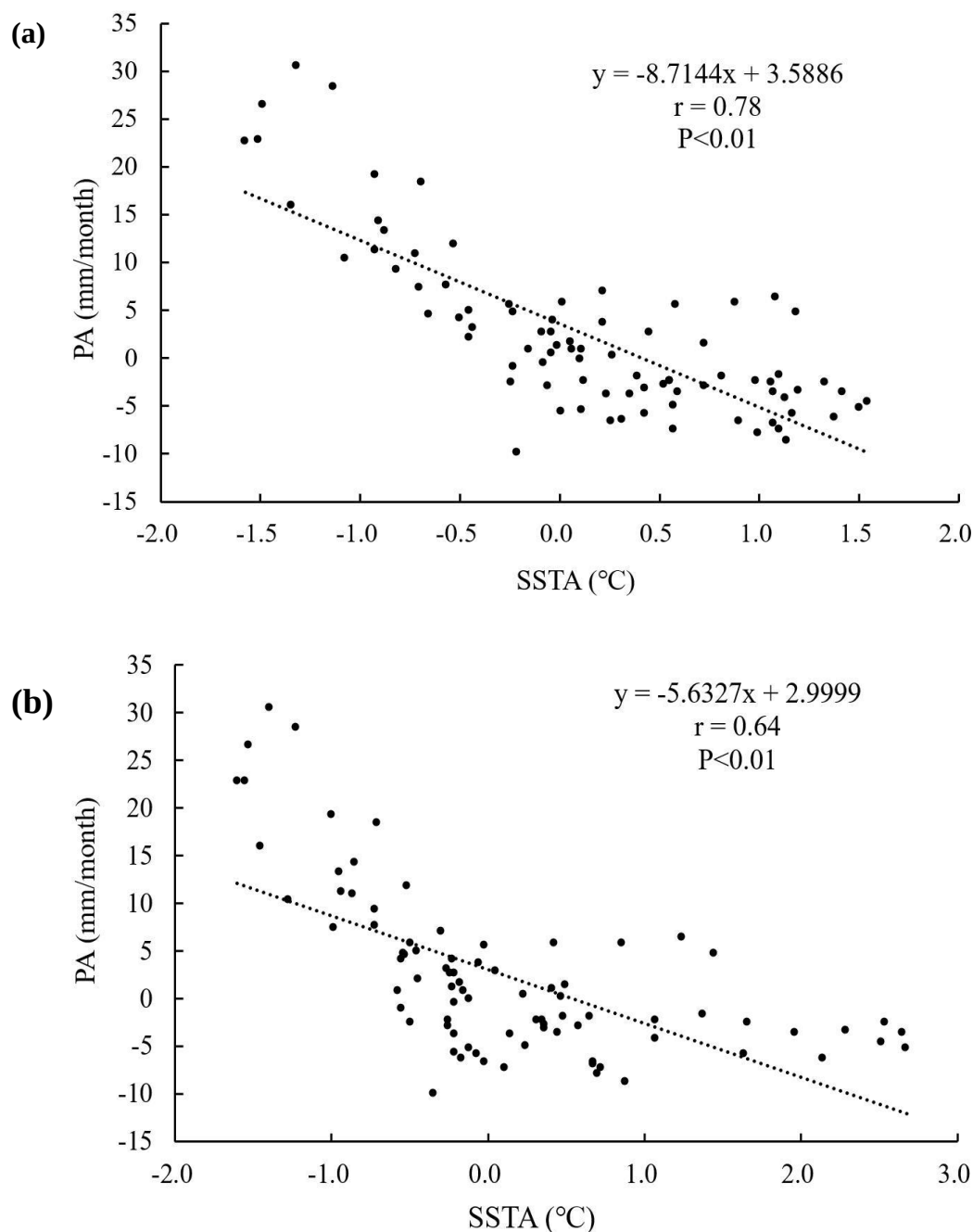
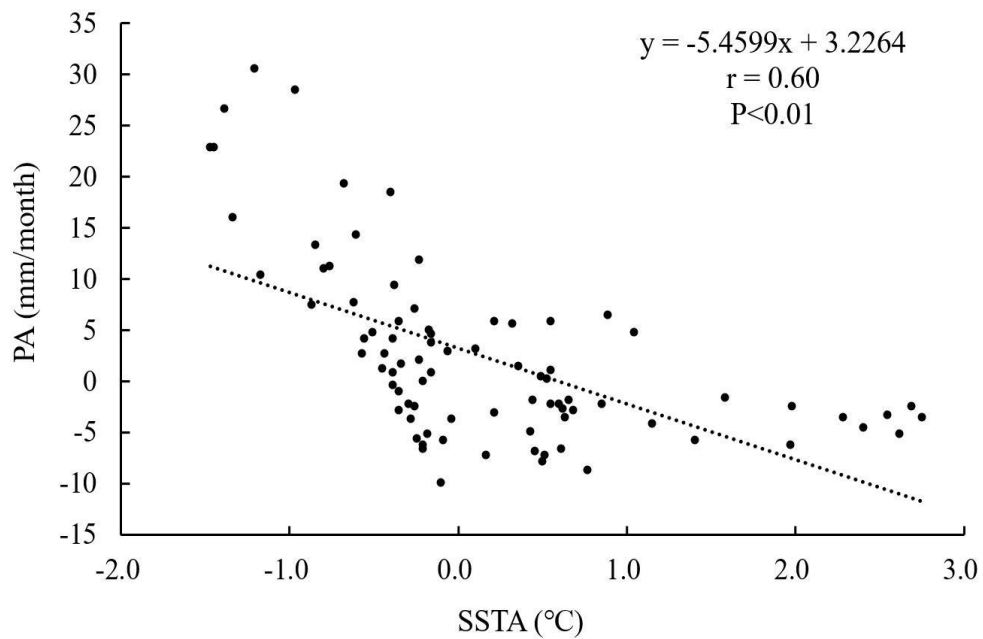


Figure 5.3 The spatial distribution of precipitation in Australia from 2010 to 2016: 2010(a); 2011(b); 2012(c); 2013(d); 2014(e); 2015(f); 2016(g); 2010-2016(h).

To analyze the changes in precipitation during an ENSO event, the 5-month running means of Precipitation Anomalies (PA) over Australia were used to be consistent with SST. For PREC/L, the temporal coverage of monthly SST was from January 1948 to the present. Precipitation from 1960 to 2009 (50 years) was used as the mean data, and the monthly precipitation minus the means was considered the PA. Fig. 5.2 shows that the 5-month running means of PA presented a total inverse fluctuation trend compared with the Niño-3.4 index and Niño-3 index. During the La Niña event, the 5-month running means of PA was much higher than usual, and in January 2011, it reached 30.56 mm/month, which was the highest of the seven years. During the El Niño event, the 5-month running means of PA were much lower. In April 2015, it reached -8.72 mm/month, which was the lowest of the seven years.



(c)



(d)

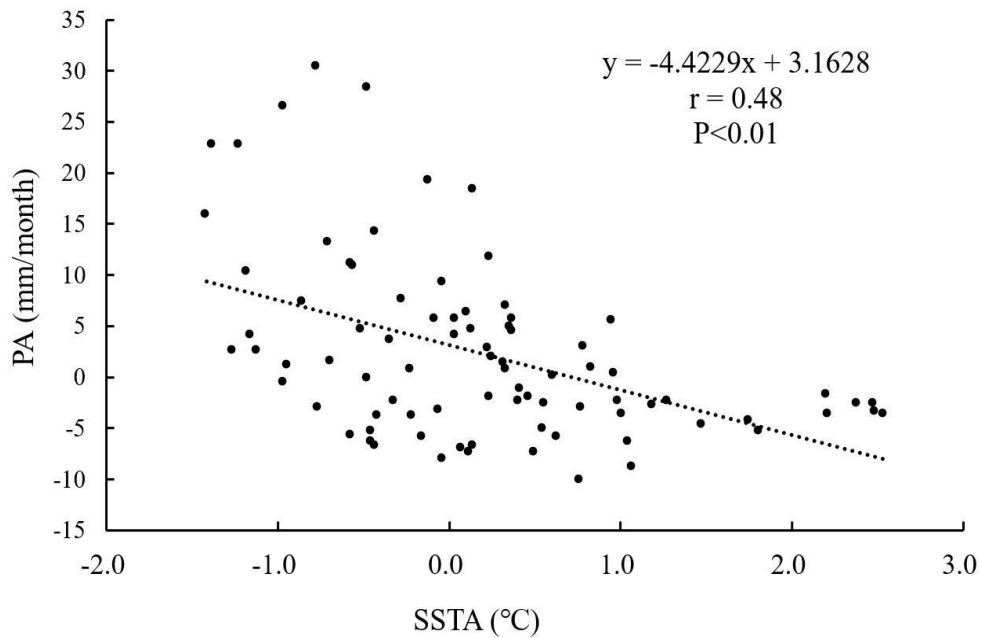


Figure 5.4 The correlation between 5-month running means of Sea Surface Temperature Anomaly (SSTA) and Precipitation Anomaly (PA) in Australia: Niño-4 index and PA (a); Niño-3.4 index and PA (b); Niño-3 index and PA(c); Niño-1+2 index and PA (d).

The 5-month running means of SSTA in Niño-1+2 (10°S-0°, 80°-90°W) and Niño-4 (5°S-5°N, 160°E-150°W) was also obtained from OISST. Fig. 5.4 shows that the correlations between the 5-month running means of PA and 5-month running means of SSTA were always negative and that the correlation coefficients r between SSTA in Niño-4, Niño-3.4, Niño-3, Niño-1+2 and PA of Australia were 0.78, 0.64, 0.60 and 0.48, respectively. I inferred that the SST variations in the east-to-central equatorial Pacific potentially affected the precipitation in Australia. As shown in Fig. 5.1, Niño-4 was much closer to Australia and that the correlation coefficients r between SSTA and PA were also higher than other areas. Niño-1+2 was the farthest from Australia, and the correlation coefficients r between SSTA and PA were the lowest among the 4 Niño zones. By combining the geographical location of the 4 Niño zones and the correlation coefficients r , I assumed that for the east-to-central equatorial Pacific area, the SSTA of inshore regions of Australia would affect the precipitation of this continent more than the SSTA of offshore regions.

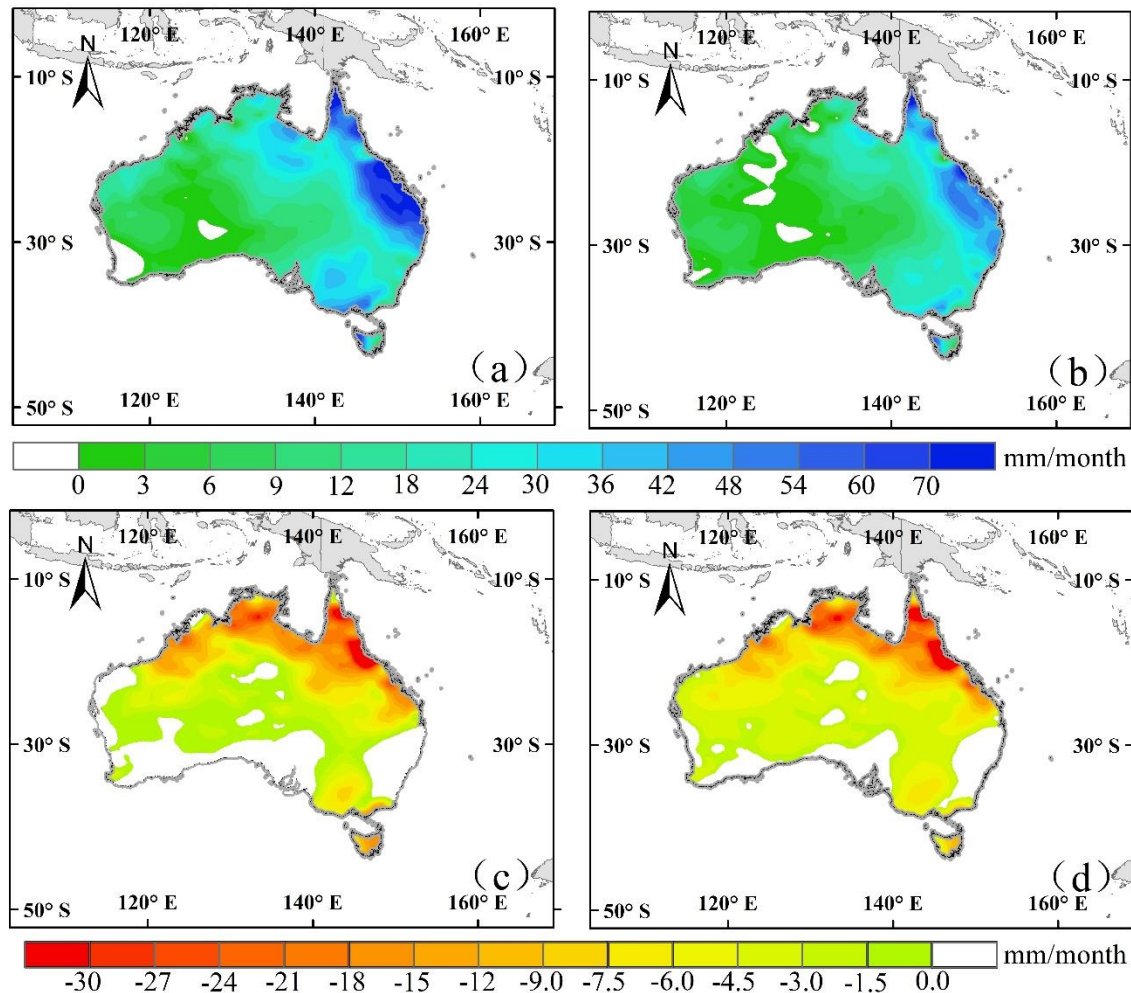


Figure 5.5 The distribution of PA during ENSO events: PA during La Niña event from June 2010 to March 2011 according to Niño-3 index(a); PA during La Niña event from June 2010 to March 2012 according to Niño-3.4 index(b); PA during El Niño event from March 2015 to April 2016 according to Niño-3 index(c); PA during El Niño event from September 2014 to April 2016 according to Niño-3.4 index(c).

During the La Niña event, the average PA of Australia (not 5-month running means) was 20.48 mm/month from June 2010 to March 2011(identified by Niño-3 index) and 14.07 mm/month from June 2010 to March 2012 (identified by Niño-3.4 index). In December 2010, PA reached the peak at 44.16 mm/month. Fig. 5.5a and 5.5b shows that in the northeast coastal regions, the PA was much higher (approximately 80 mm/month) than in other regions. Some regions in the west presented a trend of precipitation decrease when La Niña occurred. However, the area was very small, and the average precipitation decreased to only approximately -5 mm/month. This result coincided with the study of Ummenhofer et al.(2015) who found that during a strong La Niña event, there was enhanced onshore moisture transport onto eastern Australia and an anomalous ascent, resulting in increased precipitation over the East. The background warming trend further modified this circulation, resulting in even greater onshore moisture transport, a stronger ascent over eastern Australia, and additional precipitation. For the El Niño event, average PA of Australia (not 5-month running means) are -4.67 mm/month from March 2015 to April 2016 (identified by Niño-3 index) and -5.06 mm/month from September 2014 to April 2016 (identified by Niño-3.4 index). In February 2011, PA reached to the bottom at -13.77 mm/month. For the spatial distribution of PA, precipitation in the north obviously decreased more than the south part during the El Niño event, and in some parts of South Australia, precipitation even presented an increasing trend (Fig. 5.5c and 5.5d). Similar to the dramatic precipitation increase in northeast Australia during the La Niña event, the precipitation significantly decreased (-60 mm/month) in this area during the El Niño event. In contrast to Ummenhofer's study, I assumed that El Niño had an inverse effect on precipitation in Australia. Chiew et al.(1998) also concluded that the dry conditions in Australia tended to be associated with El Niño. The influence of the ENSO has been known for many years, with El Niño events associated with low rainfall over the eastern two-thirds of Australia, especially during austral spring(McBride and Nicholls, 1983; Ropelewski and Halpert, 1987).

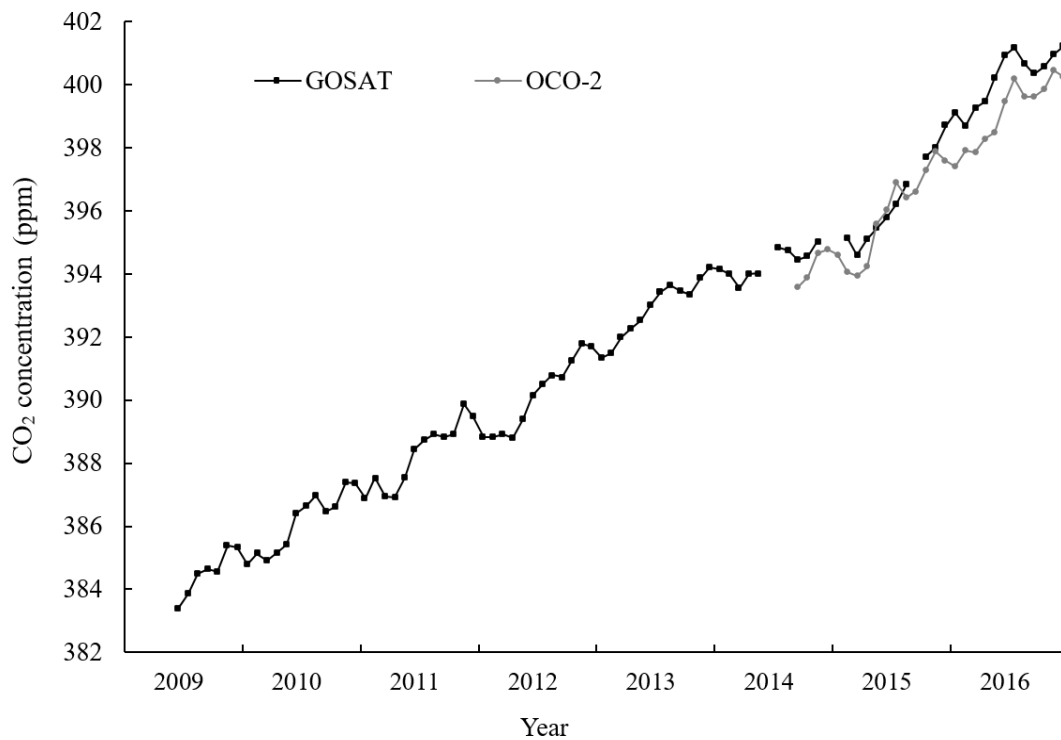
The results indicated that the SSTA around the tropical eastern Pacific Ocean would affect the precipitation in Australia, especially the SSTA in the Niño 4 zone. For the ENSO events, precipitation showed a trend of increasing during the La Niña around 2011. Precipitation showed a trend of decrease during the El Niño around 2015.

5.3.3 Spatial distribution of CO₂ and precipitation

From June 2009 to December 2016, the GOSAT TANSO-FTS SWIR Level 3 products were not available for four months: June 2014, December 2014, January 2015 and September 2015. The GOSAT project indicated that there were no FTS SWIR Level 2 data in these months. Therefore, we could not obtain GOSAT Level 3 products

that were derived from Level 2 data. GOSAT indicated that the CO₂ concentration over Australia in June 2009 was only 383.4 ppm and that it increased to 401.6 ppm in December 2016 (Fig. 5.6a). During the 91 months, CO₂ concentration increased by 18.2 ppm (2.4 ppm/year) in Australia. According to the GOSAT project, the global CO₂ concentration increased from 386.1 ppm in May 2009 to 403.4 ppm in December 2016. The annual increase was 2.3 ppm/year, which was slightly slower than the annual increase in Australia. For the OCO-2 data, CO₂ concentration increased from 393.57 ppm in September 2014 to 400.24 ppm in December 2016 and the increase speed is 2.88 ppm/year (Fig. 5.6a). Comparing with these two groups of data, CO₂ concentration from OCO-2 is about 0.1 ppm lower than the concentration from GOSAT, except the data in May, June and July 2015. Fig. 5.6b indicate the correlation between OCO-2 and GOSAT is highly significant and correlation coefficient r is 0.97.

(a)



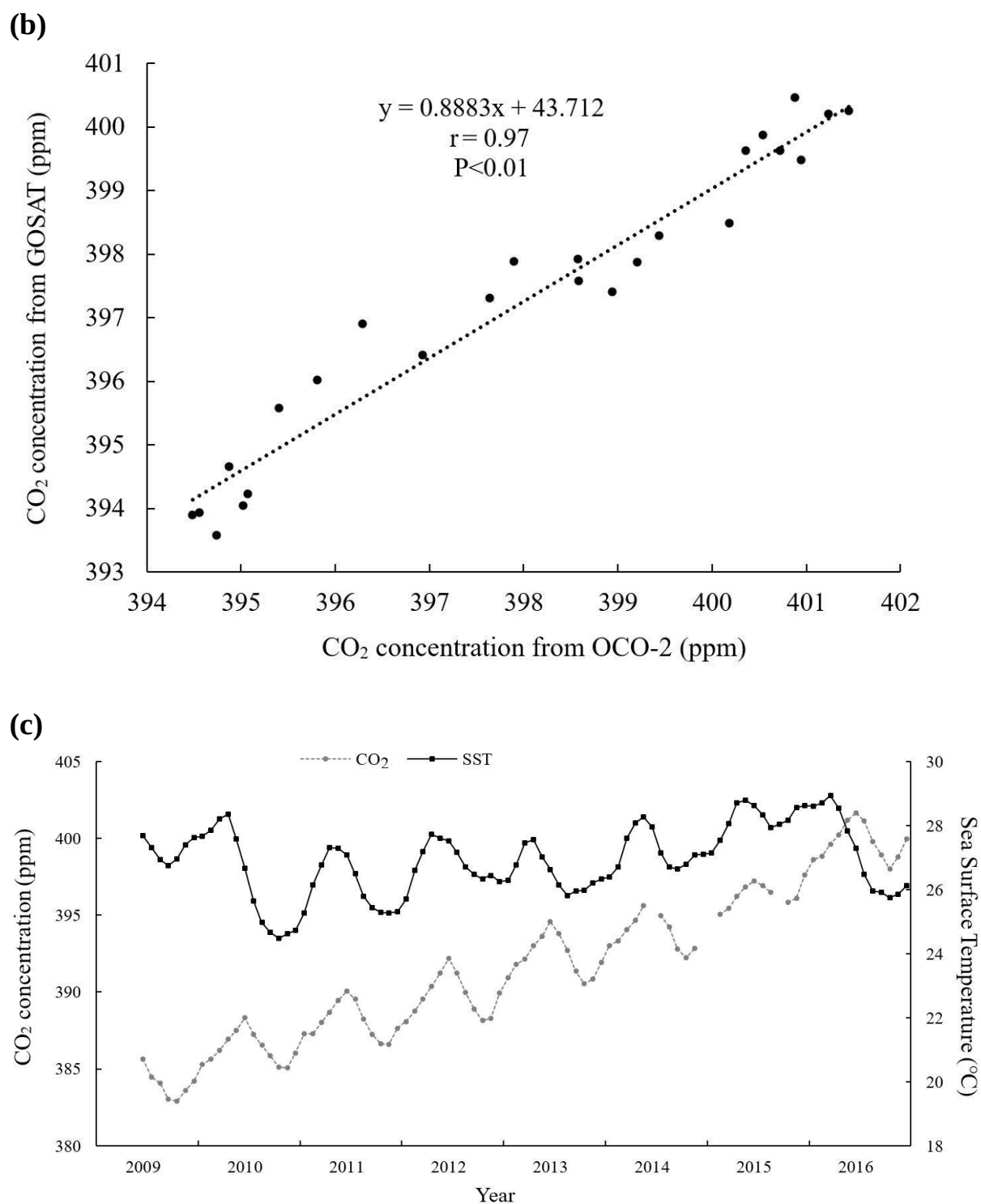


Figure 5.6 Monthly CO₂ concentration of Australia from GOSAT and OCO-2 (a); correlation between OCO-2 and GOSAT (b); SST and CO₂ concentration (GOSAT) in the Nino zones (c).

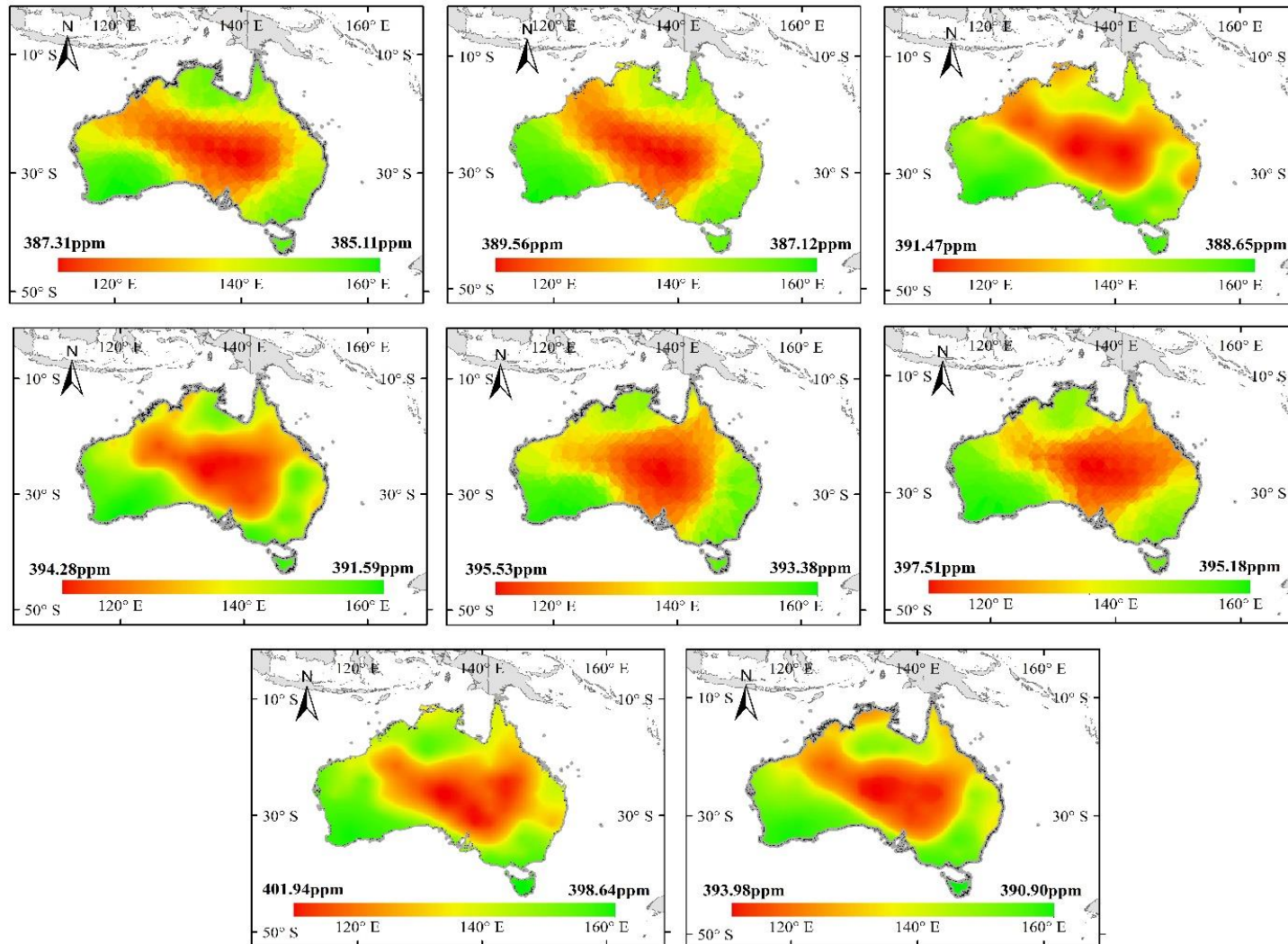


Figure 5.7 The spatial distribution of CO₂ in Australia from 2010 to 2016: 2010(a); 2011(b); 2012(c); 2013(d); 2014(e); 2015(f); 2016(g); 2010-2016(h).

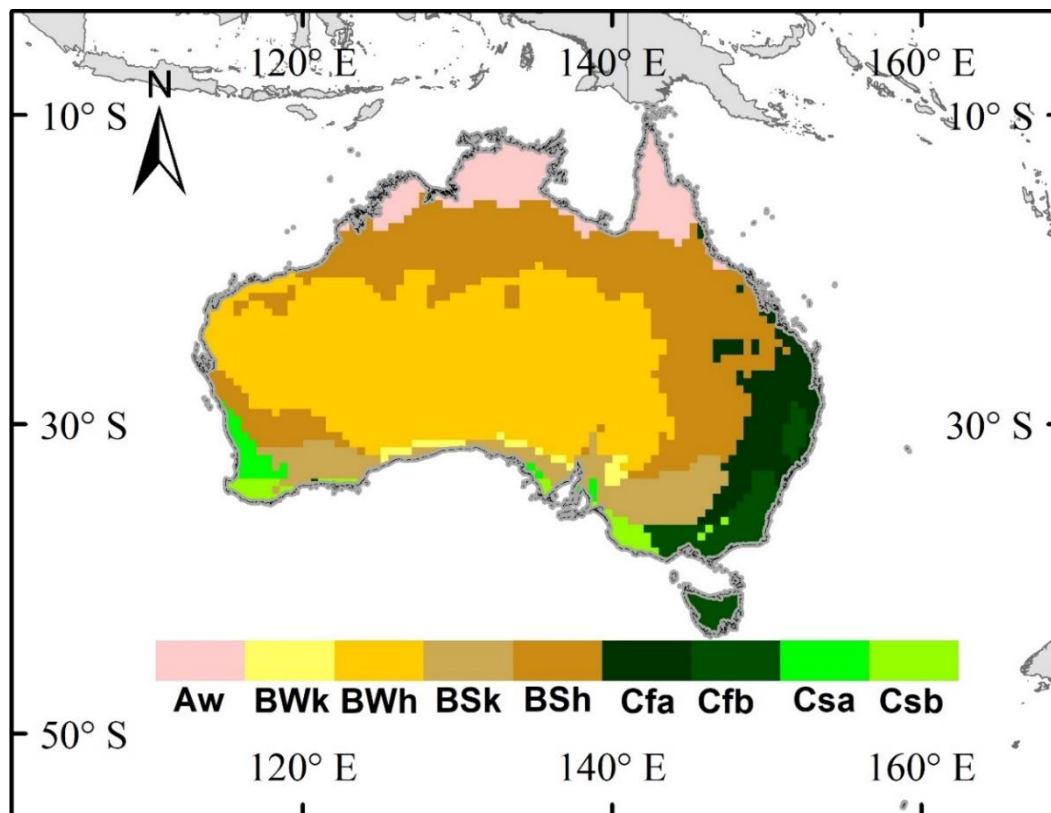
Fig. 5.7 shows that the CO₂ concentration in the central part of Australia was much higher than in other regions and that the annual average concentration in this part exceeded 400 ppm in 2016. In contrast, the distribution of precipitation presented an almost reverse pattern with CO₂, and the average precipitation in central Australia was the lowest that in some regions, where it was even below 200 mm/year from 2010 to 2016 (Fig. 5.3). The precipitation in the north and east coastal regions were much higher than in inland and Western Australia, which reached 1,000-2,000 mm/year. The precipitation in northeast Australia could exceed 2,000 mm/year. A commonly used rainfall-based definition is that an arid region receives less than 10 in or 250 mm of precipitation per year and semiarid regions are commonly defined by annual rainfalls between 10 and 20 in (250 mm and 500 mm). This criterion for aridity was used by the Intergovernmental Panel on Climate Change (Climate change 2007, IPCC). According to this definition, the annual CO₂ concentration in Australia from 2010 to 2016 in arid and semiarid regions was 392.60 ppm and 392.58 ppm, respectively. These were higher than the area with the annual precipitation (more than 500 mm), and the concentration was 392.31 ppm. According to the land cover map of Australia (Fig. 5.8b), in central Australia, the land cover was mainly dominated by open shrub land and barren or sparsely vegetated areas. The biomass carbon stocks of arid shrub lands paled in comparison with forests, hectare for hectare (Grace, 2004), and their net primary production (NPP) was among the lowest of any ecosystem type (Larcher, 2001). Some studies indicated that deserts may rival or even exceed net CO₂ uptake by forests and grasslands, at least in some years (Baldocchi et al., 2001; Falge et al., 2002). Therefore, I assumed that precipitation was one of the key factors affecting the land cover type and that the land cover type had a further effect on the CO₂ distribution.

5.3.4 Spatial distribution of CO₂ and Köppen-Geiger Climate Classification

As shown in Fig. 5.8a, there are three types of climate in central Australia: BWh (Hot desert climate), BSh (Hot semi-arid climate) and BWk (Cold desert climate). These three types of climate are defined by little precipitation. The CO₂ concentration in BWh was the highest among all the climate types and was 392.76 ppm from 2010 to 2016. The CO₂ concentrations of BSh and BWk were also higher than other climate types, and they reached 392.50 ppm (third highest) and 392.45 ppm (fourth highest), respectively. Low precipitation and sparse vegetation cover were assumed to be the causes of the high CO₂ concentrations in BWh, BSh and BWk areas. The Aw (Tropical Savanna) climate area was mainly distributed in northern coastal region. The CO₂ concentration of this climate type was the second highest, with a value of 392.64 ppm. Atmospheric CO₂ measurements indicated that less than half of the CO₂ accumulated in the atmosphere (Siegenthaler and Sarmiento, 1993). The remainder was apparently absorbed by CO₂ sinks in the ocean and the terrestrial biosphere (Quéré et al., 2009).

Since the ocean represents an important carbon sink, changes in the sea surface temperature could significantly affect the CO₂ concentration of the Earth. The Aw climate area is close to the equator, and the high SST was assumed to cause high CO₂ concentration in this coastal region. The distribution map also revealed that the CO₂ in the southern coastal region was lower than that in the northern coastal region. In addition, the CO₂ concentration on Tasmania island was lower than the mainland of Australia because this island is far away from the equator, and the low SST around the island is one of the key factors inducing the low CO₂ concentration on this island. Fig. 5.6c shows that the monthly fluctuations of CO₂ and SST in the 4 Nino areas is almost the same and CO₂ present a smooth annual increase which is consistent to the global CO₂ rising. For the CO₂ concentration in the eastern equatorial Pacific Ocean, it always reach the peak of the whole year in June or July and the SST in this period is also much higher than other months. Therefore, from Fig. 5.6c I assume the SST directly affect the CO₂ concentration in the ocean or coastal region.

(a)



(b)

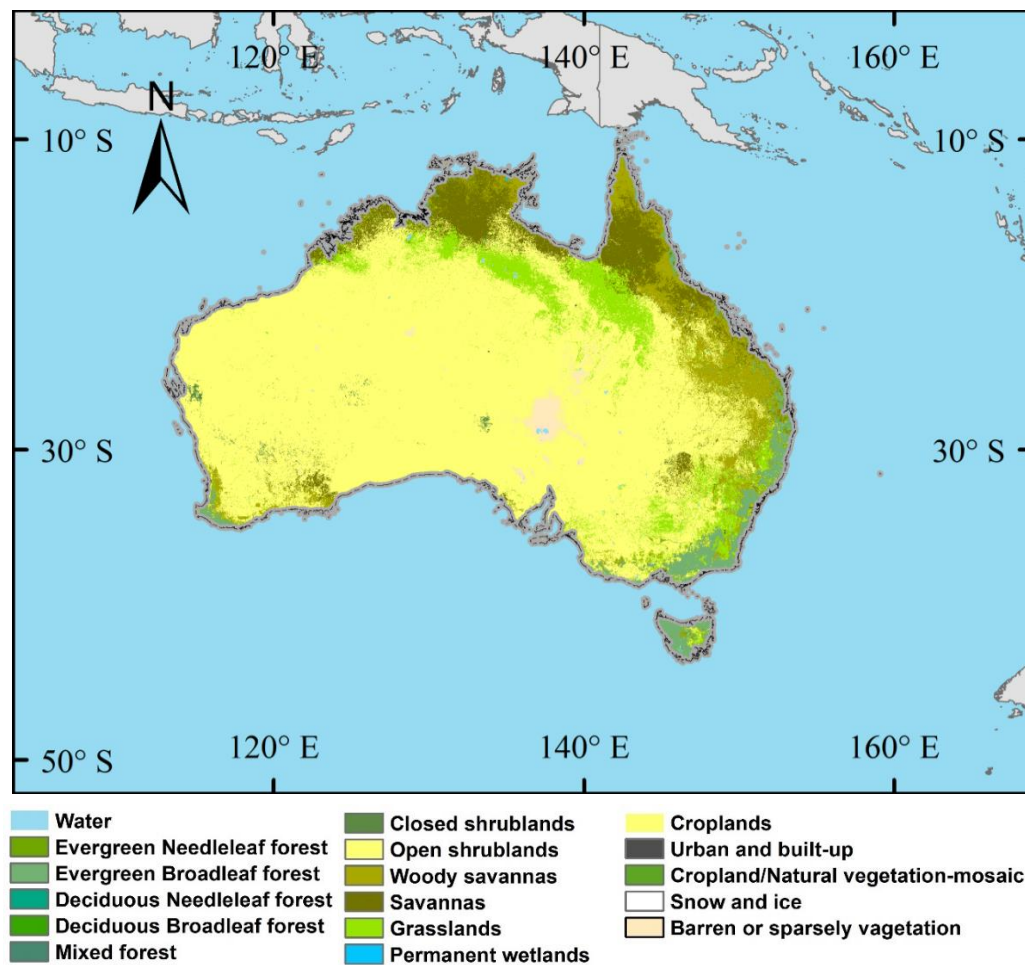


Figure 5.8 Köppen-Geiger Climate Classification (a) and Land cover types (b) in Australia.

The CO₂ in Csb (warm-summer Mediterranean climate) was 391.42 ppm during the period 2010 to 2016, and this was also the lowest among all climate types. The Köppen-Geiger Climate classification map indicated that Csb was mainly distributed in the extreme south of mainland Australia and that the other two climate types, BSk (Cold semi-arid climate) and Csa (Hot-summer Mediterranean climate), were also located in the southern coastal region. The CO₂ concentrations of BSk and Csa were 391.89 ppm and 392.02 ppm, respectively. These two values were the third and fourth lowest. I inferred that the low SST around the southern coastal region played a crucial role in effecting the CO₂ concentrations of these three climate types. The Cfb (Temperate oceanic climate) was mainly located in the southeast of mainland Australia and Tasmania island. The CO₂ concentration in this region was 391.75 ppm, which was the second lowest. Fig. 5.3 and Fig. 5.8b show that the annual precipitation in this region was abundant and that the land cover type was dominated by evergreen broadleaf forest. Therefore, I inferred that abundant precipitation, vegetation cover and relatively low SST around this region jointly caused the low CO₂ concentration. The Köppen-Geiger

Climate classification map showed that Cfa (Humid subtropical climate) was mainly distributed in the eastern coastal region. The CO₂ concentration in this area was 392.21 ppm, which was in the middle position among all the climate types. The vegetation types in this region were savannas and woody savannas, the carbon sequestration capacity of which was stronger than shrub lands but weaker than forest. Moderate SST around this region and special vegetation cover led to the CO₂ concentration of Cfa at the middle level.

The spatial distribution of CO₂ in Australia was closely related to the various climate types. Due to its specific geographical condition, precipitation, SST around the coastal region, vegetation cover and other factors jointly affect the regional CO₂ concentration in this country.

5.3.5 CO₂ concentration changes and ENSO

The Niño-3 index indicated that there were two ENSO events during the study period (2010 to 2016): a La Niña from June 2010 to March 2011 and an El Niño from March 2015 to April 2016. During the occurrence of La Niña, Fig. 5.6a shows that the CO₂ concentration in Australia changed from 386.41 ppm to 386.95 ppm and that the CO₂ concentration increase rate was much slower than the average increase rate. During the occurrence of the El Niño event, GOSAT showed that the CO₂ concentration in Australia changed from 394.58 ppm to 399.47 ppm. The increase rate was more obvious than the average increase rate. During this period, the annual increase reached 4.19 ppm/year. Fig. 5.6c also indicated that the increase rate of CO₂ concentration in Nino zones accelerated during El Niño and decelerated during La Niña. It increased from 397.21 ppm in June 2015 to 401.64 ppm in June 2016 which is much higher than the average increase rate 2.34 ppm/year. During the La Niña, CO₂ concentration in Nino zones increased from 388.33 ppm in June 2015 to 390.05 ppm in June 2016 which is slower than the average increase.

The Niño-3.4 index indicated two ENSO events from 2010 to 2016, but their durations were longer than indicated by the results from the Niño-3 index. Based on the Niño-3.4 index, La Niña was from June 2010 to March 2012, and El Niño was from September 2010 to May 2016. For La Niña, Fig. 5.6a shows that the CO₂ concentration in Australia changed from 386.41 ppm to 388.91 ppm, with an annual increase rate of 1.36 ppm. Since the average increase rate was 2.4 ppm/year, as obtained from the GOSAT data, the result also showed that the CO₂ level increased much more slowly during the occurrence of La Niña. For the El Niño event, GOSAT showed that the CO₂ concentration in Australia changed from 394.45 ppm to 399.47 ppm, the increase rate of which was 3.01 ppm/year. This rate was more obvious than in the other period.

Although the lasting time of ENSO events was different according to the Niño-3 and Niño-3.4 indices, both results revealed that the increase rate of the CO₂ concentration was slower during the occurrence of La Niña (around 2011) and faster during the occurrence of El Niño (around 2015). I assumed that the anomalous SST in the equatorial Pacific Ocean was one of the important factors underlying the abnormal change in the CO₂ concentration in Australia. During a La Niña period, the SST across the equatorial Eastern Central Pacific Ocean is lower than normal. Therefore, the ocean around this region absorbs more CO₂ or releases less CO₂ to the atmosphere, which was assumed would lead to a slower rate of increase in Australia than usual. The La Niña event caused the precipitation to rise in Australia, which promoted the growth of vegetation in the drought region and further relieved the CO₂ increase on this continent. By contrast, El Niño is the warm phase of the ENSO and is associated with a band of warm ocean water that develops in the central and east-central equatorial Pacific. The equatorial Pacific would release more CO₂ or absorb less CO₂ in the atmosphere, which was assumed could lead to the faster increase rate in Australia than usual. Fig. 5.6c have observed a sudden increase of CO₂ in Niño zones during the El Niño. In addition, the El Niño event caused a decrease in precipitation in Australia, which deteriorated the drought condition and further accelerated the CO₂ increase on this continent. Wolfgang et al. (2005) also assumed that the El Niño-related drought had a dominant impact on the rate of increase of atmospheric CO₂. Since OCO-2 data were only available from September 2014, which was when the El Niño started, according to the Niño-3.4 index, we could not identify whether the CO₂ changes were abnormal during the ENSO episodes by using OCO-2. However, both sets of data indicated that the increase rate for CO₂ in the second half of 2016 was not as fast, and the end time of El Niño was April 2016. Moreover, the annual increase rate of Australia was faster, according to OCO-2 than the result from GOSAT, which was also assumed to be related to the occurrence of El Niño.

5.4 Conclusions and discussions

In this study, I used the advantages of greenhouse gases monitoring satellites, GOSAT and OCO-2, to obtain data about the spatial distribution of CO₂ in Australia. The data of GOSAT were from June 2009 to December 2016, and the data of OCO-2 were from September 2014 to December 2016. Australia, which is surrounded by the Indian and Pacific oceans, is significantly influenced by ENSO events. Therefore, meteorological datasets, such as SST, climate types and land covers, were considered to characterize the changes in CO₂ and precipitation.

The distribution of CO₂ in Australia was assumed to be closely related to precipitation. In central Australia, the lower precipitation was the main cause of the

sparsely vegetated cover, which further increased the CO₂ concentration in this region because shrubland had a weak ability to stock carbon from the atmosphere. By combining the CO₂ spatial distribution with Köppen-Geiger Climate Types in Australia, we found that precipitation, the SST around the coastal region, vegetation cover and other factors synthetically affected the regional CO₂ concentration in this country. The CO₂ in BWh was the highest, and that in Csb was the lowest.

According to the Niño-3 and Niño-3.4 indices, there were two ENSO events from 2010 to 2016: La Niña around 2011 and El Niño around 2015. Through the analysis of SST and precipitation, the abnormal SST in the 4 Niño zones, Niño-1+2, Niño-3.4, Niño-3 and Niño-4 was found to affect the precipitation in Australia. There was a strong correlation between SSTA around the tropical equatorial Pacific and PA in Australia. Moreover, the precipitation showed a rising trend during the La Niña and a decreasing trend during the El Niño.

GOSAT and OCO-2 both indicated a persistent increase of CO₂ concentration in Australia. The increase rate was 2.4 ppm/year from GOSAT and 2.88 ppm/year from OCO-2. This result was consistent with the discoveries of the GOSAT project, which revealed that the global CO₂ increased from 385.2 ppm in May 2009 to 401.5 ppm in December 2016. The increase rate of CO₂ in Australia decelerated during the La Niña around 2011. On the contrary, the increase rate accelerated during the El Niño around 2015. I assumed the abnormal SST and precipitation in these periods led to this phenomenon. The global oceanic equatorial belt annually supplies approximately 0.6-1.6 GtC (gigatons of carbon) as CO₂ to the atmosphere and is the atmosphere's largest oceanic source (Tans et al., 1990). Most of this CO₂ flux occurs in the central and eastern equatorial Pacific. Therefore, the abnormal change of SST in this region would significantly affect the CO₂ concentration in Australia. Moreover, the abnormal precipitation had a direct effect on the vegetation, which further affected the CO₂ concentration in Australia. The study of Reichstein et al.(2002) showed that during the drought, light-saturated ecosystem gross carbon uptake and day-time averaged canopy conductance declined by up 90%. These changes were closely related to the soil water content.

This study proposed an effective method to use greenhouse gas monitoring satellites and meteorological data to analyze the temporo-spatial changes of CO₂ in Australia, and we compared the GOSAT and OCO-2. Although abnormal CO₂ changes during the ENSO events from 2010 to 2016 were found, CO₂ concentration changes are still a long, slow and complicated process, so I hope in the future more researches will be conducted using greenhouse gas monitoring satellites to obtain the final conclusions. Data from greenhouse gas monitoring satellites were only available from June 2009,

and the time-series were still not too long. However, with more data provided from these satellite, we believe that greenhouse gas monitoring satellites will become powerful tools to improve the predictions of future atmospheric CO₂ increases and their impact on the Earth's climate.

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Chapter 6 Summary and conclusions

6.1 Summary of present work

In this study, both anthropogenic activities and climate change have been considered as important factors to affect the atmospheric environment. Anthropogenic activities always induce unavoidable atmosphere pollution, such as biomass burning, fossil fuel consumption, industrialization, urbanization and so on. Excess air pollution can increase asthma, respiratory illness, cardiovascular disease, cancer, hospitalizations, emergency-room visits, work-days lost, and school-days lost, all of which decrease economic output, divert resources, and weaken the security of nations. Therefore, it is important to explore and understand the mechanism about how anthropogenic activities affect our atmospheric environment. With respect to climate change, its relationship with atmospheric environment is more subtle and complicated. For example, CO₂, coupled with other greenhouse gas in the atmosphere, is expected to cause the average temperature rising in this century. These climate changes will have an impact on ozone chemistry in the stratosphere, which will feed back on temperature, since ozone itself is an absorbing gas.

For this thesis, two hot topics were combined to analyze and characterize the change of our atmospheric environment. To achieve this target, mainly four researches have been conducted: **i.** study on the spatial distribution of crop residue burning and PM_{2.5} change in China; **ii.** analyzing the spatial distribution and formation condition of severe haze pollution in Northeastern China; **iii.** characterizing CO₂ concentration changes and their influencing factors in Indonesia; **iv.** Analyzing the effects of climate and ENSO on the temporo-spatial changes of CO₂ and precipitation in Australia. The data used for these analyses include greenhouse gas monitoring satellite, other remote sensing datasets, Meteorology data and ground-measured air quality datasets. The data used are listed in Table 6.1.

Table 6.1 Overview of data used in this thesis.

Chapter	Data category	Short name	Time scale	Cover areas
Chapter 2	Land cover	MCD12Q1	2014-2015	China
	Thermal anomalies	MOD14A1		
Chapter 3	Ground-measured PM _{2.5}	Daily average concentration of PM _{2.5}	2015.10-2015.11	Northeastern China
	Land cover	MCD12Q1		
	Thermal anomalies	MOD14A1		
	Aerosol index	MYD08		
	Ground-measured air components	OMAERUVd.003		
	Particle transporting model	MOPITT CO		
		OMTO3D.003		
		Daily average concentration of air components		
Chapter 4	GHG concentration	HYSPLIT model	2014-2016	Indonesia
	SST	OCO2_L2Std		
	Thermal anomalies	OISST		
	Vegetation index	MOD14A1		
		MOD13A3		
Chapter 5	GHG concentration	SWIRL3CO2	2009-2016	Australia
	SST	OCO2_L2Std		
	Precipitation	OISST		
	Climate classification	PREC/L		
		Köppen-Geiger Climate classification		

6.2 Limitation of this study

As mentioned before, there are so many advantages for remote sensing datasets, while, the disadvantages are also obvious. Distinct phenomena can be confused if they look the same to the sensor, leading to classification error and it is hard to achieve high spatial resolution and high temporal resolution at the same time. In this study to reduce the disadvantages of remote sensing datasets, I have used ground-measured datasets to validate the final result from remote sensing datasets. Even though, there are still some limitations in this study. The limitations did not influence to achieve the objectives in each study. In the following section, I delineated the limitations that I encountered and I think it is necessary and meaningful for our future study and other researches who want conduct similar researches.

6.2.1 Research methods

For Chapter 2 and Chapter 3, I proposed a new and effective method to extract the crop residue burning spots. The spatial resolution of MOD14A1 is only 1 km. For each

pixel of crop residue burning, it only means there is crop residue burning within the 1 km² area and it does not represent the entire 1 km² area burned. If we using the area of corresponded pixel to represent the crop residue burning area the result would likely be overestimated. Therefore, in this study we cannot acquire the accurate area of crop residue burning, which is also an important index to assess the intensity of crop residue burning and the emissions. Meanwhile, I use the MODIS land cover products to obtain the area of farmland, actually, the resolution of this product is too coarse and it is more suitable for the studies on a large-scale. If we want to conduct the study on a regional-scale, such as a city or a county, it is better to the used land cover products which were based on field investigations. Ministry of Land and Resources of China provide the GIS database of land classifications that is the result combining interpretation of remote sensing datasets with field investigation. While, this GIS database is not open to everyone if we can obtain this kind of database the accuracy of the final result would likely be improved.

In Chapter 3, I want to analyze the daily change of the aerosol index in Northeastern China but the result indicate that in some days there were even no data within the study region which impeded to acquire effective data about the pollution episodes. For remote sensing datasets, it is very common that the data are missing in certain region and during certain period. Therefore, using multisource data, such as the combination of remote sensing datasets and ground-measured datasets, is a good way to conduct effective analysis.

6.2.2 Study period

In Chapter 4, I assume the greenhouse gas emitted from forest fire is an important source to lead to CO₂ increase in Kalimantan and Sumatra. Since only two fires have been studied in this research and in the future more fire cases in Indonesia need to be analysed to obtain the final conclusion. In Chapter 5, although abnormal CO₂ changes during the ENSO events from 2010 to 2016 were found, I cannot make the conclusion that the abnormal warm SST in eastern equatorial Pacific Ocean is the main cause of this phenomenon. The data of greenhouse gas monitoring satellite are becoming available from 2009 and until now it is even less than 10 years, while, CO₂ concentration changes are still a long, slow and complicated process, so I hope in the future more researches will be conducted using greenhouse gas monitoring satellites to obtain the final conclusions.

6.3 Important findings

Several important findings have been identified in this thesis. These findings can be divided into two main categories: **i.** new methods are proposed; and **ii.** revisiting and

improving the understanding of current knowledge.

6.3.1 Newly proposed methods

In Chapter 2, I propose a method of using MOD14A1 and MCD12Q1 to extract the spatial distribution of crop residue burning spots. The number of crop residue burning spots present different change pattern in China's middle-east and China's northeast. For China's middle-east, the crop residue burning in June is the highest of the whole year and for China's northeast, the crop residue burning in March-April and October-November is much higher than other months. The results conform to the actual situation on these two regions, which prove the final results are adequately accurate. Moreover, I also make comparisons with the data released by Ministry of Environmental Protection of China and the change tendency was consistent with the result of this study.

In Chapter 3, I make a combination of remote sensing datasets with ground-measured air components to analyze the PM_{2.5} pollution episodes in Northeastern China. This comprehensive method is very effective for instant pollution episode and can help researchers finding the origin of pollutants and understanding the mechanism of the episode forming.

In Chapter 4, Level 2 products from OCO-2 cannot be used directly in the GIS platform; therefore, a database has been built to extract useful information from the original HDF5 products, such as X_{CO2}, retrieval latitude, retrieval longitude, and retrieval time. Then, the related information has been converted into a point shapefile, which can be directly used in the ArcGIS platform. To perform the distribution of CO₂, natural neighbour interpolation has been applied to obtain the distribution map. .

6.3.2 Revisited and improved the understanding of current knowledge

The spatial distribution of crop residue burning presents strong seasonal patterns in China. In summer, it mainly concentrates in China's middle-east, and in spring and autumn-winter it mainly concentrates in China's northeast. These patterns are closely related to local farming activities. Crop residue burning is close related to PM_{2.5} change in summer, China's middle-east and autumn-winter, China's northeast, they showed a spatial consistency during these two periods.

With respect to the three provinces in Northeastern China, the formation conditions of severe haze pollution for each province and each episode are totally different. The results indicated that multiple factors working together caused the severest PM_{2.5} pollution episode near the 8th November. Primary aerosols came from crop residue burning, secondary aerosols formed by special meteorological conditions, and aerosol

transportation significantly contributed to this episode. The three episodes in this study were associated with crop residue burning; therefore, I assume that reduction in crop residue burning is an effective measure to prevent severe PM_{2.5} in Northeastern China.

As an archipelago country, SST directly affects the CO₂ concentration in Indonesia and its effect is more crucial than the other factors. CO₂ concentration in Indonesia showed an annual increase that is consistent with the global increase discovered by GOSAT project. Although the forest fires in September-October 2014 and 2015 did not induce an obvious rising of CO₂ over the whole country, both CO₂ concentration in corresponded islands show a trend of increases during the forest fires. The vegetation indices in Indonesia are stable and show no correlation with CO₂ changes because of the special geographic location, climate conditions and vegetation types in Indonesia.

I assumed the distribution of CO₂ in Australia was closely related to precipitation. By combining the CO₂ spatial distribution with Köppen-Geiger Climate Types in Australia, precipitation, the SST around the coastal region, vegetation cover and other factors synthetically were found to affect the regional CO₂ concentration in this country. Through the analysis of SST and precipitation, I found that the abnormal SST in the 4 Niño zones, Niño-1+2, Niño-3.4, Niño-3 and Niño-4, affected the precipitation in Australia. Meanwhile, there is an abnormal CO₂ increase during the occurrence of ENSO event.

6.4 Further study

In this study, I only took China as study region to analyze the effects of anthropogenic activities on atmospheric countries. Actually, the air pollution in other developing countries is also severe even worse than the pollution in China. Therefore, I will conduct more researches about air pollution in developing countries and try to find the distinctive origins for each region which is important for policy maker to take certain measures to relieve air pollution. However, there are not sufficient monitoring stations of air quality and air components, the result of this study indicate there are significant correlations and spatial consistencies between remote sensing and ground-measured datasets. In the following study, I will use aerosol index and air components datasets from satellite to analyze the air pollution in the region without sufficient monitoring station.

Crop residue burning is a worldwide environmental problem. While, too much studies focus on how to improve the use ration of crop residue and barely no research about the tempo-spatial distribution of crop residue burning has been conducted. Since it is important and meaningful to understand the reality and change tendency about the global crop residue burning, in the future I will conduct the basic research to characterize the global distribution of crop residue burning.

With regard to greenhouse gas monitoring satellite, GOSAT and OCO-2 were used in this study. In the future, OCO-2 will release Level 3 products which is the global distribution of CO₂. Addition to that, TanSat, also known as CarbonSat, is a Chinese Earth observation satellite dedicated to monitoring carbon dioxide in Earth's atmosphere. It is generally classified as a minisatellite, and is the first dedicated carbon mission of the Chinese space program. The mission was formally proposed in 2010, and work began in January 2011. It is funded by the Ministry of Science and Technology (MOST) and was built by the Shanghai Institute of Microsystem And Information Technology (SIMIT). These three satellites will provide various information about greenhouse gas changing. Our following studies will focus on monitoring regional CO₂ change and try to find the factors that affect the CO₂ concentration.

6.5 Final conclusion

The main objectives of this study are analyzing the effect of anthropogenic activities and climate change on atmospheric environment. Four research tasks (from Chapter 2 to Chapter 5) have been undertaken:

I. Crop residue burning can induce severe air pollution and emit a large amount of aerosols and GHG to the atmosphere. In Chapter 2, with China as the study area, MODIS MOD14A1 and MCD12Q1 products were used to derive daily crop residue burning spots from 2014, 2015. Meanwhile, the daily air quality data from 150 cities in 2014 and 285 cities in 2015 were used to obtain daily and monthly PM_{2.5} distribution maps with the Kriging interpolation. The results indicate that crop residue burning occurs in a seasonal pattern, and its spatial distribution is closely related to farming activities. The changes in PM_{2.5} exhibit a hysteresis after crop residue burning in summer and autumn-winter. In autumn-winter, crop residue burning can induce evident PM_{2.5} increase in China's northeast, and that is more obvious than summer crop residue burning in China's middle-east. Furthermore, when data of summer and autumn-winter crop residue burning from 2014 and 2015 are compared, we can see that the change in number of crop residue burning spots significant changes PM_{2.5} in these regions. Both the summer and autumn-winter crop residue burning areas presented spatial consistency with high PM_{2.5}. By contrast, the results from many aspects indicated that the crop residue burning in spring did not cause a notable change of PM_{2.5}.

II. In autumn 2015, the severest PM_{2.5} pollution episode in Northeastern China have shocked all the nation and for the first time the air pollution in this region became a hot topic. In Chapter 3, I used ground-measured air quality, meteorological data and multiple remote sensing datasets to analyze the severe PM pollution episodes of October and November 2015 in Northeastern China. The results showed that the causes of high PM_{2.5} in three episodes and in each province were completely different. Multiple

factors working together caused the severest PM_{2.5} pollution episode near the 8th of November. Primary aerosols came from crop residue burning, secondary aerosols formed by special meteorological conditions, and aerosol transportation significantly contributed to this episode. The three episodes in this study were associated with crop residue burning; therefore, I assume that reduction in crop residue burning is an effective measure to prevent severe PM_{2.5} in Northeastern China. Moreover, some special meteorological conditions in the alternate periods of winter and autumn could accelerate the formation of secondary aerosols and exacerbate the accumulation of aerosols. This study showed that there are significant correlations and spatial consistencies between remote sensing and ground-measured datasets. In many heavily-polluted countries where we cannot obtain ground-measured data, remote sensing data could replace them and will play an important role in the study of air pollution.

III. Indonesia is the world's largest island country, with more than seventeen thousand islands. In Chapter 4, I used OCO-2 products and considered three factors that potentially affect CO₂ concentration in Indonesia: SST, forest fires and vegetation. As an archipelago country, SST directly affects the CO₂ concentration in Indonesia and its effect is more crucial than the other factors. CO₂ concentration in Indonesia showed an annual increase that is consistent with the global increase discovered by GOSAT project. Due to special geographic conditions, forest fires did not induce CO₂ concentration changes in Indonesia but CO₂ concentration in the corresponding islands, Kalimantan and Sumatra, showed a trend of increase. The vegetation indices in Indonesia are stable and show no correlation with CO₂ changes because of the special geographic location, climate conditions and vegetation types in Indonesia. This study demonstrated that OCO-2 is capable of monitoring CO₂ concentration at a regional scale.

IV. The climate of Australia is significantly influenced by ocean currents. In Chapter 5, I analyzed the temporo-spatial changes in the CO₂ concentrations in Australia from June 2009 to December 2016 using greenhouse gas monitoring satellites, GOSAT and OCO-2. I assumed the distribution of CO₂ in Australia was closely related to precipitation. By combining the CO₂ spatial distribution with Köppen-Geiger Climate Types in Australia, precipitation, the SST around the coastal region, vegetation cover and other factors were found to synthetically affect the regional CO₂ concentration in this country. Through the analysis of SST and precipitation, we found that the abnormal SST in the 4 Niño zones, Niño-1+2, Niño-3.4, Niño-3 and Niño-4, affected the precipitation in Australia. Moreover, the precipitation showed a rising trend during the La Niña and a decreasing trend during the El Niño. We found the abnormal CO₂ changing during the occurrence of ENSO events and this need to be furtherly analyzed to obtain final conclusions.

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Abbreviations

AAOD: Absorbing Aerosol Optical Depth

AOD: Aerosol Optical Depth

AVHRR: Advanced Very High Resolution Radiometer

BC: Black Carbon

BSh: Hot semi-arid climate of Köppen-Geiger Climate Classification

BSk: cold semi-arid climate of Köppen-Geiger Climate Classification

BWh: Hot desert climate of Köppen-Geiger Climate Classification

BWk: Cold desert climate of Köppen-Geiger Climate Classification

CAMS: Climate Anomaly Monitoring System

Cfa: Humid subtropical climate of Köppen-Geiger Climate Classification

Cfb: Temperate oceanic climate of Köppen-Geiger Climate Classification

CNEMC: China's National Environmental Monitoring Center

CO: carbon monoxide

CO₂: carbon dioxide

Csa: Hot-summer Mediterranean climate of Köppen-Geiger Climate Classification

Csb: warm-summer Mediterranean climate of Köppen-Geiger Climate Classification

ENSO: El Niño-Southern Oscillation

EOF: Empirical Orthogonal Function

EOS: Earth Observing System

EVI: Enhanced Vegetation Index

FMI: Finnish Meteorological Institute

FTS: Fourier Transform Spectrometer

FYP: Five Year Plan

GADM: Global ADMinistrative areas

GHG: greenhouse gas

GHCN: Global Historical Climatology Network

GIS: Geographic Information System

GOSAT: Greenhouse Gases Observing Satellite

HYSPLIT: Hybrid Single Particle Lagrangian Integrated Trajectory Model

IGBP: International Geosphere Biosphere Programme

IPCC: Intergovernmental Panel on Climate Change

JAXA: Japan Aerospace eXploration Agency

JMA: Japan Meteorological Agency

MCD12Q1: MODIS Land Cover Type product

MODIS: Moderate Resolution Imaging Spectroradiometer

MOD13A3: MODIS vegetation indices products

MOD14A1: MODIS Thermal Anomalies/Fire products

MOPITT: Measurements of Pollution in the Troposphere

MYD08_M3: MODIS monthly AOD products

MYD08_D3: MODIS daily AOD products

NASA: National Aeronautics and Space Administration

NDVI: Normalized Difference Vegetation Index

NIVR: Netherlands Agency for Aerospace Programmes

NMC: U.S. National Meteorological Center

NOAA National Oceanic and Atmospheric Administration

NO₂: nitrogen dioxide

NPP: Net Primary Production

OISST: Optimum Interpolation Sea Surface Temperature

OCO: Orbiting Carbon Observatory

OMAERUVd.003: OMI AAOD daily products

OMI: Monitoring Instrument

OMTO3D.003: OMI daily UVAI daily products

O₃: ozone

PA: Precipitation Anomalies

PM: particulate matter

PM_{2.5}: particulate matter with a diameter of 2.5 micrometers or less

PM₁₀: particulate matter with a diameter of 10 micrometers or less

PREC/L: NOAA's PRECipitation REConstruction over Land

PREC/O: NOAA's PRECipitation REConstruction over Ocean

SCIAMACHY: Scanning Imaging Absorption spectroMeter for Atmospheric CHartographY

SIA: Secondary Inorganic Aerosol

SOA: Secondary Organic Aerosol

SOI: Southern Oscillation Index

SO₂: Sulfur dioxide

SST: Sea Surface Temperature

SSTA: Sea Surface Temperature Anomalies

SWIR: Short-wavelength infrared

TANSO: Thermal And Near-infrared Sensor for carbon Observation

UVAI: UV Aerosol Index

WEO: World Energy Outlook

WHO: World Health Organization

US EPA: United States Environmental Protection Agency

X_{CO2}: CO₂ column-averaged dry air mole fraction

X_{CH4}: CH₄ column-averaged dry air mole fraction