ABSTRACT

Title of Document: SEASONAL AND INTERANNUAL VARIABILITY OF EMISSIONS FROM CROP RESIDUE BURNING IN THE CONTIGUOUS UNITED STATES

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Crop residue burning is a global agricultural practice used to remove excess residues before or after harvest. Crop residue burning in the contiguous United States (CONUS) has been documented at the regional and state-level by governmental organizations and in the scientific literature. Emissions from crop residue burning in the CONUS have been found to impair local and regional air quality, leading to serious health impacts and legal disputes. Currently, there is no baseline estimate for the area and emissions of crop residue burning in the CONUS. A bottom-up model for emissions calculations is employed to calculate CO_2, CO, CH_4, NO_2, SO_2, $PM_{2.5}$, PM_{10}, and Pb emissions from crop residue burning in the CONUS for the years 2003 through 2007. These atmospheric species have negative impacts on air quality and human health and are important to the carbon cycle. Spatially and temporally explicit cropland burned area and crop type products for the CONUS, necessary for emissions calculations, are developed using remote sensing approaches. The majority of crop

residue burning and emissions in the CONUS are shown to occur during the spring (April - June) and fall harvests (October - December). On average, 1,239,000 ha of croplands burn annually in the CONUS with an average interannual variability of ± 91,200 ha. In general, CONUS crop residue burning emissions vary less than ±10% interannually. The states of Arkansas, California, Florida, Idaho, Texas, and Washington emit 50% of PM_{10}, 51% of CO_2, 52% of CO, and 63% of $PM_{2.5}$ from all crop residue burning in the CONUS. Florida alone emits 17% of all annual CO_2, CO, and $PM_{2.5}$ emissions and 12% of annual PM_{10} emissions from crop residue burning. Crop residue burning emissions in the CONUS account for as little as 1% of global agricultural emissions and as much as 15% of all agricultural burning emissions estimates in North America, including Mexico and Canada. The results have implications for international, federal, and state-level reporting and monitoring of air quality and greenhouse gas and carbon emissions aimed at protecting human health, mitigating climate change, and understanding the carbon cycle.

SEASONAL AND INTERANNUAL VARIABILITY OF EMISSIONS FROM CROP RESIDUE BURNING IN THE CONTIGUOUS UNITED STATES

By

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Dedication

For my parents, Benny Ray and Josephine Thompson McCarty.

And for my husband, Michael Tyree.

Thank you for your love and support.

"Though these mountain people are the exponents of a retarded civilization, and show the degenerate symptoms of an arrested development, their stock is as good as any in the country."

> ---- Ellen Churchill Semple, First Female President of the American Association of Geographers
>
> From "The Anglo-Saxons of the Kentucky Mountains: A Study in Anthropogeography" (1901) *The Geographical Journal* 17(6): 588-623.

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Chapter 1: Introduction

1.1. Background

Agricultural burning is a widely practiced and diverse land use activity that includes pasture maintenance (Higgins et al., 2007), agroforestry (Binford et al., 2006; Kobizar, 2007), slash-and-burn deforestation for shifting cultivation (Fujisaka et al., 1996; Imbernon, 1999; Styger et al., 2007), pest and weed control (Ball et al., 1998; Hari et al., 2003), and harvest-related crop residue removal (Jenkins et al., 1992; Dennis et al., 2002; Jimenez et al., 2006; McCarty et al., 2007). In pre-Columbian times, fire was a management tool for development of agriculture, from expansion of arable lands to adapting grasses into cereal crops through removal of weeds and pests, utilizing ash as a natural fertilizer, and creating a stable seed supply (Pyne, 1993). During the European settlement of the U.S., fire was used to clear land for agricultural development (Houghton et al., 2000). Though fire is used for clearing land for agricultural uses, crop residue burning, where fields remain static and the residue is burned, is also an important agricultural practice. Crop residue burning is a common management tool used globally (Mazzola et al., 1997; Smil, 1999; Hari et al., 2003; Yevich and Logan, 2003; Chen et al., 2005; Ortiz de Zarate et al., 2005; Badarinth et al., 2006; Bescansa et al., 2006; Brye et al., 2006; Jimenez et al., 2006; Korontzi et al., 2006; Venkataraman et al., 2006; Yan et al., 2006). In the U.S., fire is used to burn crop residue both during and after harvest, for pest and weed control, and to prepare fields for planting (Canode and Law, 1979; Ball et al., 1998; Eiland, 1998; LSU Ag Center, 2000; Dhammapala et al., 2006). Farmers often argue that the benefits of crop residue burning, i.e., an inexpensive and effective method to remove excess residue which facilitates planting and controls pests and weeds, helps growers stay competitive and provides ash fertilization (Wulfhorst et al., 2006). Crop residue burning is defined in this dissertation as (1) the practice of burning residues post-harvest whereby the residues consist of a layer of ground-level senescent vegetation, and (2) the practice of burning residue pre-harvest (commonly used for sugarcane harvesting), whereby leaves and other biomass are burned prior to the harvest.

Burning of crop residue before or after harvest represents an important source of gaseous and particulate emissions in the context of local and regional air quality and public health (Jenkins et al., 1992; Dennis et al., 2002; Hays et al., 2005; Jimenez et al., 2007). Wiedinmyer et al. (2006) calculated emitted CO, $PM_{2.5}$, Volatile Organic Compounds (VOCs), and NO_x from agricultural burning using a remote sensing method of combining the Global Land Cover Dataset 2000 (Bartholome and Belward, 2005) and MODIS Active Fire counts (Giglio et al., 2003) as proxy for burned area. Agricultural burning accounted for approximately 0.9% of CO, 2.4% of $PM_{2.5}$, 4.7% of VOCs, and 4.5% of NO_x, respectively, of total emissions from all biomass burning in North America for 2004. Crop residue burning is also a contributor to global warming due to associated CO_2, CO, and CH_4 emissions. CO_2 is a well quantified greenhouse gas that traps infrared radiation emitted and reflected by the Earth's surface in the atmosphere. CO is an important contributor to global warming as it acts as a catalyst to increase the amounts of other greenhouse gases in the atmosphere, particularly CH_4, and eventually oxidizes into CO_2 (Hansen et al., 2000). CH_4 emissions have a high global warming potency (25 times more effective than CO_2 at trapping heat in the atmosphere), affect tropospheric O_3 and stratospheric O_3 and H_2O, and produce CO_2 (CCSP, 2006). Using an emission factor database compiled from scientific literature and biomass burning estimates from expert knowledge, Andreae and Merlet (2001) estimated that agricultural residue burning accounts for approximately 9.5% of total global biomass burning emissions as well as roughly 9% of total CO_2 released from global biomass burning. It should be noted that this estimate includes forest clearing and grassland fires but excluding biofuels and charcoal production. Comparatively, in 2005, agricultural residue burning in the U.S. emitted approximately 1% of the total global or U.S. N_2O emissions (which have a global warming potential 310 times that of CO_2) released from energy consumption through transportation, residential, industrial, commercial, and electric power production based on U.S. Environmental Protection Agency (EPA) emissions estimates (DOE/EIA, 2006).

The contiguous U.S. (CONUS) covers an area of approximately 7.7 million km^2, with over 1.5 million km^2 of cropland (USDA/NRCS, 2003). Nearly 20% of land in the CONUS is dedicated to crops. Satellite monitoring of crop residue burning provides a systematic and reliable approach over large areas (Korontzi et al., 2006). For example, the Moderate Resolution Imaging Spectrometer (MODIS) flown on board the NASA Terra and Aqua satellites (Justice et al., 2002) detected significant fire activity from 1 km MODIS active fire counts (Giglio et al., 2003) in cropland areas (Table 1-1).

In the example below and for the rest of the dissertation, croplands are defined as established cropped areas that produce food, fibers, and seeds which are part of a planting rotation, can be harvested, and/or areas that are fallow due to management practices and/or government programs. Fallow lands, which do not produce crop residues, are often burned to prepare for planting (WA DOE, 2003). Pastures and perennial croplands, such as orchards and vineyards, are not included in the "croplands" definition. Crop residue burning occurs in many CONUS states throughout the year. To show the approximate spatial and temporal extent of burning, MODIS fire counts detected by the MODIS active fire algorithm (Giglio et al., 2003) from 2001 to 2006 were selected if the points were detected within areas classified as cropland (LC 12) and cropland/natural vegetation mosaic (LC 14) International Geosphere-Biosphere Program (IGBP) classes (approximately 1.46 million km^2) by the MODIS 1 km land cover dataset (Friedl et al., 2002) (Figure 1-1). On average, crop residue burning, not including conversion to croplands, such as slash-and-burn, accounted for 16% of all fires detected in the CONUS annually (McCarty et al., 2007) (Table 1-1). Presence of clouds during harvesting could have obscured detection of cropland burning, producing the limited number of cropland active fire detections. On average, the interannual variability of cropland active fire detections was ± 3%.

Table 1-1. Fire counts and percentages of cropland burning in the CONUS for years 2001 through 2006.

Year	**Cropland Fire Points**	**Total Fire Points**	**% Cropland Burning**	**Sensor(s)**
2001	3,471	24,270	14%	Terra
2002	4,980	39,847	12%	Terra/Aqua (July 26 - Dec. 31)
2003	12,084	74,026	16%	Terra/Aqua
2004	9,567	50,724	19%	Terra/Aqua
2005	14,079	71,035	20%	Terra/Aqua
2006	10,901	85,218	13%	Terra/Aqua

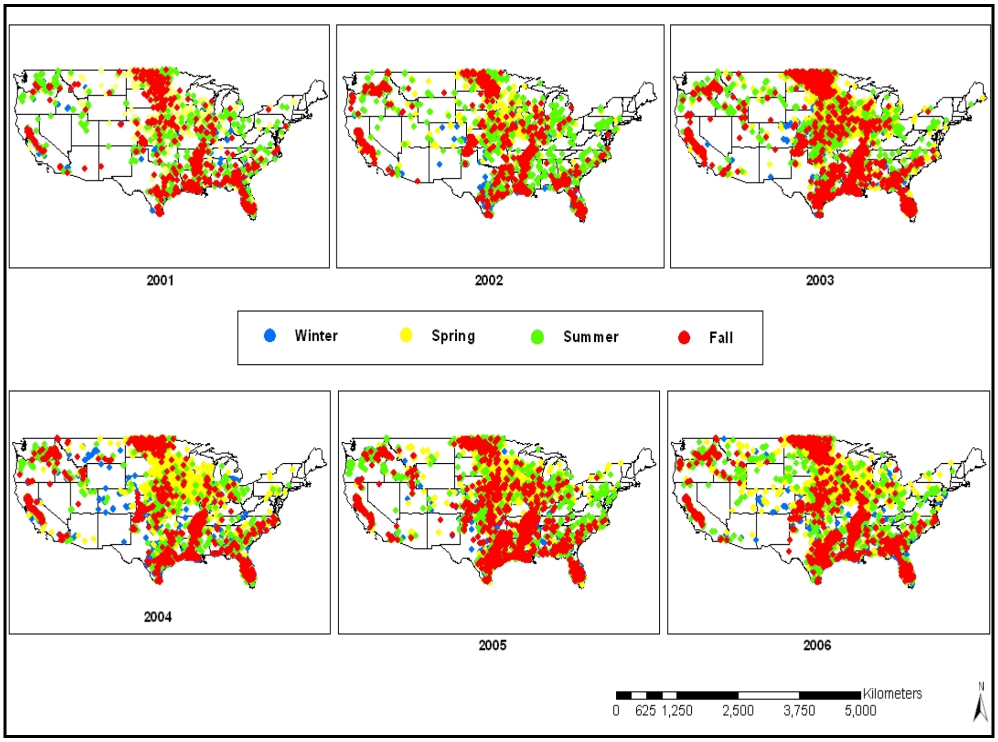

Figure 1-1. Cropland fires detected by MODIS in the CONUS from 2001-2006 (Note: Terra only for 2001 and Terra and Aqua for 2002 through 2006; projection: Geographic).

An important product of crop residue burning is the emissions. Biomass burning, including crop residues, releases different emissions during each stage of combustion (Lobert and Warnatz, 1993; Yokelson et al., 1996, 1997; Andreae and Merlet, 2001; Bertschi et al., 2003). The general combustion stages are: ignition, flaming, smoldering, glowing, and extinction (Andreae and Merlet, 2001). The ignition phase initiates burning. Flaming refers to an observed sequence whereby three processes occur at a near-simultaneous rate over the entire burning area: pyrolysis, glowing combustion, and flaming combustion. Pyrolysis is the chemical decomposition of carbon-based compounds during exposure to high temperature in the absence of oxygen (NWCG, 2006). During pyrolysis, char, tar, and volatile compounds (i.e., readily vaporized organic compounds, such as alcohols), are formed and released as white smoke. Pyrolysis becomes an exothermic process at 450 K and when temperatures exceed 800 K, glowing combustion begins and creates a flammable mixture of tar and gaseous products. When this mixtures ignites, flaming combustion begins, and CO_2, H_2O, NO, N_2O, N_2, and SO_2 are emitted. During the flaming stage, CO, CH_4, H_2, C_2H_4, C_2H_2, PAHs (polycyclic aromatic hydrocarbons), and soot particles are also released. Flaming combustion ceases when the majority of volatile compounds are released. At this point, smoldering begins, emitting CO and incompletely oxidized pyrolysis products, such as particulate matter, PAHs, and VOCs at temperatures less than 850 K. The majority of emissions released during the smoldering phase, including VOCs and CO, are directly linked to the incomplete oxidized pyrolysis (Lobert et al., 1991; Yokelson et al., 1997; Greenberg et al., 2005). Following the smoldering phase, glowing refers to the process of oxidizing solid fuel accompanied by incandescence (NWCG, 2006). Specifically, all volatiles have been emitted, oxygen has reached the surface, and there is no visible smoke. Glowing continues until the temperature drops below combustion threshold value or only non-combustible ash remains. At this point, the fire has been extinguished (extinction). Andreae and Merlet (2001) note that all combustion stages are present at any given time, and it is these combined emissions of every phase that are present in the smoke plume.

1.2. Crop Residue Burning and Air Quality

Crop residue burning is a governmental, environmental, and health policy issue at the state, national, continental, and international level. As early as the 1970s, local and state governments in the U.S. had begun to debate the benefits of crop residue burning for farmers, citing the use of fire for pest and weed control as an easy, inexpensive removal method of residues, versus the detrimental impacts of these emissions on air quality (Wedin, 1973). Due to the national growing awareness of the negative effect of crop residue burning on air quality, mainly through the enactment of the 1990 Clean Air Act by the U.S. federal government, more states in the CONUS have increased regulation of crop residue burning. In some states, compliance with the regulations is monitored through expanded in-situ, aerial photography, and satellite-based monitoring of agricultural fire and enforcement of prescribed crop residue burning permits, most commonly in the Pacific Northwest states of Washington, Idaho, and Oregon (DOE, 2005; ISDA, 2006; ODA, 2007). The regulations are mainly driven by concerns over health issues related to crop residue burning. Of particular concern are the emissions of particulate matter ($PM_{2.5}$ and PM_{10}) which negatively affect both the heart and lungs (EPA, 2007a). Studies have found a clear link between reduced air quality from agricultural residue burning and health effects. For instance, asthmatic children and adults suffer more frequent and more severe asthmatic symptoms and episodes during crop residue burning events (Long et al., 1998; Torigoe et al., 2000; Boopathy et al., 2002; Golshan et al., 2002; Mar et al., 2004). Consequently, during these events, hospitals report higher admissions for respiratory emergencies (Jacobs, 1997; Cancado et al., 2006). Farmers living in areas where crop residue burning is a common practice suffer from asthma at a higher rate than the regular population (McCurdy et al., 1996).

While most states in the U.S. are so-called “freedom to farm” or “right to farm” states, whereby the state legislature can not pass a law which limits or prejudices agricultural activities or allows for nuisance lawsuits against agricultural activity (Lapping et al., 1983), impaired air quality has forced many states to rethink past hands-off legislation on agricultural burning. For example, seven states, including Louisiana and Idaho, require that farmers must burn during the daytime only and that certified Burn Managers must be present at all fire events (LSU Ag Center, 2000; ISDA, 2006) (Table 1-2). Because of the proximity of large urban areas such as West Palm Beach, Naples, and Miami, corporate and cooperative sugar cane farmers in Florida requested a burn policy and permit system to limit nuisance complaints. Since 2004, the Florida Department of Forestry issues daily burn permits, based on wind conditions, direction, and flammability (FLDOF, 2005). The most strict agricultural burning policy occurs in Washington State, whereby the Washington Department of Ecology under the 1991 Clean Air Act of Washington issues all burning permits and has the legal right to fine farmers $10,000 for any illegal crop residue burning (DOE, 2005).

Table 1-2. Examples of state regulations for crop residue burning.

State	Crop Residue Burning Regulations
California	• Requires a burning permit; • Burning only on burn days determined by local Air Districts in consultation with the California Air Resource Board; • Residues required to be shredded and piled when possible (CARB, 2006).
Florida	• Sugar cane farmers initiated burning oversight with Florida Department of Forestry (FLDOF) in 2004; • FLDOF issues burn permits between November and March (FLDOF, 2005).
Idaho	• Pre-2007, farmers could burn during the daytime and were required to have certified Burn Managers at the burn; • Idaho State Department of Agriculture called no-burn days according to extreme wind conditions or U.S. Forest Service fire danger ratings; • Currently, all non-tribal lands are banned from burning while the state of Idaho rewrites State Implementation Plan (SAFE, 2007).
Louisiana	• Farmers can burn during the daytime and are required to have certified Burn Managers at the burn (LSU Ag Center, 2000).
Oregon	• In 1991, House Bill 3343 established an open field burning acreage phase-down, propane flaming limitation, and residue burn permitting issued by the Oregon Department of Agriculture (ODA) for the Willamette Valley; • 102,500 acres of grass seed and cereal residues can be burned per year, which is enforced through aerial and ground surveys; • ODA has the right to fine growers that burn on no-burn days (ODA, 2007).
Washington	• Washington Department of Ecology (DOE) under the 1991 Clean Air Act of Washington issues all burning permits and determines burn days based on atmospheric conditions and U.S. Forest Service fire danger ratings; • Cost of permits are $2.00 per acre to be paid by the farmers; • DOE can fine farmers $10,000 for any illegal crop residue burning; • DOE uses aerial photography, tip hotline, and remote sensing for enforcement (DOE, 2005).

Concerns over impaired regional air quality forced the state of Idaho to go to court to defend the practice of crop residue burning. In the case *Safe Air For Everyone v. U.S. Environmental Protection Agency*, the U.S. Environmental Protection Agency (EPA) Region 10, a private grower, and the State of Idaho defended the practice of crop residue burning against three petitioners: Safe Air for Everyone (an environmental group), the American Lung Association of Idaho, and the neighbor of the aforementioned private grower. On January 30, 2007, the U.S.

Ninth Circuit Court of Appeals ruled that a 2005 EPA decision to allow crop reside burning in Idaho was legally flawed (SAFE, 2007). Due to the ruling, all field burning was banned until the state of Idaho could develop a new State Implementation Plan (SIP) that provides more regulation of the practice in accordance with the 1990 Clean Air Act and subsequent EPA regulation on air quality attainment (Hagengruber, 2007). Citing tribal sovereignty, both the Nez Perce and the Coeur d'Alene tribes started burning Kentucky bluegrass fields within their tribal lands on August 13, 2007 and August 27, 2007, respectively (Cuniff, 2007; Hagengruber, 2007). Concerns over the ruling in Idaho are widely felt. For instance, the Kansas Department of Health and Environment (KDHE) has begun working with researchers at Kansas State University and the University of Maryland to quantify statewide pyrogenic emissions from agricultural burning, which includes range management in eastern Kansas and wheat residue burning in southern and western Kansas (Personal communication with Mr. Scott Weir, Kansas Department of Health and Environment, 27 April 2007). These pyrogenic emissions will be analyzed by KDHE to determine if agricultural burning regulations are needed.

Nationally, the impact of agricultural burning on air quality is an important issue. The Agricultural Air Quality Task Force (AAQTF) was established in 1996 by the U.S. Congress under the Federal Agriculture Improvement and Reform Act. The AAQTF is comprised of scientists from the EPA and the United States Department of Agriculture (USDA). The AAQTF has a congressional mandate to address air quality issues related to all aspects of agriculture, from livestock to equipment to crop residue burning (AAQTF, 2007). Based on its charter, the AAQTF must review research related to air quality issues from agricultural and associated management practices to ensure intergovernmental cooperation in agricultural air quality research issues. Additionally, the AAQTF must provide guidance on agricultural air quality issues to state and tribal governments for better regulation of crop residue burning and compliance with the 1990 Clean Air Act (CAA).

Last amended in 1990, the CAA contains pollutant limits set by the EPA. These limits, known as the National Ambient Air Quality Standards (NAAQS), focus on seven "criteria" atmospheric species known to be harmful to human health (EPA, 2005a). Table 1-3 shows the NAAQS primary standards. The primary standards of these pollutants are set limits to protect public health. It is important to note that NAAQS are the standards for emission concentrations averaged over several temporal scales, from a 1-hour to 24-hour to annual time periods, from numerous and diverse sources that affect air quality (EPA, 2005a). Refinements to the NAAQS standards are often based on findings from the EPA AP-42 series (EPA, 2007b). The most current report of the series is the AP-42 Fifth Edition, which lacks any references to crop residue burning in its detail of agricultural contributions to air pollution. This analysis defines air quality emissions as the atmospheric species that comprise the EPA NAAQS.

Table 1-3. National Ambient Air Quality Standards of emissions affecting air quality (EPA, 2008a).

Pollutant	NAAQS Primary Standards	Averaging Times
CO	40 mg/m^3	1-hour
Pb	0.015 mg/m^3	Quarterly Average
NO_2	1 mg/m^3	Annual
PM_{10}	0.150 mg/m^3	24-hour
$PM_{2.5}$	0.035 mg/m^3	24-hour
SO_2	0.370 mg/m^3	24-hour

According to the CAA, all states must prepare and submit a SIP to the EPA that covers all potential sources for air quality pollutants (i.e., NAAQS species), including crop residue burning. Currently, California, Oregon, and Washington have included crop residue burning in their SIPs (DOE, 2005; CARB, 2006; ODA, 2007). Idaho is undergoing a revision of its SIP to include crop reside burning as per the Ninth Circuit ruling in 2007 (SAFE, 2007).

1.3. Crop Residue Burning and Climate Change

As is illustrated with the changing political environment in the U.S., the future of crop residue burning is an uncertain one. The U.S. loses croplands at a rate of roughly 2% every five years (USDA/NRCS, 2003). With farmland becoming increasingly surrounded by real estate developments, farmers are likely to intensify agriculture in order to maintain current yields and profits. Intensification, in turn, could lead to increased burning as farmers add profitable crops, like rice, wheat, and corn, into their normal fallow rotation. Climate change will also alter the distribution of croplands and related burning by shifting growing zones northward and creating drier, less arable micro-climates in the southeast and southern Midwest (Cline, 2007). Southworth et al. (2002) predicts decreases in soy, corn, and winter wheat production due to global warming as far north as Indiana and Illinois by as early as 2030. This northward trend could lead to crop residue fires shifting north, with more southern farmers using fire to stay competitive. Additionally, pest and noxious weed populations are projected to grow and expand northward as the climate warms (Coakley et al., 1999), which could increase fire activity in croplands as a mitigation tool.

At both the national and international level, there is a need to quantify and report carbon and greenhouse gas emissions from biomass burning, including crop residue burning. Previous research has shown crop residue burning to be an important contributor to total biomass burning in both developing and developed countries (Yevich and Logan, 2003; Korontzi et al., 2006; McCarty et al., 2007; Korontzi et al., 2008). Internationally, the Intergovernmental Panel on Climate Change (IPCC) was established to assess and report on scientific, technical, and socio-economic research related to understanding global climate change as well as the potential impacts of climate change and options for mitigation and adaptation to climate change (IPCC, 2007a). According to its mission, the IPCC requires national reporting of all greenhouse emissions. The IPCC also aims to compile scientific data and results on climate change as well as to refine predictive climate change models. The IPCC 4th Assessment Report lists biomass burning as an important contributor to greenhouse gas emissions (CO, CH_4, CO_2, NO_x, N_2O, SO_2, VOCs) (IPCC 2007b). The IPCC includes calculations of global warming potential, i.e., the ability of greenhouse gases to trap heat in the atmosphere, of numerous atmospheric species released from all sources, including biomass burning. For instance, CH_4 and N_2O emissions have more than 25 and 298 times the global warming potential of CO_2 over a 100-year time period (IPCC, 2007b). Emissions from biomass burning also affect radiative forcing, a phenomena where changes in gases and aerosols have led to a perturbation in the radiation balance of the atmosphere. The IPCC estimates global radiative forcing values for CO_2 of +1.66 [±0.17] W m^{-2}; CH_4 of +0.48 [±0.05] W m^{-2}; and aerosols from biomass burning (such as particulate matter and black carbon) of +0.03 [±0.012] W m^{-2} (IPCC, 2007b). Other research has found larger fire-related radiative forcing values from aerosols: +5 to +15 W m^{-2} (Podgorny et al., 2003); +11.5 W m^{-2} when clouds were present (Keil and Haywood, 2003); and +10 to +35 W m^{-2} (Hodzic et al., 2007). Clearly, aerosols from biomass burning have an important effect on radiative forcing and the climate (Kaufman et al., 2002).

A number of programs have been established to better understand and quantify sources of carbon and greenhouse gas emissions. For example, the first goal of the North American Carbon Program (NACP), a multidisciplinary and multi-agency research program which seeks to develop scientific understanding of carbon sources and sinks and of changes in carbon stocks in North America, is "to determine the emissions and uptake of CO_2, CH_4, and CO" (NACP, 2002). Both the EPA and USDA produce greenhouse emissions inventories which quantify the CH_4 and CO emissions from crop residue burning for the U.S.

1.4. Previous Studies to Estimate Crop Residue Burning

Previous attempts to quantify both crop residue burning and its emissions used indirect approaches, such as non-spatial data. This necessitates the use of large simplifying assumptions. For example, Andreae (1991) estimated global agricultural waste burning based on 1986 United Nations Food and Agricultural Organization (FAO) crop production statistics. Specifically, the amount of agricultural residue able to be burned was equal to the total crop production, of which 80% of residues were burned in the developing world and 50% of residues were burned in the developed world for any given year. Hao and Liu (1994) combined FAO crop production and biofuel consumption statistics and assumed that 23% of crop residues were used for fuels and 17% of residues were burned in the field to produce an estimate of burning biomass in the tropics. Comparatively, this research found that 13% of crop residues burn in the CONUS. Both studies assumed emission factors and combustion completeness were the same for all crops. Yevich and Logan (2003) used a combination of national statistics, World Bank energy assessments, international and national technical reports, and in-country expert knowledge to estimate agricultural waste burning in the developing world. Country-specific studies have commented on the lack of data on the spatial and temporal distribution of agricultural fires for calculating associated emissions. This information gap is largely due to a reliance on governmental statistics of agricultural waste management, i.e. estimates of crop residue areas burned (Ezcurra et al., 1996; Zhang et al., 1996). Studies using indirect methods to quantify amount of crop residue burning have huge discrepancies in the assumptions of area burned. For example, Yevich and Logan (2003) assumed, based on expert knowledge, that certain regions in the developing world either never burn crop residues or completely burn all crop residues in the fields, creating both an underestimation and an overestimation of crop residue burning. Accordingly, there is no reliable reason to consider one assumption as more accurate than another. In addition, crop residue burning rates vary by crop type and region. In the U.S. alone, residue burning estimates range from less than 1% for corn residues to 70% for sugar cane fields (WRAP, 2002). Intra-crop residue burning also exists; for example, winter wheat burning estimates in Washington fluctuate between 30% to 70% depending on acreages permitted to burn by the state during each harvest season (Personal communication with Dr. Steve Van Vleet, Whitman County Extension Agent, Colfax, Washington, April 2007) while winter wheat burning estimates in Arkansas, which are not monitored by the state, remain steady at 45% of total winter wheat acreages (Personal communication with Dr. Jason Kelley, Arkansas State Wheat Specialist, Little Rock, Arkansas, June 2006).

1.5. Research Objectives

The objective of this research is to quantify emissions from crop residue burning in the CONUS. This research is a contribution to the scientific understanding and quantification of crop residue burning and associated air quality and carbon species emissions in the CONUS. Unlike previous research, which used government statistics, this study uses satellite data to derive burned area estimates. A comparison of the satellite burned area estimates with state-level governmental statistics on agricultural burning is provided for the few states with public reporting. Atmospheric species included in the analysis negatively impact air quality and contribute to the release of carbon from burning biomass. These species are CO, Pb, $PM_{2.5}$, PM_{10}, NO_2, and SO_2, criteria NAAQS pollutants (Table 1-3), and CO, CH_4, and CO_2, carbon species that are the focus of the NACP (NACP, 2002). Some of these atmospheric species have strong global warming potential (CH_4) and positive radiative forcing (CO_2, CH_4, $PM_{2.5}$, PM_{10}). To provide context for the results of this study, emissions from this research are compared to other sectors, such as transportation and industry, as well total national emissions as estimated by the EPA. Both the large spatial scale (CONUS) and the multi-temporal scales (monthly and yearly) of this crop residue emissions analysis has not been attempted in previous research.

A previous study of cropland burning in the southeastern U.S. demonstrated that active fire detections in croplands were higher in the fall, specifically the months of October through December (McCarty et al., 2007). This research hypothesized that other agricultural regions in the CONUS would experience this same peak in cropland burning. USDA statistics have demonstrated a clear decrease in wheat acreages, which are often managed with fire, while much of the Midwest has experienced an increase in corn acreages, which are burned less frequently (USDA/NASS, 2003a; 2004a; 2005; 2006). This analysis hypothesized that this observed shift from wheat to corn in much of the Midwest will decrease cropland burning and related emissions. Currently, the National Emissions Inventory and the Inventory of U.S. Greenhouse Gas Emissions and Sinks produced by the EPA relies on state-level governmental statistics of cropland burning from 23 states and do not include remote sensing-based estimates of crop residue burning and related emissions from the larger spatial scale of the CONUS (EPA, 2006a; EPA, 2006b). This analysis also assumed that state-reported statistics on crop residue burning would be under-reported statistics. Based on the general body of knowledge about crop residue burning presented above, three hypotheses were developed and tested during this research:

1. Crop residue burning emissions will peak during the months of October through December.

2. A shift from wheat to corn will cause a decrease in crop residue burning emissions.

3. Emissions from crop residue burning using direct estimates of burned area and crop types will exceed current total biomass burning emission estimates of CO, $PM_{2.5}$, PM_{10}, and SO_2 as reported by the EPA in the National Emissions Inventory and exceed agricultural burning emission estimates of CO and CH_4 as reported in the Inventory of U.S. Greenhouse Gas Emissions and Sinks.

The main approach of this research was as follows:

1. Develop a methodology to quantify the area of cropland burning in the CONUS.
2. Produce growing season-specific crop type maps to classify corresponding cropland burned area.
3. Calculate air quality and carbon emissions from crop residue burning in the CONUS.
4. Calculate the seasonal and interannual variability of air quality and carbon emissions.
5. Determine source states and regions of crop residue burning and related emissions.

6. Compare the satellite-based emission calculations of crop residue burning in the CONUS with global, North American, and national emissions estimates from crop residue burning, general agricultural burning, and total biomass burning.

7. Determine if the shift from wheat to corn is reducing crop residue burning emissions in the CONUS.

1.6. Outline of the Dissertation

This dissertation consists of six chapters (Figure 1-2). Four chapters (chapter 2 - chapter 5) are presented in the self-contained format of journal articles. The chapters are ordered in sequence of completion, whereby subsequent analysis relies on the previous data products and/or methodologies presented in previous chapters. Chapter 6 concludes the dissertation and provides a detailed discussion on the implications of the dissertation as well as future research directions.

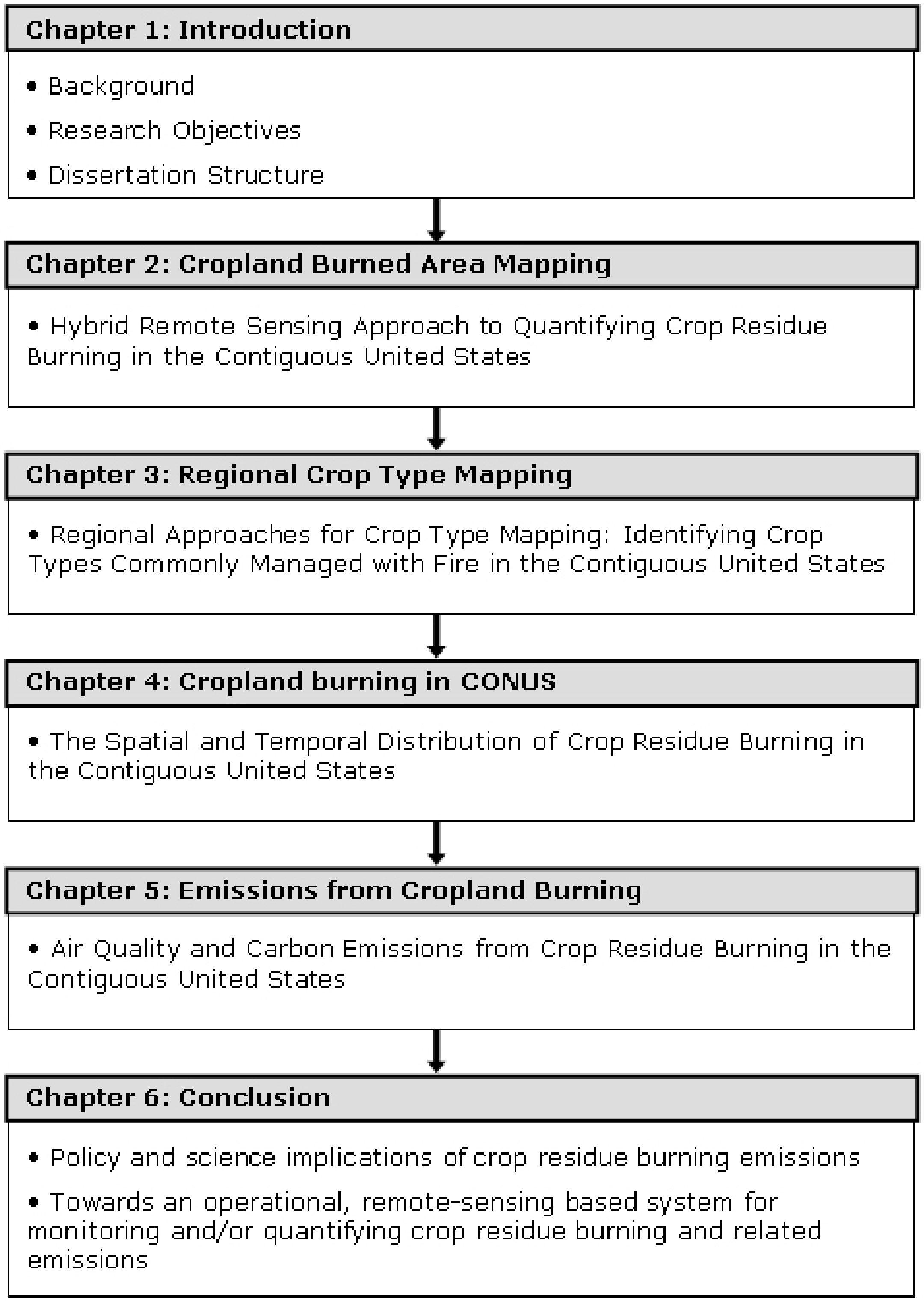

Figure 1-2. Flow of dissertation research and associated chapters.

Chapters 2 and 3 detail products generated to study crop residue burning phenomena and to provide spatially and temporally explicit data for emissions calculations. Chapter 2 describes a hybrid burned area methodology developed for detecting crop residue burning. This chapter also includes an assessment of currently available satellite-based burned area data, such as the MODIS Burned Area Product, for detecting crop residue burning. Chapter 3 introduces the regional crop type mapping methodology used to produce crop type maps from 250 m MODIS data. A validation of the crop type mapping is also included.

Chapter 4 presents the spatial and temporal distribution of crop residue burning in the CONUS using the hybrid burned area approach developed in Chapter 2. Five years of data are analyzed, 2003 through 2007, with an emphasis on crop residue burning at the near national scale and the regional scale as well as for two selected states: Florida and Kansas. For this research, regions are defined as the EPA regions. The EPA regions were chosen because state agricultural agencies are required to report crop residue burning activity to their respective EPA Regional Offices. Additionally, the AAQTF releases regional air quality recommendations based on the EPA regions. This chapter provides detailed quantification of cropland fire activity within the CONUS.

Chapter 5 reports the air quality and carbon emissions from crop residue burning in the CONUS. Combining the previously discussed crop type maps, burned area methodology, and an emission factor database compiled specifically for this project, these emissions were calculated using the bottom-up approach developed by Seiler and Crutzen (1980). This chapter calculated emissions for six of the seven criteria NAAQS species that affect air quality (omitting ozone): CO, SO_2, NO_2, PM_{10}, $PM_{2.5}$, and Pb. The carbon species of CO_2 and CH_4 were also calculated. This chapter identifies "source" regions - regions that produce large quantities of air quality emissions from crop residue burning. Air quality and carbon species emission estimates are compared to transportation, manufacturing, and other sectors of the National Emissions Inventory (NEI) and the 2008 Inventory of U.S. Greenhouse Gas Emissions and Sinks (EPA, 2008a; EPA, 2008b). This chapter places crop residue burning emissions in the context of global, North American, and national air quality and carbon emissions. This chapter tests the hypotheses identified above.

Chapter 6 presents an overall discussion of results and the conclusion to the dissertation research. This chapter describes the implications of this research for both national and state level implementation of the 1990 Clean Air Act and how the research is applicable to the goals of the AAQTF, the IPCC, and the NACP. It also presents the implications of the research findings for future local, state, and national policies towards crop residue burning, discusses the relationship between permitting crop residue burning and emission trends, and provides an overview of future research.

Chapter 2: A Hybrid Remote Sensing Approach to Quantifying Crop Residue Burning in the Contiguous United States[1]

This chapter describes a methodology for monitoring and estimating the area burned from crop residue burning. An area of diverse crop types, spanning the multi-cropped system of the Mississippi Delta and the wheat monoculture of the southern Great Plains, was selected as a case study. The methodology demonstrated in this chapter is applied in Chapter 4 to quantify the spatial and temporal distribution and variability of crop residue burning in the CONUS and the resulting burned area maps are subsequently used to estimate emissions from crop residue burning for the CONUS in Chapter 5.

2.1. Use of Remote Sensing for Cropland Burning Mapping

Satellite observations provide a reliable approach for quantifying crop residue burning consistently over large areas (Muirhead and Cracknell, 1985; Korontzi et al., 2006; McCarty et al., 2007; Korontzi et al., 2008), but existing remotely sensed burned area data within croplands publicly available for the U.S. is unsuitable for a multi-year analysis fine-tuned to the specifics of fire occurrence in agricultural areas. Heritage burned area mapping initiatives such as the GBA 2000 (Tansey et al., 2004) and GLOBSCAR projects (Simon et al., 2004) delivered the first global burned area maps from Systeme Pour l'Observation de la Terre (SPOT) VEGETATION and ATSR-2 Along Track Sounding Radiometer (ATSR-2) data respectively; however,

[1] The presented material has been previously published in part in McCarty JL, Loboda T, and Trigg S (2008) A Hybrid Remote Sensing Approach to Quantifying Crop Residue Burning in the U.S. *Applied Engineering in Agriculture*, 24(4): 515-527.

these products are limited to a spatial resolution of 1 km and are available only for the year 2000. The global burned area product derived from data collected by MODIS presents a considerable improvement in burned area mapping because it is produced yearly at a higher (500 m) resolution. This product (MCD45A1), however, has shown commission errors associated with labeling plowed fields as burned areas (Roy et al., 2005) and is currently only available provisionally.

Another remotely sensed data driven approach to estimating burned area relies on the use of active fire detections as a proxy for burned area and assumes that either a fraction or the entire pixel has burned (Kasischke et al., 2003; van der Werf et al., 2004; Wiedinmyer et al., 2006). The advantage of this approach is its ability to detect burning of smaller areas compared to burned area algorithms, though an inaccurate fraction assumption would lead to either over- or underestimating burned area. Cropland burns present a mosaic of relatively small (field-size) non-contiguous patches. As elaborated by Robinson (1991), burned areas are sensed at a scale close to pixel resolution; therefore areas of crop residue burning smaller than the pixel size are likely to be missed. In comparison, active fires, when sensed in the short wave infrared (SWIR) spectrum, constitute a signal that is highly amplified over that of the background (Robinson, 1991) allowing for detection of fires at a scale considerably smaller than pixel resolution. For example, under favorable conditions, the MODIS 1 km Active Fire Product (MOD14/MYD14 for Terra and Aqua satellites, respectively) can detect fires as small as 100 m^2 (Giglio et al., 2003). Little is known about the relationship between active fire detections and the extent of cropland burned area except that the fraction of area burned per active fire pixel depends on the regional and ecosystem specifics of fire occurrence (Giglio et al., 2006).

The inapplicability of the existing burned area products to multi-year analyses of cropland residue burning requires the development of new methodologies. This study addresses two major objectives related to mapping crop residue burning: (1) to establish requirements for mapping burned area from satellite data in croplands of the CONUS; and (2) to present a hybrid (burned area plus active fire counts calibrated into area) remotely sensed data based approach to map crop residue burning over 1.46 million km^2 of the CONUS. The presented algorithm is built on standard publicly available remotely sensed data including the MODIS surface reflectance (Vermote et al., 2002) and active fire products (Giglio et al., 2003). The inputs are analyzed within a semi-automated image processing/GIS environment to produce spatially explicit estimates of burned area in intensive croplands of the US. A similar approach of integrating MODIS burned area mapping with MODIS active fires has been found effective in mapping slash and burn agricultural burning in Borneo (Miettinen et al., 2007), but has not been tested in the intensive cropland landscapes of the CONUS. Intensive croplands, established agricultural areas that are often multi-cropped in a single calendar year, represent a unique fire management system different from slash and burn agricultural practices. Within intensive croplands, crop residue burning occurs consistently over several years, fields can be burned multiple times in one year, and the burned area is limited to field boundaries and not always contiguous. The accuracy of the burned area estimates was assessed using high resolution satellite images, field data, and Arkansas state-level statistical information on crop residue burning. This analysis further used the algorithm to quantify crop residue burning during the 2003-2006 harvest seasons. The results of this study show that this hybrid approach provides a repeatable, consistent, and realistic assessment of burned area in intensive croplands of the CONUS.

2.2. Study Area

The study area was chosen to encompass an intensive cropland landscape known to experience widespread residue burning in the U.S. (Jenkins et al., 1992; Dennis et al., 2002; Brye et al., 2006; McCarty et al., 2007). MODIS tile h10v05 (Figure 2-1), which covers an area of over 1,244,400 km^2 and is centered on 90° W and 35° N, was selected as a test area for the algorithm developments and application. Croplands make up approximately 145,370 km^2 or 12% of the tile. The study area represents a complex agricultural system that ranges from a double cropped system of soy, rice, winter wheat, and cotton in the southeastern U.S. to a monoculture grains production in the southern Great Plains. The complexity of the crop systems makes the selected area a suitable site to test the flexibility of this hybrid approach to crop residue mapping in various agricultural systems.

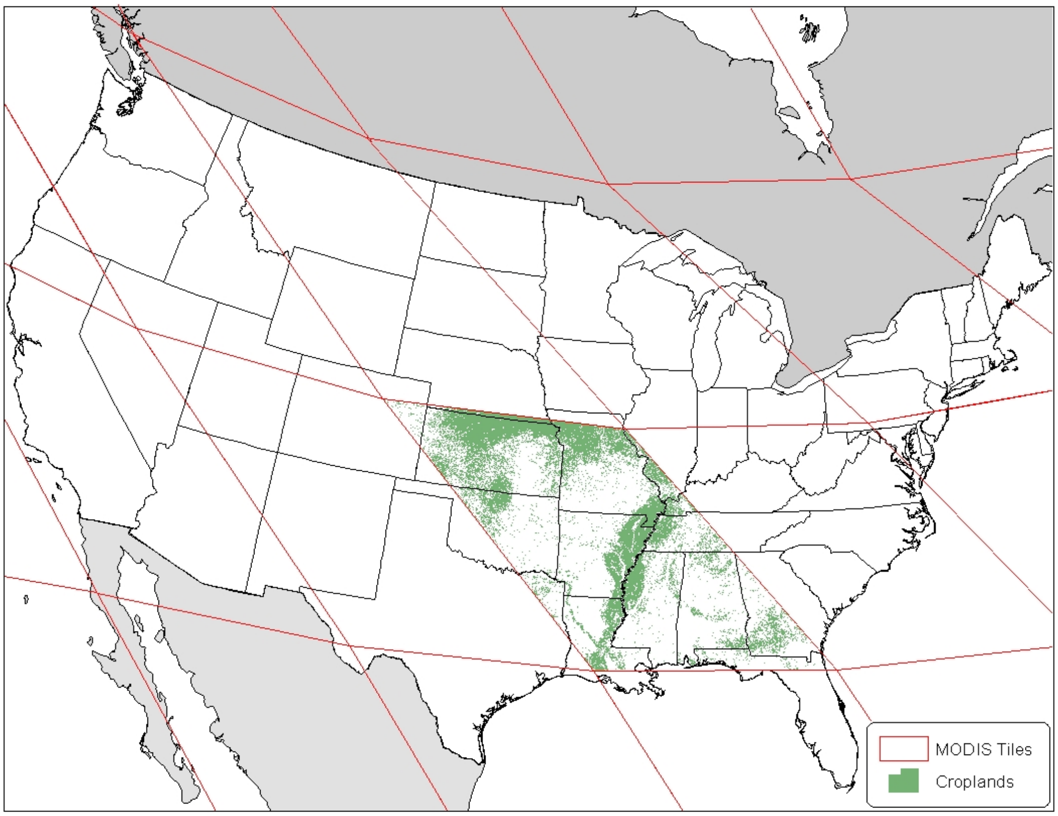

Figure 2-1. Study area of MODIS tile h10v05 with cropland mask; the MODIS tile boundaries, which cover a square in MODIS sinusoidal projection, appear skewed when displayed in the Albers Equal Area Conic Projection of this figure.

2.3. Methodology

Development of a successful algorithm for mapping burned areas in croplands requires understanding the specifics and patterns of fire occurrence in these unique managed ecosystems. Because of the variability of agricultural practices involving the use of fire worldwide, input data and algorithm parameterization requirements will differ across geographic regions and political entities. This analysis focuses on cropland residue burning in the U.S.; therefore the algorithm and findings of this project may not be applicable to agricultural areas outside the U.S.

2.3.1. Considerations in Algorithm Design

The extent of crop residue burning can be assessed through direct monitoring of on-going burning activity (active fire detection) or through observations of post-fire impacts on the surface (burn scar mapping). Due to the specifics of fire occurrence in agricultural landscapes within the U.S., each of these strategies presents a distinct set of requirements when developing satellite data driven methodologies.

Crop rotation practiced in the study area generally requires several burning events within the same fields within a year. Therefore, the first requirement for burned area estimates addresses the need for mapping burned area per burning period rather than once a year. The burning period is defined here as a timeframe during which fields may be burned as a result of various agricultural practices. For the study area, two burning periods were identified as May 1 – July 4 and September 30 – December 27. These two burning periods roughly correspond to the harvesting seasons in the southeastern and central U.S., where fire is a common management tool for crop residue management, especially along the Mississippi River (Brye et al., 2006; McCarty et al., 2007).

Cropland management fires rarely follow seasonal and diurnal fire dynamics of wildland fire occurrence. The timing and periodicity of cropland fires depend on residue management techniques and crop rotation practices (Eiland, 1998; LSU, Ag Center, 2000; Brye et al., 2006). Fires are often ignited during optimal weather conditions and generally the burning is completed within two hours. Crop residue burning during night-time is extremely rare (LSU Ag Center, 2000), thus daytime observations of fire activity are particularly important. These characteristics necessitate high frequency of observations of on-going burning activity in croplands during the harvesting periods.

High frequency of observations is also important for mapping burn scars during harvest seasons due to the limited longevity of post-burn conditions on the ground. The post-burning effects are present on the surface for a short period of time before the burned fields are plowed and/or re-seeded to facilitate the crop rotation mechanisms. This condition leaves a narrow time-window during which the burned areas can be mapped.

The last major requirement to the input datasets is driven by the field size of cropland areas. In the CONUS, average field sizes range from 0.16 km^2 (16 ha) in the southeast (McCarty et al., 2007) to 1.01 km^2 (101 ha) in the western US (Personal communication with Dr. Steve Van Vleet, Agriculture Extension Agent for Whitman County, Washington State University, Colfax, Washington, 23 April 2007). Often several fields are burned at the same time allowing for the use of coarser resolution imagery than the exact 0.16 km^2 field size of the study area; however, there is a need to account for contribution from smaller single-burned fields to the total burned area in croplands.

2.3.2. Data

The MODIS instrument on board two polar orbiting satellites –Terra and Aqua – provides daily global observations at the 250 m, 500 m, and 1 km resolutions. Although 250 m resolution provides a more detailed view of the surface and therefore is more likely to detect burning in a single 0.16 km^2 field, only two MODIS bands (red and near infrared (NIR)) are collected at this resolution. The MODIS 500 m observations are available for a broader range of the electro-magnetic spectrum including short wave near infrared (SWIR) bands. The red-NIR bi-spectral space and the conventional vegetation indices have been shown to provide a poorer discrimination of burned areas than the NIR-SWIR bi-spectral space (Trigg and Flasse, 2001). The Normalized Burn Ratio index, based on post-fire surface reflectance in the NIR and 2.1 μm SWIR range, was developed specifically for burn mapping (Lopez Garcia and Caselles, 1991). Loboda et al. (2007) have demonstrated that delta NBR (dNBR), calculated as the difference between pre- and post-burn imagery, has the largest amplitude of post-fire response and therefore has the greatest sensitivity to fire-induced change in surface reflectance compared to other NIR/SWIR-based vegetation indices commonly used for burn detection. This sensitivity is particularly important for differentiating between burned and plowed fields in agricultural landscapes. MODIS is currently the only instrument collecting daily observations in the ~2.1 μm range. Several other systems include SWIR bands, including the Satellites Pour l'Observation de la Terre (SPOT) with a 1.58 to 1.75 μm range onboard the Visible and Infrared High Resolution (HRVIR), VEGETATION, and High Resolution Geometric (HRG) sensors, respectively. Additionally, a dNBR based algorithm has been successfully applied, using MODIS surface reflectance composites, to map burned areas in herbaceous cover dominated ecosystems including the sagebrush steppes of the U.S. (Loboda et al., 2007). Therefore, this study considers the spectral resolution of the 500 m MODIS land observations of higher importance than the spatial resolution of the 250 m data.

Additionally, the spatial resolution of the MODIS 500 m data (0.25 km^2 pixel area) is sufficient to map burned fields as small as 0.16 km^2 due to the practice of burning several neighboring fields during harvest in the U.S. (Canode and Law, 1979; Brye et al., 2006). Publicly available standard MODIS land surface products provide atmospherically corrected data. More importantly, the standard MODIS 8-day surface reflectance composites within the MOD09A1 product (Vermote et al., 2002), which include MODIS bands 1 through 7 at 500 m resolution, minimize obscuration of the surface by clouds while retaining a sufficient frequency of surface observations for burned area mapping in croplands.

The information on crop residue burning in smaller fields can be acquired using the fractional assessment of burned area inferred from actively burning pixels. The MODIS active fire product provides daily observations of burning with a nominal resolution of 1 km. Currently no higher spatial resolution (< 1 km) global daily active fire detection products are available. The overlap of data acquisition swaths in the latitudes of the study area allows for multiple daily daytime observations of fire activity (up to 2 times from each Terra and Aqua satellites). However, even with four daily overpasses the MODIS active fire product provides only episodic observations of on-going burning and is likely to omit a considerable portion of agricultural burning if used as the only method for crop burned area assessment. Despite the limitation imposed by the frequency of data acquisition, the MODIS active fire product is expected to provide additional information on the extent and amount of crop residue burning missed by the burned area algorithm.

2.3.3. Description of the Algorithm

The burned area retrieval algorithm follows the scheme presented in Figure 2-2. It detects areas affected by crop residue burning by combining burned area and active fire information in a hybrid approach. The algorithm was developed and tested using MODIS data collected over the 2003-2006 period. Additional data sources, used in the algorithm development, include high resolution satellite imagery from the 30 m Landsat Thematic Mapper acquired in 2004 and 15 m Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) acquired in 2003, 2004, and 2006 and *in-situ* GPS locations of burned fields collected during the 2004 and 2006 field campaigns. Methods and data used to derive burned area and active fire estimates are now described in turn.

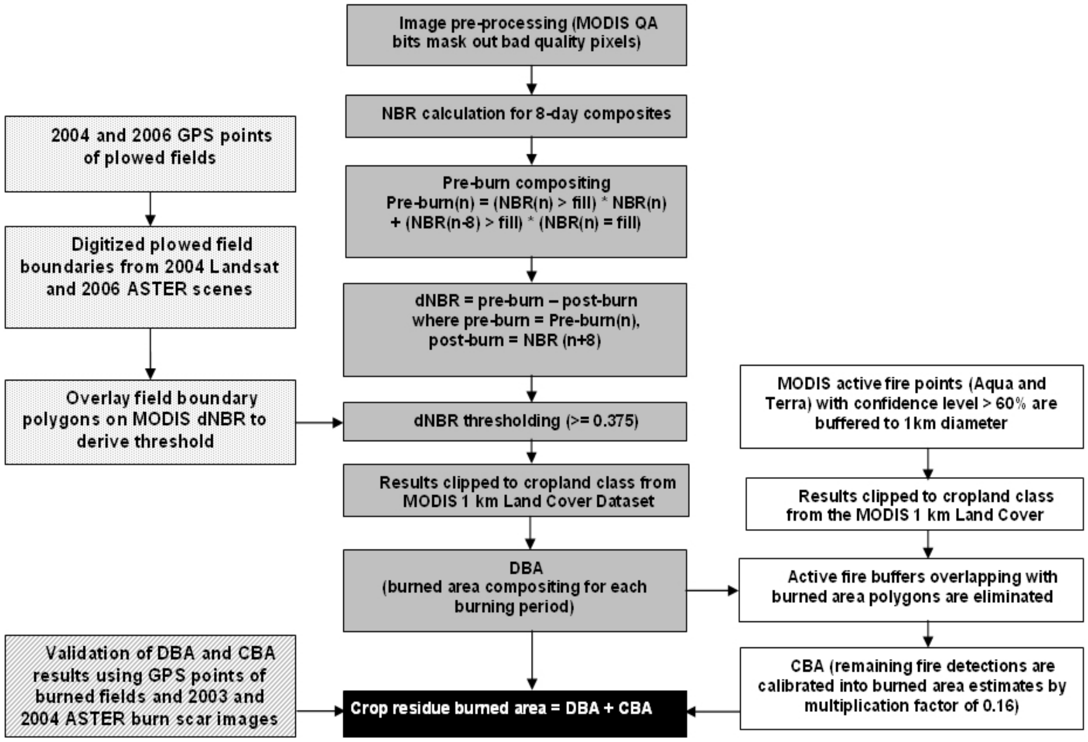

Figure 2-2. Description of data processing and burned area algorithm for croplands; n = composite date, NBR = Normalized Burn Ratio, and dNBR = differencing of the Normalized Burn Ratio. Different background colors show the data flow for different components of the hybrid approach: grey – dNBR based burned area mapping (DBA); white – calibrated active fire estimates (CBA); black – the combined estimates; grey dotted background - thresholding of dNBR values from *in-situ* data; grey diagonals - validation of DBA and CBA.

2.3.4. Processing Direct Burned Area: 500 m Burned Area Estimation from MOD09A1 MODIS 500 m 8-day Surface Reflectance Data

The MODIS 500 m 8-day surface reflectance composites were preprocessed to exclude low quality observations using the standard quality assessment bits provided within the MOD09A1 product. Table 2-1 provides a summary of quality values which were applied to the original composites. The pre-processed composites were then used to calculate NBR as the basis for detecting burned areas using MODIS Surface Reflectance product bands 2 (0.841-0.876 µm) and 7 (2.105-2.155 µm):

$$NBR = (band2 - band7)/(band2 + band7) \qquad (2.1)$$

The NBR was calculated from each pre-processed composite, then burned areas were identified through differencing of the NBR (dNBR) between pre- and post-burn images. The dNBR was calculated on the rolling 8-day differencing principle. In the rolling 8-day principle, missing NBR values for composite date *n*, resulting from removal of low quality input data at the pre-processing stage, were filled with acceptable quality values from the NBR image of composite date *n*-8. This reduced the omission of burned areas due to low quality observations in two subsequent 8-day composites. The gap-filled NBR composite was then considered to be the pre-burn NBR image *n*. The dNBR was calculated by subtracting the NBR image from day *n*+8 from the composited pre-burn NBR image *n*. The resultant 8-day dNBR images were thresholded at the value of 0.375 to identify burned areas.

Table 2-1. Accepted MODIS Surface Reflectance QA Science Data Set bit values from Loboda et al. (2007).

Quality bit parameters	cloud state	cloud shadow	land/water flag	aerosol quality	cirrus detected	PGE11 internal cloud mask	snow/ice flag	PGE11 internal snow mask
Value accepted	0	0	1	1-2	0-2	0	0	0

The 0.375 dNBR threshold was found to detect burned areas while minimizing commission error from plowed fields. To set the thresholds, GPS points were collected in 29 plowed fields during two field campaigns in Arkansas in 2004 and 2006. From these points, corresponding polygons of plowed fields were digitized from 2004 Landsat Thematic Mapper (30 m) and 2006 ASTER (15 m) images. These 29 observations had an average dNBR value of 0.276 with values ranging from 0.180 to 0.374. In order to eliminate errors of commission from plowed fields in the dNBR product to the fullest extent, the threshold was set at 0.375. It is important to note that dNBR thresholds are affected by the vegetation type and vegetative cover density (Loboda et al., 2007). Therefore, the developed threshold of 0.375 dNBR is not broadly applicable to mapping cropland burning across various geographic regions and crop types.

The thresholded dNBR images were subsequently merged into a single 'end-of-burning period' mask that retained the date of first observation as an attribute. Finally, the 'end-of-burning period' dNBR masks were clipped to a cropland mask. This cropland mask was derived from the cropland and cropland/natural vegetation mosaic classes within the MODIS 1 km Land Cover dataset (MOD12Q1) (Friedl et al., 2002). The resulting 500 m product is hereafter referred to as Direct Burned Area (DBA).

2.3.5. Processing Calibrated Burned Area: Burned Area Estimation from MOD14/MYD14 MODIS 1 km Active Fire Product

To capture the contribution from smaller “single-field” burning, active fire detections at 1 km resolution were included in the algorithm. This analysis used the

MODIS Active Fire Product provided by the University of Maryland Fire Information for Resource Management System (FIRMS) (NASA/UMD, 2002). The FIRMS system delivers point shapefiles identifying the centers of actively burning 1 km MODIS pixels. The FIRMS dataset was used instead of the standard MOD14 product due to its data format of shapefiles, which were easily integrated into this approach. Assuming the entire pixel burned would be a potential overestimation of burned area as the average agricultural field size in the MODIS tile h10v05 region is 0.16 km^2 (McCarty et al., 2007) or approximately 19% of the total 1 km pixel when accounting for true size of MODIS pixels (926 m by 926 m). The swath effect was not considered in this calculation. An assessment of burned area as a fraction of active fire detection pixel presents the basis for inferring the burned area amount from active fire detections.

To relate MODIS active fire detections to burned cropland, 10 ASTER scenes were used to assess the areas burned by fires detected by the MODIS active fire product. Both MODIS and ASTER instruments are flown on board the Terra satellite and are set to acquire temporally coincidental imagery close to the nadir viewing angle, thus providing a unique opportunity to analyze features at sub-pixel resolution within the MODIS 1 km imagery (Morisette et al., 2005). The 15 m ASTER scenes, used for the algorithm development, cover part of the Mississippi River in southeastern Missouri and eastern Arkansas and were acquired at exactly the same time as the MODIS active fire detections. Two dates were selected, the first from the spring harvest of 2003 (22 June 2003) and the second from the fall harvest of 2004 (5 October 2004) as these dates contained high numbers of active detections. For each

ASTER scene, both the visible flame/burn scar areas and the estimated field boundaries of each given fire were digitized in this synoptic comparison of Collection 4 MODIS active fire product (Giglio et al., 2003) to high resolution 15 m ASTER data. To make the burned area estimates from the active fire detections more representative of actual conditions, this analysis assumed the entire field burned rather than the fraction of field associated with the visible flame burned. This allowed two parameters to be estimated: area burned per MODIS active fire pixel area and number of false active fire detections.

The MODIS active fire product was assessed to determine the range of product confidence values that relate to flames and burned areas visually interpreted from the ASTER data. Initially, fire detections of all confidence values were included in the analysis. 42 active fire points were detected over the spatial coverage of the 2003 and 2004 ASTER images. The ASTER images from 22 June 2003 and 5 October 2004 contain 8 and 34 fire detections, respectively. Visual analysis of the ASTER data showed that 8 of the 42 total fires were false detections, whereby an active fire detection was recorded in a pixel where no fire was present. This analysis did not find any actively burning fires visible in the ASTER imagery omitted by the MODIS active fire detections. Approximately 81% of active fire detections corresponded to burned areas observed from the ASTER data. Closer inspection of the active fire metadata revealed the 8 false detections to have a product-specific confidence level less than 60%. This consistency of false detections for confidence vales less than 60% could be attributed to the sensor's modulation transfer function (MTF), which means that active fire detections with confidence values below 60%

may be responding to noise (atmospheric, surface, instrumental) rather than a thermal signal. Based on this finding, only MODIS active fires with a confidence level greater than or equal to 60% were included in the calculations. A coefficient for calibrating active fires into burned area was developed by analyzing the 34 active fire points that corresponded with the visually interpreted active fires and burn scars in the 2003 and 2004 ASTER images. Based on the ASTER analysis, the average burned area for the active fire points in cropland areas was 0.16 km^2, which is consistent with the average field size in the southeastern US. This study assumed that the presence of an active fire in the field means that the entire field ultimately burned, thus this method compensates for the omission of small burned areas by assuming that all active fire points with a confidence flag greater than or equal to 60% in cropland areas represent a burned area equal to 0.16 km^2. These active fire detection points were buffered to a 1 km diameter to simulate the MODIS 1 km pixels. This analysis also assumed that no field was burned twice during the same harvesting period. Subsequently, all active fire buffers overlapping with DBA polygons were eliminated from further analysis as the DBA pixels had accurately mapped the burned area of the active fires detected within a 1 km diameter. The final active fire burned area estimates were produced by multiplying the count of remaining non-overlapping MODIS active fire points by the correction coefficient 0.16 km^2. The resulting product is hereafter referred to as the Calibrated Burned Area (CBA).

2.4. Results

The results section provides an accuracy assessment of the DBA estimates and a brief overview of crop residue burning during 2003-2006. The calibration of the

MODIS active fire detections into amount of burned area (CBA) is based on the observed relationships between the MODIS pixels flagged as "fire" and the high resolution ASTER estimates of burned area, and thus does not require an additional accuracy assessment. However, the DBA product maps burned area independently of the input of high spatial resolution data. Therefore, an assessment of the mapping accuracy of the DBA product is crucial for understanding the overall accuracy of the burned area estimates provided by the hybrid approach.

The results from the hybrid DBA plus CBA burned area mapping approach are demonstrated for the state of Arkansas and the total study area within the MODIS tile h10v05. The results for Arkansas are compared with reported burned acreages and burn rates, estimated from the state-level statistics, to evaluate the algorithm performance during 2003-2006. Subsequently the analysis is expanded to assess the variability of cropland residue burning in the intensive agricultural landscapes within the study area of the project during 2003-2006.

2.4.1. Cropland Burned Area Accuracy Assessment

The accuracy of the DBA component of the final cropland burned area product was assessed using reference data developed from high resolution ASTER burned area and field reference data. Burned areas in ASTER images from 22 June 2003 and 5 October 2004 (described in section 3.3.2) were compared to the DBA polygons. These five scenes cover an area of approximately 26,000 km^2 or 2% of total area of MODIS tile h10v05. Field reference data was collected in burned fields during field campaigns in November 2004 and June 2006. This reference data covers more than eight counties in northeastern and eastern Arkansas and eight parishes in northeastern and southern Louisiana (Figure 2-3). Approximate locations of burned fields in Kansas for Sumner and Sedgwick counties during the 2006 summer harvest were used to qualitatively assess the accuracy of the DBA product.

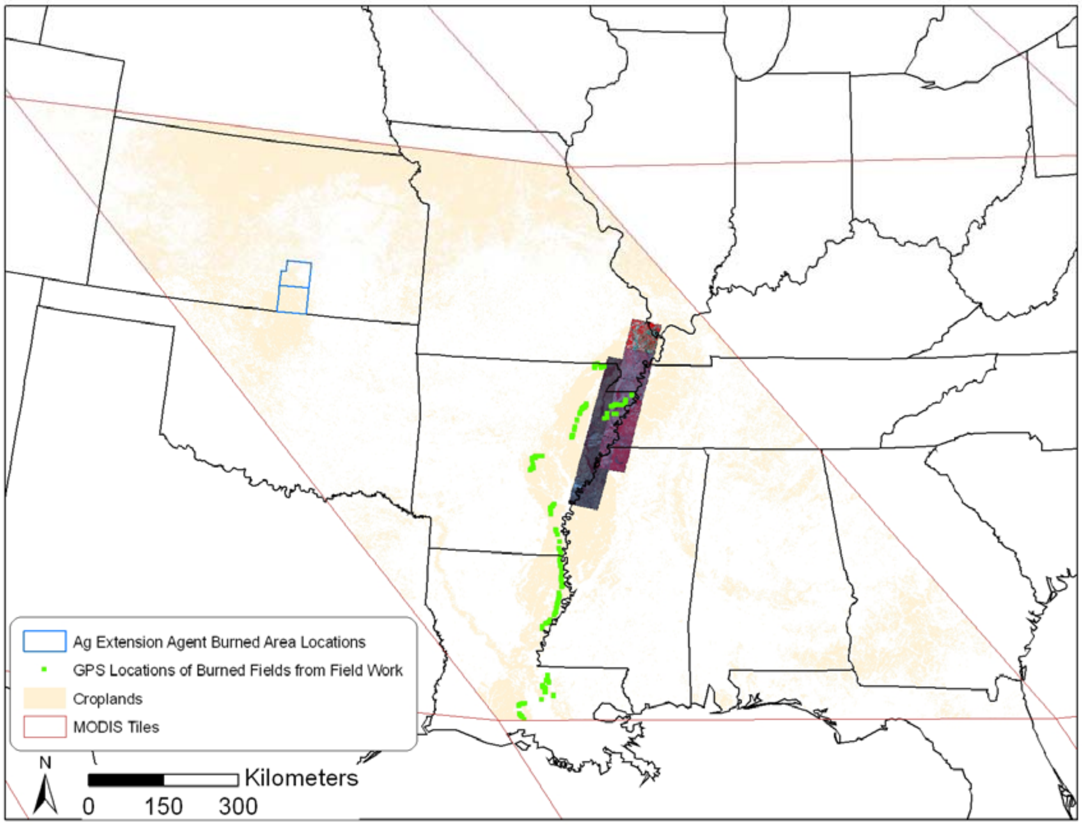

Figure 2-3. Location of validation data for MODIS tile h10v05; ASTER images shown in false color (projection: Albers Equal Area Conic).

To compare DBA estimates to burned area estimates from ASTER, MODIS validation protocols were followed (Hansen et al., 2002). Pixel averaging techniques were used to aggregate 15 m ASTER pixels to 500 m, comparable to the resolution of the DBA product. The DBA showed a slight overestimation of burned area for both

2003 (slope = 1.03, R^2 = 0.92, n = 58) and 2004 (slope = 1.06, R^2 = 0.93, n = 43) seasons (Figure 2-4). The clustering apparent in both years is related to the aggregation of the 15 m ASTER data to 500 m, where the averaged ASTER pixels produced similarly sized burned areas - a well defined artifact of averaging aggregation techniques (Bian and Butler, 1999).

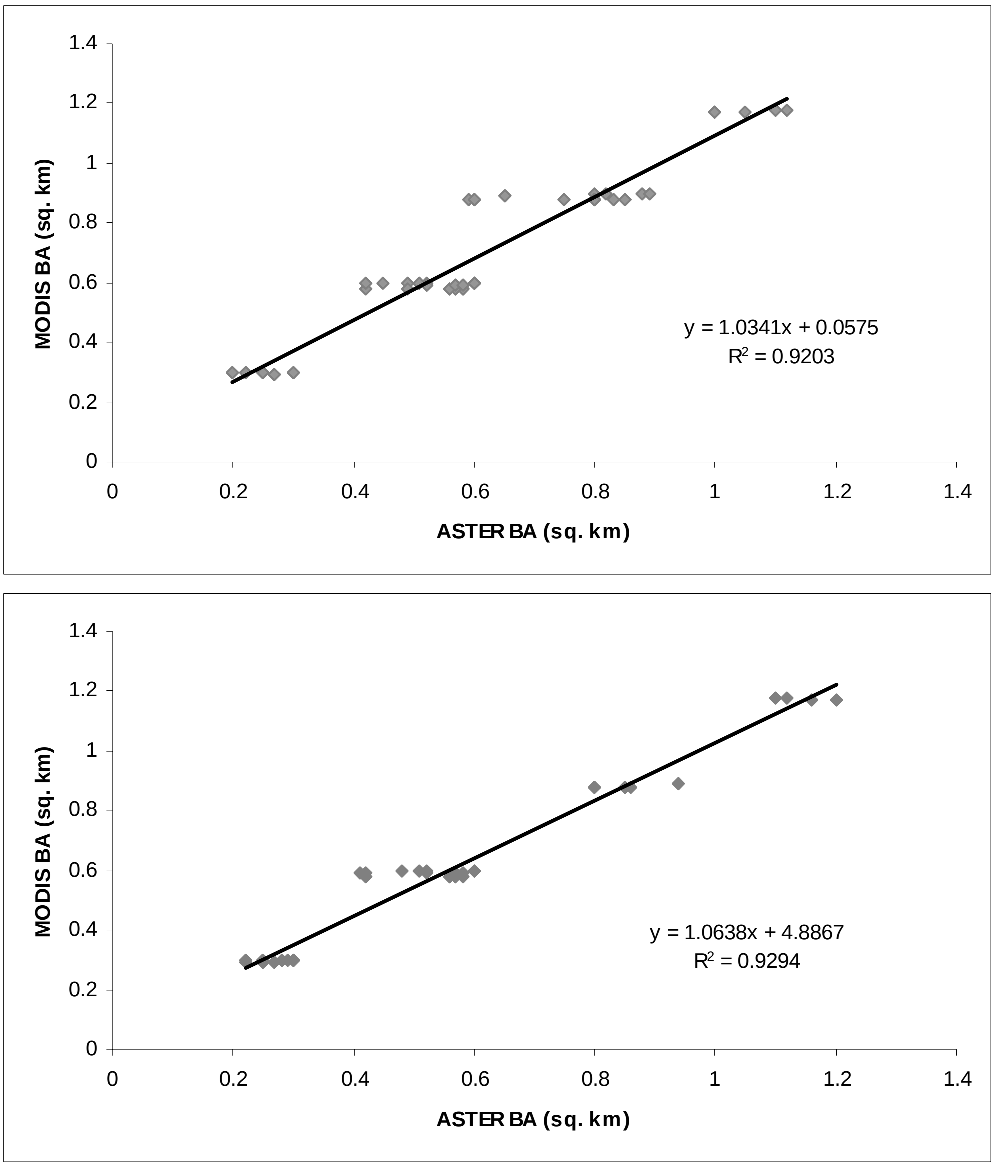

Figure 2-4. Accuracy assessment for MODIS DBA compared to ASTER burn scars aggregated to 500 m for years 2003 and 2004 (DBA = Direct Burned Area product).

There is a considerable amount of spatial disagreement between aggregated ASTER pixels and DBA mapped pixels (Tables 2-2 and 2-3); however, this is expected as a result of aggregating ASTER data to a coarser resolution. A random sample of 100 fields, both burned and unburned, was taken from both the five June and five October ASTER images and error matrices were completed. These burned and unburned field polygons were aggregated to 500 m. A DBA pixel was considered to be accurately classified as burned if 50% of the pixel overlapped with the ASTER burned field polygon or contained the entire ASTER burned field polygon. Figure 2-5 shows an example of the comparison between the 500 m DBA pixels with the digitized ASTER burned field polygons at the native 15 m ASTER resolution (prior to aggregating the pixels for comparison).

Table 2-2. Spatial accuracy of dNBR approach; error matrix comparing digitized burned and unburned polygons from the five 22 June 2003 ASTER images with DBA (DBA = Direct Burned Area Product).

	MODIS dNBR pixels				
		Burned	Unburned	Totals	User's accuracy
ASTER polygons	Burned	55	7	62	0.38
	Unburned	13	25	38	0.62
	Totals	68	32	100	
	Producer's accuracy	0.87	1.00		
	Percent correctly classified	80.0%			
	Kappa	0.79			

Table 2-3. Spatial accuracy of dNBR approach; error matrix comparing digitized burned and unburned polygons from the five 5 October 2004 ASTER images with DBA (DBA = Direct Burned Area Product).

	MODIS dNBR pixels				
		Burned	Unburned	Totals	User's accuracy
ASTER polygons	Burned	57	9	66	0.34
	Unburned	10	24	34	0.66
	Totals	67	33	100	
	Producer's accuracy	0.90	1.00		
	Percent correctly classified	81.0%			
	Kappa	0.80			

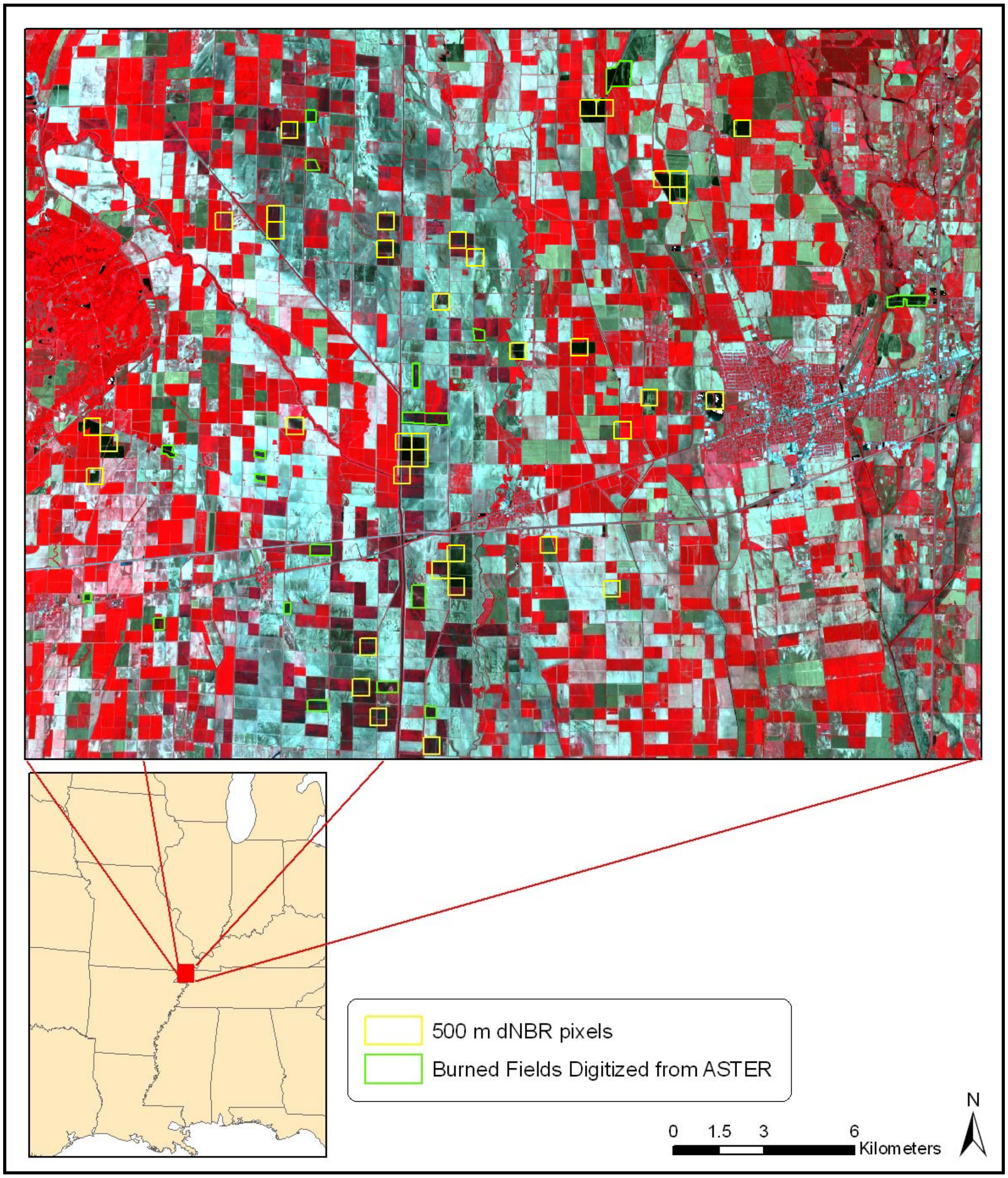

Figure 2-5. Example of spatial comparison of 22 June 2003 ASTER burned fields with estimated DBA pixels (500 m dNBR pixels) for the same time period; 500 m dNBR pixels shown in yellow and digitized burned fields from ASTER shown in green; DBA = Direct Burned Area product (projection: Albers Equal Area Conic).

The DBA estimates showed less spatial accuracy when compared with digitized polygons of burned and unburned fields from 22 June 2003 and 5 October 2004 ASTER images than the *in-situ* data. During the spring harvest in June 2003, the DBA accurately classified 80% of burned fields digitized from the ASTER images (n = 100 with Kappa of 0.79). The DBA performed marginally better during the fall harvest with 81% of burned fields accurately classified compared with the ASTER images (n = 100 with Kappa of 0.80). In both years, the user's accuracy for the predicted burned area (DBA) was low, with an average of 0.36.

The DBA also showed strong temporal agreement with the *in-situ* observations of burned fields collected over two field campaigns in Arkansas. For 2004, the DBA correctly classified 81% of the known burned fields (n = 21 with Kappa of 0.79) (Table 2-4). DBA showed greater agreement with the field data collected in 2006 with 90% of burned fields being correctly classified (n = 48 with a Kappa of 0.89) (Table 2-5). In general, the DBA produced accurate temporal estimations of cropland burned area with lower spatial accuracy compared with high resolution burn scar maps. Based on the spatial and temporal validation results, this analysis estimates the average accuracy (calculated as the mean of the percent correctly classified from all error matrices) of the DBA product to be approximately 82%. In general, this approach missed much of the cropland burning in small fields (Figure 2-5). It provides a conservative estimate of crop residue burning for MODIS tile h10v05.

Table 2-4. Temporal accuracy of dNBR approach; error matrix comparing 2004 ground truth burned area data with DBA (DBA = Direct Burned Area Product).

		DBA pixels					
		Oct 15	Oct 23	Oct 31	Nov 8	Totals	User's accuracy
Field data GPS counts	Oct 15	3	1	0	0	4	0.75
	Oct 23	0	7	1	1	9	0.78
	Oct 31	0	1	4	0	5	0.80
	Nov 8	0	0	0	3	3	1.00
	Totals	3	9	5	4	21	
	Producer's accuracy	1.00	0.78	0.80	0.75		
	Percent correctly classified	80.95%					
	Kappa	0.79					

.

Table 2-5. Temporal accuracy of dNBR approach; error matrix comparing 2006 ground truth burned area data with DBA (DBA = Direct Burned Area Product).

		MODIS dNBR pixels							
		May 9	May 17	May 25	Jun 2	Jun 10	Jun 18	Totals	User's accuracy
Field data GPS counts	May 9	3	0	0	0	0	0	3	1.00
	May 17	0	15	1	0	0	0	16	0.94
	May 25	0	0	2	0	0	0	2	1.00
	Jun 2	0	0	1	11	1	0	13	0.85
	Jun 10	0	0	0	0	6	1	7	0.86
	Jun 18	0	0	0	0	1	6	7	0.86
	Totals	3	15	4	11	8	7	48	
	Producer's accuracy	1.00	1.00	0.50	1.00	0.75	0.86		
	Percent correctly classified	89.58%							
	Kappa	0.89							

2.4.2. Localized Results: Arkansas

The hybrid DBA-CBA approach estimated the average burned area for croplands in Arkansas at approximately 1,746 km^2 for the spring harvest and 1,649 km^2 for the fall harvest (Table 2-6). Figures 2-6 and 2-7 show the burned area maps from the hybrid approach for Arkansas County, Arkansas and surrounding areas for both the spring and fall harvests of 2003 through 2006. The results demonstrate that the amount of crop residue burning changes considerably between 2003 and 2006 while the reported crop acreages remain fairly stable (USDA/NASS 2003; 2004; 2005; 2006). These crop acreages were based on the USDA statistics which are produced annually through a combination of state-submitted agricultural acreage estimates to the Agricultural Statistics Board and an annual, nation-wide ground-based survey of 11,000 parcels of land and 89,000 farm operators within the first two weeks of June (USDA/NASS, 2003). Experts estimate that ~ 40% of total winter wheat acreages are burned in Arkansas during the spring harvest (Personal communication with Dr. Jason Kelley, Arkansas State Wheat Specialist, Little Rock, Arkansas, 15 June 2006). Reid et al. (2004) used telephone and mail surveys of Agriculture Extension Service Agents to produce best estimates of acreages burned within the Central States Regional Air Planning Association. Approximately 2,651 km^2 of winter wheat burned in Arkansas in 2002, which is the same order of magnitude as the expert assessment. However, only 2003 and 2006 spring harvest crop residue burning matches these estimates.

Based on a comparison with *in-situ* data, the DBA estimates for the 2004 fall harvest and the 2006 spring harvest had accuracy rates of 81% and 90% respectively (see section 2.4.1); yet, the results for 2004 showed significantly less burned area for the spring harvest season and fall harvest seasons than the other three years. This decrease in burning might be explained by increased precipitation in 2004. During the fall harvest, precipitation in Arkansas was more than 17 cm above normal (NWS-

SRH, 2004) deterring the harvesting of soy, rice, and cotton and the planting of winter wheat (Crockett, 2004). Following the anomalously wet conditions of the harvest season in 2004, winter wheat acreages in Arkansas declined by 63% in spring 2005 (Robinson, 2005), consequently reducing the wheat residue burning during the 2005 spring harvest. The estimates from this analysis show a nearly 45% reduction in the amount of burned area in croplands during the 2005 spring harvest compared to the same time period during 2003 and 2006.

The results demonstrate more consistency in the total amount of area burned in fall crop residue burning. Although there is a large difference in the reported crop acreage between 2003 and other years (< 40% from the multi-year average), the total amount of burned area is the second largest during the 2003-2006 time period. The burn rate for fall 2003 was three times higher than 2004, 2005, and 2006. This may be explained by the record-breaking rice crop in fall 2003 (Johnson, 2003) whereby Arkansas farmers also faced record-setting residue levels in the fields.

Table 2-6. Burned area for croplands in Arkansas during the spring and fall harvest season with burn rate comparison of crops known to burn in Arkansas; crop area corresponds to wheat and rice acreages in the spring and rice and soy acreages in the fall (DBA = Direct Burned Area product; CBA = Calibrated Burned Area product).

Year	DBA (km^2)	CBA (km^2)	Total (km^2)	Crop Area (km^2)	Percent Area Burned	Harvest Season: Likely Crop Residues
2003	2,524.03	33.92	2,557.95	7,640.00	33%	Spring: Wheat/Rice
2004	863.40	19.84	883.24	7,640.00	12%	Spring: Wheat/Rice
2005	1,095.58	20.00	1,115.58	6,240.00	18%	Spring: Wheat/Rice
2006	2,395.93	32.96	2,428.89	7,332.00	33%	Spring: Wheat/Rice
Average	1,719.74	26.68	1,746.42	7,213.00	24%	Spring: Wheat/Rice
2003	1,698.13	152.48	1,850.61	5,800.00	32%	Fall: Rice/Soy
2004	1,056.24	48.48	1,104.72	18,200.00	6%	Fall: Rice/Soy
2005	1,686.14	202.88	1,889.02	18,132.00	10%	Fall: Rice/Soy
2006	1,683.84	66.72	1,750.56	17,820.00	10%	Fall: Rice/Soy
Average	1,531.09	117.64	1,648.73	14,988.00	14.5%	Fall: Rice/Soy

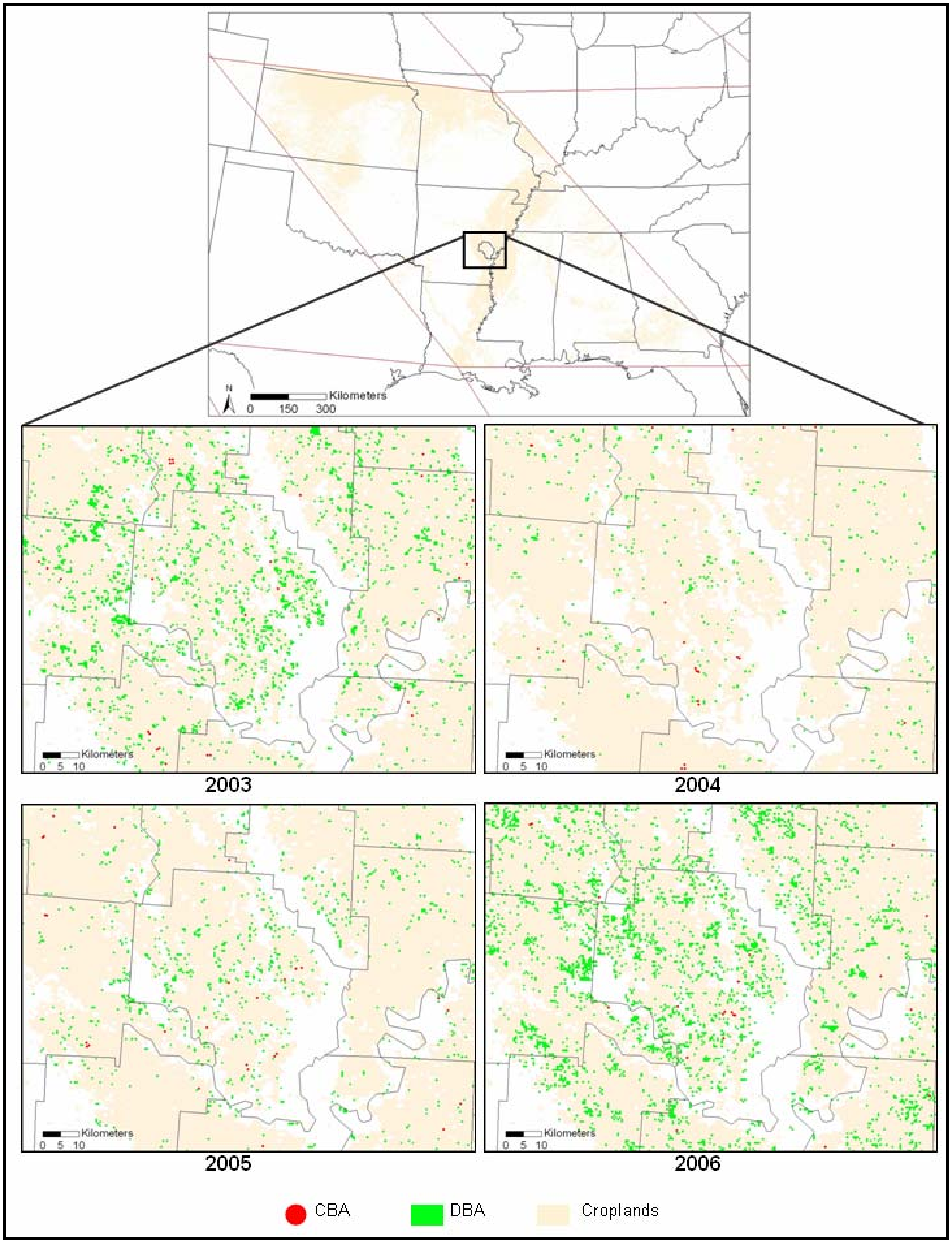

Figure 2-6. Crop residue burning results for 2003, 2004, 2005, and 2006 spring harvest for Arkansas County, Arkansas and surrounding areas (DBA = Direct Burned Area product; CBA = Calibrated Burned Area product); CBA not shown to true scale (projection: Albers Equal Area Conic).

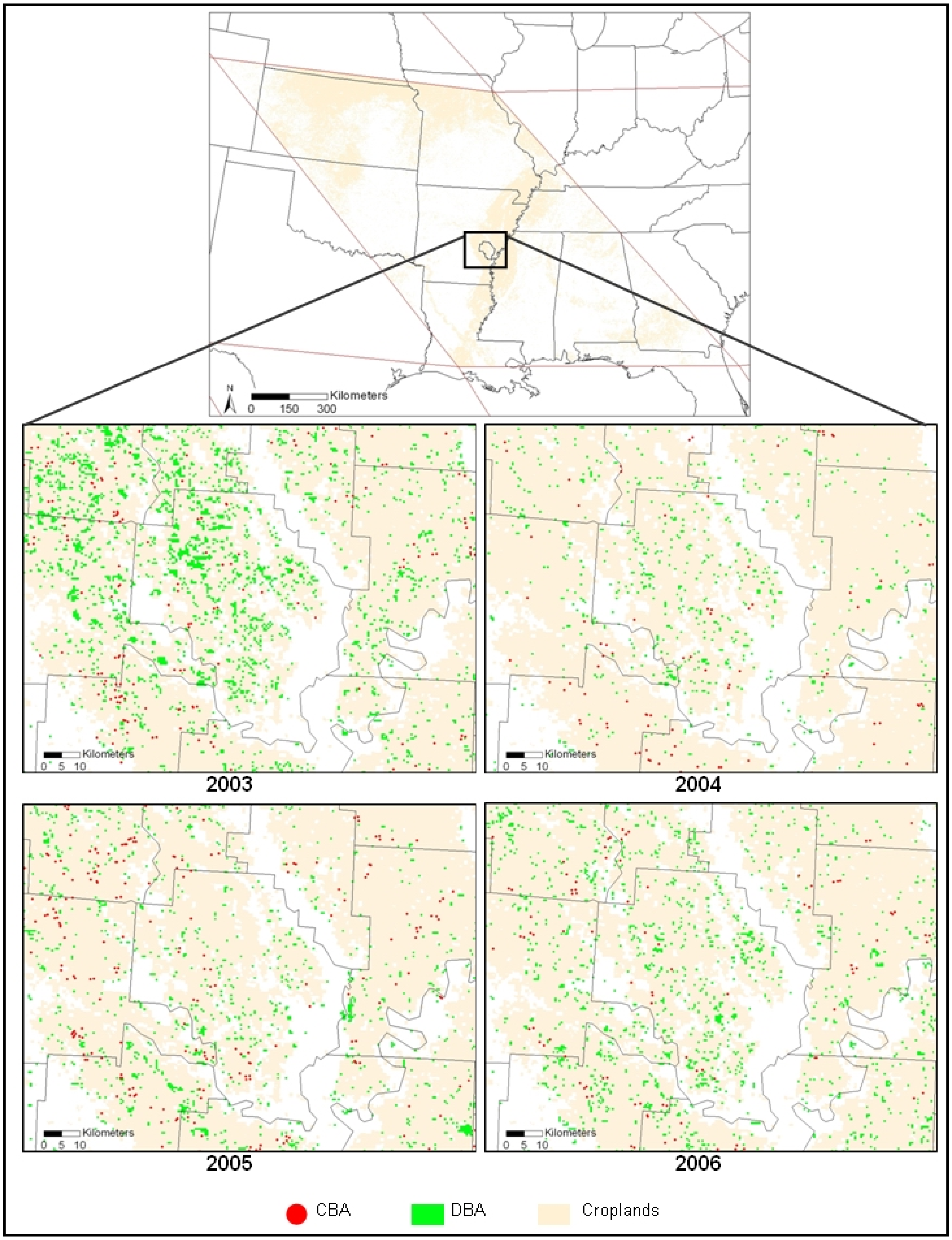

Figure 2-7. Crop residue burning results for 2003, 2004, 2005, and 2006 fall harvest for Arkansas County, Arkansas and surrounding areas (DBA = Direct Burned Area product; CBA = Calibrated Burned Area product); CBA not shown to true scale (projection: Albers Equal Area Conic).

2.4.3. Multi-Year Assessment of Crop Residue Burning for the Study Area

Similar to the findings in Arkansas, the results for the full study area show a considerable inter-annual variability in the amount of crop residue burning during 2003-2006. For 2003 the hybrid method detected approximately 19,850 km^2 of crop residue burning in harvest period 1 (spring) and 9,900 km^2 in harvest period 2 (fall); this equates to approximately 14% and 7% of the total cropland area, respectively. Year 2003 showed more burned area for the first harvest season (related to winter wheat harvest and clearing of stubble from rice and soy fields for planting) than the other three years but less burning in the second harvest season (associated with the rice harvest and clearing stubble from soy fields for planting). The area of crop residue burning for both harvest seasons for the years 2004, 2005, and 2006 was as much as 7% less than 2003. Crop residue burning for harvest seasons in years 2004, 2005, and 2006 accounted for 13%, 16%, and 15% of total cropland area respectively. Table 2-7 lists the combined burned area estimates of the DBA and CBA for croplands in the study area for both harvest seasons. On average, 12,719 km^2 and 10,836 km^2 burned in the spring and fall harvests, respectively.

State reporting of interannual crop residue burning area is unavailable for the study area. In addition to the study area of MODIS tile h10v05 having a similar interannual variability of cropland burning as in Arkansas, this analysis found that burning in Kansas followed the same pattern, with the highest levels of burning in 2003, a decrease in burning in 2004, and a gradual increase in burning both 2005 and 2006. The burning pattern related well to crop yield measurements, whereby greater amount of crop residue burning occurred in years with large crop yields. This phenomena is discussed later in Chapter 4.

Table 2-7. Burned area for croplands in MODIS tile h10v05 during the spring and fall harvest seasons (DBA = Direct Burned Area product; CBA = Calibrated Burned Area product).

Year	DBA (km^2)	CBA (km^2)	Total (km^2)	Harvest
2003	19,761.57	84.48	19,846.05	Spring
2004	7,550.12	85.12	7,635.24	Spring
2005	11,669.01	69.60	11,738.61	Spring
2006	11,577.25	79.52	11,656.77	Spring
Average	12,639.49	79.68	12,719.17	Spring
2003	9,559.28	313.92	9,873.20	Fall
2004	11,732.59	109.60	11,842.19	Fall
2005	10,966.90	416.00	11,382.90	Fall
2006	10,061.75	183.68	10,245.43	Fall
Average	10,580.13	255.80	10,835.93	Fall

The CBA estimates added between 0.5% and 4% area to the DBA estimates (Table 2-7). Although the CBA component did not change the total amounts of burned area considerably, it did improve the spatial aspects of mapping burned fields. On average during 2003-2006, 70% of active fire detections did not overlap with burned area. More importantly, 32% of non-overlapping active fire detections in MODIS tile h10v05 were detected in the same pixel location for three of the four years, indicating that the active fire points were capturing fields that repeatedly burned. On average, the CBA detected an additional cropland burned area of approximately 500 16 ha fields during the spring harvest and an additional cropland burned area of approximately 1,600 16 ha fields during the fall harvest. These detections represented small, single field fires that were missed by the direct dNBR-based assessment of burning at the 500 m spatial scale. In contrast, fire management of large tracts of continuous fields, mapped by the DBA algorithm, is unlikely to occur during sub-optimal burning conditions. Due to comparatively low crop residue biomass, the active fire product may miss cool agricultural fires and map only "special" cases. These cases may include either ideal conditions for active fire detection (e.g. low cloud cover, low aerosol emissions, close to nadir look angle) or fields with enough biomass accumulation to cause more intense burning. In addition, the current MODIS overpass times of 10:30 AM, 2:30 PM, and 6:30 PM local time provide only snapshots of crop residue burning, which was observed in the field as a continuous process from mid-morning (approximately 10:00 AM local time) until the evening (approximately 7:00 PM local time). An increase in the number of fire detections not overlapping with the DBA within the agricultural areas was found during the fall season (mean of 1400 detections in the fall compared to a mean of 500 detections in spring); this appeared to be attributed to less precipitation in the fall (NCDC, 2008a) and could also be related to the increase in rice, soy, and corn fields burning, which tend to be smaller than wheat fields.

2.5. Discussion

The specifics of crop residue burning in the intensive agricultural areas of the U.S. present a unique set of requirements for satellite monitoring of crop residue burning. Hourly observations of on-going burning activity at ≤1 km resolution in combination with daily observations of post-fire impacts in NIR and ~2.1 μm SWIR spectrum at ≤250 m resolution (based on the mean 0.16 km^2 field size of the intensive croplands in the U.S.) would be ideal for providing a close-to-comprehensive view of crop residue burning in the U.S. However, no current satellite systems are exceptionally well-suited for mapping or monitoring crop residue burning. This analysis shows that inferring the amount of crop residue burning from active fire detections acquired by polar orbiting satellites (e.g. MODIS) provide a largely limited view of fire activity in agricultural landscapes. Fire detections calibrated into burned area contributed < 4% of the total burned area estimated by the algorithm used in this analysis. However, despite the small overall contribution to the total amount of burned area, active fire detections add important information on the spatial distribution of agricultural burning omitted by the DBA-based burn maps. Nearly 70% of active fires were detected in areas non-overlapping with DBA maps, representing a large group of small sources of potential emissions and pollutants not accounted for within the estimates from multi-field burning practices. Consequently, if burned area mapping is undertaken in part for spatially explicit air quality assessment purposes, the inclusion of the CBA component is highly important as burning of crop residues affect nearby rural and urban populations (Dhammapala et al., 2006).

The DBA approach provides better estimates of the amount of crop residue burning than the CBA. However, the current resolution of the input data, particularly for the 500 m MODIS ~2.1 μm band, limits its capabilities to fully map burned fields. Mapping phenomena that occur at finer scale than pixel resolution lowers the algorithm's ability to map a similar object (e.g. burned field) consistently. The position of a burned field of 0.16 km^2 within the MODIS 500 m pixel (~ 0.25 km^2) influences the magnitude of dNBR change; the dNBR will be higher if the 500 m pixel is centered on the entire field compared to a position of the field in the corner of the MODIS pixel or on the boundary of two neighboring 500 m pixels. The spatial resolution of 250 m (~0.0625 km^2) is smaller than the average field size and is more likely to capture the change due to burning within a single field and thus improve the total burned area estimates.

The presented hybrid approach focuses on mapping harvest related crop residue burning. Although management fires occur in croplands during seasons other than harvest, this assessment shows that the amount of area burned during non-harvest related management fires (e.g. pest and weed management) is close to negligible. The analysis of active fire detections shows that ~94% of cumulative yearly active fires are found within the two time windows identified in this analysis as harvest periods. In terms of air quality, this cropland burning occurring before and after the harvest periods is unlikely to be a significant contributor, as these fires are more than likely the burning of fallow fields (Personal communication with Dr. Steve Van Vleet, Agriculture Extension Agent for Whitman County, Washington State University, 7 April 2008).

The large inter-annual variability of burned area estimates shown by these results emphasizes the importance of developing direct monitoring approaches for crop residue burning assessment. The analysis of crop residue burning in Arkansas demonstrates that indirect assessment methods (e.g. burned area as a fractional assessment of crop acreage) can over- or underestimate the actual amount of burned area during a single year by a large margin. In addition, the direct observations allow for developing spatially explicit and temporally dynamic models of emissions and air quality estimates.

2.6. Conclusions

Crop residue burning is a widespread agricultural practice in the established intensive agricultural landscapes of the U.S. The emissions from these fires have local and regional impacts on atmospheric composition and air quality. Indirect methods of emission estimates rely on large, simplifying assumptions and often lead to estimates of unknown accuracy. Satellite observations provide an opportunity for development of direct observations of crop residue burning and strengthen the understanding of the contribution from cropland fires to the biogeochemical cycles. Although the current satellite systems do not meet the exact requirements posed by the specifics of agricultural burning, the combination of multiple daytime observations of on-going fire activity at 1 km resolution and daily observations of surface reflectance in the NIR and ~2.1µm SWIR range at 500 m resolution presents MODIS as the most appropriate instrument for mapping burned areas in croplands of the CONUS.

The hybrid approach of combining the dNBR-based approach with calibrated active fire detections has strong potential for cropland burned area mapping applications. The hybrid approach shows moderate agreement with known burned areas from both ground reference data and high resolution ASTER images. Both the DBA and the CBA products within the hybrid algorithm can be readily replicated by various users as they are based on operational MODIS products. The DBA accounts for more than 96% of total crop residue burned area estimated by the hybrid approach. The contribution of the CBA to the burned area mapping capabilities is that is provides additional information about the volume and geographic distribution of total crop residue burns. This analysis found that the CBA consistently mapped the same small fields which burned for three of the four years. In addition, 70% of the CBA detections did not overlap with the DBA estimates. The small improvement in areal estimates and spatial precision of crop residue burning from the CBA would be useful for near-real time air quality monitoring. In addition, the CBA estimates can calculated between 1 to 2 days from detection of burning, meaning that the burned area estimates from the CBA could provide real-time information on crop residue burning distributed to policy makers, agriculture officials, and farmers. The current DBA production requires a 16 day lag in order to produce the dNBR estimates from two 8-day MODIS surface reflectance composites. The combination of the DBA and CBA estimates in the hybrid approach presents a more comprehensive assessment of crop residue burning at the regional and national scales.

The intra- and inter-annual dynamics of crop residue burning, demonstrated in this study, promote the need for development of better systems aimed at monitoring crop residue fires in the CONUS. Such systems or constellations of systems should include enhanced capabilities for hourly observations of ongoing burning activity at ≤ 1 km resolution and daily mapping of burned area at ≤ 250 m resolution in the NIR and ~2.1µm SWIR spectral space. In the absence of systems specifically adapted for fire monitoring in croplands, the hybrid MODIS burned area mapping approach provides a reliable and accurate method to quantify burned area. A threshold, set for this study area of MODIS tile h10v05 at 0.375, successfully eliminated plowed fields in the selected study area. However, a different threshold may be needed for cropland areas with lighter or darker soil. Due to its moderate accuracy, readily available data, and relatively short processing time from satellite retrieval to end product, the presented approach could be used to monitor and quantify local, state, and regional crop residue burning - a burgeoning concern and initiative for a growing number of users in the agricultural community (FL DOF, 2007; ISDA, 2007; WA DOE, 2007).

Chapter 3: Regional Approaches for Crop Type Mapping: Identifying Crop Types Commonly Managed with Fire in the Contiguous United States[2]

This chapter presents a decision tree-based classification methodology for crop type mapping using coarse MODIS data at the resolution of 250 m. This approach divides the CONUS into 10 crop regions based on crop distributions, management practices, and crop rotation patterns. Region and growing season-specific crop type maps developed with this approach are large area classifications of crop types and crop rotation patterns, particularly for non-commodity crops that are managed by fire. Results from this analysis are further used in chapter 5 to estimate air quality and carbon emissions from crop residue burning.

3.1. Use of Remote Sensing for Agricultural Mapping

Remote sensing has long been used for land cover and land use mapping (Tucker et al., 1985; Townshend et al., 1987; Loveland et al., 1991; DeFries and Townshend, 1994; Hansen et al., 2003). Natural vegetation, like forests, shrublands, and grasslands, has been the main focus of land cover and land use mapping initiatives. In many coarse and moderate resolution land cover maps, all crop types are aggregated into one agriculture class (Loveland et al., 1999; Friedl et al., 2002; Bartholomé and Belward, 2005; McCarty et al., 2007).

Historically, remote sensing has been a useful tool to monitor crop conditions and to provide estimations of crop area and type. Starting in the 1970s, Landsat data

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[2] Much of the presented material in this chapter has been submitted for publication in McCarty JL, Carroll M, and DiMiceli C (submitted) Regional approaches from crop type mapping in the contiguous US. *Journal of Applied Remote Sensing*.

drove agricultural mapping initiatives such as the Corn Blight Experiment (MacDonald et al., 1972), the Large Area Crop Inventory Experiment (LACIE) (MacDonald and Hall, 1980), and the Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing (AgRISTARS) (NASA, 1984). While the Corn Blight Experiment proved to be less than successful in identifying crops before disease on-set (Bauer et al., 1971), the LACIE and AgRISTARS programs developed robust methods and demonstrated the usefulness of moderate resolution data for crop identification assessments (Moran et al., 1997).

Mapping specific crops has been difficult to accomplish at coarse resolutions, specifically as individual cropped fields comprise small areas within a larger agricultural region. Loveland et al. (1991) differentiated winter and spring wheat from other crops in the CONUS using 1 km Advanced Very High Resolution Radiometer (AVHRR) data, but were forced to group all other crop types into a "row crop" class. Similarly, Salazar et al. (2007) used 1 km AVHRR data to map winter wheat distributions and related yield estimates in Kansas. MODIS data at the 250 m and 500 m resolutions were successfully used to distinguish spring wheat and maize rotation in the Yaqui Valley, Mexico and winter wheat in Oklahoma, U.S. (Lobell and Asner, 2004) and rice paddies in southern China (Xiao et al., 2005), respectively. Most analyses combined data over a few months or a year to produce their single date or single year classifications (Loveland et al., 1991; Lobell and Asner, 2004; Van Niel and McVicar, 2004), failing to capture crop rotations, i.e., multiple crop type maps in a calendar year or over many years.

Detailed and consistent crop type mapping is an important component of remotely-sensed land use and land cover mapping that provides independent assessments of crop areas, crop distributions, and input for crop yield modeling (Salazar et al., 2007; USDA/NASS, 2002; Chang et al., 2007). Unlike natural ecosystems, croplands are intensely managed through human actions like plowing, crop rotation, burning residues, application of pesticides and herbicides, irrigation, and other activities. The management of croplands can have serious impacts on local and regional soil and water quality, ecosystem functions, climate, air quality, and human health (Brye et al., 2006; Dhammapala et al., 2006; Wardlow and Egbert, 2008).

Remote sensing-based analyses of crop type are often focused on small study sites representing a single research field to a state or province (Weissteiner and Kuhbauch, 2005; Patel et al., 2006; Ortiz-Monasterio and Lobell, 2007). Del Frate et al. (2003) used C-Band Synthetic Aperture Radar (SAR) data with a spatial resolution of 30 m to distinguish seven separate crop types (barley, maize, grass, potato, rapeseed, sugar beet, and wheat) at the Flevoland research site in The Netherlands. Crop rotation patterns in a wheat-maize-soybean production system for the years 1993 and 1994 were distinguishable in the Yaqui Valley, Mexico using 30 m Landsat data (Lobell et al., 2002). Ren et al. (2007) used 250 m MODIS Normalized Difference Vegetation Index (NDVI) to estimate yields of winter wheat in Shandong Province, China. On a larger scale, Wardlow and Egbert (2008) showed the effectiveness of using an annual time-series of 16-day composite 250 m MODIS NDVI data to map a single year distribution (2001) of alfalfa, corn, sorghum, soybeans, winter wheat, and fallow areas in Kansas. Similarly, Chang et al. (2007) used 32-day composite 500 m MODIS visible, near infrared, mid infrared, NDVI, with 1 km land surface temperature data to classify corn and soy for the 2002 summer growing season in the central U.S. What is lacking in the published literature is the application of regional classifications to create near-national scale crop type classification maps over several years.

The objective of this research is to accurately classify crop types where fire is a common tool for removal of residue. Current crop type mapping research focuses on commodity crops (Lobell et al., 2003; Patel et al., 2006; Chang et al., 2007; Ren et al., 2007), potentially missing crops and associated residues known to burn. Crop types managed with fire included in this study are wheat, rice, sugarcane, Kentucky bluegrass, and lentils (Canode and Law, 1979; Eiland, 1998; LSU Ag Center, 2000; Dennis et al., 2002; Brye et al., 2006; Dhammapala et al., 2006; McCarty et al., 2007), in addition to the commodity crops of soy, corn, and cotton. Of particular interest to this study is the sub-objective to determine if regional approaches to crop type classification using 250 m MODIS 16-day composites will produce accurate multiyear crop type maps for the CONUS. To map areas with well-defined intra-annual and inter-annual crop rotation patterns, growing season crop type maps were produced using the 250 m MODIS 16-day composites for 10 crop management regions in the CONUS.

3.2. Data and Methods for Crop Type Mapping

3.2.1. Definition of Crop Management Regions in the CONUS

To complete regional-based crop type mapping, crop management regions were developed for this study. Figure 3-1 shows the ten crop management regions for the CONUS. These ten different crop type regions are based on known crop distributions (Leff et al., 2004) and management practices related to crop residue burning. For example, regions 4 and 5 in the southeastern U.S. were developed to isolate areas which have distinct intra-annual crop rotations and unique crop types from the annual crop rotation patterns of the majority of the CONUS. Two intra-annual crop type maps were then produced for regions 4 and 5, providing more accurate crop type mapping due to the intra-annual rotation of crops between the spring and fall harvest. The USDA provides comprehensive statistics on average field size and crop type by state (USDA, 2002). This detailed agriculture information was also used to develop the crop management regions.

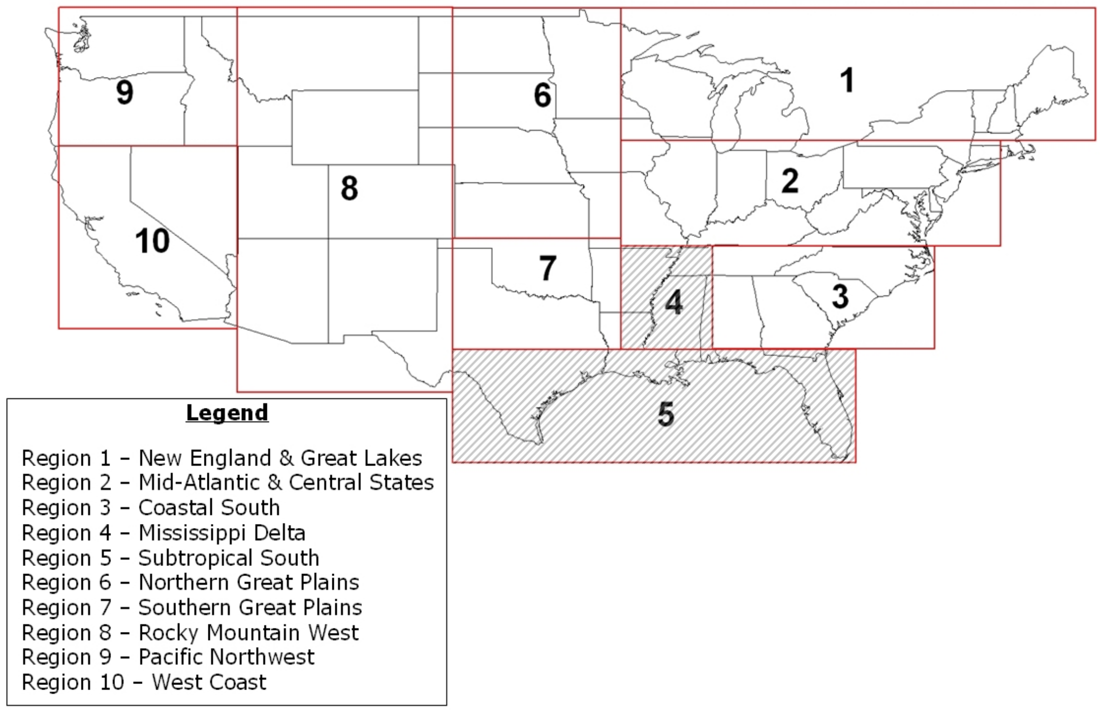


Figure 3-1. Crop management regions for CONUS crop type mapping; regions with dashed boxes indicate biannual crop type maps for the spring and fall harvests; regions with white boxes indicate crop type maps for fall harvest only; regions defined using USDA statistics and reports (projection: Geographic).

The crop management regions delineate areas of similar cropping patterns and rotations and do not follow political boundaries. Crop patterns are defined in this analysis as a cropping system which is characterized by its dominant crop types (Leff et al., 2004). Dominant crop types were gathered from USDA statistics (USDA, 2002) and annual acreage reports (USDA/NASS, 2003a; 2004a; 2005; 2006). Most states fall into one crop management region but some states are split between regions. For example, Arkansas was split between regions 4 and 7 in order to delineate the multi-cropped system along the Mississippi River (region 4) and the corn and wheat-dominated system in western Arkansas (region 7). Likewise, Louisiana was split between three regions due to the variety of crop patterns in the state that range from winter wheat, soy, cotton, and rice in the northeast (region 4), to a sugarcane-rice mosaic in the south (region 5), and a wheat-corn system in the northwest (region 7).

Two crop management regions cover the northern and eastern U.S. Both regions 1 and 2 have highly urbanized and suburbanized landscapes along the coast. Since 1900, farmland has been converted to forests and residential development (Houghton and Hackler, 2000). In region 1, agriculture is mainly in the form of dairies, orchards, and vegetable farms, though large areas of corn, soy, and wheat are present, especially in New York. Much of region 2 encompasses a large urban area (megalopolis) and a large mountainous region (the central Appalachians). The majority of crops in this region are fruit and vegetable crops grown for local markets or as subsistence farming in the Appalachian Mountains. Corn, sorghum, soy, and winter wheat are also grown. Along the Great Lakes and the Central U.S., corn, soy, and winter wheat are the dominant crops. Corn grown in these two regions is used for both silage (livestock feed) and grain (food production). Dairies and orchards are also common. For regions 1 and 2 the average field size ranges from 0.16 km^2 (16 ha) to 0.24 km^2 (24 ha) along the coasts and as large as 0.48 km^2 (48 ha) in the western parts of the regions.

Regions 3, 4, and 5 represent the diverse agricultural regions in the southeastern U.S. The main crops in region 3 are cotton and soybean. Corn and winter wheat are grown but generally as rotation or cover crops, i.e. planted to renew nutrients in top soils, and therefore make up much smaller areas. Region 4 has a well defined intra-annual crop rotation whereby winter wheat is harvested in May and June and replaced by soy or rice. Cotton and corn are also major crops for this region. Crops grown in region 5, like sugarcane and rice, thrive in this hot, humid climate. Cotton is a secondary crop for this region. For regions 3, 4, and 5 the average field size is 0.16 km^2 (16 ha) though some fields are as large as 0.24 km^2 (24 ha). All major crops grown in regions 3, 4, and 5 are managed through residue burning (Brye et al., 2006; McCarty et al., 2007).

Regions 6 and 7 comprise the "bread basket" of the CONUS. Wheat, both the winter and summer varietals, is the dominant crop for much of these regions, with corn and soy dominating the states of Iowa, Nebraska, and Missouri. Other grains also grown here include sorghum, barley, hops, and hay for livestock feed. Burning grain crop residues after harvest in the spring and summer and/or before planting in the fall is common (KDHE, 2008). The average field size for these two regions is 0.48 km^2 (48 ha).

Region 8 is mainly the mountainous areas of the western and southwestern U.S. Much of this region, including the Rocky Mountains, is covered by open rangelands and forests. This region has remnants of the corn and wheat belt in the eastern sub-region and the beginning of the potato and sugar beet belt in the northwest sub-region. Sorghum, barley, and other grains are also common. In contrast, much of northeastern Utah is used for both fruit and vegetable cropping to support the growing population near Salt Lake City and represents a $1.8 million industry in the state (USU, 2003a). Arizona and New Mexico are also included in this region and mainly grow irrigated cotton and wheat. These two states have a total cropland area of approximately 34,500 km^2 (3,450,000 ha), which is just 60% of the total cropland area reported in Colorado. However, Arizona and New Mexico are included in region 10 as crop residue burning is a common tool in these states (WRAP, 2002). Like regions 8 and 9, the average field size in region 8 is 0.48 km^2 (48 ha).

The west coast of the CONUS is split into regions 9 and 10. Though large tracts of forest are present in region 9 (Pacific Northwest), a significant agricultural area exists in eastern Washington, northern and southwestern Idaho, and northeastern and southern Oregon. In eastern Washington, northern Idaho, and northeastern Oregon, winter and summer wheat and Kentucky bluegrass seed production dominate the agricultural landscape (Dhammapala et al., 2006). Other crops, such as lentils, mustard seed, potatoes, mint, and barley, are also grown but in smaller fields (Personal communication with Dr. Steve Van Vleet, Whitman County Extension Agent, Colfax, Washington, April 2007). In southwestern Idaho, the major crops are grown in the Snake River Valley and include potatoes, sugar beets, and various vegetable crops (ISDA, 2006). In southern Oregon, potatoes and sugar beets are grown as well as onions and alfalfa hay (ODA, 2007). Additionally, much of the land in southern Oregon is used for grazing cattle and dairies. Crop residue burning is a major management activity in region 9 with wheat, bluegrass, lentils, and other small grain residues burned after harvest and/or before the planting (Dhammapala et al., 2006).

Croplands in region 10 are mainly found in California, particularly the areas of the Central Valley and the Salton Sea. The Central Valley is a very large agricultural and agro-industrial area. Many crops are grown in the Central Valley, including rice, wheat, cotton, fruits (berries and orchards), and vegetables (spinach, broccoli, various squash, beans) (CDFA, 2007a). Around the Salton Sea, the Imperial and Coachella Valleys have become major agricultural areas, producing fruits and vegetables year-round. In addition to various fruits and vegetables, wheat, sugar beets, and sorghum are grown in the Imperial and Coachella Valleys (CDFA, 2007b). Many crops are managed with fire in region 10, including wheat, rice, and cotton (CARB, 2006). For regions 9 and 10 the average field size ranges from 0.48 km^2 (48 ha) to 1.01 km^2 (101 ha).

3.2.2. MODIS Data

Daily MODIS surface reflectance data were combined for each 16-day period to create a single output that is representative of the period. This was done to reduce total data volume, and it has been shown that this can still produce a representative value useful to most applications (Holben et al., 1986). The compositing procedure happens inside the MODIS Adaptive Processing System (MODAPS) as part of the standard production of MODIS products. The MOD44C composite is the base product for both MODIS Vegetative Cover Conversion (Collection 4) and MODIS Vegetation Continuous Fields (Collection 5) (Carroll et al., unpublished book chapter). The basic rule for compositing is to obtain the most cloud free, near nadir observation to represent the composite period.

Previous research has shown the effectiveness of using 250 m and 500 m MODIS to map individual crops (Lobell and Asner, 2004; Xiao et al., 2005; Chang et al., 2007; Ren et al., 2007; Wardlow and Egbert, 2008). For this study MODIS 250 m red, NIR, and NDVI data were used to classify crop types for all crop management regions of the CONUS. Figure 3-2 shows the spectral signatures derived for the seven focus crops of this analysis and the fallow/other class. These spectral signatures are the mean values of 100 non-cloudy pixels extracted per crop type for each year of the study (2003-2007), resulting in a sample size of 500 pixels. While many of the focus crops have similar red and NIR values, consistent with other signature-based analyses (Lobell et al., 2003; Roa, 2008), the NDVI values show a larger degree of separability that could be utilized to identify individual crop types. Thus, the 250 m MOD44C composites provide enough information for crop type mapping.

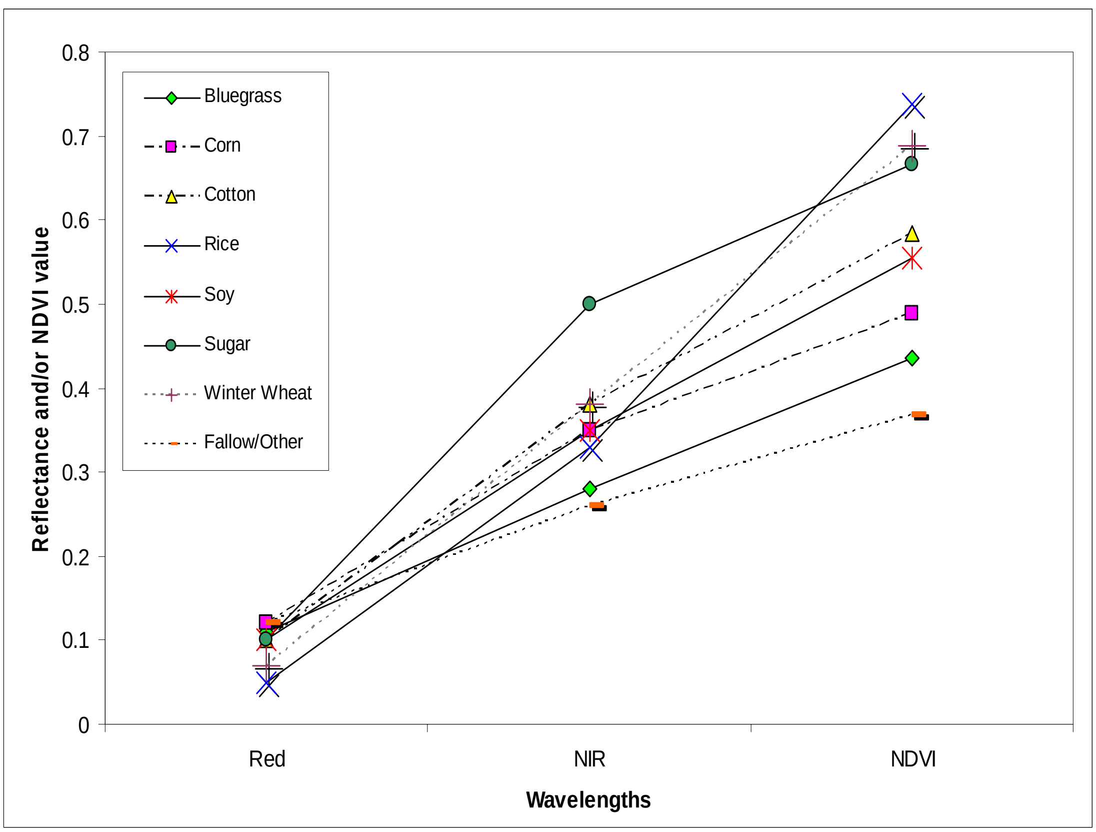


Figure 3-2. Spectral signatures of MODIS 250 m red, NIR, and NDVI bands for eight focus crops in the CONUS.

The 250 m spatial resolution was specifically used in order to accurately map smaller fields in much of the eastern U.S. For example, the fields in crop management regions 1, 2, 3, 4, and 5 can be as small as 16 ha in the southeast and as large as 48 ha in the central states. Approximately two 250 m pixels are needed to accurately map a field the size of 16 ha, approximately four 250 m pixels can map a 24 ha field, and eight 250 m MODIS pixels are needed to map a 48 ha field. Therefore, even the smallest average field size requires more than one 250 m MODIS pixel.

High rates of misclassification are a possibility for regions with average field sizes of 16 ha, whereby approximately two 250 m pixels comprise a single field and adjacent pixels of differing crop types (and spectral values) would produce confusion in any classification method. This effect was particularly evident in crop management regions 1 through 5, which have average field sizes ranging from 16 ha to 24 ha. A preliminary analysis of the USDA National Agricultural Statistics Services (NASS) Cropland Data Layer (CDL) product showed that individual crop types in the eastern and southeastern U.S. were predominantly clustered - which produces large, contiguous areas of single crop types. Though a single, small field was comprised of two 250 m pixels, the surrounding fields were in general the same crop type, meaning that several 250 m pixels were needed to map these areas. Therefore, crop type mapping in regions with 16 ha fields was not performed at the field-level but rather at a sub-regional scale.

For the majority of regions a single, annual crop type map was produced using two 16-day composites that are representative of summer peak greenness. The 16-day composites representing summer peak greenness were Julian dates (JD) 225 (13

August - 28 August) and 241 (29 August - 13 September). The results from the summer growing season classification will be referred to in this paper as the fall harvest classifications. For crop management regions 4 and 5 (Figure 3-1), an additional set of two 16-day composites were used to produce a crop type classification that coincides with the winter-spring growing season, which is harvested in the end of May and beginning of June (McCarty et al., 2007). The winter-spring growing season results were produced using 16-day composites from Julian dates 113 (23 April - 8 May) and 129 (9 May - 24 May). The results from the spring classification will be referred to in this paper as spring harvest classifications.

3.2.3. Crop Type Training Data

Consistently, the USDA NASS Spatial Analysis Research Section has produced fine resolution CDL product since 1997 using both 30 m Landsat (1997 to 2005) and the 56 m Indian Remote Sensing Advanced Wide Field Sensor (AWiFS) (2006 to present) (Personal communication with Mr. Rick Mueller, Section Head of USDA NASS Spatial Analysis Research Section, Fairfax, Virginia, February 2008). The purpose of the CDL is to enhance state-level crop acreage estimates for the USDA NASS. Yield estimates from the CDL have consistently matched ground-based yield estimates (USDA/NASS/RDD/SARS, 2002). USDA/NASS follows a regional approach for crop acreage estimation that compares satellite imagery with ground truth data (USDA/NASS/RDD/SARS, 2007). Since 2006, cloud-free AWiFS scenes from both the spring and mid-summer are selected for optimal crop signature separation. The AWiFS scenes are combined with 7-day 250 m MODIS NDVI data and resampled to the 56 m native AWiFS resolution. This "stacked" product is then spatially sampled using the USDA Farm Service Agency (FSA) Common Land Unit (CLU) layers (USDA/FSA, 2008). The CLU program delineates individual fields from producers participating in USDA farm programs for 17 major crop producing states during each growing season. Each field is labeled with its respective planted crop type, acreage, and owner. The sampled images are classified using the decision tree software See5. The classification accuracy is assessed using the PEDITOR regression estimator to compare categorized pixel counts to the CLU ground reference data (USDA/NASS/RDD/SARS, 2005). Yearly crop type maps clipped to state boundaries are the result of this methodology, with crop acreage accuracy ranging from Kappa coefficient of 0.80 to 0.95 (USDA/NASS/RDD/SARS, 2002).

This research utilized the CDL for pixel training and validation of the decision trees and the classified images. Individual state CDL images were aggregated to 250 m and combined with other CDL images. By aggregating the CDL to the larger 250 m pixel size, minor crops that cover less area were "averaged" out of the resulting aggregated image and replaced by contiguous major crop classes. This averaging effect is a common artifact of aggregation techniques (Bian and Butler, 1999). For a region with available CDL data, training, prediction, and validation pixels were selected from the aggregated CDL images. This process is described in detail in section 3.2.4. In addition to the CDL, the cropland (LC12) and cropland/natural vegetation mosaic (LC14) classes from the 1 km MODIS Land Cover Product (Friedl et al., 2002) were resampled to 250 m and used to mask non-cropland areas in the CONUS. Isolating the croplands allowed the decision tree to train for fewer classes.

3.2.4. Decision Tree Approach

This analysis utilized a decision tree approach to produce regional crop type classifications (Breiman et al., 1984; Hansen et al., 1996). A similar decision tree approach was used in many previous land cover classifications (Friedl and Brodley, 1997; Simard et al., 2000; Yang et al., 2003; Yang et al., 2004; Xu et al., 2005; Brown de Colstoun and Walthall, 2006) and crop type mapping analyses (Wardlow et al., 2006; Chang et al., 2007). Previous research has found decision trees to be ideal for large area crop type mapping as there is large intra-class variability in MODIS NDVI data (Wardlow and Egbert, 2008). In addition, decision trees produce accurate crop type classification despite the regional variations in crop classes due to climate and management practices (Wardlow et al., 2006; Wardlow et al., 2007).

For this study, decision trees were created for each crop management region, for each year, and for the appropriate growing season(s). Regions 4 and 5 have well-defined intra-annual crop rotation patterns and, therefore, two decision trees were created for each year to reflect these different growing seasons. Regions 1, 2, 4, 5, 6, 7, 8, and 9 have CDL training data for years 2003 and 2007 (Table 3-1). Each regional crop classification had at least 5,000 training pixels from region-specific CDL images.

Table 3-1. Total training, prediction, and validation pixels for each crop management region.

Region	Available state CDL images	Total training pixels	Total prediction pixels	Total validation pixels	Total available 250 m CDL pixels
1	Wisconsin, Iowa	10,000	10,000	5,000	468,400
2	Illinois, Indiana, Missouri	15,000	15,000	5,000	872,650
4	Arkansas, Mississippi	10,000	10,000	5,000	416,900
5	Louisiana, Mississippi	5,000	5,000	5,000	265,250
6	Iowa, Nebraska, North Dakota	15,000	15,000	5,000	790,250
7	Arkansas, Missouri	10,000	10,000	5,000	409,250
8	Nebraska, North Dakota	10,000	10,000	5,000	388,650
9	Washington	5,000	5,000	5,000	275,500

Training and prediction data sets were generated from the aggregated CDL images and were used to label the classes. Several sets of training data were selected and decision trees were created using each set. The resultant tree models were compared and one tree model was selected that showed the best results for each time period, an exploratory process that has been shown to enhance the final classification (Yang et al., 2003). The optimal regional tree model had a minimum deviation of 0.01 with a misclassification error rate less than 0.20 (20%). For this study, misclassification error rates for decision trees ranged from 0.18 (region 5) to 0.05 (region 2), with misclassification error rates increasing directly in relation to diversity of crop types in a region. Thus, a classification image was created for each harvest season using optimal regional models.

Training, prediction, and validation pixels were selectively sampled by choosing every 15th CDL pixel until the region-specific threshold was met. This approach selectively trained for approximately 2% of the total 250 m CDL pixels per each region as training pixels for tree development (Table 3-1). A separate and equal amount of 250 m CDL prediction pixels were set aside to replicate the original decision trees, a common statistical validation practice (Kaluzny et al., 1998). Additionally, 5,000 pixels were selected from the prediction pixel sets for validation of the classifications through the creation of error matrices. Regions 5 and 9 were exceptions; here the validation pixels were separate selections from both the prediction and training pixels, as these regions contained only one state CDL image. This process was repeated annually and for each growing season for regions with available data.

As previously mentioned, the regions which did not have coincident CDL data were classified by using the trees from contiguous regions with similar cropping systems. Regions 3 and 10 were classified by using a tree from the fall harvest seasons of region 4. Table 3-2 shows the major crop classes that are the focus of each regional classification. In addition to the crop classes, a water class was also included in the training data.

Table 3-2. Regional crop training classes for corresponding harvest seasons.

Regions	Crop training classes	Harvest season (classification time period)
1	corn, soy, wheat, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
2	corn, soy, wheat, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
3 and 10	corn, rice, soy, wheat, cotton, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
4	corn, rice, wheat, cotton, and other crop/fallow	Spring Harvest (Julian dates 113 and 129)
4	corn, rice, soy, wheat, cotton, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
5	sugarcane, rice, wheat, cotton, and other crop/fallow	Spring Harvest (Julian dates 113 and 129)
5	sugarcane, rice, soy, cotton, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
6 and 7	corn, soy, wheat, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
8	corn, soy, wheat, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)
9	wheat, Kentucky bluegrass, lentils, and other crop/fallow	Fall Harvest (Julian dates 225 and 241)

Figure 3-3 shows a representative tree for crop management region 4 for the 2003 spring harvest classification. For this region, the decision tree was limited to classifying cropland areas as corn, rice, wheat, cotton, and other crop/fallow (Table 3-1). The number of occurrences (six) for the other crop/fallow class was equal to the number of occurrences for the dominant spring harvest crop - winter wheat. The prevalence of the other/fallow class was realistic given that many summer crops, like soy, would not have been planted. Additionally, region 4 has small field sizes (16 ha) where 1 field may span multiple 250 m pixels and it is difficult to identify 'pure' crop classes. This created a situation where the other/fallow class contained a large range of spectral classes representing mixed information, some of which was the crop being mapped. These mixed pixels introduced confusion into the decision tree that may have resulted in sub-optimal performance in some trees.

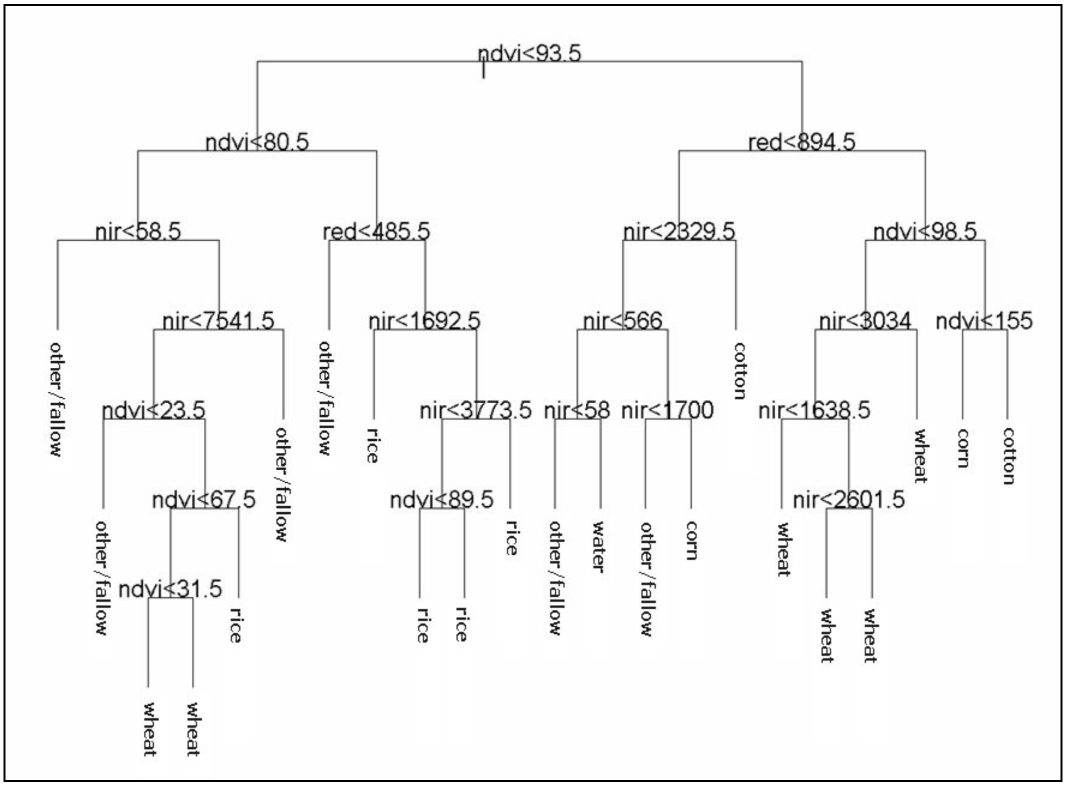


Figure 3-3. Classification tree for region 4 for the 2003 spring harvest classification.

3.2.5. Product Combination to Create Classified Images

For all regions, the classified images for JDs 225 and 241 for the fall harvest season were combined to create the growing season crop type classifications. The classified image of the first time period (JD 225) of each respective growing season was used as the base map. Presence of clouds was determined from the data quality information stored in the composite product. Results from the second composite (JD 241) were substituted in the resultant map for any pixel that had clouds in the first composite. This process was repeated for regions 4 and 5 for the spring harvest whereby the classified JD 113 image was the base map, and classified JD 129 pixels were used for substitution of cloudy pixels from the first time period. This method was used to produce the most cloud free map possible, though it did not remove all cloud contamination. For example, in regions 3, 4, and 5, cloud contaminated pixels were typically classified as other/fallow. Results from a cloud contamination analysis of the crop type maps are detailed in section 3.3.1.

3.2.6. Validation

The results from this study were validated using statistical accuracy measures. Error matrices were calculated for the eight regions with available validation pixels for years 2003 through 2007. The objective of this validation step was to determine if the decision tree classification accurately mapped crop type compared to ground truth pixels, i.e., the validation pixels. Common measures of classification accuracy were derived from this validation effort including Cohen's kappa coefficient, user's accuracy, producer's accuracy, and percent correctly classified. Definitions for these statistics were derived from Foody (2002). Equations for these standard statistics are listed in Appendix A.

3.3. Results

3.3.1. Cloud Contamination

A cloud contamination analysis was completed to determine if the overrepresentation of the other/fallow class was related to cloudy pixels, i.e., cloud flags, still present in the 250 m MODIS data after compositing two time periods. Table 3-3 shows the number of persistently cloudy pixels, i.e., cloudy pixels that remained after compositing, per region and harvest period with corresponding misclassified crop types. In general, the other/fallow class was the predominant crop type assigned to the persistently cloudy pixels. Additionally, the crop types most likely assigned to the cloudy pixels generally corresponded to the lowest user's accuracy; likewise, crop types least likely assigned to cloudy pixels had the highest user's accuracy.

Table 3-3. Regional cloud contamination and associated misclassified crop types most likely to be confused with cloudy pixels (second to end column) and least likely to be confused with cloudy pixels (end column).

Region	Harvest/Year	Number of persistent cloudy pixels	Most likely misclassified crop type	Least likely misclassified crop type
1	Fall/2003	25	Fallow	Wheat
1	Fall/2004	45	Soy	Wheat
1	Fall/2005	53	Fallow	Wheat
1	Fall/2006	64	Fallow	Wheat
1	Fall/2007	31	Soy	Wheat
2	Fall/2003	19	Fallow	Wheat
2	Fall/2004	22	Fallow	Wheat
2	Fall/2005	37	Fallow	Wheat
2	Fall/2006	59	Fallow	Wheat
2	Fall/2007	28	Fallow	Wheat
4	Spring/2003	85	Fallow	Wheat
4	Spring/2004	92	Fallow	Wheat
4	Spring/2005	97	Fallow	Cotton
4	Spring/2006	105	Rice	Cotton
4	Spring/2007	92	Rice	Wheat
4	Fall/2003	98	Fallow	Soy
4	Fall/2004	103	Fallow	Soy
4	Fall/2005	119	Fallow	Soy
4	Fall/2006	125	Rice	Soy
4	Fall/2007	115	Rice	Cotton

Table 3-3. Regional cloud contamination and associated misclassified crop types most likely to be confused with cloudy pixels (second to end column) and least likely to be confused with cloudy pixels (end column) (cont.).

5	Spring/2003	96	Fallow	Cotton
5	Spring/2004	107	Fallow	Cotton
5	Spring/2005	115	Fallow	Sugar
5	Spring/2006	117	Fallow	Sugar
5	Spring/2007	110	Fallow	Rice
5	Fall/2003	89	Fallow	Cotton
5	Fall/2004	95	Fallow	Cotton
5	Fall/2005	113	Fallow	Rice
5	Fall/2006	108	Fallow	Cotton
5	Fall/2007	102	Fallow	Rice
6	Fall/2003	25	Fallow	Wheat
6	Fall/2004	36	Soy	Wheat
6	Fall/2005	20	Soy	Wheat
6	Fall/2006	42	Soy	Wheat
6	Fall/2007	27	Soy	Wheat
7	Fall/2003	16	Soy	Corn
7	Fall/2004	32	Soy	Corn
7	Fall/2005	21	Soy	Corn
7	Fall/2006	14	Soy	Corn
7	Fall/2007	25	Soy	Corn
8	Fall/2003	23	Fallow	Wheat
8	Fall/2004	19	Fallow	Wheat
8	Fall/2005	32	Soy	Wheat
8	Fall/2006	39	Fallow	Wheat
8	Fall/2007	25	Fallow	Wheat

Table 3-3. Regional cloud contamination and associated misclassified crop types most likely to be confused with cloudy pixels (second to end column) and least likely to be confused with cloudy pixels (end column) (cont.).

9	Fall/2003	45	Fallow	Lentils
9	Fall/2004	38	Fallow	Wheat
9	Fall/2005	65	Bluegrass	Lentils
9	Fall/2006	59	Fallow	Wheat
9	Fall/2007	48	Wheat	Lentils

A sensitivity analysis on persistent clouds was performed for regions 4 and 5, the cloudiest regions and the regional crop type classifications with the lowest accuracy. The objective was to determine how many 16-day 250 m composites would be needed to produce completely cloud-free data for the classification. For the spring harvest period, the original classification consisted of 16-day composites from JDs 113 (23 April - 8 May) and 129 (9 May - 24 May). By adding composite JD 97 (7 April - 22 Apr) and composite JD 145 (25 May - 9 June), all but 10 persistently cloudy pixels were removed from both regions 4 and 5. These persistently cloudy pixels were always land pixels adjacent to the Mississippi River. It is possible that these 'cloudy' pixels were incorrectly flagged as clouds due to problems with the land-water mask in the cloud detection algorithms. Additionally, the 16-day USVI product uses both the 1 km MOD35 (MODIS Cloud Mask) and the 500 m MOD09 (MODIS Surface Reflectance) cloud flags. This creates a further complication in determining where the mislabeling of pixels as clouds was occurring.

Adding the early (before JD 113 16-day composite) and late (after JD 145 16-day composite) composites of 7 April and 25 May created other potential problems for the regional crop type classifications. Specifically, the 7 April composite did not provide representative data of the spring crops at peak greenness as it was retrieved before maturation of the crops. Similarly, the 25 May composite contained data during the spring harvest, meaning that many of the pixels likely contained burned and plowed fields and/or newly planted crops, therefore missing the crops that are the focus of the classification. The existing classification utilizing two composite periods provided the best approach for classifying spring harvest crops even though cloudy pixels will be present.

The fall harvest classifications had similar data requirements, whereby retrieving data after the harvest produced a less accurate crop type classification due to crop residue burning and plowing of fields. The original fall harvest 16-day composites of JD 225 (13 August - 28 August) and JD 241 (29 August - 13 September) was combined with an earlier composite of JD 209 (28 July - August 12) and a later composite of JD 257 (14 September - 29 September). For years 2003 through 2007, all persistently cloudy pixels were removed from the regions 4 and 5 classifications. Less than 5 persistently cloudy pixels remained in the regions 4 and 5 classifications when the later JD 257 composite (beginning of the fall harvest) was removed from the process. Again, these persistently cloudy pixels were adjacent to the Mississippi River and therefore potentially could have been flagged incorrectly by the cloud masks. Therefore, the existing method for the fall harvest classifications could be enhanced slightly by including a third and earlier composite time period (28 July) as this produced less cloud contamination in the resulting classification.

3.3.2. Validation

Annual validation was completed for the seven, of the twelve, regions where CDL data is available. As previously mentioned, 5,000 validation pixels were selected from the prediction pixel data sets. For this study, Kappa statistics were calculated from error matrices as well as the commission and omission error and the user's and producer's accuracy of each class. Table 3-4 shows the average Kappa and percent correctly classified for the fall harvest season over years 2003 through 2007. Table 3-5 shows the average validation statistics of the spring harvest season for regions 4 and 5.

Table 3-4. Regional Kappa statistics for the fall harvest crop type classifications for years 2003 through 2007.

Regions	2003	2004	2005	2006	2007	Average
1	0.914	0.876	0.878	0.835	0.888	0.878
2	0.922	0.855	0.872	0.909	0.892	0.890
4	0.743	0.747	0.717	0.701	0.726	0.727
5	0.781	0.775	0.72	0.727	0.755	0.752
6	0.913	0.895	0.892	0.855	0.907	0.892
7	0.924	0.912	0.893	0.874	0.910	0.903
8	0.925	0.903	0.883	0.887	0.908	0.901
9	0.889	0.868	0.806	0.828	0.879	0.854

Table 3-5. Regional Kappa statistics for the spring harvest crop type classifications for years 2003 through 2007.

Regions	2003	2004	2005	2006	2007	Average
4	0.778	0.758	0.738	0.73	0.76	0.753
5	0.776	0.76	0.74	0.728	0.765	0.754

The regions with lowest accuracy were regions 4 and 5. These regions have diverse cropping systems and two growing seasons within the same year. Cloud contamination was a serious issue for these regions as both the spring and fall harvest seasons are rainy periods, thus allowing the farmers to harvest and plant the subsequent rotation crop. As discussed in section 3.3.1, the spring and fall composites for years 2004 through 2007 contained approximately 100 persistently cloudy pixels within the cropland areas. The presence of cloudy pixels after compositing was likely lowering the accuracy of the crop type classifications for regions 4 and 5. For both the spring and fall harvest growing seasons, the user's accuracy for the individual crops types (regions 4 and 5 average user's accuracy = 80%) was higher than the Kappa value (regions 4 and 5 average Kappa = 0.747). The other regions had higher accuracy statistics, ranging from a Kappa of 0.854 in region 9 to a Kappa of 0.903 in region 7. Given that the Kappa coefficient for the AWiFS- and Landsat 5-based CDL images range from 0.80 to 0.95 (USDA/NASS/RDD/SARS, 2002), the accuracy of the 250 m classifications is comparable.

3.3.3. Areal Comparison

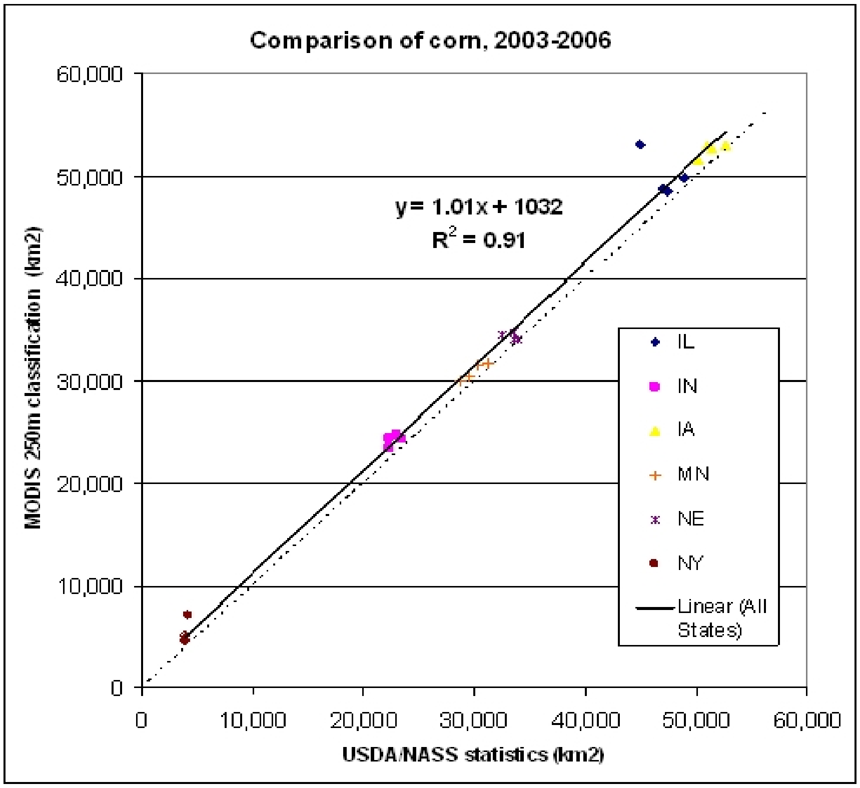
The resulting crop areas from the regional MODIS 250 m crop type maps for years 2003 through 2006 were compared with known areas of wheat, corn, soy, rice, and sugar cane from annual agriculture statistics collected by the USDA/NASS (USDA/NASS, 2003a; 2004a; 2005; 2006) using a regression analysis. Year 2007 crop areas were not compared to federal agriculture statistics as corrected crop area data has not been released (USDA/NASS, 2007). Each areal comparison aimed to select states from geographically distant crop management regions in order to test both the reliability of the regional classification method as well as the effectiveness of individual classifications. The wheat comparison included Arkansas, Kansas, Maryland, North Dakota, Oklahoma, and Washington. The corn comparison included Illinois, Indiana, Iowa, Minnesota, Nebraska, and New York. The comparison for soy included the states of Arkansas, Illinois, Indiana, Iowa, Minnesota, and Nebraska. The states of Arkansas, California, Louisiana, Mississippi, Missouri, and Texas are included for the rice analysis while the sugar cane comparison was limited to Louisiana, Florida, and Texas.

The USDA produces annual crop acreage statistics through a combination of state-submitted agricultural acreage estimates and an annual, nation-wide ground-based survey of 11,000 parcels of land and 89,000 farm operators within the first two weeks of June (USDA/NASS, 2004a). The linear regression showed a statistically significant relationship between the official harvested acreages statistics and the regionally-tuned 250 m crop classifications, with r^2 values ranging from 0.90 (wheat) to 0.93 (soy and sugar) (Figure 3-4). Based on this simple regression analysis, the regional crop type classification method provided fairly accurate, though overestimated, predictions of crop area. The soy classification ($MODIS_{soy} = 0.99 *$ USDA/NASS + 1218; $r^2 = 0.93$) had the highest r^2 value and slope closest to 1 but it represented an average 5% overestimation of soy areas between 2003 and 2006, which was equivalent to an over-fitting classification of 206 fields (Table 3-6). The average overestimation for corn was 7%, equivalent to 94 fields with an average size of 48 ha. Rice areas in the 250 m classifications were overestimated by 10% or 29 fields, while 17 extra sugar fields were included in the classifications, equivalent to a

19% overestimation of the USDA/NASS statistics. Wheat areas were overestimated by 11% or 76 fields.

Table 3-6. Average overestimation of crop areas from the regression analysis of 250 m MODIS crop type classification with reported USDA crop areal statistics, 2003 - 2006.

Crop	Average overestimation (%)	Average areal overestimation (ha)	Average overestimation (in 0.48 ha fields)
Wheat	11%	3,700	76
Corn	7%	4,600	94
Soy	5%	10,100	206
Rice	10%	1,400	29
Sugar	19%	800	17



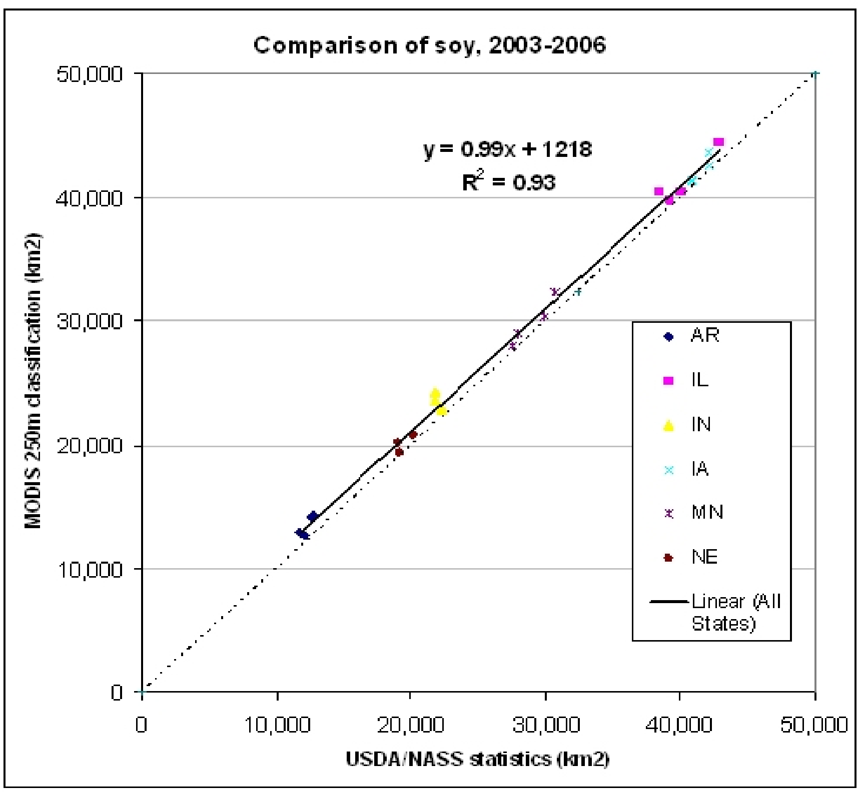
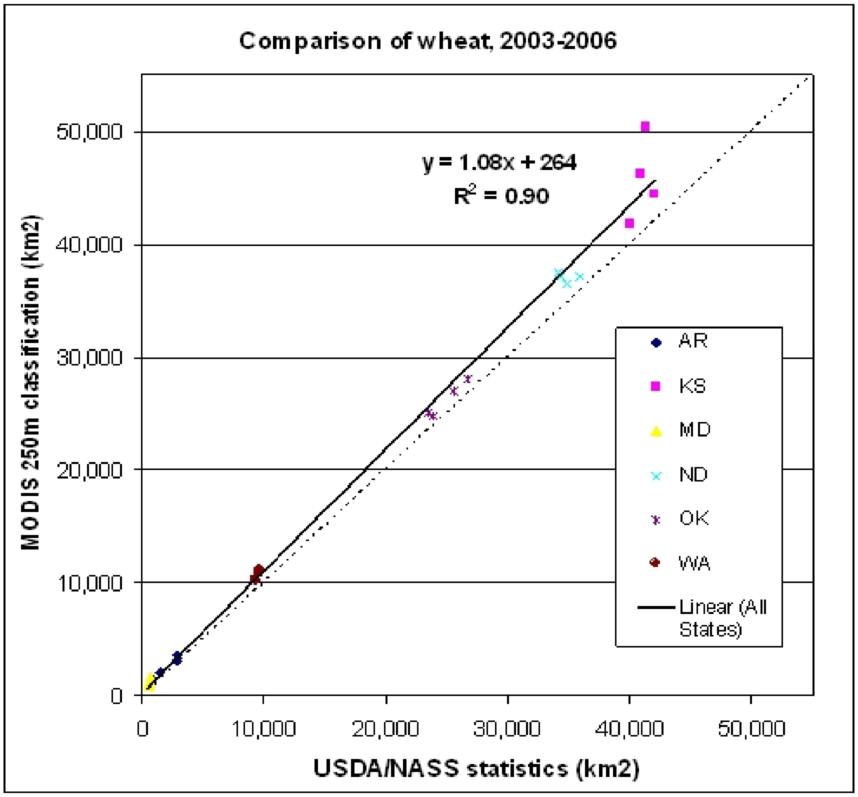


Figure 3-4. Comparison of MODIS classification crop area (km^2) to USDA/NASS statistics for years 2003-2006; dashed line is 1 to 1 line.



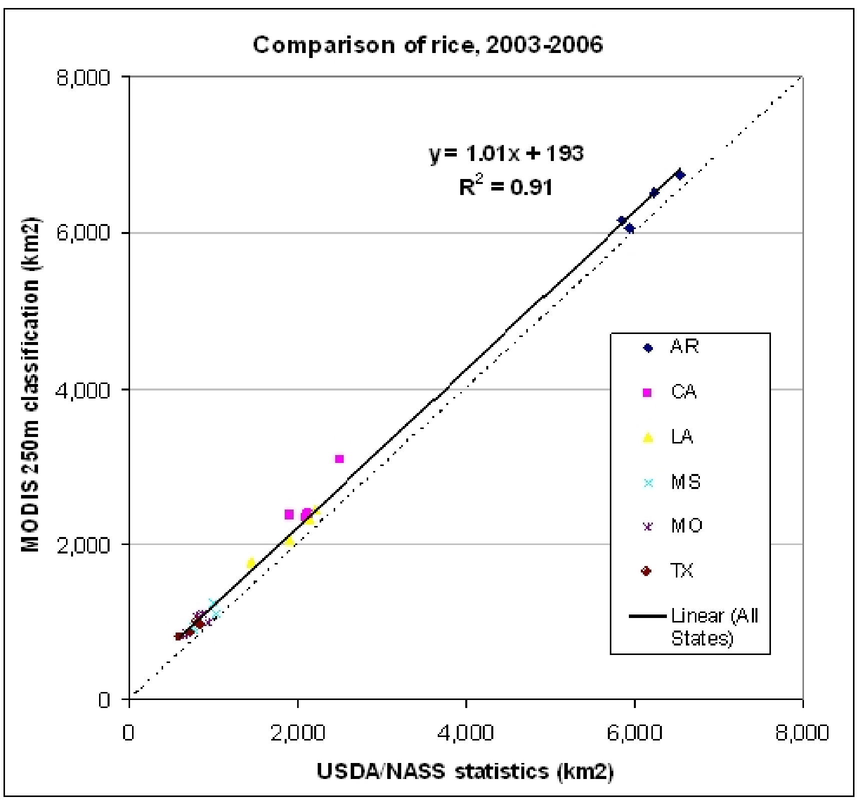


Figure 3-4. Comparison of MODIS classification crop area (km^2) to USDA/NASS statistics for years 2003-2006; dashed line is 1 to 1 line (cont.).

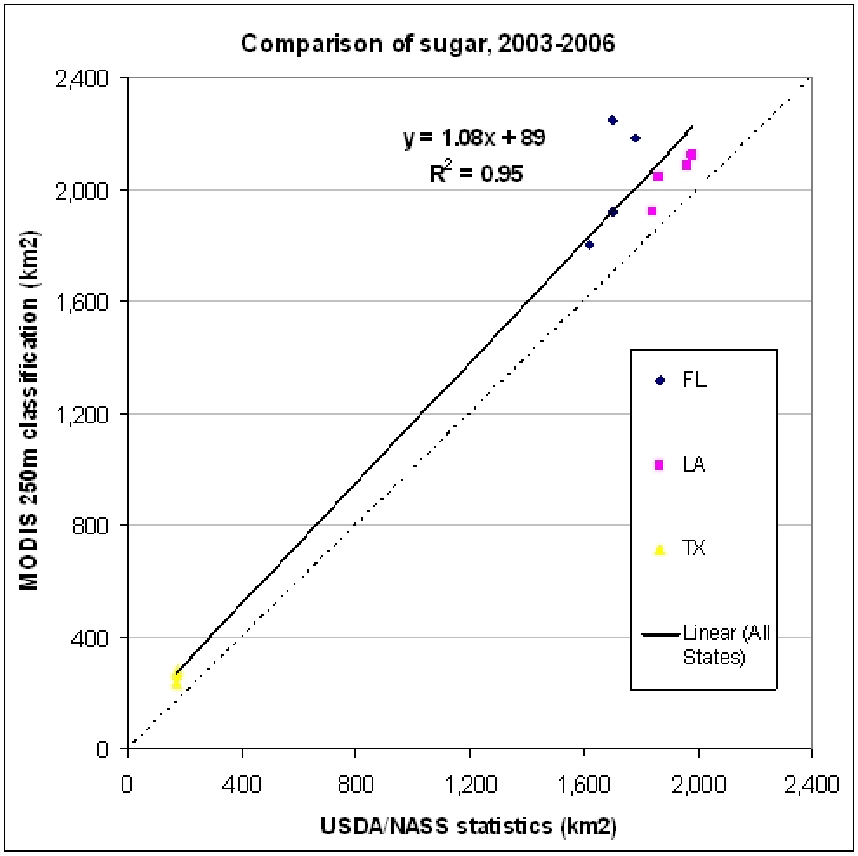


Figure 3-4. Comparison of MODIS classification crop area (km^2) to USDA/NASS statistics for years 2003-2006; dashed line is 1 to 1 line (cont.).

At the state-level, Arkansas had a 10% overestimation of soy. Similarly, the worst performing wheat classification was in Arkansas, with a 15% overestimation of wheat fields. The worst performing corn classification was New York, which had an areal overestimation of 7%. For both the rice and sugar classifications, Texas had the highest overestimation of 14% and 30%, respectively.

By excluding the states with the extreme overestimations for each crop type, the average areal overestimation was lowered by 2 to 8% (Table 3-7). The outlying states with the highest areal overestimation in the linear regression analysis were produced from decision tree models for crop management regions with both spring and fall harvest crop type maps (Arkansas, Texas, and Missouri) or decision tree models that did not have region-specific training data (New York). The areal overestimation of crop in Arkansas, Texas, and Missouri was not surprising as both seasonal crop type classifications for regions 4 and 5 had lower mapping accuracy (section 3.3.2), and these states have highly diverse crop types. It is likely that the general overestimation of all crop types, even when excluding outliers, was caused by the oversimplification of the trees caused by the reduced number of classes in the model (De'ath and Fabricius, 2000). All decision tree models were limited to a range of 4 to 5 crop classes, including the other/fallow class. The areal overestimation would likely be reduced by including more crop classes, a crop/natural vegetation mosaic class, or even splitting the other/fallow class into two separate classes (Pal and Mather, 2003). As 'fallow' pixels were spectrally dissimilar from crops included in this analysis (Figure 3-2), separating the other/fallow class may allow pixels that were classified as other/fallow and were not target crop types for this analysis to be classified as an 'other' crop rather than forced into a wheat, corn, rice, etc., class.

Table 3-7. Average overestimation of crop areas minus outlying states, 2003 through 2006.

Crop	Average overestimation (%)	Average areal overestimation (ha)	Average overestimation (in 0.48 ha fields)
Wheat	9%	3,000	61
Corn	5%	3,300	67
Soy	3%	6,100	125
Rice	7%	1,000	20
Sugar	11%	500	10

3.3.4. Crop Type Maps

The regional crop type classifications provided an accurate spatial model of known crop patterns. Figure 3-5 shows the multi-year results for the Midwest sub-section of crop management region 2, a dominant soy-corn agriculture system. The crop type map for year 2004 appeared to overestimate the other crop/fallow and wheat classes. The 2007 crop type map shows a clear decrease of wheat and other crop/fallow classes, likely due to shifting cropping systems related to abandonment of wheat in favor of corn for ethanol production. A visual analysis of the original composites for years 2004 and 2007 showed higher cloud concentrations in region 2 than other years. For this region, 2004 had the lowest mapping accuracy (Kappa = 0.86), which suggests that the decision tree approach created an overestimation of the other/fallow and wheat classes. The average accuracy for region 2 is 89% (Kappa = 0.89) for all years.

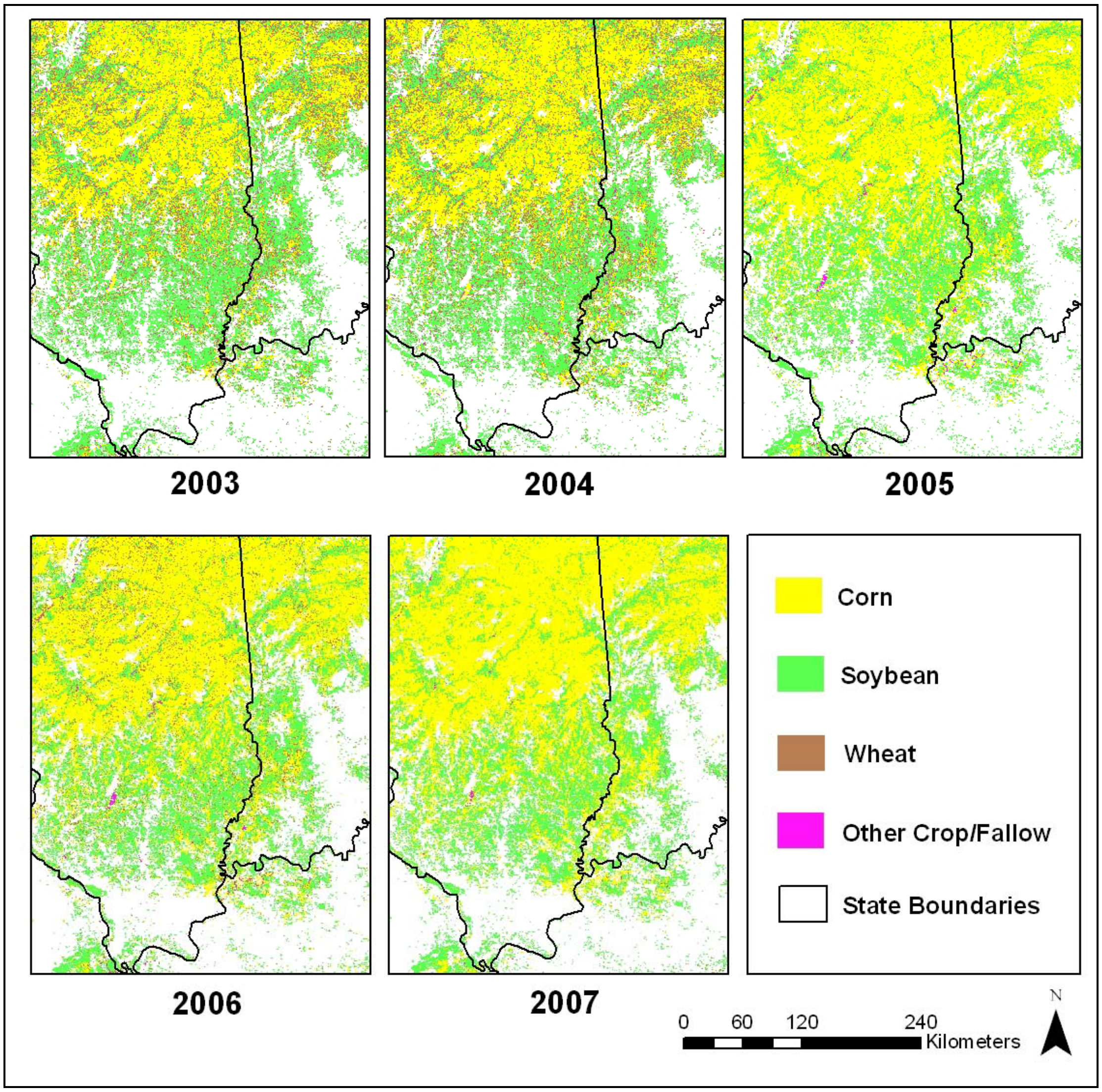


Figure 3-5. MODIS 250 m classification results for a sub-section of crop management region 2, years 2003 through 2007; states in the subset include Indiana, Illinois, Kentucky, and Missouri (projection: Albers Equal Area Conic).

Figure 3-6 illustrates the multi-year classification of crop management region 9. This region is dominated by cereals and grass seed, particularly wheat and Kentucky bluegrass, with small clusters of lentils in eastern Washington and the Willamette Valley in western Oregon. Unlike region 2, cloud contamination was not an issue for the MODIS composites used for this classification. The wheat classification was fairly static across the years, a true representation of crop management in the region. However, year 2005 overestimated the other crop/fallow class and subsequently had a lower mapping accuracy (Kappa = 0.806). The average accuracy for region 9 was 85% (Kappa = 0.854) between 2003 and 2007. The crop type classification would likely be improved by splitting the other/fallow class into two separate classes to allow for the delineation of smaller regional crops like potatoes, mint, canola, and mustard from the fallow class.

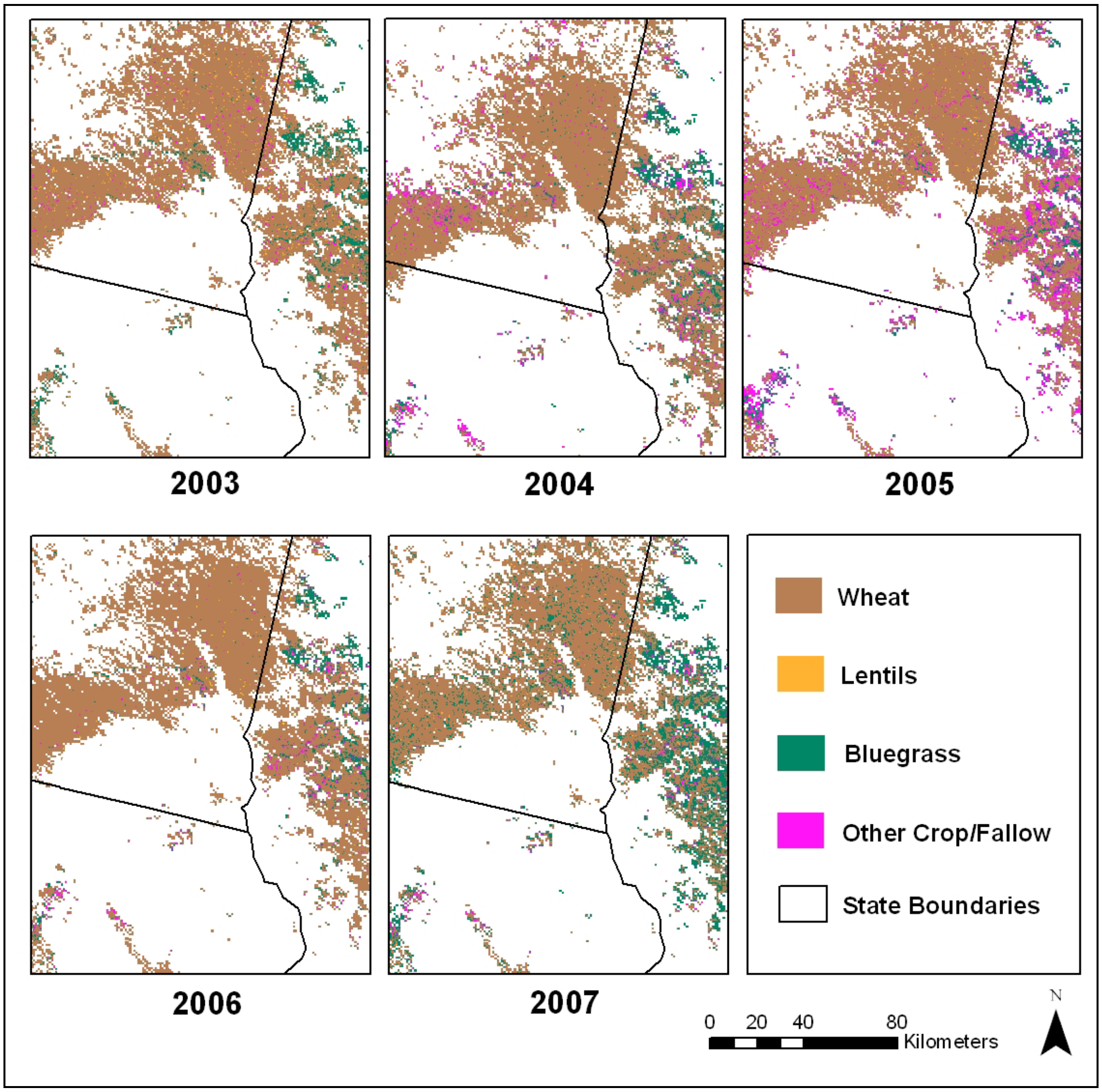


Figure 3-6. MODIS 250 m classification results for the Palouse area of crop management region 9, years 2003 through 2007; states in the subset include northern Idaho, eastern Oregon, and eastern Washington (projection: Albers Equal Area Conic).

A visual assessment of the 250 m regional crop type map for northeastern Arkansas showed similar crop and field patterns interpreted from the higher resolution CDL crop type maps. Figure 3-7 illustrates the example of the 2003 fall harvest map for region 4. This region had lower mapping accuracy (Kappa = 0.778;

percent correctly classified = 78%) than other regions and was less accurate than the 2003 Arkansas CDL image, which has an intra-class accuracy range of 85% to 95% (USDA/NASS/RDD/SARS, 2003). However, the resulting 250 m classification shows a similar spatial pattern of rice and soy fields compared to the 30 m CDL. Cotton fields, shown as purple, were mapped in the same locations in both images but the amount of cotton fields were underestimated in the 250 m classification compared to the CDL. The 30 m CDL also showed more non-crop (i.e., natural vegetation) areas. Several pixels that were likely mosaics of croplands and natural vegetation at the 250 m spatial scale were classified as soy and rice in the region 4 spring harvest map, thus overestimating the areas of these crops. In general, there is a good visual agreement between CDL images and the regional crop type maps.

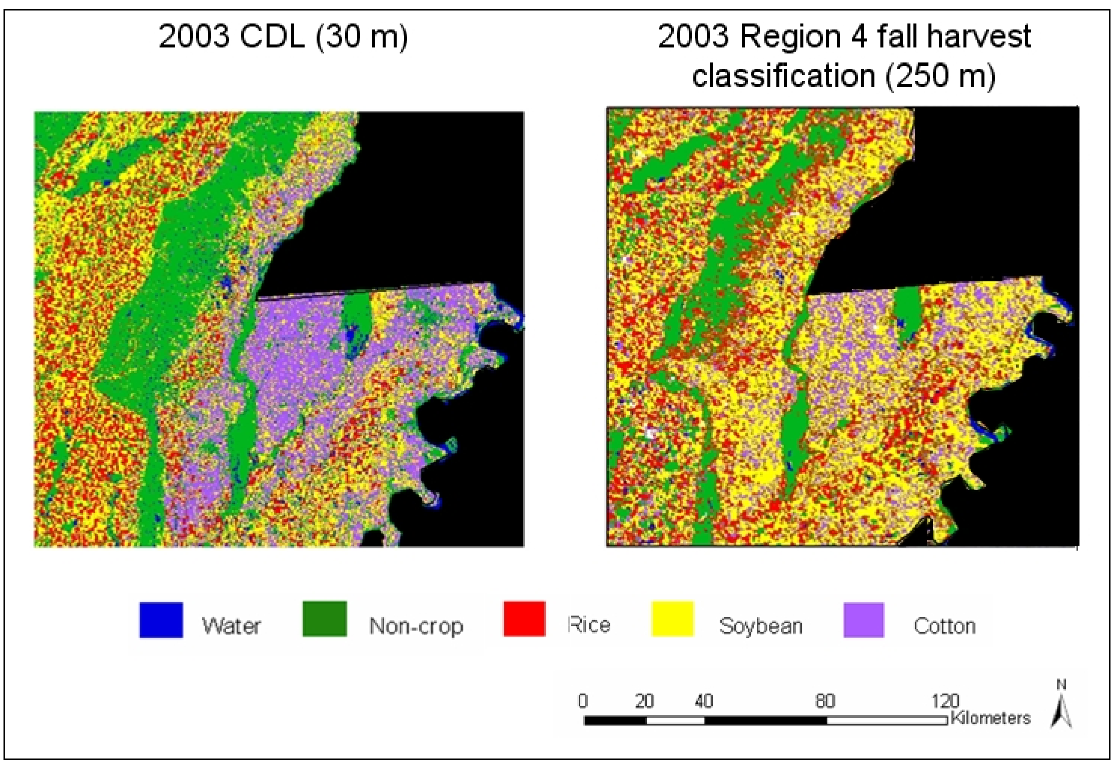


Figure 3-7. Comparison of higher resolution crop type map of Arkansas (left) to

250 m region 4 fall harvest crop type map (right); (projection: Albers Equal Area Conic).

3.4. Conclusions

This study has demonstrated that 250 m MODIS data are suitable for regional crop type mapping, building on previous research looking at moderate and coarse resolution mapping at the state and regional levels (Chang et al., 2007; Wardlow et al., 2007; Wardlow and Egbert, 2008). Moreover, this analysis provides further proof that regional approaches for satellite-based land use and land cover mapping are effective and accurate. By breaking up the CONUS into regions, a range of crop types were mapped, allowing the decision tree to be trained for crop types where fire is used for residue management. The resulting 250 m regional classifications provided areal estimations comparable to those obtained from high resolution data, though the 250 m maps tended to overestimate crop area on average by 7%. The 250 m regional classification maps also matched the spatial pattern of known crop types, including those patterns illustrated in the CDL training data.

This methodology produced regional crop type maps with accuracy ranges of 73% to 91%. These crop type maps did not require large data inputs and computational capabilities. This methodology could be readily repeated and refined for other regions around the world given that all data used for this study are freely available. The decision tree classification approach used in this study is available through many statistical and remote sensing software packages. Therefore, this approach could be applied to any agricultural region that had adequate training data to develop the decision tree.

Multi-year and multi-season crop type maps produced in this study provide spatially explicit information about crop rotation patterns. Satellite crop rotation information is essential to calculating crop residue burning emissions and carbon sequestration of crops (Sauerback, 2001; Brye et al., 2006). This approach can be utilized to create accurate and timely (approximately 32 days after harvest with the combination of two 16-day composites to eliminate approximately 83% of clouds) predictions of crop area, which are critical for commodity markets, world aid organizations seeking information on food security, and policymakers and researchers aiming to understand shifts in agriculture.

Production of multi-year crop type maps for the CONUS was essential to quantifying crop residue burning. Current crop type maps produced by the USDA NASS (CDL) do not have sufficient temporal resolution (i.e., multi-year for the southeastern U.S.) or spatial coverage (i.e., limited to specific states). The MODIS crop type maps produced during this research were further used in chapter 5 to identify the burning crop residues in the CONUS and to calculate related emissions.

Chapter 4: The Spatial and Temporal Distribution of Crop Residue Burning in the Contiguous United States[3]

This chapter presents the application of the cropland burned area methodology described in chapter 2 for the CONUS. To expand beyond the original study area of MODIS tile h10v05 used in chapter 2, two distinct dNBR thresholds were developed. This modification and a complete validation of the hybrid cropland burned area approach are provided. The seasonal and interannual variability of crop residue burning is calculated. Observed variability in the remote sensing-based cropland burned area product is related to state-level changes in crop yield and area as well as local climatic events. Burned area results from this analysis are further used in chapter 5 to estimate air quality and carbon emissions from crop residue burning.

4.1. Background

At present, only a handful of states (California, Florida, Oregon, and Washington) complete annual estimates of crop residue burned area. These estimates are usually aggregated at the county or state level (WA DOE, 2006) and are generally based on self-reporting by farmers and/or calculated from burn permits issued. A satellite-based approach is the only feasible, systematic method for providing consistent, synoptic, quantitative, spatially and temporally explicit measurements of the area of crop residue burned at the CONUS and regional scale (Korontzi et al.,

[3] Much of the presented material has been submitted for publication in McCarty JL, Korontzi S, Justice CO, and Loboda T (in preparation). The spatial and temporal distribution of crop residue burning in the contiguous United States. *Science of the Total Environment*.

2006; McCarty et al., 2007; Korontzi et al., 2008; Punia et al., 2008; McCarty et al., 2008).

This chapter details the implementation of a remote sensing-based cropland burned area mapping approach for the CONUS, using the methodology developed and tested in chapter 2. The results are used to examine the spatio-temporal distribution and variability of crop residue burning in the CONUS for the years 2003 through 2007. Burned area is analyzed by location, time of year, and crop type. The results of this analysis provide a baseline estimate of crop residue burning for the CONUS, which is heretofore unavailable (Pouliot et al., 2008).

4.2. Data and Methods

This analysis employed a regionally adaptive, hybrid method of mapping burned area in croplands and crop-dominated landscapes described in chapter 2 (McCarty et al., 2008). This method combines information obtained from changes in satellite-observed surface reflectance due to burning, with information provided by active fire detections. Two standard Collection 5 MODIS products are utilized in this approach: the 500 m MODIS 8-day Surface Reflectance Product (MOD09A1) (Vermote et al., 2002) and the 1 km MODIS Active Fire Product (TERRA/AQUA, MOD14/MYD14) (Giglio et al., 2003). The MODIS land products are generated in tiles, which correspond to 1200 by 1200 km (Wolfe et al., 2002). For ease of computation all analyses in this study are undertaken on a per-tile basis.

As part of this approach, change in surface reflectance due to burning is identified using a dNBR approach (Lopez Garcia and Caselles, 1991; Key and

Benson, 1999) with the specific “burn” thresholds defined for each tile, using field GPS training data to separate burned and plowed fields in the dNBR spectral space. A total of 296 GPS data points were collected in five states, of which 72% were burned fields and 28% were plowed fields. This method was applied within a broad cropland mask, derived from the cropland (LC12) and cropland/natural vegetation mosaic (LC14) classes of the MODIS 1 km Land Cover Data Set (MOD12) (Friedl et al., 2002). With a spatial resolution of 1 km, the total area of both classes corresponded well (97%) to the USDA statistics on cropland extent in the CONUS (USDA/NRCS, 2003). The cropland/natural vegetation mosaic class was included to identify potential cropland areas, and to delineate burning that spread from a wildland source or burning in cropped fields that bordered non-cropland areas. The specific tile-based thresholds applied in this study are discussed in more detail in section 4.2.1.

Active fire detections proved to be essential to mapping cropland burning. Based on a limited comparison between 15 m ASTER burn scar images and the 500 m dNBR in the southeastern U.S., this analysis found that at least 80% of a 500 m pixel (20 ha) must be burned in order for the dNBR approach to identify the burned area, which is slightly larger than the average field size of 16 ha for much of the eastern and southern U.S. (USDA, 2002). To capture the contribution from a single-field burning, for areas smaller than 20 ha, TERRA and AQUA sub pixel active fire detections at 1 km resolution were used. Active fire data were obtained from the MODIS Fire Information for Resource Management System (FIRMS) (Davies et al., in press), which provides GIS shapefiles of the centroid location of actively burning 1 km MODIS pixels. The 1 km active fire points which did not overlap with previously identified dNBR “burned areas” at 500 m resolution were calibrated using empirically derived relationships of average field size for different agricultural regions and used in the area estimates. For the CONUS, an average of 65% of active fire detections within a MODIS tile did not overlap with the 500 m dNBR pixels. Therefore, the active fire detections were capturing fires that were not being detected by the dNBR approach. Figure 4-1 illustrates the workflow for calculating crop residue burned area estimates for the CONUS.

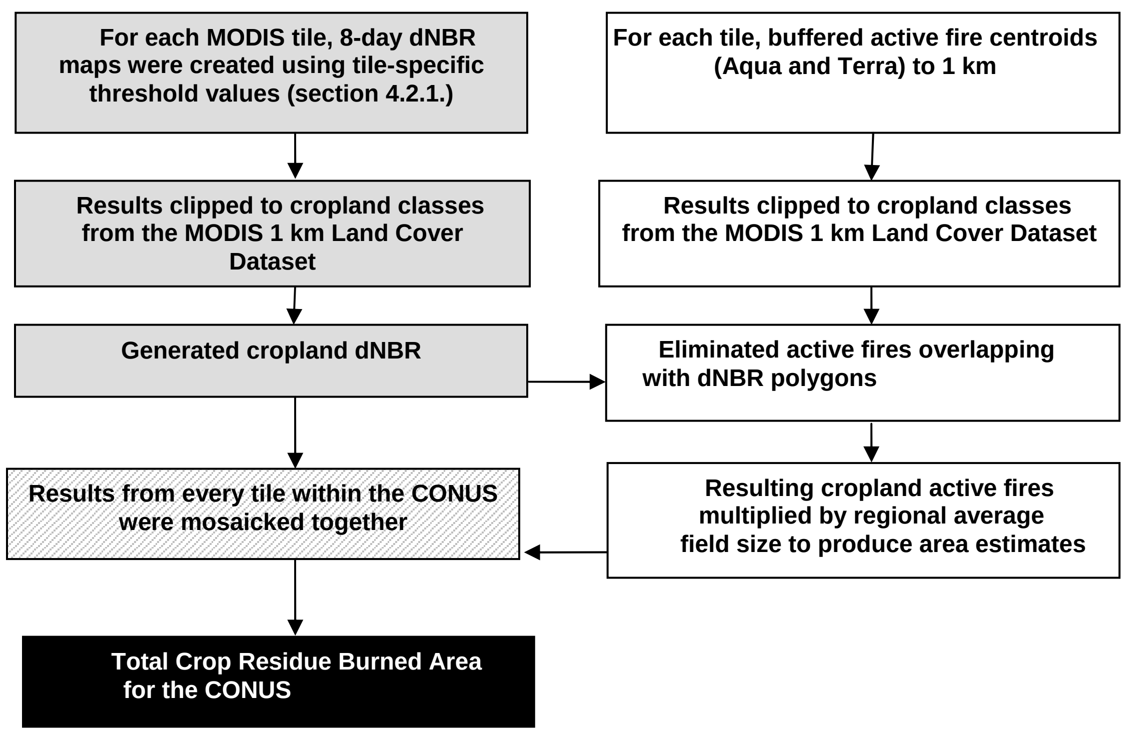


Figure 4-1. Workflow for calculating the crop residue burned area for the CONUS.

4.2.1. Development of the dNBR Regional Thresholds

To develop a robust and computationally efficient data processing system, the burned area mapping was constrained to harvest periods for different regions and the dNBR thresholds were adjusted based on soil properties and irrigation practices for the MODIS tiles. The dNBR images were generated for the 12 MODIS tiles, shown in Figure 4-2, for their corresponding harvesting seasons for the years 2003 through 2007. The MODIS tiles h13v04 (northern Maine) and h08v06 (small tip of southwest Texas) were excluded from the analyses, as they showed no cropland active fire detections between 2003 and 2007. The harvest temporal windows for each tile were determined primarily from the time periods of most frequent agricultural burning, as detected by MODIS active fires and averaged over the five year period (Figures 4-3 and 4-4), which corresponded well with published agricultural reports (USDA/NASS, 2007). The harvest periods were established to account for the interannual temporal shifts of frequent cropland active fire detections, i.e., 2 or more unique daily active fire detections. Harvest periods were defined as beginning with the earliest observed burning of each harvest season each year and ended with the latest observed burning. This approach accounted for interannual variation in the timing of harvest caused by precipitation and/or permitting delays. Table 4-1 lists the major crops and cropping systems found in each tile, the associated harvest seasons and data sources used to corroborate the determined harvest seasons from active fire detections for each MODIS tile.

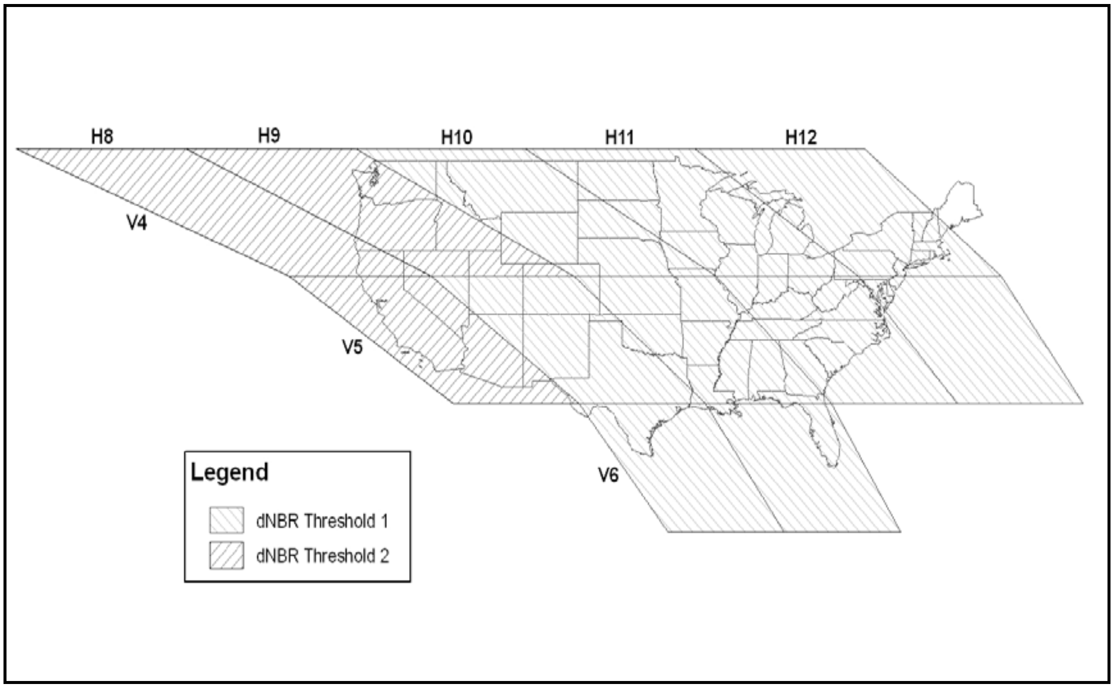


Figure 4-2. MODIS tiles included in the analysis for cropland burned area in the CONUS and the distribution of the two dNBR thresholds used (projection: Albers Equal Area Conic).

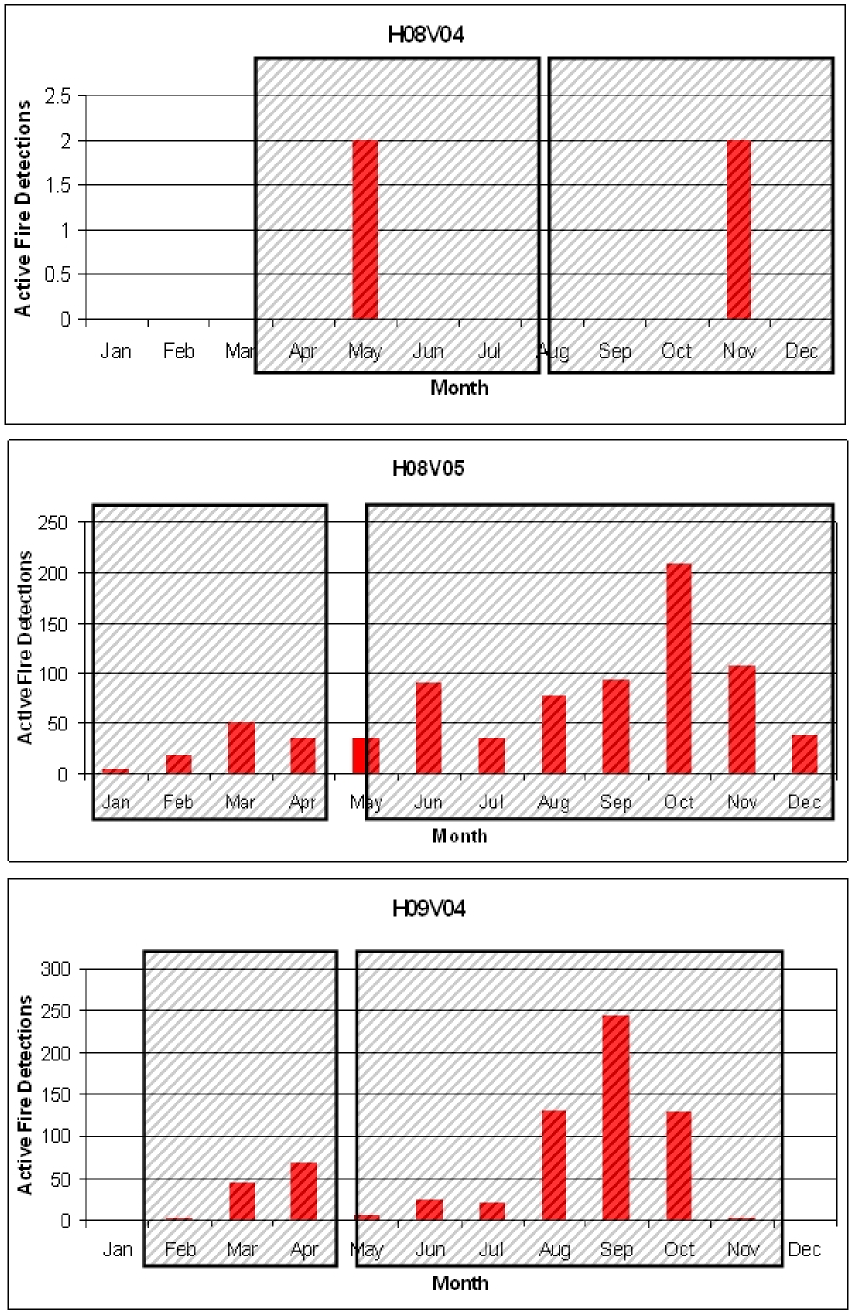
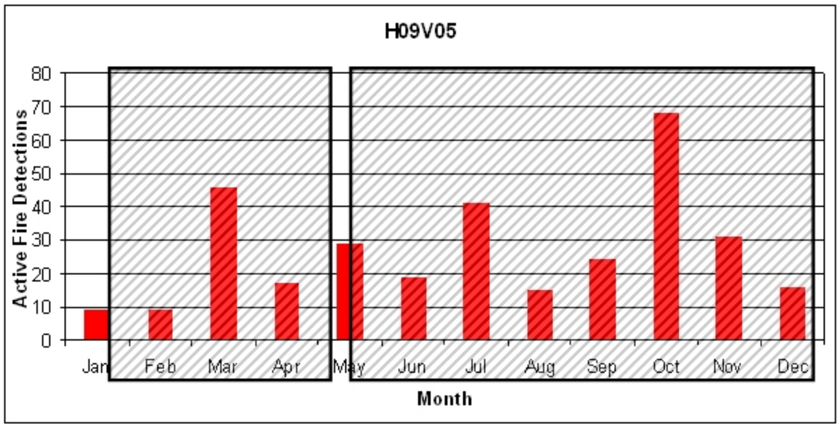
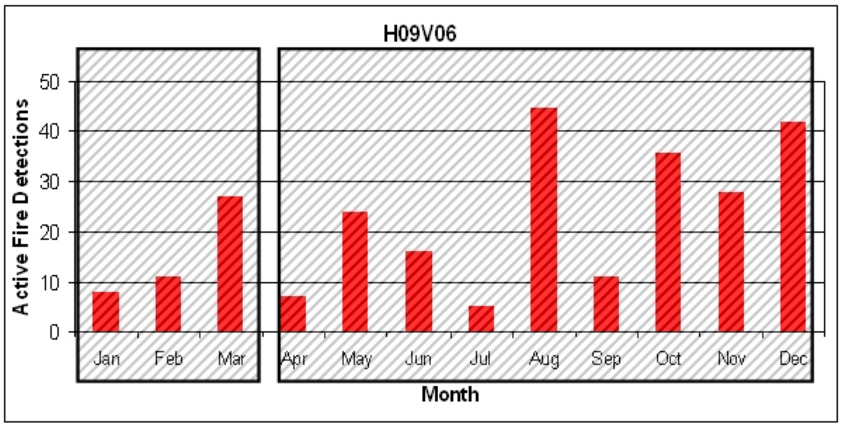
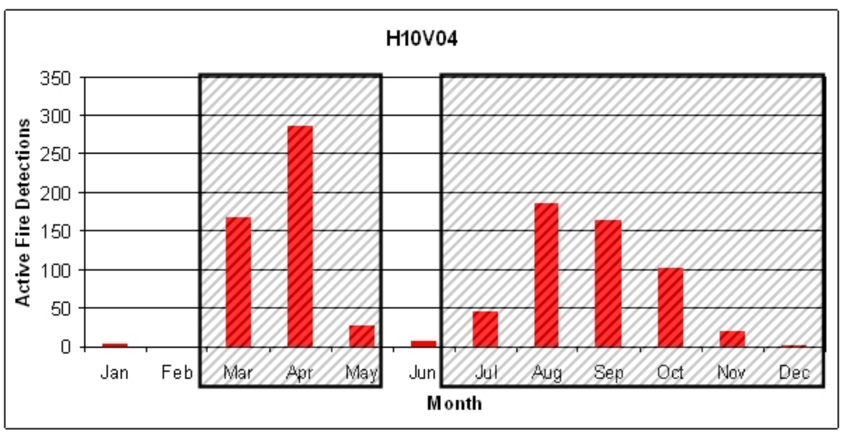
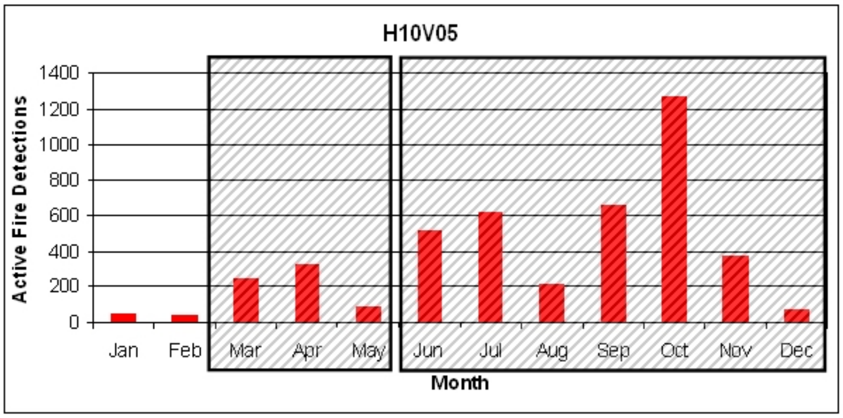


Figure 4-3. Average number of MODIS 1 km Active Fire Detections (red bars) in croplands with corresponding harvest temporal windows (grey-striped boxes) for all MODIS tiles used in this analysis for years 2003 – 2007 (Terra and Aqua); harvest temporal windows split months where the start and/or finish cropland burning does not correspond with the first day (active fires) or the first 8-day time period (dNBR).


H09V05
Active Fire Detections
80
70
60
50
40
30
20
10
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month


H09V06
Active Fire Detections
50
40
30
20
10
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month


H10V04
Active Fire Detections
350
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month


H10V05
Active Fire Detections
1400
1200
1000
800
600
400
200
0
Jan
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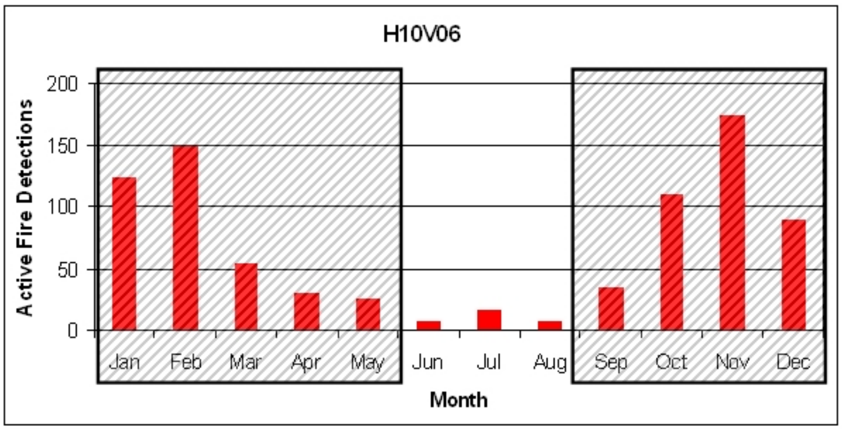
Sep
Oct
Nov
Dec
Month


H10V06
Active Fire Detections
200
150
100
50
0
Jan
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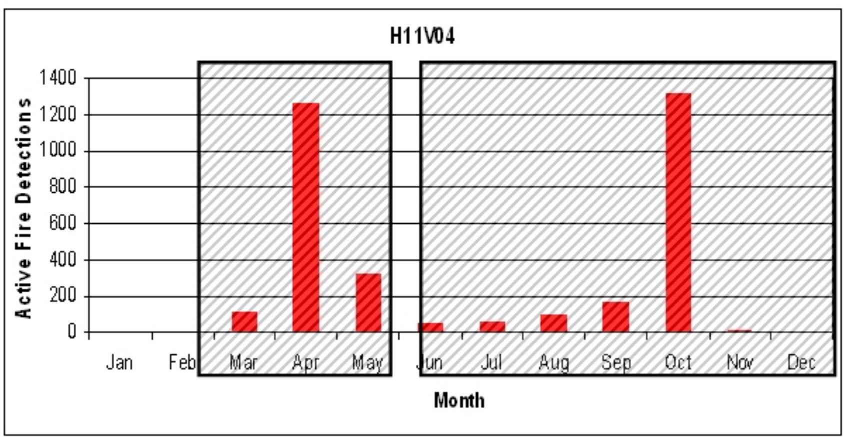
Month


H11V04
Active Fire Detections
1400
1200
1000
800
600
400
200
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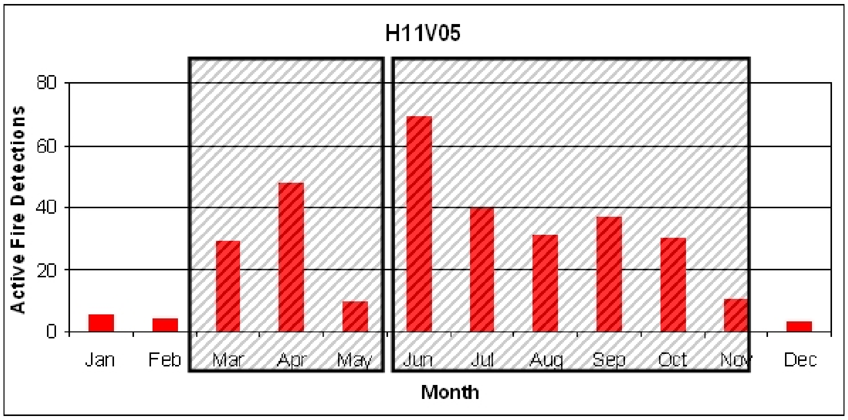
H11V05
Active Fire Detections
0
20
40
60
80
Jan
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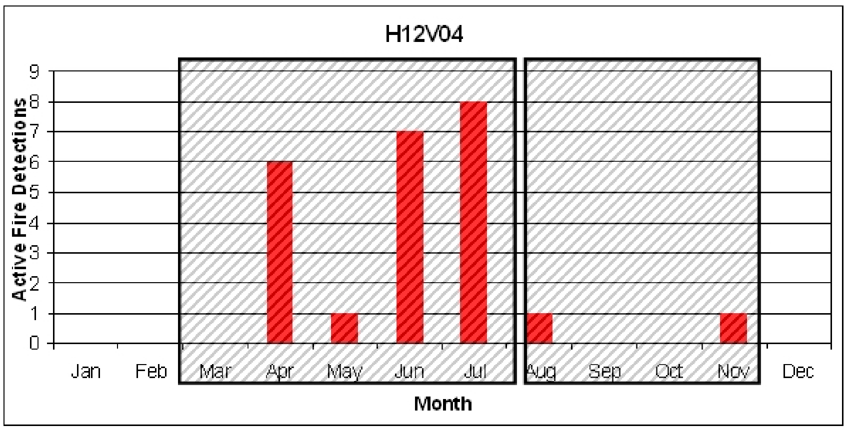
H12V04
Active Fire Detections
0
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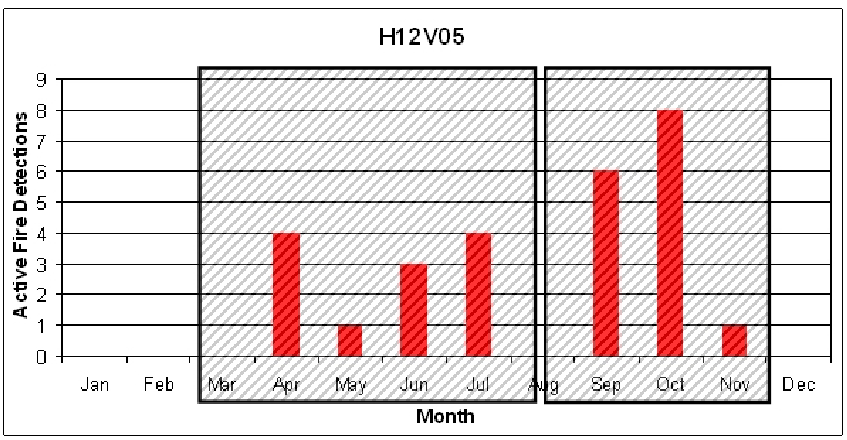
H12V05
Active Fire Detections
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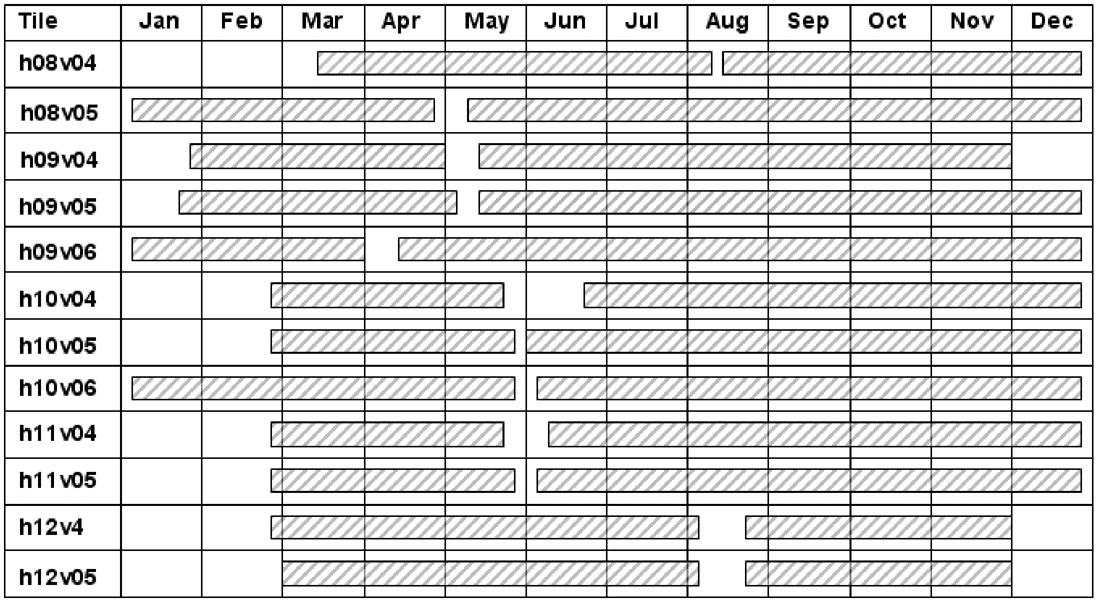

Figure 4-4. Comparison of harvest temporal windows (grey-striped boxes) for all MODIS tiles used in this analysis for a calendar year; harvest temporal windows split months where the start and/or finish cropland burning does not correspond with the first day (active fires) or the first 8-day time period (dNBR).

Table 4-1. Region-specific cropping systems (USDA/NASS, 2007), crop information, and the harvest periods used for the creation of the cropland dNBR maps.

Tile	Cropping Systems	Harvest Season 1	Harvest Season 2	Sources
h08v04	Bluegrass seed, hay/alfalfa, fruits and vegetables	7 Apr - 5 Aug	29 Aug - 3 Dec	Multi-year active fire analysis; Ball et al. 1998; CDFA 2007; USDA\NASS harvest reports.
h08v05	Cotton, winter wheat, rice, soy, fruits and vegetables	25 Jan - 15 Apr	9 May - 27 Dec	Multi-year active fire analysis; Jenkins et al. 1992; CDFA 2007; AZDA 2008; USDA\NASS harvest reports.
h09v04	Winter and summer wheat, bluegrass seed system; potatoes, sugar beets, fruits and vegetables system	18 Feb - 1 May	25 May - 3 Dec	Multi-year active fire analysis; Canode and Law 1979; Ball et al. 1998; WA DOE 2005; WRAP 2005; Dhammapala et al. 2006; Jimenez et al. 2007; ODA 2007; Extension agent interviews; USDA\NASS harvest reports; Field validation of burned fields.
h09v05	Wheat and other grains	25 Jan - 1 Apr	15 Apr - 3 Dec	Multi-year active fire analysis; Dennis et al. 2002; AZDA 2008; USDA\NASS harvest reports.
h9v06	Wheat, cotton, rice, sugarcane, soy	25 Jan - 26 Jun	20 Jul - 27 Dec	Multi-year active fire analysis; USDA\NASS harvest reports; LSU 2000.
h10v04	Wheat and other grains system; soy, corn, winter wheat system	6 Mar - 2 Jun	4 Jul - 27 Dec	Multi-year active fire analysis; Canode and Law 1979; WA DOE 2005; WRAP 2005; Dhammapala et al. 2006; ISDA 2007; Jimenez et al. 2007; Extension agent interviews; USDA\NASS harvest reports; Field validation of burned fields.
h10v05	Wheat and other grains system; winter wheat, cotton, rice, soy, corn system	26 Feb- 1 May	2 Jun - 27 Dec	Multi-year active fire analysis; U of A 2000; LSU 2000; Reid et al. 2004; Farmer surveys from field work; Extension agent interviews; USDA\NASS harvest reports; Field validation of burned fields.
h10v06	Sugarcane, rice, fruits and vegetables	1 Jan - 2 Jun	29 Aug - 27 Dec	Multi-year active fire analysis; Eiland 1998; LSU 2000; Farmer surveys from field work; Extension agent interviews; USDA\NASS harvest reports; Field validation of burned fields.
h11v04	Wheat and other grains system; soy, corn, winter wheat system	26 Feb - 2 Jun	18 Jun - 27 Dec	Multi-year active fire analysis; USDA\NASS harvest reports.
h11v05	soy, corn, winter wheat, tobacco system; winter wheat, cotton, tobacco, soy, corn system	1 Mar - 2 Jun	14 Sep - 3 Dec	Multi-year active fire analysis; USDA\NASS harvest reports.

Table 4-1. Region-specific cropping systems (USDA/NASS, 2007), crop information, and the harvest periods used for the creation of the cropland dNBR maps (cont.).

h12v04	Corn, soy, winter wheat, fruits and vegetables	7 Apr - 5 Aug	29 Aug - 3 Dec	Multi-year active fire analysis; USDA\NASS harvest reports.
h12v05	Corn, soy, winter wheat, sorghum, fruits and vegetables	7 Apr - 5 Aug	29 Aug - 3 Dec	Multi-year active fire analysis; USDA\NASS harvest reports; Field validation of burned fields.

Soil properties and irrigation practices were taken into consideration in the dNBR threshold determination in order to minimize errors of commission. In particular, plowed fields with dark soils and wet soils can cause commission errors in remote sensing burned area mapping, as the dark surface can have a similar reflectance signal to a burned area (Roy et al., 2005). This approach took these complex environmental factors into account by developing tile-specific thresholds to eliminate dNBR values that did not correspond to burned areas. Establishing dNBR values at a threshold to eliminate plowed and/or irrigated fields produced some small errors of omission, discussed in detail in section 4.3.2.

Five sample MODIS tiles were selected to develop dNBR thresholds. These sample tiles represented a variety of cropping systems, from monoculture wheat production in the Pacific Northwest to the double-cropping system of Mississippi Delta, as well as differing soil properties and areas of high crop residue burning frequencies (Canode and Law, 1979; Pudup and Watts, 1987; Jenkins et al., 1992; Bottcher and Izuno, 1994). The tiles were also chosen due to availability of GPS data and information from local collaborators. Tiles h08v05, h09v04, and h10v04 represented much of the western coast and the northern Great Plains. Tiles h10v05 and h10v06 encompassed the southern Great Plains and much of the southeast, including Florida.

Threshold development was completed in a multi-step process. First, burned, plowed, and irrigated fields data were collected *in situ* and digitized from high resolution satellite data, i.e., 15 m ASTER, 30 m Landsat 5 Thematic Mapper, and 56 m Advanced Wide Field Sensor (AWiFS), for areas within MODIS tiles h08v05, h09v04, h10v04, h10v05, and h10v06 were converted to GIS polygons. Table 4-2 lists the high resolution imagery and *in-situ* data sets used for the sample tiles during threshold development. The *in-situ* field data, consisting of GPS tagged burned, plowed, and irrigated fields, were collected during harvest seasons. All field campaigns followed a systematic transect sampling design, i.e., sampling of transects followed every other field row road, except in cases of actively burning fields that were visited with local agricultural extension agents. Attributes of the collected GPS data included values that identified burned fields, burning fields, plowed fields, and planted fields as well as information on crop type and crop rotation including previous crop types (if plowed or burned), planned crop type (if farmer and/or extension agent present), planted crop types, and field size.

For each tile, the high resolution Landsat, ASTER, and AWiFS scenes represented an area equivalent to 10% of the total area of a MODIS tile. Plowed fields were easily identified and digitized from Landsat, ASTER, and AWiFS data, using appropriate combinations of near- and mid-infrared bands that highlighted the difference between bare ground and burn scars following the methodology of Maingi (2005). When possible, irrigated fields were also identified from the GPS data and the high resolution data, often relying on the shape of the fields for identification. A minimum of 15 irrigated fields were detected and digitized for each high resolution image. The resulting polygons of plowed and irrigated fields from the GPS data and high resolution data were used to extract the corresponding 500 m dNBR values. The burned area threshold for each sample tile was defined as 1 standard deviation from the mean dNBR values of all plowed and irrigated field samples. Given the reliance of the threshold development on exclusion by one standard deviation rather than the mean, it is possible that this approach is overestimating the dNBR values of plowed and irrigated fields and thus creating conservative burned area estimates. An average error of omission is detailed further in section 4.3.2.

Table 4-2. The sample MODIS tiles with the corresponding data used for the dNBR threshold development and the dNBR threshold values for identifying burned fields.

MODIS Tile	Data	Data Source	dNBR Threshold Values
h08v05	Digitized polygons of burned, plowed, and irrigated fields from AWiFS data	AWiFS polygons only	425
h09v04	Digitized polygons from Landsat TM data and GPS polygons of plowed and irrigated fields	Landsat TM polygons; *in-situ* data collected during two field campaigns in eight counties in Washington and four counties in Idaho during August 2005 and August 2006	425
h10v04	GPS polygons of plowed and irrigated fields	*in-situ* data collected during two field campaigns in eight counties in Washington and four counties in Idaho during August 2005 and August 2006	375

Table 4-2. The sample MODIS tiles with the corresponding data used for the dNBR threshold development and the dNBR threshold values for identifying burned fields (cont.).

h10v05	Digitized polygons from ASTER data and GPS polygons of plowed and irrigated fields	ASTER polygons; *in-situ* data collected during two field campaigns in twelve counties in Arkansas during November 2004 and June 2006	375
h10v06	Digitized polygons from ASTER data and GPS polygons of plowed and irrigated fields	ASTER polygons; *in-situ* data collected during one field campaign in six parishes in Louisiana and the Everglades Agricultural Area in Florida during November 2004	375

Higher burned area thresholds were needed for the western U.S. This was expected, as darker soils and increased usage of irrigation is more prevalent in the western U.S. (Turner et al., 2003). Accordingly, the 12 MODIS tiles used in the analysis were grouped into two categories that represented similar cropping systems, soil properties, and irrigation activities (Figure 4-2). The dNBR threshold for category 1, containing the eastern and central U.S., was 375. The dNBR threshold for category 2, covering the Pacific Coast of the U.S., was set at 425.

4.2.2. Validation Data and Methods

The goal of the validation was to quantify the accuracy of the burned area estimations using independent and more accurate data (Morisette et al., 2002). Validation data used in this analysis came from various sources and all validation data were independent of the data used to derive the dNBR thresholds. GPS polygons of burned field boundaries as well as the associated crop type were collected over several harvest seasons (Table 4-3). High resolution imagery was utilized to produce burned area polygons within cropland areas to compare with calculated dNBR values. Actively burning or burned fields were digitized by visual examination of ASTER, Landsat TM, and AWiFS data and used to produce burn scar-only images using a masking tool (Dwyer et al., 2002). The comparison followed the MODIS validation protocol used by Hansen et al. (2002) and used pixel averaging techniques to aggregate 15 m, 30 m, and 56 m burn scar pixels to 500 m, comparable to the resolution of the dNBR estimates (Bian and Butler, 1999). In addition to these various validation data sets, approximate locations (i.e., both Public Land Survey System and latitude/longitude coordinates) of burned fields documented by agriculture extension agents on the ground in Louisiana, Kansas, and Washington were used for qualitative assessments of the performance of the crop residue burned area estimates. Results from this validation assessment are described in detail in section 4.3.1.

Table 4-3. Validation data sources for assessing the accuracy of crop residue burning estimates from the regional hybrid approach.

Data Type	Location	Month and Year	Description
GPS Polygons of burned fields	Arkansas	November 2004	Field campaign during fall rice, soy, and cotton harvest
	Arkansas	June 2006	Field campaign during spring winter wheat harvest
	Louisiana	November 2004	Field campaign during fall rice and sugarcane harvest
	Florida	November 2004	Field campaign during fall sugarcane harvest
	Washington/Idaho	August 2005	Field campaign during fall wheat and bluegrass seed harvest
	Washington/Idaho	August 2006	Field campaign during fall wheat and bluegrass seed harvest
15 m ASTER burn scars	Arkansas/Missouri	October 2004	Digitized polygons of actively burning and burned rice, soy, and cotton fields; Classified burn scar image s (five scenes)
	Arkansas/Mississippi	June 2006	Digitized polygons of actively burning and burned winter wheat and rice fields; Classified burn scar images (five scenes)
	Florida	January 2005	Digitized polygons of actively burning and burned sugarcane fields; Classified burn scar image
30 m Landsat TM burn scars	Washington	July 2004 and September 2004	Digitized polygons of burned bluegrass seed and wheat fields; Classified burn scar image
56 m AWiFS burn scars	California	June 2007	Digitized polygons of burned rice, cotton, and other crops fields; Classified burn scar image

4.3. Validation Results of Burned Area Product

4.3.1. Results of MODIS Crop Reside Burned Area Validation Using GPS Data

The accuracy of the cropland burned area estimates were first assessed using the 214 GPS polygons of burned fields collected during the field campaigns listed in Table 4-3. The sample field boundary data were compared against the dNBR burned area pixels for the same dates and areas. Error matrices were calculated for each individual field campaign using the statistics detailed in Appendix A. Table 4-4 reports the percent correctly classified, Kappa statistics, and User's accuracy derived from these calculations.

Table 4-4. Accuracy statistics for GPS burned field boundary data compared with 500 m dNBR product; detailed statistics for Arkansas adapted from (McCarty et al., 2008).

State	Season/Year	Number of Burned Area Polygons	Percent Correctly Classified	Kappa Value	User's Accuracy
Arkansas	Fall/2004	21	80.95%	0.81	0.79
Arkansas	Spring/2006	48	89.58%	0.90	0. 71
Florida	Fall/2004	35	82.85%	0.83	0.66
Idaho	Fall/2005	18	87.10%	0.86	0.69
Idaho	Fall/2006	22	88.35%	0.88	0.71
Louisiana	Fall/2004	12	80.67%	0.79	0.64
Washington	Fall/2005	38	85.90%	0.85	0.70
Washington	Fall/2006	20	84.75%	0.83	0.76

Generally, there was a strong agreement (>80%) between the field data and the dNBR burned area estimates for croplands (Table 4-4). For Arkansas, the dNBR approach mapped spring burning associated with winter wheat harvesting (n = 48, Kappa ~0.90) better than the fall burning related to the rice, soy, and cotton harvests (n = 21, Kappa ~ 0.81). This result was likely due to increased precipitation in the fall that inhibited the detection of these burned areas (McCarty et al., 2008). The dNBR approach performed less well in the sugarcane growing areas of Florida (n = 35, Kappa ~ 0.83) and Louisiana (n = 12, Kappa ~ 0.79), which is likely due to confusion between burned fields and the dark-colored peat soils in those regions, indicated by the highest errors of commission. The fall harvest season in Florida and Louisiana also experiences frequent precipitation events, resulting in significant cloud cover (McCarty et al., 2007). It is possible that the 8-day dNBR estimates may not be able to consistently detect fall burning in the southeast U.S. due to large amounts of cloud contaminated pixels. A cloud contamination analysis of 500 m 8-day MODIS surface reflectance data of the Mississippi Delta found an average of 111 cloudy pixels for each of the nine 8-day time periods between 30 September and 3 December; higher than the average 47 cloudy pixels per 8-day image during the spring harvest season between the 7 April and 4 July. This dNBR approach performed better in the Pacific Northwest. There was a moderate to strong agreement between GPS burned fields and dNBR burned area pixels for both Idaho (n = 18, Kappa ~ 0.86 and n = 22, Kappa ~ 0.88, respectively) and Washington (n = 38, Kappa ~ 0.85 and n = 20, Kappa ~ 0.83).

4.3.2. Validation of MODIS Crop Residue Burned Area Using High Resolution Data

High resolution burn scar polygons were used to produce additional error matrices. ASTER, Landsat TM, and AWiFS burn scar images used for the ground truth validation were compared with MODIS-based maps of cropland burning in the states of Arkansas, Missouri, Mississippi, Florida, Louisiana, Washington, and California, respectively (Table 4-3). Table 4-5 provides a detailed comparison between the aggregated, high resolution burn scar pixels and the dNBR product.

Table 4-5. Accuracy assessment of dNBR burned area estimates compared with derived burn scar polygons from high resolution satellite data.

State	Month/Year	Number of Burned Scar Polygons	Percent Correctly Classified	Kappa Value	User's Accuracy
Arkansas	June 2003	100	80.00%	0.79	0.38
Arkansas	October 2004	100	81.00%	0.80	0.34
Missouri	October 2004	12	83.33%	0.82	0.34
Mississippi	June 2003	15	86.07%	0.85	0.34
Florida	January 2005	35	78.38%	0.77	0.58
Louisiana	November 2006	24	79.17%	0.79	0.67
Washington	July 2004	32	84.38%	0.84	0.30
Washington	September 2004	44	79.55%	0.80	0.25

The validation results showed a good correspondence ranging from 79 to 86%. The dNBR approach did not perform as well in Florida and Louisiana as in other states when compared with GPS boundaries of burned fields. Higher commission errors, defined as the number of unburned pixels incorrectly mapped as burned by the dNBR product, were also present in these two states. This approach performed well in the western states of Idaho and Washington for both the GPS and the high resolution burn scar comparison. An average omission error of 16%, defined as the number of burned pixels missed by the dNBR approach, occurred in each scene due to burned pixels from the high resolution data not being mapped as burned in the 500 m dNBR images. In all instances, the corresponding dNBR values of these omitted burned pixels fell below the established dNBR threshold. Overall, the results suggest that this method is an accurate and consistent approach to quantify crop residue burning in the CONUS, providing a conservative estimate of crop residue burned area.

4.4. Results of Burned Area Estimates

4.4.1. Crop Residue Burning in the CONUS

The results of this analysis show that crop residue burning in the CONUS occurred consistently each year in specific regions, particularly the Mississippi Delta states of Arkansas, Mississippi, and Louisiana; the Blackbelt of southern Georgia and Alabama; the Everglades Agricultural Area in south Florida; the southern Great Plains of Texas, Oklahoma, and Kansas; the northern Great Plains of eastern Colorado, Minnesota, South Dakota, and North Dakota; the Snake River region in southern Idaho; the Inland Pacific Northwest of eastern Washington, northern Idaho, and northeastern Oregon; the Willamette Valley in Oregon; and the Central Valley of California. This spatial distribution is directly related to the kinds of crops grown within these regions, particularly wheat, soy, corn, rice, sugarcane, and grass seed. Figures 4-5 and 4-6 show the spatial distribution of seasonal burned area for the insets of the Central Valley of California and southern Louisiana as well as eastern Washington and southern North Dakota, respectively.

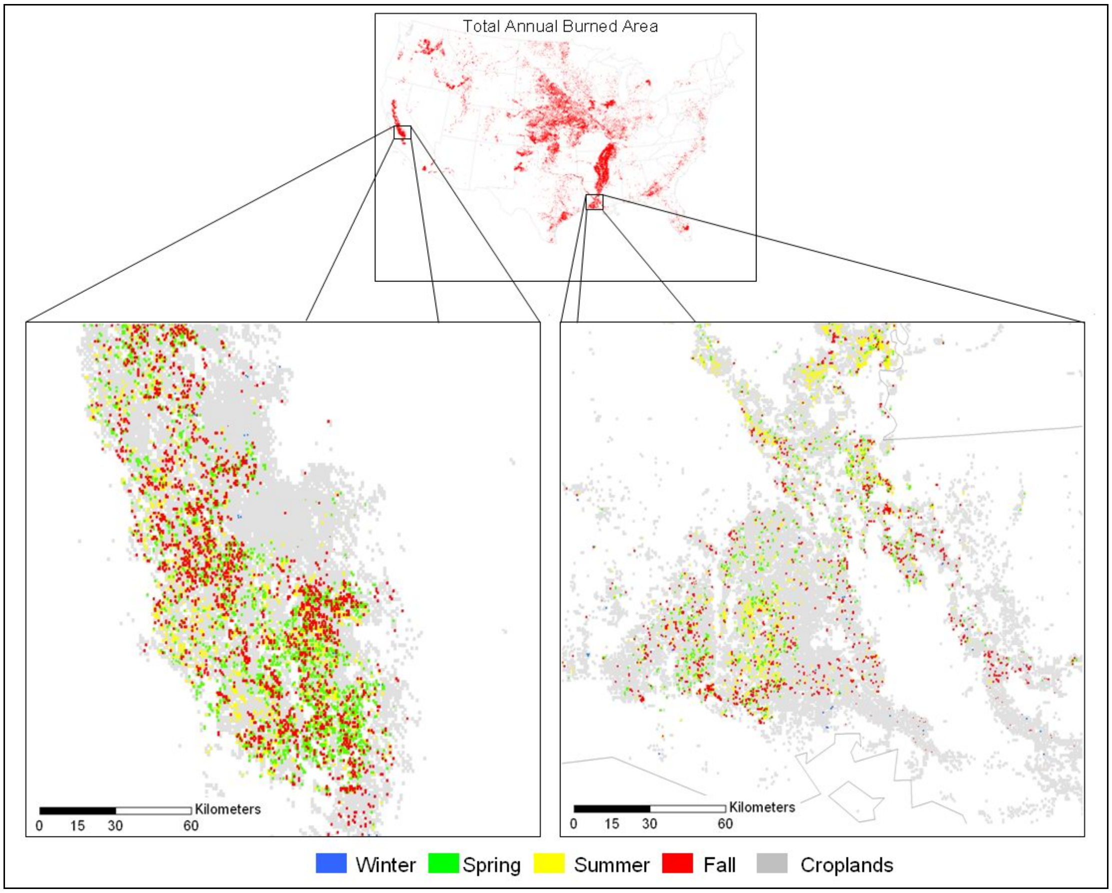

Figure 4-5. Seasonal cropland burned area for sub-regions of California (left) and Louisiana (right) for years 2003-2007; burned area is a combination of dNBR maps and active fire points; for mapping purposes, active fire detections were not calibrated into area for display purposes and remain as original point shapefiles but symbolized as squares instead of circles; seasons are defined as Winter: January - March; Spring: April-June; Summer: July - September; and Fall: October – December; (projection: Albers Equal Area Conic).

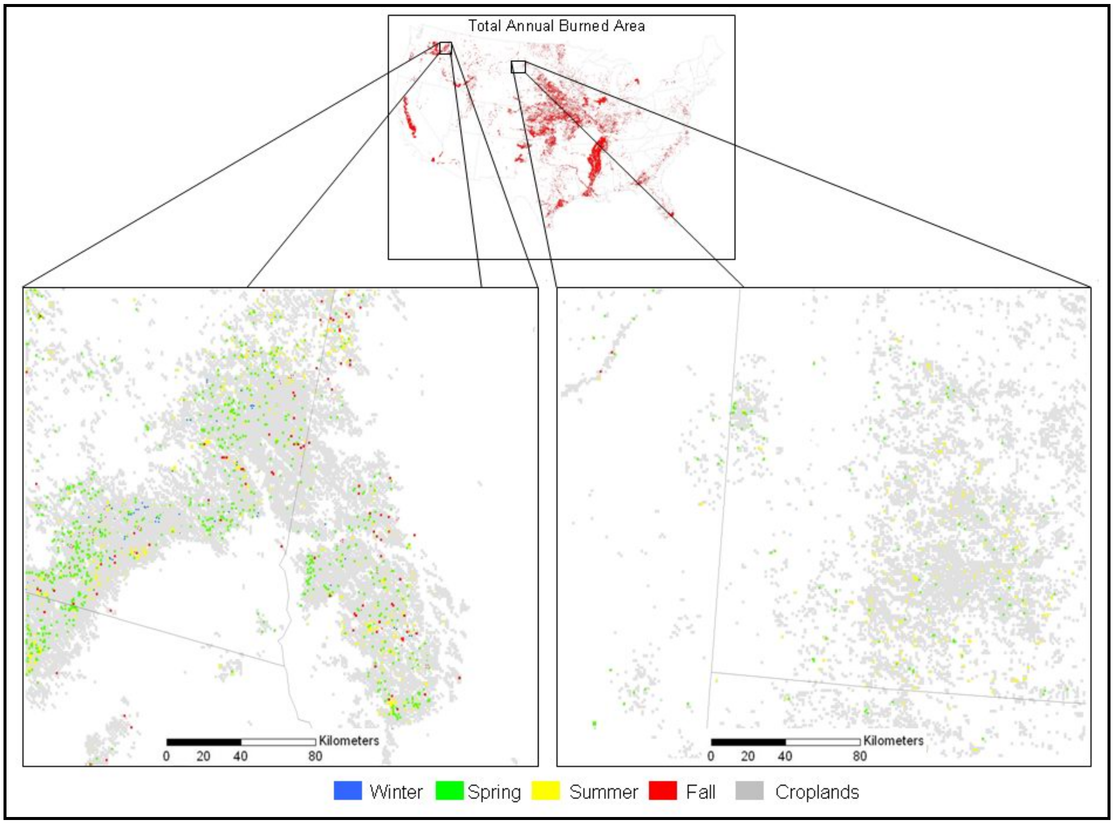

Figure 4-6. Seasonal cropland burned area for sub-regions of Washington (left) and North Dakota (right) for years 2003-2007; burned area is a combination of dNBR maps and active fire points; for mapping purposes, active fire detections were not calibrated into area for display purposes and remain as original point shapefiles but symbolized as squares instead of circles; seasons are defined as Winter: January - March; Spring: April-June; Summer: July - September; and Fall: October – December; (projection: Albers Equal Area Conic).

Thirteen states with the average annual burned cropland area of 75,875 ha accounted for 80% of total cropland burned area in the CONUS. Each of these states had an annual average of crop residue burned area greater than 30,000 ha. The thirteen states with the largest cropland burned area, in descending order, are: Florida, Arkansas, Idaho, California, Texas, Washington, Kansas, North Dakota, Colorado, South Dakota, Louisiana, Oklahoma, and Oregon.

On average, 1% of the total harvested agricultural areas, as defined by the state statistics from the 2002 USDA Agricultural Census (USDA/NASS, 2002), in the CONUS are burned annually. These harvested areas include all crops grown and harvested in a state, including field crops, horticulture crops, and orchards. Much of the harvested agricultural areas included crops that are not managed by fire. This analysis used the harvested area statistic to produce realistic comparisons of the proportion of cropland burned area to all potential harvested agricultural areas in the CONUS and a given state. For crops targeted in this analysis, i.e., bluegrass, corn, cotton, rice, soy, sugarcane, wheat, 15% of the total harvested area burned annually.

Table 4-6 shows the distribution of annual cropland burned area statistics for each state in the CONUS. For ten of the 48 contiguous states, cropland burned area was larger than twice the CONUS burning average of harvested agricultural areas. The MODIS-based burned area estimates show that Florida has the highest annual percentage of harvested cropland burned area, with an average of 34.1%. Cropland burning in Florida is further described in section 4.4.3. Arizona had the second highest percentage of harvested areas burned with 5.8% mainly in areas of irrigated wheat and cotton that are known to burn (Coates, 2000; WRAP, 2002; Choi and Fernando, 2007). An average of 4.8% of the harvested agricultural areas in Idaho burned annually, in areas of Kentucky bluegrass seed and wheat production (Lamb and Murray, 1999; Holman et al., 2007). Utah farmers burned 4.3% of harvested areas, corresponding to wheat, other grains, and orchard production areas (USU, 2003b). The 3.7% of harvested agricultural areas burning in Washington was clustered in wheat and grass seed production regions (Dhammapala et al., 2006; Jimenez et al., 2006; Jimenez et al., 2007). Annually 3.1% of total harvested areas in Arkansas burned, related to winter wheat, rice, soy, and cotton residue burning after spring and fall harvests (Brye et al., 2006; McCarty et al., 2007). 2.5% of total harvested areas burned in Louisiana in the mono-culture region of sugarcane and the rotation crops of winter wheat and rice (LSU Ag Center, 2000; McCarty et al., 2007). Burning in Oregon, 2.5% of total harvested areas, was concentrated in areas that produce Kentucky bluegrass seed and wheat (Chastain et al., 1997; ODA, 2007). California's burned cropland, 2.3% of harvested areas, was concentrated in mostly rice, cotton, wheat, and orchard areas (Jenkins et al., 1992; Coatney, 2000). An average of 2.1% of harvested agricultural areas burned annually in eastern Colorado, mainly in wheat producing areas (CDPHE, 2008). These ten states account for approximately 61% of all crop residue burned area in the CONUS. These results show that Florida is the only state with more than 1/3 of its harvested agricultural areas managed with fire. This analysis also showed a consistent cluster of burning in Arizona, Idaho, Utah, Washington, Arkansas, Louisiana, Oregon, California, and Colorado, meaning that the same areas (and likely fields) within these states burned year after year.

Table 4-6. Yearly, average, and total crop residue burned area per state for years 2003-2007 (ha); average percent of harvested croplands burns are calculated using harvest cropland areas from (USDA/NASS, 2002); state abbreviations substituted for state names; Connecticut, Maine, and New Hampshire experienced no crop residue burning and are omitted from the table .

State	2003	2004	2005	2006	2007	Five year Total	Average yearly burned area	Average percentage of harvested agricultural areas burned
AL	8,112	4,849	4,258	8,284	8,930	34,433	6,887	0.9%
AZ	20,705	20,776	26,410	18,480	17,304	103,675	20,735	5.8%
AR	103,000	89,596	94,654	96,157	80,887	464,294	92,859	3.1%
CA	88,612	109,855	85,762	54,312	62,433	400,975	80,195	2.3%
CO	42,093	40,572	38,154	26,462	35,012	182,293	36,459	2.1%
DE	825	950	816	767	1,023	4,381	876	0.5%
FL	368,086	327,276	322,187	282,751	294,814	1,595,113	319,023	34.1%
GA	3,741	4,349	3,511	6,577	7,847	26,024	5,205	0.4%
ID	64,966	88,651	96,380	95,588	74,844	420,428	84,086	4.8%
IL	11,340	7,748	10,822	10,087	11,122	51,119	10,224	0.1%
IN	9,589	8,306	8,461	9,959	7,300	43,616	8,723	0.2%
IA	4,810	9,439	16,684	16,283	17,667	64,883	12,977	0.1%
KS	67,043	30,021	56,729	44,778	55,353	253,923	50,785	0.7%
KY	944	708	645	1,872	1,998	6,167	1,233	0.1%
LA	27,746	22,137	38,379	24,984	53,129	166,375	33,275	2.5%
MD	1,215	1,420	1,597	1,500	1,924	7,657	1,531	0.3%
MA	156	185	216	178	347	1,082	216	0.3%
MI	16,798	12,618	16,505	15,392	8,142	69,455	13,891	0.5%
MN	12,824	12,025	14,601	15,738	13,666	68,854	13,771	0.2%
MS	14,042	6,810	12,761	14,195	14,046	61,854	12,371	0.7%
MO	34,028	18,549	31,230	20,473	39,465	143,745	28,749	0.5%
MT	28,663	23,776	22,414	32,440	34,846	142,139	28,428	0.8%
NE	9,102	9,018	11,060	14,569	16,522	60,272	12,054	0.2%
NV	2,395	2,808	2,751	3,467	3,054	14,475	2,895	1.3%
NJ	644	1,729	1,219	1,117	1,768	6,477	1,295	0.7%
NM	3,397	5,854	5,486	4,782	3,300	22,819	4,564	1.3%
NY	3,519	2,228	1,609	1,939	2,505	11,800	2,360	0.2%
NC	5,979	6,921	7,313	4,418	6,067	30,698	6,140	0.4%
ND	44,893	34,290	38,836	28,699	44,797	191,515	38,303	0.5%
OH	9,438	8,389	10,836	10,978	8,701	48,342	9,668	0.2%
OK	21,128	26,895	33,669	34,988	48,730	165,410	33,082	1.1%
OR	29,979	24,775	34,961	30,735	37,140	157,590	31,518	2.5%
PA	1,842	1,309	2,863	2,350	3,987	12,352	2,470	0.1%
RI	0	32	32	62	24	148	30	0.4%
SC	936	2,797	2,682	3,138	3,524	10,280	2,056	0.4%
SD	35,864	32,219	40,323	24,277	40,220	172,903	34,581	0.6%
TN	1,962	3,011	2,948	3,084	5,691	16,697	3,339	0.2%

Table 4-6. Yearly, average, and total crop residue burned area per state for years 2003-2007 (ha); average percent of harvested croplands burns are calculated using harvest cropland areas from (USDA/NASS, 2002); state abbreviations substituted for state names (cont.).

TX	98,253	81,418	66,645	76,220	72,703	395,238	79,048	1.1%
UT	18,866	10,400	16,591	19,918	17,149	82,924	16,585	4.3%
VT	655	421	216	123	972	2,387	477	0.3%
VA	823	911	1,557	1,488	1,970	6,749	1,350	0.1%
WA	43,240	96,091	81,081	48,075	97,291	365,778	73,156	3.7%
WV	139	511	738	584	485	2,457	491	0.2%
WI	12,289	9,411	10,547	10,555	9,642	52,444	10,489	0.3%
WY	11,756	7,361	13,864	12,095	7,969	53,046	10,609	2.0%

Several states showed little to no crop residue burning. In three New England states, Connecticut, Maine, and New Hampshire crop residue burning did not occur, likely related to absence of crops most commonly managed with fire. Five other states experienced insignificant crop residue burning (~ 0.1% of total harvested agricultural areas): Illinois, Iowa, Kentucky, Pennsylvania, and Virginia. While crop residue burning did occur in these states (Table 4-6), the large agricultural areas ranging from over 1 million ha in Virginia to almost ten million ha in Iowa meant that the small amount of crop residue burning did not significantly account for total harvested area.

Crop residue burning for much of the CONUS showed considerable interannual variability. The greatest interannual variation of cropland burned area occurred in the state of Vermont, which had an interannual variation ± 57% of cropland burned area. Cropland burned area in Arkansas, Florida, Minnesota, and Wisconsin varied by less than ± 10% interannually. On average, crop residue burned area for the CONUS varied interannually by ± 22%.

Crop residue burned area in the CONUS was also compared to reported wildland fire area in the U.S. (including Alaska) compiled by the National Interagency Fire Center (NIFC) (NIFC, 2008). On average, the area of crop residue in the CONUS comprised 43% of total wildland burned area (Table 4-7). In 2003, crop residue burned area in the CONUS was equal to nearly 79% of the area of wildland burning suggesting that crop residue burning is a major fire activity for the U.S.

Table 4-7. Comparison of cropland burned area to wildland burned area for years 2003 -2007.

Year	Wildland burned area (ha)	Cropland burned area (ha)	% Cropland burned area
2003	1,623,945	1,276,310	78.59%
2004	3,320,131	1,134,918	34.18%
2005	3,562,834	1,291,003	36.24%
2006	4,048,235	1,209,415	29.88%
2007	3,824,498	1,286,437	33.64%

The states of California, Florida, Idaho, Louisiana, Oregon, and Washington monitor crop residue burning through permitting systems and/or burn management education programs, as detailed in chapter 1. Of these six states, only California and Florida showed both a net decrease in cropland burned area and a negative percent change between 2003 and 2007 (Table 4-8). California has a fee-based crop residue burn permitting system and a burn limit for rice fields of approximately 50,886 ha for the spring and fall harvests, respectively (CARB, 2003). Florida has a voluntary permitting system that is not fee-based or enforced by fines (FLDOF, 2005). Like California, Washington and Oregon also require farmers to pay for burning crop residues (DOE, 2005; ODA, 2007). Compared to the other five states, Washington had the highest net gain in cropland burned area with over 54,000 ha and average annual percent increase in cropland burned area of 5%. Oregon, with a net gain in crop residue burned area of approximately 7,100 ha, had an average annual increase in cropland burned area of 3%. Louisiana, which has a voluntary burn management education program and does not require farmers to have a permit to burn (LSU Ag Center, 2000), experienced the second highest net gain in cropland burned area with over 25,000 ha and average annual percent increase in cropland burned area of 4%. Similarly, Idaho state regulations require Burn Managers to present at all agricultural fires (ISDA, 2006). This analysis demonstrated that the average percent change in cropland burned area in Idaho was +2%, with a net increase of cropland burned area between 2003 and 2007 of 9,878 ha. None of these six states showed a consistent decrease or increase in crop residue burned area. Even California and Florida, which had an average decrease in crop residue burned area from 2003 and 2007, experienced years of increased burning. This analysis demonstrates that the impact of state-level permitting systems, restrictions on field burning, and/or burn management education programs can reduce total cropland burned area.

Table 4-8. Comparison of interannual percent changes and net change of cropland burned area for states which permit crop residue burning and/or provide burn management education; state abbreviations substituted for state names.

State	Percent change, 2003-2004	Percent change, 2004-2005	Percent change, 2005-2006	Percent change, 2006- 2007	Average percent change, 2003-2007	Net change of burned area, 2003-2007
CA	+19%	-28%	-58%	+13%	-13%	-26,179
FL	-12%	-2%	-14%	+4%	-6%	-73,272
ID	+27%	+8%	-1%	-28%	+2%	+9,878
LA	-25%	+42%	-54%	+53%	+4%	+25,383
OR	-21%	+29%	-14%	+17%	+3%	+7,161
WA	+55%	-19%	-69%	+51%	+5%	+54,051

4.4.2. Focused Results: Kansas

Historically, Kansas farmers used crop residue burning to remove excess biomass from the fields and to prevent plant diseases (Watkins and Boosalis, 1994). This analysis focuses on Kansas due to its current policy needs to quantify and reduce trans-boundary air quality issues. Recent air pollution events in neighboring cities like Kansas City, Missouri from agricultural burning in Kansas (Dillon, 2004) have forced the state to investigate the necessity to monitor and restrict all forms of agricultural burning, including crop residue burning (Personal communication with Mr. Scott Weir, Kansas Department of Health and Environment, 7 August 2008). Current state law allows farmers to burn agricultural residues as long as certain fire safety precautions are met under Kansas Air Regulation 28-19-648 (KDHE, 2008). Corn and soy residues are burned in eastern Kansas during the fall. Wheat residues account for the vast majority of cropland burning in Kansas (Personal communication with Dr. Gary Cramer, Sedgwick County Extension Agent, Wichita, KS, 28 July 2008). Wheat is harvested between late May and July, with a second burning season during

September and October to clear fields before the fall planting. Figure 4-7 shows the crop residue burning in Kansas for years 2003 through 2007.

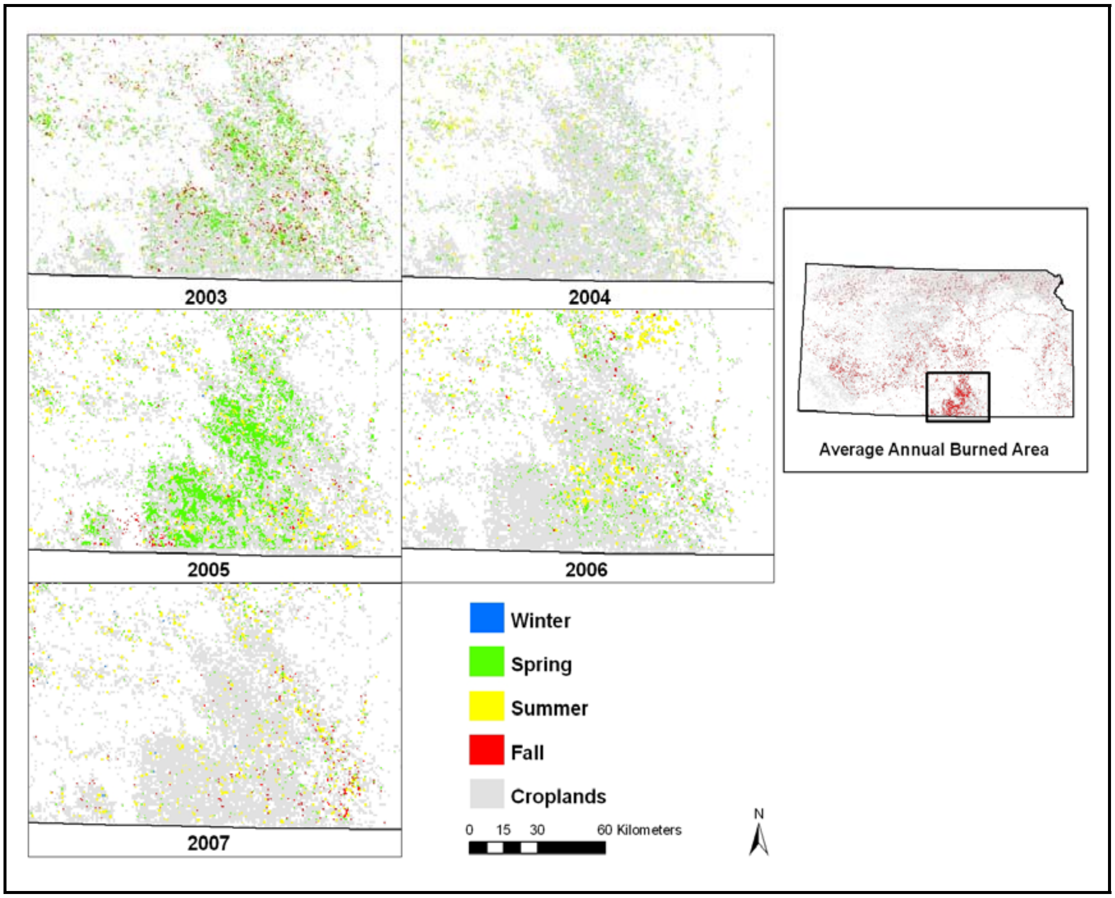

Figure 4-7. Seasonal crop residue burning for a sub-region of Kansas for years 2003-2007; burned area is a combination of dNBR maps and active fire points; for mapping purposes, active fire detections were not calibrated into area for display purposes and remain as original point shapefiles but symbolized as squares instead of circles; seasons are defined as Winter: January - March; Spring: April-June; Summer: July - September; and Fall: October – December; (projection: Albers Equal Area Conic).

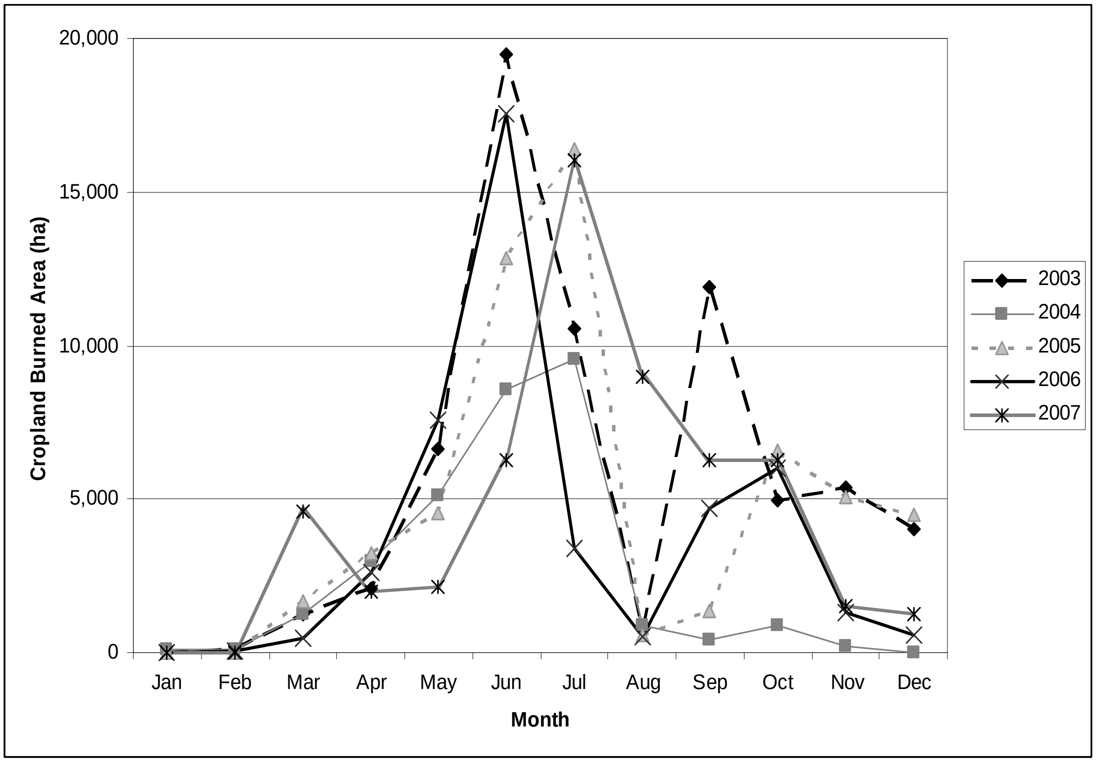

Figure 4-8. Monthly variability of crop residue burning in Kansas for years 2003-2007.

This analysis showed the highest peaks of crop residue burning in the summer and fall of 2003 with considerable year to year variability (Figure 4-8). Wheat yields for 2003 were extraordinary, with an 80% increase in production over 2002 (USDA/NASS, 2003b). Approximately 4 million ha of wheat were harvested in Kansas in 2003 and an additional 4.2 million ha of wheat were planted (USDA/NASS, 2008). Year 2004 had the least amount of burning (~ 30,000 ha) with a peak during the summer harvest season. Wheat production in Kansas was lower in 2004 by 34% (compared to 2003), with a total of 3.4 million ha harvested and less than 4 million ha of wheat planted in the fall (USDA/NASS, 2004b; USDA/NASS, 2008). Burning in 2005 increased from 2004 during June and July and in the fall, corresponding to a reported increase of 21% in wheat production in 2005 (USDA/NASS, 2005b). Summer burning in 2006 was nearly as high as 2003, though significantly less burning occurred in the fall. The Kansas wheat yields were low in 2006 due to hot and dry weather during the growing season and were noted locally to be the worst yields in a decade (Long, 2006). It is likely that farmers burned more during the low yield summer harvest, perhaps even burning fields that were not harvested due to low quality grain. This would have left fewer fields to be cleared of residue during the fall, as is indicated by the burned area mapping. The summer harvest in 2007 was delayed, with most of the burning occurring in July rather than June. Reduced burning continued from August through October, with a sharp drop in November. Yields in 2007 were nearly as low as 2004, with approximately 3.5 million ha of wheat harvested Kansas (USDA/NASS, 2008). The vast majority of crop residue burning in 2007 occurred in western Kansas (Figure 4-7), which matched reported harvesting rates. Wheat harvests for western Kansas were average in 2007, but the harvest in central Kansas was nearly a record low, with zero to few fields harvested in each county, due to the extreme weather events in the spring of 2007, including ice storms, wind storms, and tornadoes (Anderson, 2007).

4.4.3. Focused Results: Florida

Crop residue burning in Florida is clustered in the Everglades Agricultural Area south of Lake Okeechobee (Figure 4-9). This agricultural area mainly grows sugarcane, which is harvested from October to April (Bottcher and Izuno, 1994; Eiland, 1998). Sugarcane fields are often burned prior to harvest to remove dead leaves and other so-called "trash" biomass that can impede mechanical and conventional harvesting, increase transportation costs, and absorb sugar during the milling extraction process (Baucum et al., 2006). Nearly all sugarcane fields are burned prior to harvest (Eiland, 1998). Sugarcane is a big agricultural industry in Florida, accounting for 25% of all domestic sugar production (Juarez et al., 2008). On average, Florida farmers grow approximately 162,000 ha of sugarcane each year (Baucum et al., 2006). Due to the large amounts of burning, sugarcane farmers currently submit to a volunteer burn permitting system through the Florida Department of Forestry (FLDOF, 2005).

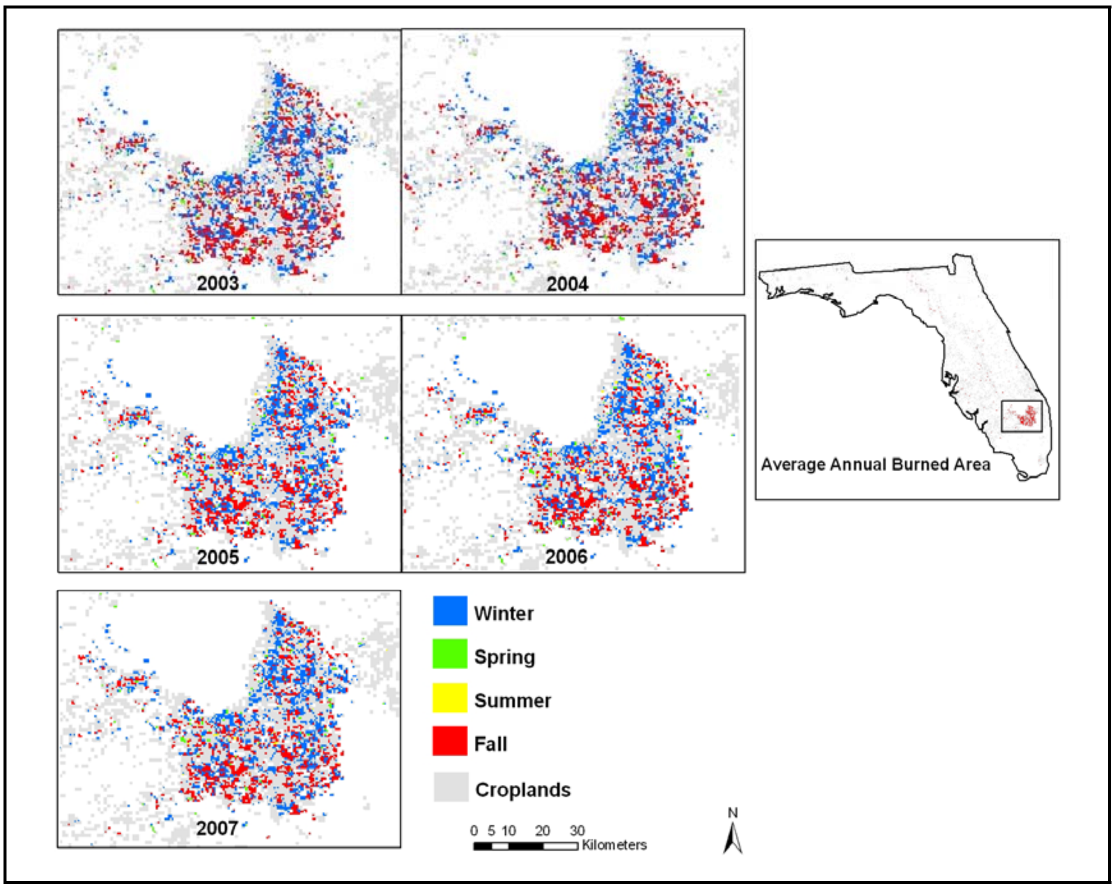

Figure 4-9. Seasonal crop residue burning for the Everglades Agricultural Complex in Florida for years 2003-2007; burned area is a combination of dNBR maps and active

fire points; for mapping purposes, active fire detections were not calibrated into area for display purposes and remain as original point shapefiles but symbolized as squares instead of circles; seasons are defined as Winter: January - March; Spring: April-June; Summer: July - September; and Fall: October – December; (projection: Albers Equal Area Conic).

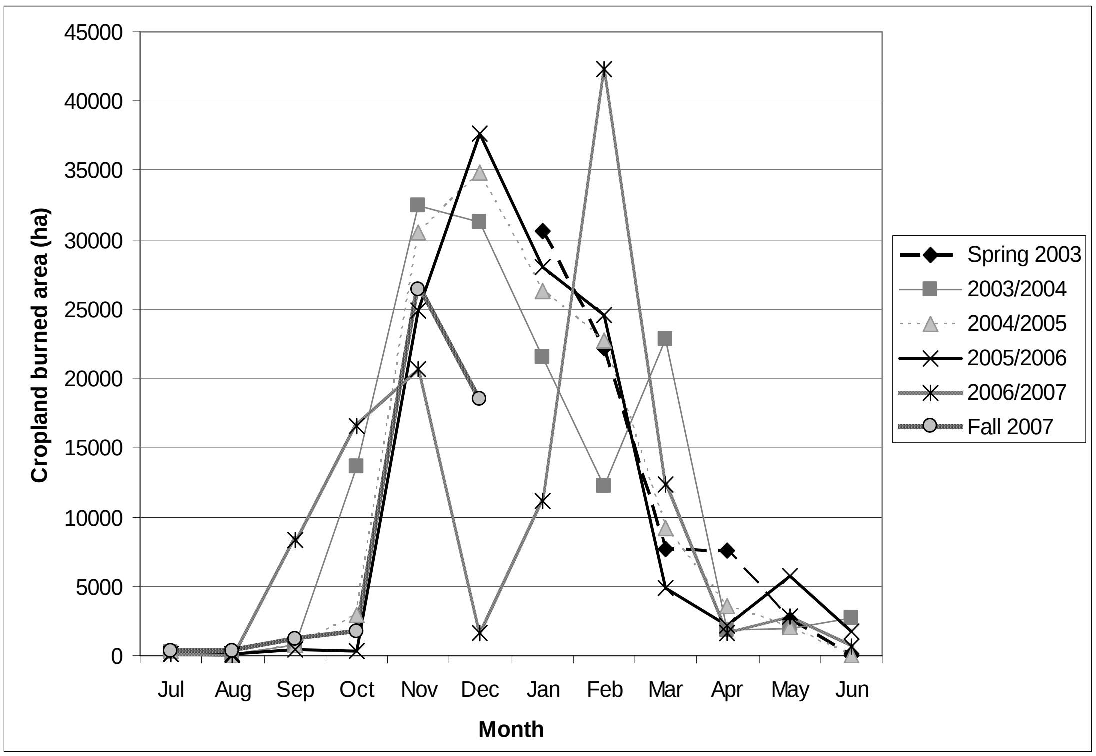

Figure 4-10. Monthly variability of crop residue burning in Florida for years 2003-2007; note the x-axis begins with July and ends with June and that each line is defined as a harvest period, i.e., combining the end and beginning of two years to emphasize the October to April sugar harvest.

Figure 4-10 shows that the majority of cropland burning in Florida occurs between the months of October and April, which coincides with the sugarcane harvest. For each year, there was a clear increase in burning between October and November. Crop residue burning increased in December 2004 and 2005 but decreased in the same month for years 2003, 2006, and 2007. The anomalously lower decrease in December 2006 coincides with reported increase in precipitation, which was 21% higher than average (NCDC, 2008b). Higher precipitation levels can impede harvesting and reduce the likelihood of farmers using fire prior to harvesting the sugarcane. Below average precipitation was recorded for the months of December 2003 and December 2007, making it unlikely for inclement weather to have impeded harvesting. However, exact harvesting dates are dictated by the local mills and sugar cooperatives to the sugarcane farmers throughout the six month harvest season (Baucum et al., 2006). Therefore, rates of harvesting are determined by the industrial processes of refining and shipping processed sugar before more cane can be harvested. The months of January, February, March, and April show similar variability that is most likely related to both changing precipitation patterns and the harvesting schedule.

4.5. Comparison with Government Statistics

Several states compile reports on agricultural burning, but 8 states, including much of the Midwest, include rangeland burning in their estimates (Reid et al., 2004) and do not provide independent reporting of cropland burning. Four states, however, have published government-sponsored statistics specifically on cropland burning. Table 4-9 compares the reported cropland burned area with the remote sensing burned area estimates for the states of Arkansas, Florida, Louisiana, and Washington from this analysis. Average burned area estimates are used in the comparison for states with reported statistics for years not included in this analysis or for states that provided annual average cropland burned area estimates.

Table 4-9. Comparison of state level cropland burned area with remote sensing estimates of cropland burned area; average cropland burned area estimates for 2003-2007 used for Arkansas, the Everglades Agricultural Area, and Louisiana (shown in italics).

State and/or Agricultural Area	Data Collection Year	Reported Burned Area (ha)	THIS STUDY Estimated Burned Area (ha)	Percent Difference (- for underestimation; + for overestimation)	Source
Arkansas	2002	265,193	*92,859*	-65%	(Reid et al. 2004)
Everglades Agricultural Area (Florida)	Annually	162,000	*123,652*	-24%	(Baucum et al. 2006)
Louisiana	2002	196,856	*33,265*	-83%	(Reid et al. 2004)
Washington	2003	58,503	43,240	-26%	(WA DOE 2003)
Washington	2004	63,390	96,091	+52%	(WA DOE 2003)
Washington	2005	56,885	81,081	+43%	(WA DOE 2003)
Washington	2006	87,095	48,075	-45%	(WA DOE 2003)

Government statistics for Arkansas and Louisiana were collected in 2002 for the Central Regional Air Planning Association by Sonoma Technology, Inc. (Reid et al., 2004). Agricultural burning activity was reported using a self-reporting mail and telephone survey of county Agriculture Extension Agents. The remote sensing-based estimates of cropland burning for Arkansas and Louisiana represent 35% and 17%, respectively, of the self-reported estimates from Reid et al. (2004). When the satellite burned area was compared to the annual harvested area of wheat, rice, soy, and cotton reported by the USDA (USDA/NASS, 2008), the estimates from this analysis constituted the same burning rate, i.e., percentage of cropland area burned, as reported by the county extension agents (McCarty et al., 2008). Clearly, there is a discrepancy between the government data and the remote sensing estimates. Based on this comparison, determining which data set is an under- or overestimation of burned area is difficult.

For the Everglades Agricultural Area in Florida, the remote sensing estimates were on average 38,000 ha lower than the numbers reported by the government statistics (Table 4-9). The Florida Sugarcane Handbook reported that an average of 173,000 ha of sugarcane is grown each year in Florida. However, the USDA statistics on harvested sugarcane area showed a significant decline in sugarcane acres between 2003 and 2007 (USDA/NASS, 2008). Using the extent of burning of sugarcane published in (Baucum et al., 2006), estimated sugarcane burned area in the Everglades Agricultural Area was compared to USDA statistics on harvested sugarcane areas (USDA/NASS, 2008). The methodology presented here captured an average of 96% of sugarcane burning in the Everglade Agricultural Area.

The Washington Department of Ecology monitors and permits all forms of agricultural burning in the state, including crop residue burning. Both the reported burning and the remote sensing estimates of cropland burning show moderate levels of inter-annual variability (Table 4-9). In both 2003 and 2006, this method reported less cropland burned area in Washington than the reported values. The remote sensing estimates mapped 74% of reported burned area, missing 15,000 ha of burned area, in 2003 and mapped 55% of the reported burned, missing 39,000 ha, in 2006. It is likely that the crop residue burning estimates from this analysis were lower due to the exclusion of other forms of agricultural burning included in the WA DOE statistics, such as burn barrels, orchard tear outs, pasture maintenance, and debris piles (WA DOE, 2003). In 2004 and 2005, the remote sensing approach overestimated burned area by 32,700 ha and 24,200 ha, respectively, when compared to the WA DOE burned area and may possibly be related to illegal burning. Field work conducted in central Washington in 2006 did produce several GPS polygons of illegally burned fields (i.e., not permitted by the WA DOE) not included in the official reporting. A further inspection of burned area for all years shows a clustering of burning in southern Washington in heavily irrigated areas. It appears that there are errors of commission associated with irrigated fields that the dNBR thresholds failed to exclude. For example, the September 2004 Landsat comparison with 500 m dNBR product in southern Washington had a commission error of 0.97. Therefore, it is likely that the overestimation of burned area in Washington is due to a combination of illegal burning and confusion of burned and irrigated fields. Modifying the threshold to specifically exclude irrigated fields would likely exclude actual burning. On average, the hybrid remote sensing method created an annual crop residue burned area underestimation of 654 ha or approximately fourteen 49 ha cropped fields.

4.6. Discussion and Conclusions

On average, 1,239,000 ha of croplands burn each year in the CONUS. The average interannual variability for the CONUS cropland burned area over the five year period was ± 91,200 ha. The results from this analysis showed that ten states accounted for approximately 61% and thirteen states accounted for nearly 80% of the total cropland burning activity in the CONUS with an annual average are burned of more than 30,000 ha. These thirteen states in descending rank are: Florida, Arkansas, Idaho, California, Texas, Washington, Kansas, North Dakota, Colorado, South Dakota, Louisiana, Oklahoma, and Oregon. These results indicate that crop residue is a significant fire activity in the U.S. when compared to yearly wildland burned area, averaging 43% of the area reported for wildland fires. An analysis of a subset of states with varying restrictions and/or education requirements for crop residue burning demonstrated that even states with an average decrease in cropland burned area, i.e., California and Florida, experienced years with increased burning. More data and further analysis is needed to quantify the relationship between state-level permitting laws and/or education programs with increases or decreases in crop residue burned area.

The burned area products produced in this analysis had a moderate to strong agreement with high resolution burn scar images (79 to 86% correctly classified). Based on the detailed statistical analyses and the state-level case studies, this approach provides estimates of cropland burned area with ~ 84% accuracy. There was also a strong agreement between field-collected burned fields and the dNBR burned area estimates (approximately 81 to 90% correctly classified). Intra- and inter-annual variability of cropland burning quantified by this method was directly related to changing crop conditions, such as yield and area planted, as well as precipitation trends, as illustrated by the case studies of Kansas and Florida.

This methodology exhibited problems, most notably in irrigated agricultural areas in the western U.S. Irrigated areas in central and southern Washington caused errors of commission due to the spectral similarities of wet volcanic soils and burned fields. Based on visual analysis of the wheat and durum areas of western North and

South Dakota, this dNBR approach failed to map burned fields in these two states even though several active fires were detected in this region during the harvest seasons. This consistent omission error is likely amplified by the common management practice of tilling directly after burning in the Dakotas. For these areas, this approach relied on the active fire detections calibrated into average field size to provide burned area estimates. An underestimation of cropland burned area for both North and South Dakota is possible and the results presented in this analysis can be considered as a conservative estimate of crop residue burned area.

Though active fire detection added approximately 4% more area than was calculated by the dNBR, the active fire product is still useful identifying crop residue burning in the CONUS. On average, 65% of active fire detections in croplands did not overlap with the 500 m dNBR pixels for the CONUS. In the southeastern U.S., over 70% of active detections did not overlap with the dNBR pixels. Therefore, the 1 km MODIS active fire product is detecting fires that are being missed by the dNBR product.

This study provides the first satellite-based estimate of crop residue burned area for the CONUS. The large data record of MODIS allowed for a five year analysis of the burning. Further years can be added as the MODIS data record continues. The results from this analysis are combined with the crop type maps (discussed in chapter 3) to calculate air quality and carbon emissions from crop residue burning in the CONUS (chapter 5).

Chapter 5: Air Quality and Carbon Emissions from Crop Residue Burning in the Contiguous United States[4]

The focus of this chapter is aimed at completing air quality and carbon emission calculations for crop residue burning using the data and results produced in chapters 3 and 4. Calculated emissions for crop residue burning in the CONUS are compared with current estimates of global, continental, and international agricultural burning emissions. The resulting seasonal and interannual variability analyses of the CONUS crop residue burning emission estimates address the major research questions of the doctoral research and hypotheses defined in chapter 1.

5.1. Introduction

The aim of this analysis was to advance crop residue burning emissions estimates beyond current studies that generalize agricultural burning as one land use class and that do not specify particular crop types in emissions calculations (Wiedenmyer et al., 2006; Pouiliot et al., 2008; Al-Saadi et al., 2008). This analysis focused on three carbon species, CO_2, CO, and CH_4, which are important greenhouse gases and are essential to quantify the sinks and sources of carbon in North America for carbon management purposes (NACP, 2002). The air quality species are CO, NO_2, SO_2, $PM_{2.5}$, PM_{10}, and Pb, a subset of the NAAQS. Carbon and air quality emissions were calculated for eight crop types that represent approximately 90% of crop residue burning in the CONUS (Canode and Law, 1979; Jenkins et al., 1992;

[4] Much of the presented material is in preparation for publication in McCarty JL, Korontzi S, and Justice CO (in preparation) Air quality and carbon emissions from crop residue burning in the contiguous United States. *Atmospheric Chemistry and Physics.*

Jenkins, 1996; Dennis et al., 2002; Jimenez et al., 2006; McCarty et al, 2007; McCarty et al., 2008). These eight crop types are: Kentucky bluegrass seed, corn, cotton, rice, soy, sugarcane, wheat, and "other/fallow" crops. Remote sensing was the primary tool to quantify both burned area and crop type. Recent studies have illustrated the utility, accuracy, and consistency of using remote sensing to quantify crop residue burning (Badarinath et al., 2006; Korontzi et al., 2006; McCarty et al., 2007; Korontzi et al., 2008; McCarty et al., 2008). Crop type-specific emissions were calculated for the years 2003 through 2007. The 5-year carbon and air quality emissions resulting from this analysis were subsequently evaluated through comparisons with existing emission estimates of agricultural burning from global, regional, and international studies. The results from this analysis were also compared with forest fire emissions, the Global Fire Emissions Database, and EPA publications on both national air quality and greenhouse gas emissions. Finally, the contribution of crop residue burning as a carbon source was analyzed.

5.2. Fire Emissions Methodology

5.2.1. Burned Area

This fire emissions analysis used remote sensing products to quantify burned area and to assign crop type to the burned area. To create burned area estimates, a regionally-adapted hybrid method of mapping burned area in crop-dominated landscapes was employed (McCarty et al., 2008) (described in detail in chapter 2). This method combines changes in surface reflectance due to burning, with locations of on-going burning provided by active fire detections. The overall accuracy of the hybrid approach which combined 500 m MODIS dNBR images with 1 km MODIS active fire points calibrated into area was determined to be 84% (described in detail in chapter 4).

5.2.2. Crop Type Characterization

Crop type information for this analysis was taken from regional crop type maps following the decision tree method developed by Hansen et al. (2002) (described in detail in chapter 3). The target crop types of bluegrass, corn, cotton, rice, soybean, sugarcane, wheat, and "other/fallow" were readily mapped using satellite data due to their good spectral separability. A classification tree approach was utilized to produce regional and seasonal crop type classifications using multiyear and multitemporal 250 m MODIS USVI product, which includes red, infrared, and NDVI bands. Accuracy of the regional crop type maps was determined through error matrices comparing CDL validation pixels averaged to 250 m with the classified regional crop type maps. The percent of correctly classified pixels per regional classification ranged from 73% to 91%. A visual assessment of spatial crop patterns in Arkansas, Mississippi, and Washington showed good agreement between the 250 m crop type maps and the higher resolution CDL. Due to this reasonable range in accuracy, these crop type maps were used to assign burned area pixels and active fire detections to a corresponding crop type to estimate emissions.

5.2.3. Emissions Factor Database

Emission factors (g species emitted per kg^{-1} biomass burned) were assigned to the eight target crop types from the published literature (i.e., IPCC, 1996; Jenkins et al., 1996; UK EFDB, 2000; Andreae and Merlet, 2001; Dennis et al., 2002; Air Sciences, Inc., 2003; Johnston and Golob, 2004; Lemieux et al., 2004; Hays et al., 2004; WRAP, 2005; Dhammapala et al., 2006). As previously mentioned, this analysis focused on the eight atmospheric species of CO_2, CO, CH_4, NO_2, SO_2, $PM_{2.5}$, PM_{10}, and Pb. To develop the crop-type emission factor database, atmospheric species with two emission factor values were reported as the mean plus or minus half of the range ($\bar{x} \pm$ range). This reporting scheme was employed for the CO_2 emission factors for bluegrass and corn, the $PM_{2.5}$ emission factors for soy and cotton, and the PM_{10} emission factor for sugarcane. Atmospheric species with three or more emission factor values from the literature were reported as means and standard deviations ($\bar{x} \pm s$). Emission factors with a single measurement were reported without an uncertainty estimate. Table 5-1 shows the emission factors used in this analysis.

Table 5-1. Emission factors for crop types (g/kg); sources include: [1]Air Sciences, Inc. (2003); [2]Andreae and Merlet (2001); [3]Dennis et al. (2002); [4]Dhammapala et al (2006); [5]Hays et al. (2005); [6]IPCC (1996); [7]Jenkins et al. (1996); [8]Johnston and Golob (2004); [9]Lemieux et al. (2004); [10]UK EFDB (2000); [11]WRAP (2005).

	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}	Pb
Bluegrass 2,3,7,8,9,10	1551.22 ± 50.25	5.11 ± 4.32	91.05 ± 43.79	2.16 ± 0.64	0.40	11.61 ± 7.69	15.82 ± 10.40	0.0005
Corn 2,3,6,7,,9,10,11	1515.69	2.24 ± 0.49	53.05 ± 24.13	2.30 ± 1.59	1.19 ± 1.85	4.97 ± 0.93	10.68 ± 10.31	0.0005
Cotton 2,,9,10,11	1515.69	3.30 ± 1.04	73.06 ± 15.36	3.44 ± 1.63	1.57 ± 2.08	6.19 ± 3.23	8.87	0.0005
Rice 2,5,6,7,9,10,11	1515.69	2.09 ± 0.94	52.63 ± 28.07	3.12 ± 1.25	1.38 ± 1.72	5.76 ± 4.82	3.31 ± 0.22	0.0005
Soy 2,6,9,10,11	1515.69	3.15 ± 1.00	68.85 ± 24.52	3.16 ± 1.44	1.56 ± 2.08	6.19 ± 3.23	8.87	0.0005
Sugarcane 2,3,9,10,11	1515.69	1.19 ± 1.31	58.48 ± 27.54	3.03 ± 1.65	1.66 ± 2.00	4.35 ± 0.57	4.92 ± 0.73	0.0005
Wheat 1,2,3,4,5,6,7,9,10,11	1631.97 ± 135.78	2.12 ± 1.20	55.14 ± 22.04	1.99 ± 0.83	0.44 ± 0.04	4.03 ± 1.46	6.61 ± 2.98	0.0005
Other 1,2,3,4,5,6,7,8,9,10,11	1515.69 ± 93.39	2.82 ± 1.47	63.90 ± 26.49	2.80 ± 1.29	1.17 ± 1.39	6.16 ± 3.13	8.50 ± 4.93	0.0005

5.2.4. Emissions Calculations

This analysis estimated pyrogenic emissions from agricultural burning using the bottom-up methodology developed by Seiler and Crutzen (1980):

$$\text{Emissions} = A * B * \text{CE} * e_i \tag{5.1}$$

Where A is cropland burned area, B is the fuel load variable (mass of biomass per area), CE is combustion efficiency (fraction of biomass consumed by fire), and e_i is the emission factor for species_i (mass of species per mass of biomass burned). For this analysis, B, CE, and e_i are crop type dependent. As previously mentioned, variable A was developed to map cropland burned area, with an associated crop type from the satellite crop type classification maps assigned to variable A. Combustion efficiency (CE) is dependent upon moisture content of the fuels (Kasischke and Penner, 2004). Examples of crop residue burning during the several field campaigns demonstrated that farmers waited for crop residues to dry, i.e., low moisture content, before burning, with the exclusion of sugarcane, which is always burned before harvest and while vegetation is still green. The CE values were derived from expert knowledge from agriculture extension agents in Arkansas, Louisiana, Florida, Kansas, and Washington during field campaigns in 2004, 2005, and 2006 as well as from the scientific literature (Dennis et al., 2002; Johnston and Golob, 2004). In general, the CE variables ranged from 0.65 for cotton and sugarcane and 0.85 for wheat and bluegrass, which are in good agreement with the CE value used by the EPA of 0.88 (EPA, 2008b). This analysis did not use the EPA CE value as it was a best guess estimate of combustion completeness of all types of biomass for international methane emissions (EPA, 1994).

This analysis did not follow the fuel load methodology outlined in the EPA Greenhouse Gas Inventory (EPA, 2008b), whereby fuel load for crop residue burning was the product of annual crop production, residue-to-crop ratio, and dry matter of residue. The fuel load values in the EPA Greenhouse Gas Inventory were an update of the previously published EPA-42 publication of all crop residue fuel loads (EPA, 1992). The updated EPA fuel load calculation was not used for three important reasons. First, the annual fuel loadings for wheat, rice, sugarcane, and corn varied less than 10%, which was directly linked to the near-static annual production of crops in the CONUS (USDA/NASS, 2003; 2004; 2005; 2006; 2007). Secondly, the residue-to-crop ratio, the amount of crop residue left on the field after harvest, used by the EPA (Strehler and Stützle, 1987) did not match the residue-to-crop ratio statistics gathered from in-field collaborators (Personal communication with Dr. Gary Cramer, Sedgwick County Extension Agent, Wichita, KS, 28 July 2008). Including the residue-to-crop ratio statistics in a fuel loads calculation can be misleading, as the amount of residue remaining in the field is determined by what type of mechanical harvesting tool was used to harvest the crops and how long the residues were left to weather in the field before burning. Finally, residue dry matter content used by the EPA was calculated from 3 or less samples of specific crop types in northern California (Turn et al., 1997), which are not representative of all crops and cropping locations in CONUS. Residue dry matter content for sugarcane was also problematic as this sample was taken from Hawaii, where sugar yields are three times higher than the CONUS (EPA, 2008a).

In general, the updated EPA fuel load calculations did not match the fuel load estimates gathered by extension agents through a process of bailing and weighing remaining residues in wheat fields in Arkansas, Kansas, and Washington. The total sample size of fuel load estimates from in-field collaborators was insignificant (n = 3), but strongly agreed with the fuel load values reported in the EPA AP-42 publication. Therefore, this analysis used published fuel load values considered to be the standard for crop residue emission calculations (Dennis et al., 2002; Dhammapala et al., 2006) and that were verified by in-field collaborators. Variable *B* was assigned to each crop type from the EPA AP-42 publication (EPA, 1992), with the exceptions of the fuel load values for bluegrass, which was taken from Johnston and Golob (2004), and for the other crop/fallow class, which was calculated as the average of the fuel load values for the other crops. Table 5-2 shows the fuel load and combustion completeness values used for this analysis.

Table 5-2. Fuel load (*B*) and combustion completeness (CE) values used for emission estimates; the sugarcane fuel load value excludes estimates from Hawaii.

Crop	Fuel Load (kg/ha)	Fuel Load Source	Combustion Completeness
Bluegrass	6,510	(Johnston and Golob, 2004)	
Corn	9,400	(EPA, 1992)	0.75
Cotton	3,800	(EPA, 1992)	0.65
Rice	6,700	(EPA, 1992)	0.75
Soybeans	5,600	(EPA, 1992)	0.75
Sugarcane	10,000	(EPA, 1992)	0.65
Wheat	4,300	(EPA, 1992)	0.85
Other/Fallow	6,600	(EPA, 1992)	0.75

5.2.5. Uncertainties and Errors

The emission factors used in the analysis represent a limited sample. The results from 11 scientific sources were synthesized. Following the methodology developed by Andreae and Merlet (2001), emission factors for each atmospheric species were averaged within each crop type, with an error range equal to the first standard deviation. Two or more scientific sources were available for CO_4, CO, NO_2, and $PM_{2.5}$ (Table 5-1). Two or more sources were not available for CO_2 emissions factors for the crop types of corn, cotton, rice, soy, and sugarcane. All CO_2 emissions factors for these crops were taken from (Andreae and Merlet, 2001). Similarly, Andreae and Merlet (2001) was the source for the SO_2 emission factor for bluegrass. The source for PM_{10} emission factors for cotton and soy was WRAP (2005). Pb emission factors for all crop types were taken from the United Kingdom Emission Factor Database (UK EFDB, 2000). Table 5-3 shows the range of emission factor values for all atmospheric species.

Table 5-3. Range of emission factors values for crop types (g/kg); sources include: [1]Air Sciences, Inc. (2003); [2]Andreae and Merlet (2001); [3]Dennis et al. (2002); [4]Dhammapala et al (2006); [5]Hays et al. (2005); [6]IPCC (1996); [7]Jenkins et al. (1996); [8]Johnston and Golob (2004); [9]Lemieux et al. (2004); [10]UK EFDB (2000); [11]WRAP (2005).

	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}	Pb
Bluegrass 2,3,7,8,9,10	1515.69 - 1586.75	2.70 - 12.75	51.82 - 171.25	1.42 - 2.55	0.40	3.90 - 22.00	8.70 - 27.75	0.0005
Corn 2,3,6,7,,9,10,11	1515.69	1.70 - 2.70	28.27 - 92.00	0.66 - 5.32	0.20 - 3.96	3.90 - 5.98	4.70 - 26.11	0.0005
Cotton 2,,9,10,11	1515.69	2.70 - 4.50	58.00 - 92.00	2.50 - 5.32	0.34 - 3.96	3.90 - 8.48	8.87	0.0005
Rice 2,5,6,7,9,10,11	1515.69	0.72 - 2.70	27.00 - 92.00	2.30 - 5.30	0.40 - 3.96	2.95 - 12.96	3.15 - 3.46	0.0005
Soy 2,6,9,10,11	1515.69	2.25 - 4.50	27.00 - 92.00	2.32 - 5.32	0.40 - 3.96	3.90 - 8.48	8.87	0.0005
Sugarcane 2,3,9,10,11	1515.69	0.41 - 2.70	25.48 - 92.00	1.40 - 5.32	0.40 - 3.96	3.90 - 4.99	4.40 - 5.43	0.0005
Wheat 1,2,3,4,5,6,7,9,10, 11	1515.69 - 1773.00	0.45 - 4.27	21.11 - 92.00	1.42 - 2.90	0.40 - 0.47	0.80 - 5.44	4.40 - 11.00	0.0005
Other 1,2,3,4,5,6,7,8,9, 10,11	1515.69 - 1773.00	0.41 - 4.50	21.11 - 92.00	0.66 - 5.32	0.20 - 3.96	0.80 - 22.00	3.15 - 27.75	0.0005

In general, there was moderate agreement between the various emission factor sources (Table 5-3). The atmospheric species of CO and SO_2 had the largest ranges, which resulted in standard deviation values that were often greater than or equal to 50% of the value of the calculated mean. Based on this range comparison, it is possible that the SO_2 and NO_2 emission factors from the UK EFDB are uncertain. The SO_2 and NO_2 emission factors from the UK EFDB are approximately two times larger than the smallest SO_2 and NO_2 emission factors from the literature for the crops of corn, cotton, rice, soybean, and sugarcane. Other published sources of emission factors derived from laboratory experiments showed a similar relationship for wheat and bluegrass (Johnston and Golob, 2004; Dhammapala et al., 2006). Therefore, this analysis did include the SO_2 and NO_2 emission factors from the UK EFDB for the calculation of average emission factors for crop residue burning emissions (Table 5-1).

Several sources provided error ranges for the emission factors (IPCC, 1996; Andreae and Merlet, 2001; Air Sciences, Inc., 2003; Johnston and Golob, 2004; Hays et al., 2004; Dhammapala et al., 2006). This analysis calculated the cumulative error for all emission factors from the literature and this analysis, i.e., error from the literature plus the error calculated from this analysis ($\pm s$). Table 5-4 shows the total error for all emission factors. On average, the total emission factor error accounts for approximately 13% of the average CO_2 emission factors for all crop types used in this analysis, 62% of the CH_4 emission factors, 264% of CO emission factors, 83% of the NO_2 emission factors, 133% of the SO_2 emission factors, 52% of the $PM_{2.5}$ emission factors, and 55% of the PM_{10} emission factors. Current emission factors for crop residue burning contain a high level of uncertainty when the total error is considered.

Table 5-4. Error range of emission factor values for crop types (g/kg); dashes indicate no error calculations, i.e., one source for the emission factor with no available error estimate; total error for 'other' crop calculated as the average of the emission factor error for bluegrass, corn, cotton, rice, soy, sugarcane, and wheat; dashes indicate one source for emission factor that did not report an error estimate.

	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}	Pb
Bluegrass	± 244.97	± 7.10	± 154.54	± 1.64	± 0.40	± 12.44	± 16.33	____
Corn	± 177.00	± 0.53	± 193.22	± 2.59	± 2.25	± 0.93	± 9.32	____
Cotton	± 177.00	± 1.04	± 99.36	± 2.63	± 2.48	± 2.29	____	____
Rice	± 177.00	± 0.99	± 193.73	± 2.25	± 2.12	± 5.12	± 0.15	____
Soy	± 177.00	± 0.81	± 183.77	± 2.44	± 2.48	± 2.29	____	____
Sugarcane	± 177.00	± 1.31	± 111.54	± 2.65	± 2.40	± 0.57	± 0.52	____
Wheat	± 323.03	± 1.40	± 199.14	± 1.83	± 0.44	± 2.39	± 2.98	____
Other	± 207.57	± 1.88	± 162.61	± 2.29	± 1.79	± 3.72	± 4.19	____

Currently available emission factors do not provide for calculating seasonal difference in spring versus fall burning for all atmospheric species. Differences between spring and fall emissions from crop residue burning are expected due to increased moisture content in residues, and thus less efficient burning, during the spring. Spring and fall emission factors have been developed for wheat in Washington only for the atmospheric species of CO_2, CH_4, CO, and $PM_{2.5}$ (Air Sciences, Inc., 2003; Dhammapala et al., 2006). The spring emission factors for CH_4, CO, and $PM_{2.5}$ were an average of 44%, 40%, and 36% less than the fall emissions factors, respectively. However, the CO_2 emission factor for spring wheat residues was 3% higher than the fall emission factor for wheat (Air Sciences, Inc., 2003). This analysis assumed that moisture content of crop residues from the spring harvest within the CONUS will vary considerably over time and space; for example, the moisture content of wheat residues in Washington would not be the same for wheat residues in Arkansas. Due to the lack of seasonal emission factors in the literature, this analysis did not account for seasonal emission differences for wheat residue burning. All emission factors for both spring and fall wheat burning from all sources were average and reported as means and standard deviation ($\bar{x} \pm s$). The lack of seasonality in emission factors for the emissions calculations of crop residue burning does create an uncertainty whereby emissions for certain atmospheric species during the spring harvest may be underestimated (CO_2) or overestimated (CH_4, CO, and $PM_{2..5}$).

In general, there is a considerable amount of uncertainty inherent in calculating crop residue burning emissions. This analysis showed that the total errors from emission factors for crop residue burning range from 13% (CO_2) to 264% (CO) of the mean emission factor value used to calculate emission in this analysis. This analysis also used remote sensing approaches to calculate burned area and associated crop type. The cropland burned area product had an area estimation accuracy that ranged from 78 to 90%, with an average percent estimation accuracy of 84% (error of 16%). State-level analyses in Kansas and Florida showed a consistent underestimation compared with reported cropland fires. Misclassification errors in the crop type maps could produce incorrect emission estimates by assigning the wrong crop type to a burned area or active fire detection in the emissions calculations. The regional crop type maps had an average accuracy of 84% (error of 16%). Finally, fuel load and CE values also contain uncertainty as many of the fuel load values in the literature were derived from expert knowledge and laboratory studies using limited samples. Quantifying the total error from emission factors, burned area, assigned crop type, fuel load, and combustion completeness to calculated emissions would require iterations of the emissions modeling with varying values of the input parameters within their respective error ranges as there is a non-linear relationship between the input parameters and the calculated emissions (Kühlwein and Friedrich, 2000). In general, this analysis concludes that there is moderate amount of uncertainty in these emission calculations related to errors associated with the emission factors and the other input parameters of burned area, assigned crop type, fuel load, and combustion completeness.

5.3. Results

5.3.1. State-level Emissions

The states with the largest areas of crop residue burning (described in chapter 4) were generally the states with the highest air quality emissions. The states with higher than average annual CO emissions are (in descending order): Florida, Washington, Idaho, Texas, California, Arkansas, Kansas, South Dakota, Louisiana, Oregon, North Dakota, Colorado, Missouri, Oklahoma, Montana, Illinois, Arizona, and Indiana (Table 5-5). States with above average $PM_{2.5}$ and PM_{10} emissions are (in descending order): Florida, Idaho, Washington, Arkansas, California, Texas, and Kansas. Consistently, six states, Arkansas, California, Florida, Idaho, Texas, and Washington, had the highest carbon and air quality emissions. Not surprisingly, these six states represented the highest percent of total emissions. Arkansas, California, Florida, Idaho, Texas, and Washington account for a total of 51% of all CO_2

emissions, 52% of CO emissions, and 46% of CH_4 emissions from crop residue burning annually. These six states also emitted the majority of $PM_{2.5}$ and PM_{10}, representing 62% and 50% of total emissions, respectively. The state with the most crop residue burning emissions was Florida, which emitted 17% of all annual CO_2, CO, and $PM_{2.5}$ emissions, 12% of all annual PM_{10} emissions, and 9.5% of all CH_4 emissions from crop residue burning. Lead emissions from crop residue burning were small at the state-level, approximately zero (Gg) annual emissions, and were not reported. Previous research for prescribed wildland fire also found small lead emissions (Einfeld et al., 1991).

Table 5-5. Annual carbon and air quality emissions from crop residue burning by state averaged over the years 2003 - 2007; CO_2 reported in Tg yr^{-1}; all other species reported in Gg yr^{-1}; state abbreviations used in place of state names; dashes signify zero emissions; Connecticut, Maine, New Hampshire, and Rhode Island are omitted from the table due to zero emissions from crop residue burning.

State	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}
AL	0.04	0.07	1.70	0.08	0.03	0.15	0.24
AZ	0.13	0.06	2.78	0.24	0.09	0.09	0.11
AR	0.46	0.70	16.80	0.82	0.33	1.57	2.10
CA	0.51	0.14	11.40	0.96	0.36	0.17	0.24
CO	0.23	0.30	8.14	0.36	0.11	0.67	1.14
DE	0.01	0.01	0.20	0.01	4.00 10^-3	0.02	0.03
FL	1.32	1.00	47.61	2.50	1.34	3.60	4.00
GA	0.05	0.08	1.90	0.08	0.03	0.16	0.26
ID	0.50	1.16	22.50	0.77	0.21	2.38	3.41
IL	0.14	0.23	5.40	0.25	0.11	0.50	0.80
IN	0.12	0.20	4.50	0.20	0.09	0.41	0.71
IA	0.11	0.20	4.30	0.20	0.08	0.38	0.64
KS	0.32	0.50	11.60	0.51	0.17	0.98	1.62
KY	0.01	0.02	0.43	0.02	0.01	0.04	0.07
LA	0.26	0.33	10.00	0.50	0.20	0.86	1.03
MD	0.01	0.02	0.40	0.02	0.01	0.04	0.07
MA	2.00 10^-3	3.00 10^-3	0.06	3.00 10^-3	1.00 10^-3	0.01	0.01
MI	0.10	0.16	3.70	0.17	0.07	0.30	0.60
MN	0.10	0.15	3.60	0.16	0.06	0.30	0.50
MS	0.08	0.13	3.10	0.15	0.06	0.29	0.37
MO	0.22	0.33	8.00	0.37	0.15	0.73	1.07
MT	0.18	0.27	6.49	0.29	0.10	0.55	0.90
NE	0.11	0.18	4.24	0.19	0.08	0.38	0.65
NV	0.02	0.03	0.73	0.03	0.01	0.05	0.07
NJ	0.01	0.02	0.40	0.02	0.01	0.04	0.07
NM	0.03	0.04	1.00	0.01	0.01	0.08	0.10
NY	0.02	0.03	0.76	0.03	0.02	0.07	0.13
NC	0.04	0.08	1.70	0.08	0.03	0.15	0.23
ND	0.23	0.34	8.50	0.37	0.12	0.72	1.15
OH	0.08	0.13	3.00	0.14	0.06	0.30	0.50
OK	0.20	0.30	7.40	0.30	0.10	0.60	1.10
OR	0.19	0.45	8.57	0.30	0.08	0.92	1.31
PA	0.02	0.03	0.70	0.03	0.01	0.06	0.11
SC	0.03	0.05	1.12	0.05	0.02	0.10	0.20
SD	0.29	0.40	10.18	0.44	0.12	0.82	1.37

Table 5-5. Annual carbon and air quality emissions from crop residue burning by state averaged over the years 2003 - 2007; CO_2 reported in Tg yr^{-1}; all other species reported in Gg yr^{-1}; state abbreviations used in place of state names; dashes signify zero emissions; Connecticut, Maine, New Hampshire, and Rhode Island are omitted from the table due to zero emissions from crop residue burning (cont.).

State	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}
TN	0.02	0.04	0.85	0.04	0.02	0.08	0.12
TX	0.55	0.80	21.00	1.04	0.51	1.90	2.30
UT	0.11	0.17	4.15	0.18	0.07	0.36	0.60
VT	4.00 10^-3	0.00	0.15	0.00	3.00 10^-3	0.01	0.02
VA	0.01	0.02	0.40	0.02	0.01	0.04	0.07
WA	0.56	1.06	22.56	0.83	0.21	2.16	3.25
WV	4.00 10^-3	0.00	0.15	0.01	3.00 10^-3	0.01	0.03
WI	0.10	0.15	3.50	0.15	0.10	0.30	0.60
WY	0.07	0.10	2.49	0.11	0.04	0.22	0.35
Total	7.59	10.50	278.14	13.05	5.24	23.57	34.25

The emission calculations were repeated with the substitution of the upper estimate ($\bar{x}+s$) of the emission factors from Table 5-1. Table 5-6 reports the maximum estimates of emissions from crop residue burning in the CONUS. The pattern of emissions was similar, with Idaho, Florida, Arkansas, Texas, Washington, and California, (in descending order) staying the top six source states for emissions. The total emissions calculated using the maximum emission factor values were higher than the total emission calculated using the average emission factor. Specifically, the upper estimate of emissions were 10% higher than the average total CO_2 emissions, 38% higher than the total CH_4, 72% higher than the total CO, 42% higher than the total NO_2, 57% higher than the total SO_2, 35% higher than the total $PM_{2.5}$, and 30% higher than the total PM_{10}.

Table 5-6. Annual carbon and air quality emissions from crop residue burning by state averaged over the years 2003 - 2007 calculated from the upper estimates of emission factors; CO_2 reported in Tg yr^{-1}; all other species reported in Gg yr^{-1}; state abbreviations used in place of state names; dashes signify zero emissions; Connecticut, Maine, New Hampshire, and Rhode Island are omitted from the table due to zero emissions from crop residue burning.

State	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}
AL	0.05	0.11	6.49	0.14	0.08	0.21	0.33
AZ	0.15	0.30	20.21	0.42	0.23	0.76	0.68
AR	0.68	1.29	92.27	1.85	0.99	3.10	3.65
CA	0.59	0.70	51.08	1.68	0.92	2.11	1.94
CO	0.27	0.51	35.77	0.66	0.27	1.02	1.72
DE	0.01	0.02	0.87	0.02	0.01	0.03	0.05
FL	1.46	1.96	131.58	4.40	3.08	4.09	4.43
GA	0.04	0.08	5.05	0.11	0.06	0.16	0.27
ID	0.58	2.31	76.76	1.38	0.50	4.43	5.97
IL	0.09	0.17	10.27	0.23	0.13	0.37	0.69
IN	0.07	0.14	9.84	0.20	0.12	0.29	0.57
IA	0.10	0.20	13.73	0.27	0.15	0.42	0.74
KS	0.37	0.74	49.53	0.94	0.41	1.49	2.34
KY	0.01	0.02	1.30	0.03	0.01	0.04	0.07
LA	0.29	0.53	34.98	0.92	0.60	1.21	1.25
MD	0.01	0.03	1.76	0.04	0.02	0.05	0.11
MA	1.63 10^-3	3.41 10^-3	0.17	4.17 10^-3	2.50 10^-3	7.37 10^-3	0.01
MI	0.11	0.22	14.89	0.30	0.17	0.46	0.82
MN	0.11	0.22	14.89	0.30	0.17	0.46	0.82
MS	0.09	0.19	12.41	0.27	0.16	0.45	0.50
MO	0.22	0.44	30.27	0.61	0.34	1.00	1.39
MT	0.21	0.42	27.38	0.52	0.23	0.84	1.31
NE	0.10	0.19	13.57	0.27	0.16	0.40	0.77
NV	0.02	0.07	2.31	0.05	0.02	0.14	0.18
NJ	0.01	0.02	0.43	0.02	0.01	0.04	0.07
NM	0.03	0.06	3.86	0.08	0.03	0.12	0.17
NY	0.02	0.03	0.76	0.03	0.02	0.07	0.13
NC	0.04	0.09	5.70	0.12	0.07	0.19	0.26
ND	0.27	0.55	35.74	0.67	0.28	1.10	1.68
OH	0.08	0.16	11.73	0.24	0.16	0.34	0.69
OK	0.25	0.47	33.10	0.61	0.25	0.95	1.71
OR	0.22	0.89	28.87	0.52	0.19	1.71	2.30
PA	0.02	0.04	2.88	0.06	0.04	0.09	0.17
SC	0.02	0.04	2.31	0.05	0.03	0.08	0.11
SD	0.25	0.49	32.52	0.61	0.24	0.98	1.53

Table 5-6. Annual carbon and air quality emissions from crop residue burning by state averaged over the years 2003 - 2007 calculated from the upper estimates of emission factors; CO_2 reported in Tg yr^{-1}; all other species reported in Gg yr^{-1}; state abbreviations used in place of state names; dashes signify zero emissions; Connecticut, Maine, New Hampshire, and Rhode Island are omitted from the table due to zero emissions from crop residue burning (cont.).

State	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}
TN	0.03	0.05	3.49	0.07	0.04	0.11	0.17
TX	0.63	1.22	80.26	1.87	1.13	2.93	2.92
UT	0.12	0.25	16.67	0.32	0.16	0.51	0.85
VT	3.57 10^-3	0.01	0.36	0.01	0.01	0.02	0.03
VA	0.01	0.02	1.66	0.03	0.02	0.05	0.11
WA	0.57	1.45	61.17	1.07	0.33	2.77	3.87
WV	4.39 10^-3	0.01	0.61	0.01	0.01	0.02	0.04
WI	0.09	0.17	11.86	0.24	0.15	0.35	0.70
WY	0.08	0.16	10.37	0.20	0.10	0.32	0.52
Total	8.37	17.04	1 001.73	22.44	12.10	36.28	48.64

The spatial distribution of the most significant air quality emissions in terms of highest emissions, CO, and health impacts, CO and $PM_{2.5}$, were mapped according to average percent of total emissions. For both CO and $PM_{2.5}$, the average annual percent of total emissions per state was calculated as 2.1% of total emissions. Therefore, states with percent of total CO and $PM_{2.5}$ emissions greater than the mean of 2.1% were considered above average sources of these emissions. Figure 5-1 shows the average annual CO emissions (Gg) per state from crop residue burning. Much of the CO emissions were concentrated in the Great Plains, the Mississippi Delta, and along the Pacific Coast. The highest average annual percent of total CO emissions occurred in Florida with 16.7% of total CO emissions from all states. Washington, Idaho, and Texas emitted 8.0%, 7.7%, and 7.3% of total CO emissions, respectively.

California, Arkansas, Kansas, Louisiana, Oregon, and South Dakota emitted between 3.3% and 6.7% of total CO emissions. Four other states also exceeded the mean of 2.1% percent of total CO emissions, namely Colorado, Missouri, North Dakota, and Oklahoma. Figure 5-2 shows the average annual $PM_{2.5}$ emissions (Gg) per state from crop residue burning emissions. Florida and Idaho had the highest percent of total $PM_{2.5}$ emissions with 16.7% and 12.5% of total emissions, respectively. The states of Arkansas, California, Texas, and Washington emitted 8.3% of total $PM_{2.5}$ emissions, respectively. Nine states individually emitted 4.2% of total $PM_{2.5}$ emissions: Colorado, Kansas, Louisiana, Missouri, Montana, North Dakota, Oklahoma, Oregon, and South Dakota. This analysis expected the major Kentucky bluegrass seed producing states of Idaho, Oregon, and Washington to have above average $PM_{2.5}$ emissions due to the high bluegrass seed $PM_{2.5}$ emission factor, which is nearly twice the value of the next highest $PM_{2.5}$ emissions factors of cotton and soy. The remaining states showed significant burning in rice (Arkansas, California, Texas), wheat (Arkansas, Colorado, Kansas, Missouri, Montana, North Dakota, South Dakota, Washington) and sugarcane (Florida, Louisiana) areas.

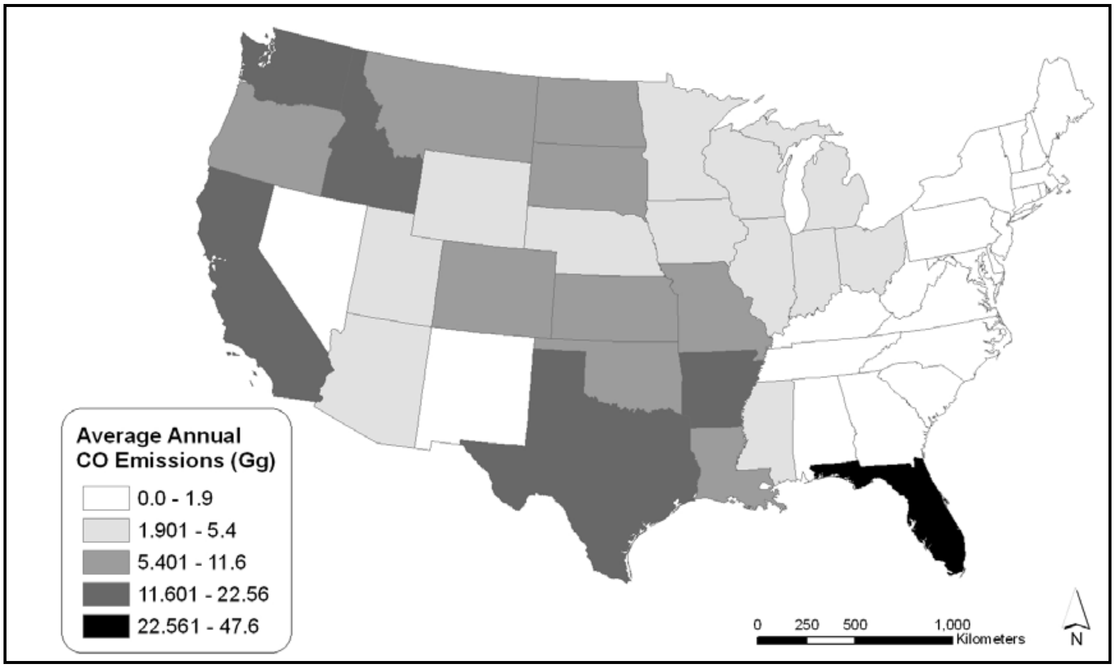

Figure 5-1. Average annual CO emissions (Gg) from crop residue burning by state for the CONUS (projection: Albers Equal Area Conic).

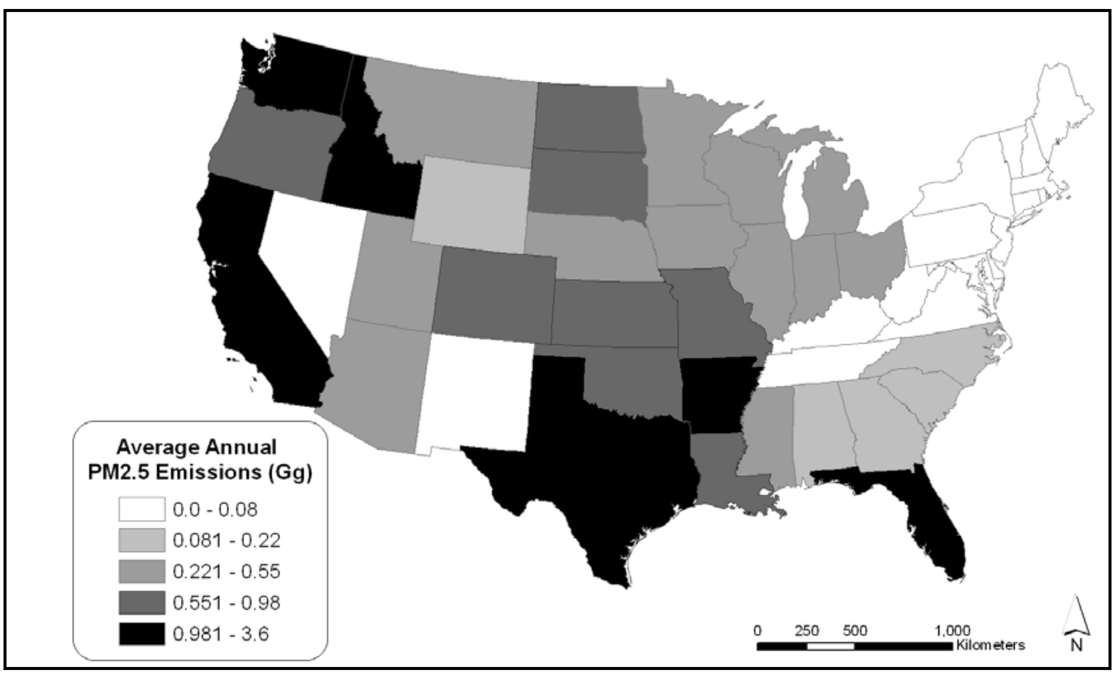

Figure 5-2. Average annual $PM_{2.5}$ emissions (Gg) from crop residue burning by state for the CONUS (projection: Albers Equal Area Conic).

Specific counties within the top six source states of Arkansas, California, Florida, Idaho, Texas, and Washington were the main sources for emissions from crop residue burning (Table 5-7). Figure 5-3 highlights the counties and cities contained within and/or contiguous to these sources of crop residue burning. The total population of these counties is approximately 15.5 million people according to the 2007 and 2008 population estimates from the U.S. Census Bureau (U.S. Census Bureau, 2007; 2008), which is roughly 5.2% of the total population of the CONUS. Within the states, the proportion of people living within these source areas is higher. 13.8% of the total population in Texas lives in counties with the highest emissions from crop residue burning. In Washington, 17.5% of the states' population resides in the source counties, which is similar to California (17.3%) and Florida (17.9%). Approximately 25% of the population in Arkansas lives in the source counties and almost half of the population of Idaho (46.6%) reside in the counties with the highest emissions from crop residue burning. At the very least, one in ten people in the states of Arkansas, California, Florida, Idaho, Texas, and Washington live near the consistent source of emissions from crop residue burning.

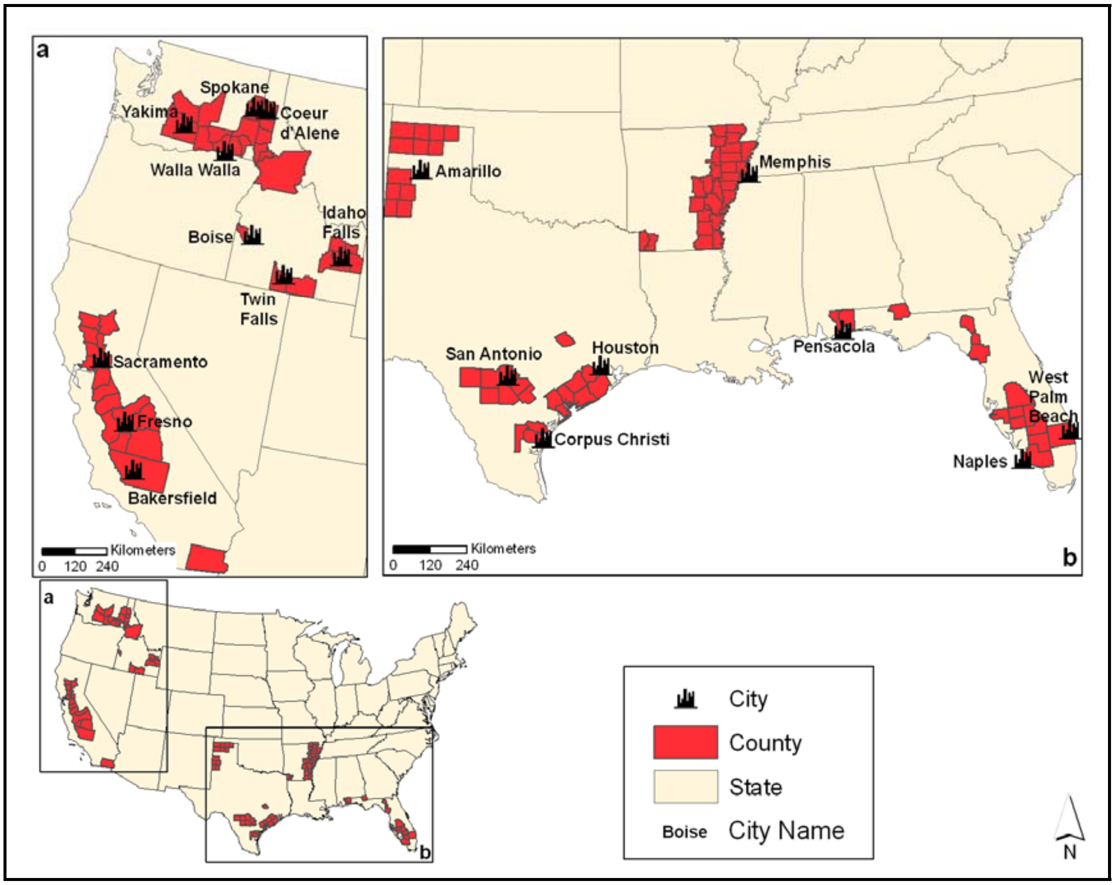

Figure 5-3. Source counties of crop residue burning emissions; cities contained within and/or contiguous to these source counties are labeled (projection: Albers Equal Area Conic).

Table 5-7. List of source counties of crop residue burning emissions from the states of Arkansas, California, Florida, Idaho, Texas, and Washington.

Arkansas Counties		California Counties	Florida Counties	Idaho Counties	Texas Counties		Washington Counties
Arkansas	Lonoke	Butte	Collier	Benewah	Atascosa	Karnes	Benton
Ashley	Miller	Colusa	DeSoto	Bingham	Bailey	Lamb	Columbia
Chicot	Mississippi	Fresno	Escambia	Bonneville	Bexar	Matagorda	Franklin
Clay	Monroe	Glenn	Gilchrist	Canyon	Brazoria	Medina	Garfield
Craighead	Phillips	Imperial	Glades	Cassia	Burleson	Moore	Grant
Crittenden	Poinsett	Kern	Hardee	Idaho	Calhoun	Nueces	Kittitas
Cross	Prairie	Kings	Hendry	Jefferson	Castro	Ochiltree	Spokane
Desha	Randolph	Madera	Highlands	Kootenai	Dallam	Parmer	Walla Walla
Drew	St. Francis	Merced	Jackson	Latah	Deaf Smith	San Patricio	Whitman
Greene	Woodruff	Sacramento	Levy	Lewis	Fort Bend	Sherman	Yakima
Jackson		San Joaquin	Manatee	Madison	Frio	Uvalde	
Jefferson		Solano	Palm Beach	Nez Perce	Hansford	Victoria	
Lafayette		Stanislaus	Polk	Twin Falls	Hartley	Wharton	
Lawrence		Sutter	Santa Rosa		Hutchinson	Wilson	
Lee		Tulare	Suwannee		Jackson		
Lincoln		Yolo			Jim Wells		

5.3.2. Annual Emissions for the EPA Regions

A regional analysis of crop residue burning emissions was completed for the EPA regions, which allow the results to be easily integrated in to the EPA's National Emissions Inventory (EPA, 2008a) and utilized by the AAQTF (AAQTF, 2007). Figure 5-4 shows the EPA regions for the CONUS used in the regional analysis.

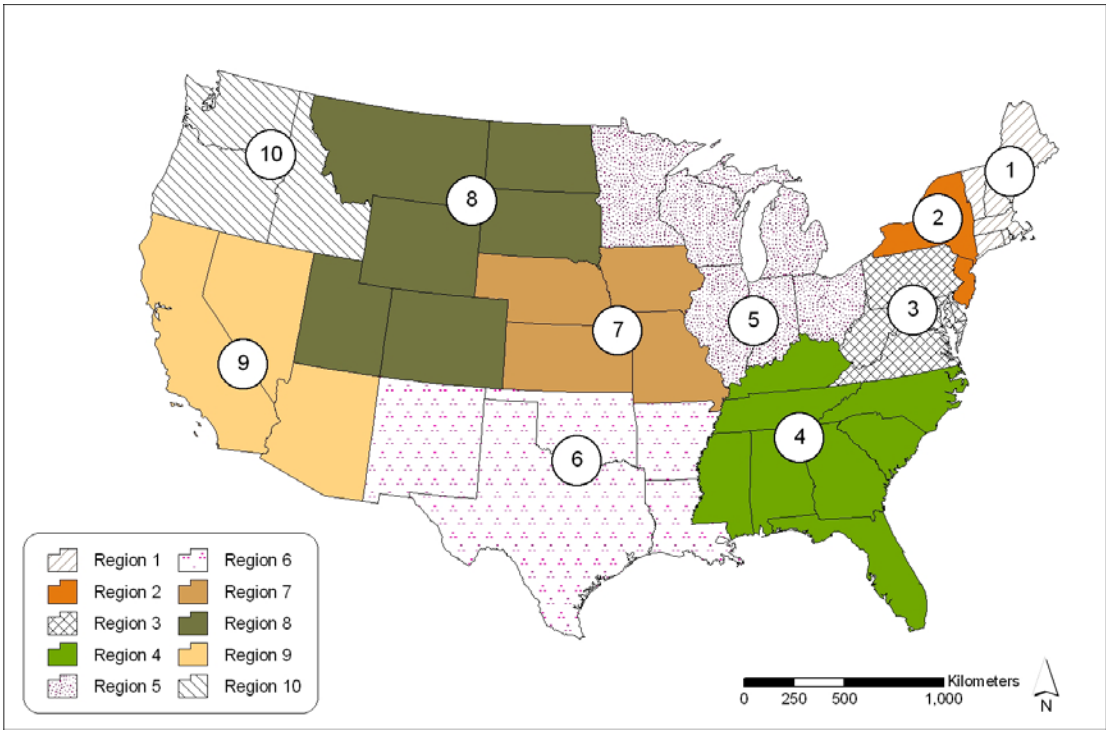

Figure 5-4. The ten EPA regions for the CONUS (projection: Albers Equal Area Conic).

Table 5-8 lists the average annual regional emissions for the air quality and the carbon species. These regional emissions were calculated by summing the emissions of all states that comprised an EPA region. Consistently, regions 4, 6, 10, 8, and 7 are the main sources of emissions from crop residue burning, in descending order. These five source regions represent approximately 82% of CO_2, 94% of CH_4, 91% of CO, 86% of NO_2 and SO_2, and 95% of $PM_{2.5}$ and PM_{10} crop residue burning emissions for the CONUS. This analysis found that the more than 50% of the emissions from crop residue burning originated from the EPA regions which comprise the southeastern U.S, the Great Plains, and the Pacific Coast. If region 9, which comprises much of the Pacific Coast and southwest, is added to this list, then these 6 EPA regions account for an average of 97% of all CO_2, CH_4, CO, NO_2, SO_2, $PM_{2.5}$, and PM_{10} crop residue burning emissions for the CONUS.

Table 5-8. Average annual carbon and air quality emissions from crop residue burning for EPA regions for the years 2003 - 2007; CO_2 reported in Tg yr^{-1}; all other species reported in Gg yr^{-1}; state abbreviations used in place of state names.

EPA Regions: States	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}
1: CT, MA, ME, NH, RI, VT	1.86 10^-3	3.11 10^-6	7.26 10^-5	3.19 10^-6	1.48 10^-6	6.92 10^-6	1.16 10^-5
2: NJ, NY	0.03	0.03	0.60	0.03	0.01	0.06	0.10
3: DE, MD, PA, VA, WV	0.05	0.08	1.80	0.08	0.04	0.16	0.30
4: AL, FL, GA, KY, MS, NC, SC, TN	1.60	1.50	58.40	2.96	1.50	4.50	5.50
5: IL, IN, MI, MN, OH, WI	0.63	0.17	3.90	0.18	0.08	0.36	0.62
6: AR, LA, NM, OK, TX	1.51	2.10	56.10	2.70	1.10	5.00	6.50
7: IA, KS, MO, NE	0.76	1.20	28.00	1.30	0.50	2.50	4.00
8: CO, MT, ND, SD, UT, WY	1.11	0.27	6.70	0.30	0.09	0.56	0.92
9: AZ, CA, NV	0.66	0.23	13.90	1.20	0.47	0.30	0.40
10: ID, OR, WA	1.24	2.70	53.60	1.90	0.48	5.50	8.00
Total	7.59	8.28	233.10	10.65	4.27	18.90	26.40

In regions 4, 6, 10, 8, and 7, the greatest amounts of emissions were calculated from wheat, rice, and sugarcane fields. These three crops accounted for 65%, 17%, and 5% of total burned area in these regions, respectively. In general, crop residue burning emissions were a function of burned area, with larger field sizes in the western U.S. producing greater emissions and smaller fields but more frequent fires (i.e., two harvest seasons per year and/or near complete burning of the Everglades Agricultural Area) in the southeastern U.S. Emission factors did contribute to higher emissions from bluegrass fields. Burning bluegrass fields in Idaho, Oregon, and

Washington accounted for only 3% of total burned area in these regions. For example, CH_4 and $PM_{2.5}$ emission factors were twice as high for bluegrass and CO and PM_{10} emission factors for bluegrass were 20% and 32% higher than the next highest emission factors, respectively.

5.3.3. Seasonal Variability of Regional Emissions

Figure 5-5 shows the monthly distribution of average CO emissions from crop residue burning for five EPA source regions: regions 4, 6, 7, 8, and 10. Every region, excluding region 4, showed peaks of CO emissions between the months of April to July and September to November, corresponding to the spring harvest and fall harvest that occurs throughout much of the CONUS. Region 4 was a unique case. Though there was a small spring peak between April to June and an increase of burning beginning in September, the largest peaks spanned from November to February. The multi-year harvest was directly related to the sugarcane harvesting in Florida which occurs between October to March (Baucum, 2006). Region 6, with sugarcane in Louisiana and Texas, showed a smaller decrease in emissions in November and December compared to the other regions but retained higher emissions levels.

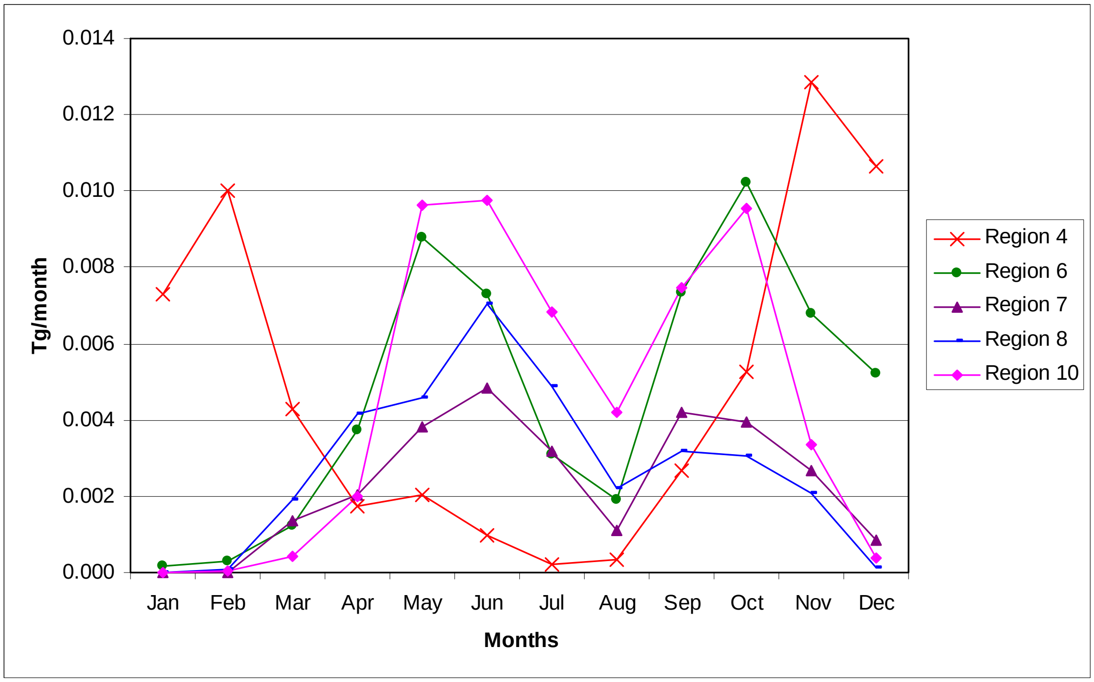

Figure 5-5. Monthly distribution of average CO emissions from crop residue burning by EPA source region for years 2003 - 2007.

Emissions from these five major source regions showed considerable seasonal variability. This analysis defined seasons as: Winter - January to March; Spring - April to June; Summer - July to September; and Fall - October to December. Figure 5-6 illustrates the seasonal variability of average monthly emissions of CO for the EPA source regions. In general, the highest CO emissions occurred in the spring and fall. Region 8, dominated by summer wheat harvesting in the northern Great Plains, had a continual increase in emissions from winter to spring, leveled off in summer related to the continuing wheat harvest, and a decrease in the fall. Similarly, region 6 has spring and summer wheat harvesting in the southern Great Plains, but showed a sharp increase in emissions in the fall due to sugarcane and rice harvesting in the Mississippi Delta and Texas. Regions 7 and 10 had similar trends with a peak in summer burning and nearly equal amounts of burning in the spring and fall. Both of these regions are home to major wheat production, with the majority of burning in region 7 during the summer and the majority of wheat residue burning in region 10 during the spring, summer, and fall due to a double wheat crop system. Higher summer burning in region 10 is also due to Kentucky bluegrass seed harvesting. The seasonality of CO emissions for Region 4 is nearly the opposite of the other regions, with the lowest amount of burning in spring and summer, and the majority of burning in winter and fall due to sugarcane in Florida and the fall harvest of rice and soy in other southeastern states.

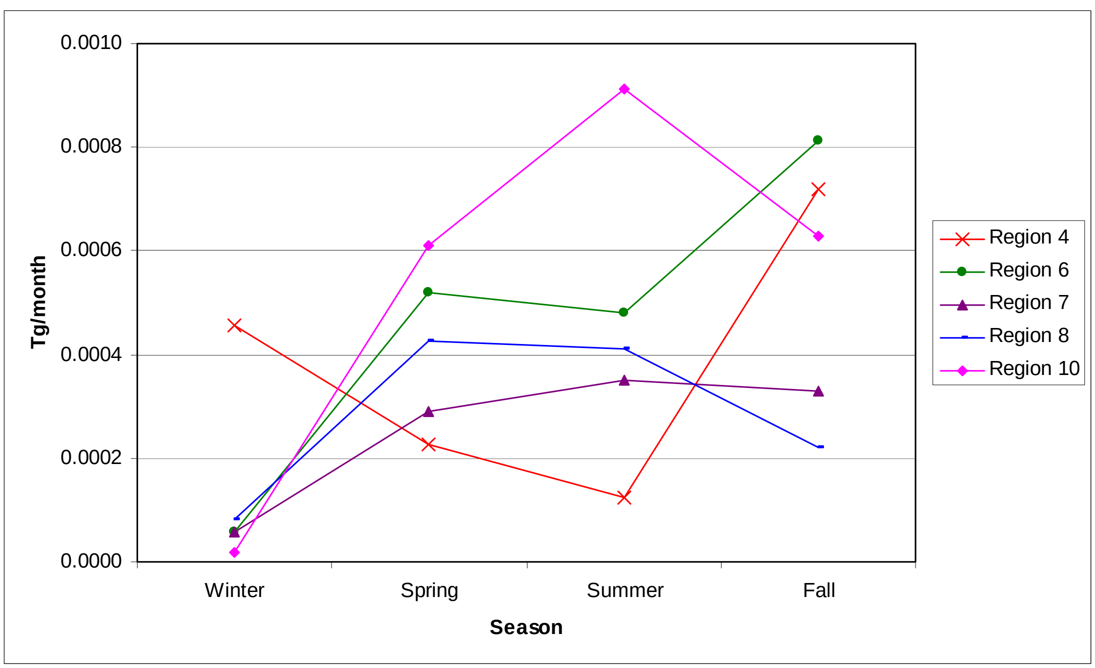

Figure 5-6. Seasonal variability of average CO emissions from crop residue burning for EPA source regions for years 2003-2007.

Between the years 2003 and 2007, 34% of all emissions originated from sugarcane residue burning (Figure 5-7). Wheat residue burning accounted for 22% of all emissions, followed by rice with 14% of total emissions. Other crops/fallow, Kentucky bluegrass seed, soybean, cotton, corn, and lentils accounted for less than or equal to 10% of all emissions, respectively. The results do not match the EPA estimate of crop residue burning by crop type. The EPA estimates that 77% of all crop residue burning emissions are released from corn and soybean residue burning, with only 23% of emissions attributed to sugarcane (3%), wheat (10%), and rice (10%) (EPA, 2008b).

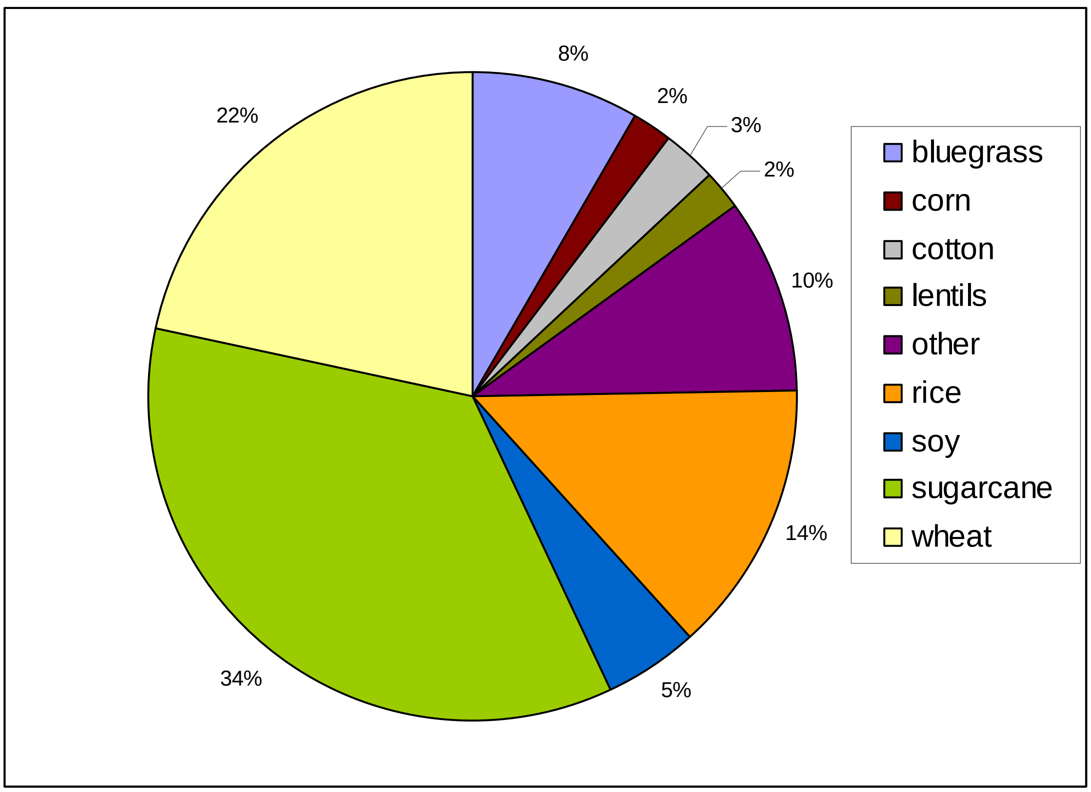

Figure 5-7. Average contribution of emissions by crop type for the EPA source regions for years 2003-2007.

5.3.4. Crop Residue Burning Emissions for the CONUS

On average, crop residue burning in the CONUS emitted 6.1 Tg of CO_2, 0.009 Tg of CH_4, and 0.2 Tg of CO per year (Table 5-9). PM_{10} and $PM_{2.5}$ emissions were an average of 0.03 Tg and 0.02 Tg, respectively. NO_2 and SO_2 were less, with average emissions of 0.01 Tg and 0.004 Tg respectively. As previously mentioned, lead emissions were insignificant, totaling 0.001 Tg between the years 2003 and 2007. Air quality emissions from CO, $PM_{2.5}$, and PM_{10} were the most significant air quality emissions from crop residue burning in the CONUS in terms of quantity.

Table 5-9. Total and average carbon and air quality emissions (Tg yr^{-1}) from crop residue burning for the CONUS, 2003-2007; CO_2 reported in Tg yr^{-1}; all other species reported in Gg yr^{-1}.

Years	CO_2	CH_4	CO	NO_2	SO_2	$PM_{2.5}$	PM_{10}
2003	6.46	9.03	247.34	11.59	4.95	21.93	29.36
2004	6.03	8.95	233.78	10.71	4.41	21.27	28.10
2005	6.07	9.14	234.16	10.56	4.29	21.38	29.09
2006	5.72	8.19	207.61	9.22	3.60	18.75	26.43
2007	6.15	9.07	239.30	10.96	4.59	21.38	29.33
Total	30.45	44.39	1162.19	53.04	21.83	104.70	142.33
Average	6.09	8.87	232.44	10.61	4.37	20.94	28.46
Average Interannual Variability (± value)	0.31	0.52	18.04	1.03	0.59	1.51	1.95
Average Interannual Variability (%)	5.07	5.90	7.76	9.70	13.45	7.20	7.03

The average interannual variability was higher for the air quality emissions of CO, NO_2, SO_2, $PM_{2.5}$, and PM_{10} than the carbon emissions of CO_2 and CH_4 (Table 5-9). The highest average interannual variability was calculated for SO_2 at 13.4%, followed by NO_2 at 9.7%. Particulate emissions from crop residue burning, $PM_{2.5}$ and

PM_{10}, had an average interannual variability of 7.2%, slightly below the CO average interannual variability of 7.8%. In general, besides SO_2, air quality and carbon emissions from crop residue burning in the CONUS varied less than 10% interannually.

5.4. Comparison with Published Emission Estimates

5.4.2. Comparison with Previously Published Agricultural Emissions

The following analysis presents a comparison of the estimates of crop residue burning emissions from this study with published estimates of emissions from all agricultural emissions at the global and continental scale as well as comparisons with emission estimates of specific crops from Asian countries. These comparisons provide a context in which to place CONUS crop residue emissions within the estimated global agricultural fire emissions and North American agricultural fire emissions. In addition, the aim of this comparison is to demonstrate the different emissions levels from crop residue burning in developed and developing countries.

The results of this analysis were compared with both global estimates of crop residue burning (Andreae and Merlet, 2001; Yevich and Logan, 2003) and North American estimates of agricultural burning (Wiedinmyer et al., 2006). Two of these studies, Andreae and Merlet (2001) and Wiedinmyer et al. (2006), grouped all agricultural emissions and did not specify by crop type. Yevich and Logan (2003) did specify by crop type, though that study and this analysis did not completely share the same crop types, i.e., Kentucky bluegrass seed. The CONUS crop residue burning accounted for an average of 1% of total global CO_2, CO, CH_4, $PM_{2.5}$, and SO_2 emissions from crop residue burning calculated by Andreae and Merlet (2001) (Table

5-10). Comparing the three atmospheric species of CO_2, CO, and CH_4, calculated by both Andreae and Merlet (2001) and Yevich and Logan (2003), the average CONUS emissions for the same species accounted for 0.6% and 2.1% of total global emissions from these two sources, respectively. The North American estimates from Wiedinmyer et al. (2006) included all forms of agricultural burning in much of Central America, Mexico, U.S., and Canada. Estimates from this study accounted for an average of 15.1% of total CO and $PM_{2.5}$ emissions from agricultural burning in North America (Wiedinmyer et al., 2006). Though crop residue burning in the CONUS was a minor source of agricultural burning emissions on a global scale, it appeared to be a significant source within North America.

Table 5-10. Comparison of global and continental agricultural burning emissions with estimated emissions from this analysis; the percent CONUS cropland fire emissions below were calculated by dividing the average CONUS crop residue burning emissions by the published estimates of agricultural burning emissions; emissions reported in Tg yr^{-1}.

Source	Scale	CO_2	CO	CH_4	$PM_{2.5}$	SO_2
Andreae and Merlet (2001)	Global	818.00	50.00	1.50	2.10	0.22
Yevich and Logan (2003)	Global	140.00	23.00	1.00		
Wiedinmyer et al. (2006)	North America		1.62		0.13	
This analysis	CONUS	6.09	0.23	8.88 10^-3	2.09 10^-2	4.37 10^-3
Andreae and Merlet (2001)	% CONUS cropland fire emissions	0.74	0.46	0.59	1.00	1.98
Yevich and Logan (2003)	% CONUS cropland fire emissions	4.35	1.01	0.89		
Wiedinmyer et al. (2006)	% CONUS cropland fire emissions		14.32		15.88	

The results from this analysis were also compared with three scientific studies completed in China and India using remote sensing to quantify cropland burning and related air quality and carbon emissions. Table 5-11 shows the comparison between this analysis and the results from crop residue burning in these two developing Asian countries. The CO_2 emissions estimates from wheat residue burning for the entire country of India (Sahia et al., 2007) were 17 times higher than the average estimates for wheat in the CONUS. CO, NO_2, and CH_4 emissions for India were also substantially higher than the estimates from this analysis, representing a magnitude of 8 times, 4 times, and 29 times higher, respectively, than the CONUS emissions. Provincial-level analyses in China (Yang et al., 2008) and India (Badarinath et al., 2006) for wheat and rice residue burning showed consistently higher CO and CH_4 emissions in these areas than in the CONUS. The regional estimates from Badarinath et al. (2006) accounted for 4 times, 6 times, 1.3 times, 4 times and 5 times higher estimates of CO, NO_2, CH_4, PM_{10}, and $PM_{2.5}$, respectively, than the estimates for the CONUS. Badarinath et al. (2006) detected approximately 1,818,900 ha of cropland burned area, more than 260,000 ha greater in area than the cropland burned area detected in the CONUS. In addition, the methodology used for the Punjab region assumed a fuel load of 5.94 t/ha (or 5.94 Mg/ha), which was 0.42 Mg/ha higher than the average fuel loads of wheat and rice used in this study. Compared to the emissions estimates for the Suqian Province of China (Yang et al., 2008), the estimates from this analysis were 1.4 times higher for CO_2 and NO_2 emissions, 1.3 times higher for PM_{10} emissions, and approximately 2 times higher than the SO_2

emission estimates. The CONUS crop residue burning emissions accounted for an average of 79% of total emissions from residue burning for China and India.

Table 5-11. Comparison of crop residue burning emissions in China and India with estimated emissions from this analysis; emissions reported in Tg yr^{-1}; the percent CONUS cropland fire emissions below were calculated by dividing the average CONUS crop residue burning emissions by the published estimates of crop residue burning emissions in India and China.

Source	Country /Region	Crop	CO_2	CO	NO_2	CH_4	PM_{10}	$PM_{2.5}$	SO_2
Sahai et al. (2007)	India	Wheat	34.44	0.54	0.01	0.07			
Yang et al. (2008)	China /Suqian	Wheat/ Rice	1.98	0.12	3.28 10^-3	3.54 10^-3	7.57 10^-3		5.24 10^-4
Badari-nath et al. (2006)	India /Punjab	Wheat/ Rice		0.37	0.03	4.33 10^-3	0.04	0.04	
This Analysis	CONUS	Wheat	1.96	0.07	2.78 10^-3	2.38 10^-3			
	CONUS	Wheat/ Rice	2.74	0.09	4.39 10^-3	3.36 10^-3	0.01		1.23 10^-3
	CONUS	Wheat/ Rice		0.09	4.39 10^-3	3.36 10^-3	0.01	0.01	
	% CONUS cropland fire emissions		5.68	11.92	25.26	3.51			
	% CONUS cropland fire emissions		137.62	75.91	133.70	94.79	131.41		233.94
	% CONUS cropland fire emissions			24.51	15.44	77.59	23.14	19.08	

Based on these comparisons, crop residue burning emissions in the CONUS generally accounted for a smaller magnitude of carbon and air quality emissions at the global scale and the national- and provincial-level estimates when compared with

India and China. In comparison with Wiedinmyer et al. (2006), CONUS crop residue burning emissions appeared overall to be a significant source for North American agricultural fire emissions.

5.4.2. Comparison with Wildfire Emissions

Wildfire emissions are an important source of carbon and air quality emissions at the global, continental, and regional scale (Seiler and Crutzen, 1980; Andreae and Merlet, 2001; Liu, 2004; Yokelson et al., 2008). CONUS crop residue burning emissions were compared to North American estimates of forest fires and total pyrogenic emissions from all burning sources for the U.S., including Alaska and Hawaii (Wiedinmyer et al., 2006). CONUS crop residue burning emissions accounted for approximately 0.5% of total emissions of CO and $PM_{2.5}$ from forest fires in North America (Table 5-12). However, crop residue burning did account for a higher average of emissions in the U.S., averaging 1.5% of total CO_2, CO, CH_4, $PM_{2.5}$, and SO_2 emissions from all fires.

Table 5-12. Comparison of North American forest fire emissions and U.S. total pyrogenic emissions with estimated crop residue burning emissions from this analysis; the percent CONUS cropland fire emissions below were calculated by dividing the average CONUS crop residue burning emissions by the published estimate of North American forest fires and total pyrogenic emissions in the U.S.; emissions reported in Tg yr^{-1}.

Source	Scale	CO_2	CO	CH_4	$PM_{2.5}$	SO_2
Wiedinmyer et al. (2006)	North American Forest Fires	[redacted]	44.20	[redacted]	5.1	[redacted]
Wiedinmyer et al. (2006)	U.S. total pyrogenic	356.00	19.80	1.00	2.40	0.16
This analysis	CONUS croplands	6.09	0.23	8.88 10^-3	2.09 10^-2	4.37 10^-3
Wiedinmyer et al (2006)	% CONUS cropland fires	[redacted]	0.53	[redacted]	0.41	[redacted]
Wiedinmyer et al (2006)	% CONUS cropland fires	1.71	1.17	0.89	0.87	2.73

5.4.3. Comparison with the Global Fire Emissions Database

The Global Fire Emissions Database (GFED) is a global 1° by 1° gridded burned area, combustion completeness, fuel loads, and fire emissions database for January 1997 to December 2005 (van der Werf et al., 2006). The GFED reports several carbon, gaseous, and particulate emissions, including CO_2, CO, CH_4, and $PM_{2.5}$. The GFED uses the MODIS 1 km Active Fire Data Set to quantify global fire activity and model burned area (van der Werf et al., 2006). The average emissions of CO_2, CO, CH_4, and $PM_{2.5}$ from crop residue burning in the CONUS were compared to the average emissions for the same species as reported by the GFEDv2.1 (Randerson et al., 2007) (Table 5-13). Annual emissions of CO_2, CO, CH_4, and $PM_{2.5}$ for years 2003 through 2006 were averaged from the GFED at the global and CONUS scale. In general, crop residue burning emissions in the CONUS accounted for an average of 0.1% of total global fire emissions for CO_2, CO, CH_4, and $PM_{2.5}$. Compared to the GFED estimates for CONUS, crop residue burning over the same area was equivalent to approximately 7% of CO_2, 4% of CO and CH_4, and 3% of $PM_{2.5}$ emissions, respectively. Based on this comparison, CONUS crop residue burning emissions are minor contributors to global and CONUS emissions of biomass burning as modeled by the GFED.

Table 5-13. Comparison of GFEDv2.1 from biomass burning emissions (Randerson et al., 2007) and the annual average crop residue burning emission estimates from this analysis for the CONUS, 2003 - 2007; emissions reported in Tg yr^{-1}.

Source	Scale	CO_2	CO	CH_4	$PM_{2.5}$
Randerson et al. (2007)	Global all sources	8867.00	430.00	21.10	37.80
Randerson et al. (2007)	CONUS all sources	91.85	5.5	0.2	0.61
This analysis	CONUS croplands	6.09	0.23	8.88 10^-3	2.09 10^-2
	% CONUS cropland fires in GFED global burning emissions	0.07	0.05	0.04	0.05
	% CONUS cropland fires in GFED CONUS burning emissions	6.63	4.18	4.44	3.43

5.5. *Implications for National Emissions Reporting*

5.5.1. Implications for the National Emissions Inventory

Currently, the EPA NEI includes pyrogenic sources of air pollution. In 2002, the NEI did provide explicit emission estimates from fires, grouped together in one class that included agricultural fires, prescribed/slash burning, wildfires, structural fires, and other burning (EPA, 2002). The 2002 NEI burning estimates for agricultural fires were limited to 23 states and included burning activity ranging from pasture maintenance fires, burn piles, and crop residue burning (Pouliot et al., 2008). Subsequent NEI reports for 2005 and 2008 have relied on the fire emissions estimated from 2002. The average emissions from this analysis were compared with the 2002 NEI fire emissions (Table 5-14). The average annual crop residue burning emissions from this analysis accounted for approximately 6% of total CO, $PM_{2.5}$, PM_{10}, and SO_2 emissions of all burning activity reported in the 2002 NEI. Future NEI reports would benefit from separating different categories of fire activities in order to determine the relative contributions of the different burning sources and whether agricultural burning, i.e., crop residue fire emissions, is a significant contributor to total pyrogenic emissions.

Table 5-14. Comparison of 2002 NEI air quality emissions from fire emissions (EPA, 2002) and the annual average crop residue burning emission estimates for the CONUS, 2003 - 2007, from this analysis; emissions reported in Tg yr^{-1}.

Species	2002 NEI Fire Emissions Estimates from all Fire Sources (Tg)	Average Annual Crop Residue Burning Emissions This Analysis (Tg)	Percent Crop Residue Emissions in 2002 NEI Estimates
CO	16.791	0.232	1.4%
$PM_{2.5}$	1.385	0.021	1.5%
PM_{10}	1.634	0.028	1.7%
SO_2	0.350	0.001	0.3%

The following comparison with the various industrial and transportation sectors in the NEI demonstrates the contribution of air quality and carbon emissions from crop reside burning in the CONUS to current estimates of air pollution by the EPA. The EPA utilizes the NEI to track air pollutants over time, to develop regional pollution mitigation strategies, and to set and analyze current air quality regulations (EPA, 2006a). If crop residue burning emissions are equal to or greater than current NEI estimates of pollutants, the results would be beneficial to the EPA for revising current and future pollution reduction strategies and air quality regulations. Table 5-15 lists the emissions from industrial sources that were comparable with crop residue burning emissions, including sectors where crop residue burning emissions were more than triple the industrial sources. The 'Miscellaneous' sector, which includes estimates for all fire emissions (EPA, 2002), was included in this comparison to quantify the contribution of crop residue burning emissions to the EPA's estimated fire emissions. The 'All sectors' row is the total of all thirteen sectors reported in the 2002 NEI not just the selected sectors that were comparable to crop residue burning emissions.

Compared with NEI trend data for species SO_2, $PM_{2.5}$, PM_{10}, and CO for years 2003 through 2007, crop residue burning emissions from this analysis represented small percentages (< 2%) of both the total emissions from various sectors, including energy, waste disposal, and transportation, and the 'Miscellaneous' sector. Note that the $PM_{2.5}$ estimates from the NEI do not include condensibles, i.e., $PM_{2.5}$ that is formed in the atmosphere from precursor gases such as SO_2 and NO_x. On average, cropland fire emission estimated from this analysis accounted for 0.4% of total emissions from all species for all sectors. Crop residue burning emissions accounted for approximately 0.04% of SO_2 emissions, 1% of $PM_{2.5}$ emissions, 0.2% of PM_{10} emissions, and 0.3% of CO emissions, respectively. Consistently, emissions from crop residue burning exceeded the national trends for emissions from solvent utilization, which includes architectural surface coating, automobile refinishing, traffic painting, pesticide applications, dry cleaning, industrial adhesives and sealants, surface cleaning, and other operations. For SO_2, $PM_{2.5}$, and CO, crop residue burning emissions also exceeded the storage and transport sector, which includes storage and transport of petroleum and petroleum products, organic chemicals, and bulk items. Crop residue burning emissions from CO, $PM_{2.5}$, and PM_{10} nearly exceeded and/or exceeded the estimated emissions for the chemical manufacturing, petroleum and related industries, and metals processing sectors. Clearly, crop residue burning emits more SO_2, $PM_{2.5}$, PM_{10}, and CO in the CONUS than several industrial activities.

Table 5-15. Comparison of National Emission Trends for SO_2, $PM_{2.5}$, PM_{10}, and CO from selected sectors with the crop residue burning emissions from this analysis; the Miscellaneous sector is consistent across comparison due to the inclusion of all estimated pyrogenic emissions in this category (EPA, 2006a); the 'All sectors' row is the total of all thirteen sectors reported in the 2002 NEI not just the selected sectors; emissions reported in Tg yr^{-1}.

SO_2							
Source Category	2003	2004	2005	2006	2007	Average	% Cropland Fire Emissions
Storage & Transport of Petroleum Products	4.54 10^-3	4.54 10^-3	4.54 10^-3	4.54 10^-3	4.54 10^-3	4.54 10^-3	101.23%
Waste Disposal & Recycling	0.02	0.02	0.02	0.02	0.02	0.02	19.47%
Miscellaneous	0.12	0.12	0.12	0.12	0.11	0.12	3.83%
This Analysis: Cropland Fire	4.59 10^-3	4.41 10^-3	4.29 10^-3	3.60 10^-3	4.59 10^-3	4.59 10^-3	
All sectors	13.39	13.37	13.35	12.26	11.73	12.82	0.04%
$PM_{2.5}$ (Without Condensibles)							
Source Category	2003	2004	2005	2006	2007	Average	% Cropland Fire Emissions
Fuel Combustion - Electric Utility	0.11	0.11	0.11	0.08	0.05	0.09	24.25%
Fuel Combustion - Industrial	0.11	0.11	0.11	0.10	0.10	0.11	27.19%
Fuel Combustion - Other	0.05	0.05	0.05	0.05	0.05	0.05	58.54%
Chemical & Allied Product Mfg	0.02	0.02	0.02	0.02	0.02	0.02	120.68%
Metals Processing	0.04	0.04	0.04	0.04	0.03	0.04	79.64%
Petroleum & Related Industries	0.02	0.02	0.02	0.01	0.01	0.01	201.14%
Solvent Utilization	0.005	0.005	0.005	0.005	0.005	0.005	627.54%
Storage & Transport of Petroleum Products	0.016	0.016	0.016	0.016	0.015	0.016	176.28%
Highway Vehicles	0.128	0.122	0.115	0.097	0.091	0.110	25.76%
Miscellaneous	1.628	1.628	1.628	1.639	1.651	1.635	1.74%
This Analysis: Cropland Fire	0.02	0.02	0.02	0.02	0.02	0.02	
All sectors	2.81	2.80	2.80	2.72	2.68	2.76	1.03%

Table 5-15. Comparison of National Emission Trends for SO_2, $PM_{2.5}$, PM_{10}, and CO with the crop residue burning emissions from this analysis; the Miscellaneous sector is consistent across comparison due to the inclusion of all estimated pyrogenic emissions in this category (EPA, 2006a); the 'All sectors' row is the total of all thirteen sectors reported in the 2002 NEI not just the selected sectors; emissions reported in Tg yr^{-1} (cont.).

PM_{10}							
Source Category	2003	2004	2005	2006	2007	Average	% Cropland Fire Emissions
Chemical & Allied Product Mfg	0.03	0.04	0.04	0.04	0.04	0.04	78.44%
Metals Processing	0.07	0.07	0.07	0.07	0.07	0.07	39.03%
Petroleum & Related Industries	0.02	0.02	0.02	0.02	0.02	0.02	128.60%
Solvent Utilization	0.01	0.01	0.01	0.01	0.01	0.01	392.21%
Storage & Transport of Petroleum Products	0.05	0.05	0.05	0.05	0.05	0.05	52.82%
Miscellaneous	16.22	16.22	16.22	14.50	12.78	15.19	0.19%
This Analysis: Cropland Fire	0.03	0.03	0.03	0.03	0.03	0.03	
All sectors	19.34	19.32	19.31	17.53	15.76	18.25	0.16%
CO							
Source Category	2003	2004	2005	2006	2007	Average	% Cropland Fire Emissions
Fuel Combustion - Electric Utility	0.60	0.60	0.60	0.61	0.63	0.60	38.49%
Fuel Combustion - Industrial	1.15	1.15	1.15	1.14	1.14	1.15	20.29%
Chemical & Allied Product Mfg	0.26	0.26	0.26	0.26	0.26	0.26	90.22%
Metals Processing	0.90	0.90	0.90	0.90	0.90	0.90	25.96%
Petroleum & Related Industries	0.32	0.32	0.32	0.32	0.32	0.32	71.85%
Other Industrial Processes	0.45	0.45	0.45	0.44	0.44	0.44	52.33%
Solvent Utilization	1.81 10^-3	1.81 10^3	1.81 10^-3	1.81 10^3	1.81 10^-3	1.81 10^3	12811.00%
Storage & Transport of Petroleum Products	0.11	0.11	0.11	0.11	0.11	0.11	217.14%
Miscellaneous	16.78	16.78	16.78	16.89	17.01	16.85	1.38%
This Analysis: Cropland Fire	0.25	0.23	0.23	0.21	0.24	0.23	
All sectors	96.38	92.02	87.65	83.58	80.06	87.94	0.26%

5.5.2. Implications for the Greenhouse Gas Emissions Inventories

The EPA prepares an inventory of national greenhouse gas sources and sinks for the U.S. annually. The most recent publication, the 2008 Inventory of Greenhouse Gas Emissions and Sinks (EPA, 2008b), included CH_4 and CO emissions estimates from field burning of agricultural residues for the years 1990 through 2006. Crops included in the EPA's greenhouse gas inventory included barley, corn, peanuts, rice, soybean, sugarcane, and wheat. This analysis did not include barley and peanuts, however, emissions these two crops accounted for less than 3% of the total emissions reported by the EPA. Methodologies for emission estimates were different, with the largest divergence coming from the emission factors, the fraction of residue burned (CE), fuel load, and the burned area estimates. The greatest uncertainty in the EPA emissions calculations was fuel load (discussed below), noted in the greenhouse gas inventory document (EPA, 2008b). In the case of the emission factors, the EPA greenhouse inventory used their own emission factors from the EPA AP-42 document (EPA, 1992) and this analysis used calculated emission factors from the scientific literature which included the EPA emission factors, as reported by Dennis et al. (2002). The CE factor used by the EPA was 0.88, 15% higher than the average CE factor used by this analysis of 0.75. As for burned area, the EPA assumed that 3% of the area for all targeted crops burned, except for rice (EPA, 2008b). Burned rice acreages were taken from state estimates. Combining these estimates, the EPA assumed a cropland burned area that was on average two times the area that was detected using the hybrid remote sensing approach detailed in Chapters 2 and 4.

Fuel loads have been noted as having high uncertainty values in bottom-up emissions calculations (Korontzi et al., 2004). As previously mentioned in section 5.2.4, the EPA methodology for fuel load calculation outlined in the Greenhouse Gas Inventory (EPA, 2008b) was not utilized in this analysis. Table 5-16 shows the comparison between the fuel loading variables used in this analysis with average fuel loads from the EPA Greenhouse Gas Inventory for the four crops that were common to both studies: corn, rice, sugarcane, and wheat. The EPA Greenhouse Gas Inventory estimated emissions using higher fuel load variables for the crops of rice and sugarcane. The fuel load values from this analysis and the greenhouse gas inventory were the same for wheat. Corn was the exception, with this analysis utilizing a fuel load estimate that was 38% higher than the EPA's fuel load variable.

Table 5-16. Comparison of fuel loads from the average EPA greenhouse gas inventory fuel load variables and the fuel load variables used in this analysis for the crops of corn, rice, sugarcane, and wheat; average EPA fuel loads calculated from data for years 2003 through 2006; percent difference was calculated as the relative change between the EPA GHG Inventory fuel loads and the fuel loads in this analysis; negative average percent difference indicates a higher fuel load variable used in this analysis.

Crop	Fuel Load from EPA Greenhouse Gas Inventory (kg/ha)	Fuel Load for This Analysis (kg/ha)	Percent Difference
Corn	6,819	9,408	-38%
Rice	9,993	6,720	33%
Sugarcane	36,748	10,640	71%
Wheat	2,752	2,752	0%

Table 5-17 shows the comparison of the EPA estimates with this analysis. This analysis estimated CH_4 and CO emissions to be an average of 78% and 73% less than the EPA estimates, respectively. Table 5-18 compares the results of crop residue burning emissions calculated using the average emissions factors and the maximum emission factors (Table 5-4). Using the maximum emission factors, the average annual emissions from crop residue burning for CH_4 and CO were 0.017 Tg and 0.972 Tg, respectively. These maximum CH_4 and CO emissions were 52% and 23% higher than the emissions calculated from the average emission factors, respectively. The CH_4 and CO emission estimates calculated using the maximum emission factor values accounted for 50% and 119%, respectively, of the average annual EPA estimation of CH_4 and CO emissions from crop residue burning. Based on the results of this analysis, it is likely that the EPA is overestimating CH_4 emissions from crop residue burning. However, the CO emissions reported by the EPA fall well within the range of emission estimates from this analysis calculated using the average and maximum emission factors. Therefore, the EPA estimation of CO emissions of crop residue burning appears reasonable.

Table 5-17. Comparison of greenhouse gas emission estimates from crop residue burning estimated by the EPA with results from this analysis for 2003 through 2006; emissions reported in Tg yr^{-1}.

	Species	2003	2004	2005	2006
EPA	CH_4	0.04	0.04	0.04	0.04
	CO	0.80	0.88	0.86	0.83
This Analysis	CH_4	9.00 10^-3	9.00 10^-3	9.00 10^-3	8.00 10^-3
	CO	0.25	0.23	0.23	0.21
Percent CONUS cropland burning emissions in the EPA estimates (%)	CH_4	22.50	22.50	22.50	20.00
	CO	31.25	26.14	26.74	25.30

Table 5-18. Comparison of average greenhouse gas emission estimates from crop residue burning estimated by the EPA with results from this analysis for 2003 through 2006; emissions from this analysis calculated using both the average emission factors and the maximum emission factors; emissions reported in Tg yr^{-1}.

	Species	Average (2003 - 2006)
Average EPA Estimate	CH_4	0.04
	CO	0.84
This Analysis (average emission factors)	CH_4	9.00 10^-3
	CO	0.23
This Analysis (maximum emission factors)	CH_4	0.02
	CO	1.00
Percent CONUS cropland burning emissions using the maximum emission factors in the average EPA estimates (%)	CH_4	50.00
	CO	119.05

Crop residue burning emissions are a minor source of CH_4 emissions compared to the CH_4 emissions from other agricultural sources, specifically enteric fermentation, manure management, and rice cultivation (Table 5-19). Crop residue burning emissions accounted for less than 1% of the annual emissions from enteric fermentation, manure management, and rice cultivation.

Table 5-19. Comparison of annual CH_4 emission estimates from other agricultural activities estimated by the EPA with crop residue burning emissions from this analysis for 2003 through 2006; emissions reported in Tg yr^{-1}.

Activity	Source	2003	2004	2005	2006
Enteric fermentation	EPA	8.24	8.14	8.28	8.30
Manure management	EPA	5.93	5.83	5.93	6.04
Rice cultivation	EPA	1.94	1.91	1.99	1.97
Crop residue burning	This Analysis	9.00 10^-3	9.00 10^-3	9.00 10^-3	8.00 10^-3
Percent crop residue burning emissions from this analysis in EPA estimates	Enteric fermentation	0.11%	0.11%	0.11%	0.10%
	Manure management	0.15%	0.15%	0.15%	0.13%
	Rice cultivation	0.46%	0.47%	0.45%	0.41%

The USDA also compiles a greenhouse gas inventory focused on CH_4 and CO emissions from agricultural and forestry sources (USDA GCPO, 2008). Using the crop residue burning emission estimates from the EPA Greenhouse Gas Inventory, the USDA ranks the states of Iowa, Illinois, Minnesota, Nebraska, Arizona, Indiana, Kansas, Arkansas, Ohio, and South Dakota, in descending order, as the largest sources of CH_4 emissions. In general, this analysis showed that a different set of states are the main sources of CH_4 emissions from crop residue burning (in descending order): Idaho, Washington, Florida, Texas, Arkansas, Kansas, Oregon, South Dakota, North Dakota, and Missouri. The states of Arkansas, Kansas, and South Dakota were shared between the two studies. The USDA's greenhouse gas inventory overestimates the contribution of crop residue burning emissions from the Midwestern states of Illinois, Iowa, Indiana, Minnesota, Nebraska, and Ohio.

Comparing the crop residue burning CO_2 emission results to estimates of emitted CO_2 from burning of fossil fuels shows that crop residue burning is an insignificant CO_2 source for the CONUS. The U.S. Department of Energy estimated the average annual CO_2 emissions in the CONUS from all fossil fuel burning (FFB) sources for 2004 as 4997 Tg CO_2 (DOE, 2008). The 2004 annual CO_2 emissions from crop residue burning for the CONUS was 6.035 Tg CO_2, equivalent to 0.12% of the annual FFB emissions. Continued monitoring of crop residue burning emissions is needed to further quantify the contribution of crop reside burning CO_2 emissions to fossil fuel burning sources. Additionally, though not as large as the fossil fuel burning sources, crop residue burning is a source of CO_2 that has heretofore not been included in CO_2 estimations for the CONUS.

5.7. Conclusions

The majority of crop residue burning emissions in the CONUS were emitted in the spring, summer, and fall. CONUS crop residue burning emissions had an average interannual variability of ± 10%, ranging from 5.1% for CO_2 and 13.4% for SO_2. Six states emitted the majority of air quality and carbon emissions from crop residue burning (ranked in descending order): Florida, Washington, Texas, California, Idaho, and Arkansas. These six states accounted for 50% of PM_{10}, 51% of CO_2, 52% of CO, and 63% of $PM_{2.5}$. Florida alone emitted 17% of all annual CO_2, CO, and $PM_{2.5}$ emissions as well as 12% of all annual PM_{10} emissions from crop residue burning. From a regional perspective, EPA regions 4, 6, 10, 8, and 7, in descending order, were the main sources of emissions. These 5 EPA regions, comprising the southeastern U.S., the Great Plains, and the Pacific Northwest, represented 85% of all emission for crop residue burning for the atmospheric species of CO_2, CO, CH_4, NO_2, SO_2, $PM_{2.5}$, and PM_{10}. Approximately 71% of all crop residue burning emissions in the EPA source regions originated from three crops of sugarcane, wheat, and rice. Compared to estimates of all agricultural burning emissions in North America which included all types of agricultural burning, which included slash-and-burn, land clearing, pasture maintenance, etc., the CONUS crop residue burning emissions represented 15% of total emissions.

Compared with crop residue burning emissions estimates at the global-scale and the national and provincial-scale for China and India, crop residue burning in the CONUS was a minor source of air quality and carbon emissions. CONUS crop residue burning emissions accounted for as little as 1% of global agricultural emissions, which includes crop residue burning as well as other forms of agricultural burning. Additionally, CONUS crop residue burning emissions accounted for 26% of total crop residue burning emissions reported for selected provinces in China and India.

CONUS crop residue burning emissions were also significantly less than estimated wildfire emissions. Forest fire emissions in North America of CO and $PM_{2.5}$ were significantly higher than the estimates from this analysis, with cropland burning being approximately equivalent to 0.5% of North American forest fire emissions. At the national level, crop residue burning emission estimates accounted for 1.5% of total CO_2, CO, CH_4, $PM_{2.5}$, and SO_2 emissions from all pyrogenic emissions in the U.S., including Alaska and Hawaii.

Results from this analysis show that crop residue burning emission estimates accounted for 6% of total emissions from current fire emission estimates in the EPA NEI. Compared with other sectors, CONUS crop residue burning consistently emitted more SO_2, $PM_{2.5}$, and CO than the storage and transport sector. Cropland burning emissions of CO, $PM_{2.5}$, and PM_{10} in the CONUS also exceeded the chemical manufacturing, petroleum and related industries, and metals processing sectors.

This analysis provided an independent assessment of crop residue burning to be compared with the 2008 Inventory of Greenhouse Gas Emissions and Sinks (EPA, 2008b) and the U.S. Agriculture and Forestry Greenhouse Gas Inventory (USDA GCPO, 2008). For example, compared with this study, the EPA consistently overestimated cropland burned area by a factor of 2. Accordingly, the EPA estimates of CO and CH_4 were 73% to 78% higher than the CO and CH_4 emission estimates from this analysis, respectively. However, when emissions are calculated using the maximum emission factor values, the EPA estimates of CH_4 were 50% higher than this analysis while the EPA estimates of CO were 19% lower than this analysis. Based on these results, it is likely that the EPA is overestimating CH_4 emissions but current CO emissions are well within the ranges estimated by this analysis. This analysis also showed that crop residue burning emissions are a minor source of CH_4 emissions (< 1%) compared to the CH_4 emissions from other agricultural sources, specifically enteric fermentation, manure management, and rice cultivation. When compared to all fossil fuel burning sources of CO_2 in the U.S. for 2004, the crop residue burning emissions in the CONUS accounted for 0.12% of CO_2 emissions from these commercial, industrial, residential, and transportation sectors. This analysis has demonstrated that carbon emissions from crop residue burning are not as significant as emissions which negatively impact air quality.

Chapter 6: Scientific and Operational Potential of Quantifying Crop Residue Burning and Related Emissions Using Remote Sensing for the Contiguous United States, Policy Implications, and Future Research Directions

6.1. Quantifying Crop Residue Burning in the CONUS

This research presents the first estimates of the spatial and temporal distribution of crop residue burning and related carbon and air quality emissions in the CONUS. An average of 1,239,000 ha of croplands burn annually, which represents approximately 43% of the average area reported for wildland fires in the U.S. by the U.S. Forest Service (USFS) annually. The average interannual variability of the CONUS cropland burned area was 7% or roughly ± 91,200 ha. Several states experience extensive crop residue burning, including Arkansas, California, Colorado, Florida, Idaho, Louisiana, Oregon, and Washington. Air quality and carbon emissions from crop residue burning were mainly concentrated in spring and fall with an average interannual variability of approximately ± 10%. Approximately 71% of all emissions originated from sugarcane, wheat, and rice residue burning.

Remote sensing has proven to be a useful tool in quantifying crop residue burning. Previous research on crop residue burning relied on reported burning that was often aggregated to political boundaries, i.e., states and/or countries. The remote sensing products used in this analysis, both burned area and crop type, provided spatially and temporally explicit measurements of crop residue burning and related emissions. The remote sensing approach also allowed for a seasonal analysis of emission estimates as well as an interannual comparison of cropland burned area and areal decreases of crop types. In addition, emissions were also analyzed by crop type based on the remotely sensed crop type maps. This analysis, through the use of remote sensing, established an independent baseline of crop residue burned area and related emissions for the CONUS which is heretofore unavailable.

Like all remote sensing analyses, scale was an important issue. At MODIS spatial scales of 500 m and 1 km, both the burned area and active fire product are needed to detect crop residue burning activity and extent that is approximate to on-the-ground conditions. The main contribution of the active fire product is the detection of small, single field fires. In much of the northern Great Plains, active fire detections provided the only remote sensing-based measurement of cropland burned area due to the common practice of tilling immediately after burning, thus eliminating the applicability of the current burned area algorithm presented in this analysis with an 8-day (McCarty et al., 2008) temporal constraints for detection.

Crop type mapping was also essential for quantifying crop residue burning. This research shows that the MODIS spatial scale of 250 m was adequate to map crop types. In the eastern U.S., the average field size (16 ha) is equal to approximately two 250 m pixels, which can cause confusion in a classification due to mixed pixels. The current cropping patterns, whereby large areas of the same crop type are grown contiguously, permitted the use of 250 m MODIS data to produce crop type maps.

This analysis found that carbon emissions from crop residue burning emissions are not as important as emissions which impacted air quality. Carbon emissions from crop residue burning accounted for approximately 0.05% of global CO_2, CO, and CH_4 emissions from all fire activity as estimated by the Global Fire Emissions Database (van der Werf et al., 2006; Randerson et al., 2007), 0.6% of global CO_2, CO, and CH_4 emissions from agricultural burning as estimated by Andreae and Merlet (2001), 2.1% of global CO_2, CO, and CH_4 emissions from agricultural burning as estimated by Yevich and Logan (2003), and 14.3% of North American CO emissions from agricultural burning as estimated by Wiedinmyer et al. (2006). These previously published models of fire emissions have not been validated, though the accuracy of a common input into the GFED (van der Werf et al., 2006; Randerson et al., 2007) and the North American fire emissions model (Wiedinmyer et al., 2006), the MODIS active fire product, has been rigorously tested (Giglio et al., 2006). Therefore, due to the lack of validation for these pyrogenic emission models, the resulting comparisons may be an over- and/or underestimation of the contribution of CONUS crop residue burning emissions to total biomass and crop residue burning emissions at the global and North American scale.

This analysis also contained uncertainties and errors. Through validation efforts, the remote sensing products of burned area and crop type mapping were found to have moderate accuracy. The cropland burned area product had an area estimation accuracy that ranged from 78 to 90%, with an average area estimation accuracy of 84% (error of 16%). This result suggests that the approach utilized in this analysis likely underestimated total crop residue burned area. The regional crop type maps had an average classification accuracy of 84% (error of 16%). Misclassification errors in the crop type maps could produce incorrect emission estimates by assigning the wrong crop type to a burned area or active fire detection in the emissions calculations. This analysis showed that the total standard errors of emission factors for crop residue burning range from 13% (CO_2) to 264% (CO) of the mean emission factor value used to calculate emission in this analysis. Fuel load and CE values also contain uncertainty as many of the fuel load values in the literature were derived from expert knowledge and laboratory studies using limited samples. The non-linear relationship between the input parameters and the calculated emissions complicates the total error estimation, as several iterations of emission modeling with varying emission factors, burned area values, assigned crop types, fuel load variables, and combustion completeness values would be required to estimate emission errors (Kühlwein and Friedrich, 2000). In general, a moderate amount of uncertainty is present in this analysis as the emission calculations contain inherent errors associated with the emission factors and the other input parameters of burned area, assigned crop type, fuel load, and combustion completeness.

Crop residue burning and related emissions were concentrated in both the spring (April to June) and fall (October to December). Emissions from crop residue burning in the Pacific Northwest states of Idaho, Oregon, and Washington did not peak in the fall. The peak of emissions for these states occurred in the summer (July to September). However, at the CONUS-scale the peak of total crop burning emissions occurred during the months of October and December. The results of this analysis failed to reject hypothesis 1.

The crop type mapping results and USDA statistics indicated a clear shift from wheat to corn in the Midwest. The states of Illinois and Iowa experienced an average 12% decrease of emissions between 2003 and 2007 while simultaneously experiencing a decrease in wheat acreages. This decrease in emissions was greater than the average interannual variability of ±10%. Based on these results, this analysis failed to reject hypothesis 2.

Crop residue burning emits moderate levels of certain air quality species measured by the NAAQS and tracked by the EPA NEI. Average annual crop residue burning emissions accounted for approximately 6% of total CO, $PM_{2.5}$, PM_{10}, and SO_2 emissions of all burning activity reported in the 2002 NEI. Crop residue burning emissions accounted for approximately 0.04% of total SO_2 emissions, 1% of total $PM_{2.5}$ emissions, 0.2% of total PM_{10} emissions, and 0.3% of total CO emissions from all sectors, including energy, manufacturing, and transportation. Hypothesis 3 stated that CO, $PM_{2.5}$, PM_{10}, and SO_2 emissions would exceed the current NEI emission estimates from biomass burning, which was rejected by these results. However, crop residue burning emissions approximately equaled or exceeded estimated emissions from the sectors of solvent utilization, storage and transport of petroleum products, chemical manufacturing, petroleum and related industries, and metals processing.

This study demonstrated that crop residue burning emissions did not exceed the CO and CH_4 emission estimates in the 2008 Inventory of Greenhouse Gas Emissions and Sinks (EPA, 2008b). On average, crop residue burning emissions from this analysis accounted for 22% of reported CH_4 and 27% of reported CO emissions. The CH_4 and CO emission estimates calculated using the maximum emission factor values accounted for 43% and 116%, respectively, of the average annual EPA estimation of CH_4 and CO emissions from crop residue burning. EPA is likely overestimating CH_4 emissions from crop residue burning. However, the CO emissions reported by the EPA fall well within the range of emission estimates calculated using the average and maximum emission factors. Therefore, the EPA estimation of CO emissions of crop residue burning appears reasonable. Based on these results, hypothesis 3 was partially rejected as crop residue burning emission estimates were lower than current CH_4 emission estimates in the Inventory of Greenhouse Gas Emissions and Sinks.

Results from this research show that crop residue burning occurs in most states in the CONUS. However, the majority of burning is confined to specific states, particularly Arkansas, California, Florida, Idaho, Texas, and Washington, and to specific agricultural areas within these states. A regional analysis showed over 75% of air quality and carbon emissions from crop residue burning originated in the EPA regions of 4, 6, 10, 8, and 7, in descending order. The CONUS source regions for crop residue burning are the southeastern U.S., the Great Plains, and the Pacific Northwest.

6.2. The Scientific Contribution of This Research for Agricultural Burning Emissions Inventories and Future Research Needs

This research presents an inventory of crop residue burning for the CONUS and advances our scientific understanding of the phenomenon. It differs from previous analyses which have focused on regional scales (Reid et al., 2004) or included all forms of agricultural burning (Wiedinmyer et al., 2006) instead of analyzing by specific crop types. Cropland burned area estimations for this research were derived from a combination of remotely sensed products of burned area and areal estimations from active fire detections rather than reliance on active fire pixel counts (Wiedinmyer et al., 2006) or synthesis of government statistics (Andreae, 1991; Hao and Liu, 1994; Dennis et al., 2002; Yevich and Logan, 2003; Dhammapala et al., 2006). Due to the utilization of remote sensing-based crop type maps, this research provided an independent assessment of which crops were the main sources for emissions. Finally, fuel load and combustion efficiency values were verified and derived from several field campaigns in the CONUS.

The bottom-up approach developed by Seiler and Crutzen (1980) is the standard for pyrogenic emissions calculation and relies heavily on the variables of emission factor, combustion completeness, and fuel loading. These variables have often been based on assumptions that crop residue burning is essentially a small scale version of grassland fires (Andreae and Merlet, 2001; Yevich and Logan, 2003; EPA, 1992). Many of the standard emission factors for agricultural residue burning are based on assumptions derived from expert knowledge (IPCC, 1996; Andreae and Merlet, 2001; Yevich and Logan, 2003). In addition, the majority of existing field and laboratory experiments to develop crop specific emission factors have focused on select crops, mainly corn, rice, and wheat (IPCC, 1996; Jenkins et al., 1996; UK EFDB, 2000; Dennis et al., 2002; Air Sciences, Inc., 2003; Hays et al., 2005; WRAP, 2005; Dhammapala et al., 2006) and more recently Kentucky bluegrass seed (UK EFDB, 2000; Johnston and Golob, 2004; Dhammapala et al., 2006). This lack of research is a continuing problem for quantifying crop residue burning. For example, sugarcane burning was the source for 34% of all emissions in the six EPA source regions. Crop specific emission factors for sugarcane burning in the CONUS are currently limited to one source (WRAP, 2005). In addition, there is a clear paucity of seasonal emission factors for crop residue burning. In general, crop residue emission factors have been calculated using field and laboratory experiments during the fall harvest (Jenkins et al., 1996; UK EFDB, 2000; Dennis et al., 2002; Johnston and Golob, 2004; Hays et al., 2005; WRAP, 2005). Spring emission factors have been developed for wheat only in the state of Washington for the atmospheric species of CO_2, CH_4, CO, and $PM_{2.5}$ (Air Sciences, Inc., 2003; Dhammapala et al., 2006). Spring wheat emission factors for CH_4, CO, and $PM_{2.5}$ are on average 40% less than the fall wheat emission factors, while the CO_2 emission factor for spring wheat burning is 3% higher than the fall emission factor. If this study utilized the fall emission factors only, calculated average wheat emissions for CH_4, CO, and $PM_{2.5}$ would have been approximately 11% higher and average CO_2 emissions would have been approximately 2% less than the emission calculated by this analysis, respectively. An inherent uncertainty to the bottom-up emissions calculated during this analysis is the lack of seasonal emission factors that would have allowed for more accurate emission estimates for the spring harvest. Further development of seasonal- and crop-specific emission factors for all crops managed with fires is required to advance the science of crop residue burning emissions estimations.

Similar to emission factors, the variables of fuel load and combustion completeness are also in need of refinement for more accurate emission estimates. Currently, most emission calculations use fuel loads that are assumed to be fractions of crop yield (Andreae, 1991; Hao and Liu, 1994; Yevich and Logan, 2003). This research relied on the fuel load estimates derived from a government report (EPA,

1992) and from field experiments for bluegrass seed burning calculated by Johnston and Golob (2004). Wheat fuel loads were verified in the field through assistance from state-level collaborators. Likewise, combustion completeness is currently based on expert knowledge that generally assumes all crop residues are consumed at the same rate (Andreae and Merlet, 2001; EPA, 2008b). This research used a combination of expert knowledge from field work and published literature to derive varying rates of combustion completeness for the different crop types. Future research in quantifying the fuel loads and combustion completeness of all crop types would be necessary to improve bottom-up emission estimates.

6.3. Towards Operational Monitoring of Crop Residue Burning

The scale of remotely sensed products is the most important factor in building operational capacity for monitoring crop residue burning. This research showed that a 500 m dNBR approach resulted in an average underestimation of crop residue burning of 16% for the CONUS. 500 m MODIS 8-day surface reflectance data were able to map burned fields greater than or equal to approximately 28 ha, which is essentially the native resolution of a 500 m pixel. MODIS active fire detections were included in this research in order to capture single field fire events as well as general crop residue burning in the eastern and southern U.S. where the average field size is 16 ha - less than the native resolution of a 500 m MODIS pixel.

Current state governments seeking to build an operational monitoring system want satellite products that allow for near-real time detection of burning (Personal communication with Ms. Karen Wood, Washington Department of Ecology, 24 April 2007). The 500 m MODIS burned area maps used in this analysis requires at least an

8-day or 16-day temporal window to map burned area (Loboda et al., 2007, McCarty et al., 2008), making its implementation in an operational monitoring system problematic. To operationalize burned area approaches, polar-orbiting and/or geostationary sensors with resolutions less than or equal to 250 m, or approximately 8 ha, would be ideal to reduce current omission errors of crop residue burning and allow for greater detection of small field burning. The planned launch of the second AWiFS instrument in 2009-2010 could provide near operational monitoring of crop residue burning with a spatial resolution of 56 m (IRS, 2006). Additional refinements of temporal windows (2- to 3-day windows) for burned area detection would also be required to implement burned area algorithms into operational monitoring systems.

MODIS active fire detections have been shown to accurately map single field fires in agricultural areas (McCarty et al., 2007; McCarty et al., 2008) but the temporal coverage of approximately 10:30 AM (Terra), 1:30 PM (Aqua), and 6:30 PM (Terra) provides only snapshots of crop residue burning. Combining burned area and active fire detections from current sensors such as MODIS and GOES has shown some promise for operational fire monitoring systems (Al-Saadi et al., 2008; Schroeder, 2008; Schroeder et al., 2008). Future development of operational monitoring systems of crop residue burning using a calculation of area from active fire detections in the CONUS or any other locale would benefit from geostationary sensors with high temporal resolutions (~ 15 minutes) and a spatial resolution less than or equal to 1 km given the success of the current 1 km MODIS active fire algorithm to map fires as small as 100 m^2 (Giglio et al., 2003; Giglio et al., 2006).

6.4. Implications for Policy

This document provides an initial and independent assessment of emissions from crop residue burning that is applicable to the goals of several environmental reporting efforts and task forces, including the IPCC, the NACP, and the AAQTF. The greenhouse gas emission estimates from this analysis of crop residue burning that are of particular interest to the IPCC are the estimates of CO, CO_2, CH_4 and SO_2 (IPCC, 2007b). This analysis found that carbon emissions from crop residue burning, important to the NACP, are not as significant as the air quality emissions. Results from this analysis show that the vast majority of crop residue burning is confined to five EPA regions, i.e., regions 4, 6, 7, 8, and 10, and six states, i.e., Arkansas, California, Florida, Idaho, Texas, and Washington. AAQTF resources would be best used if focused to these source regions and states of crop residue burning in order to further quantify that ground-level and dispersed emissions meet the air quality standards set by the 1990 CAA and the continuously revised NAAQS and to aid state-level governments in the refinement of existing SIPs.

The results from this research have clear implications for two EPA reports: the NEI and the Greenhouse Gas Inventory. The NEI tracks trends of the air quality species of CO, $PM_{2.5}$, PM_{10}, and SO_2 from all industrial and transportation sources. The 2002 NEI burning estimates for agricultural fires were limited to 23 states and included burning activity ranging from pasture maintenance fires, burn piles, and crop residue burning (Pouliot et al., 2008). This research shows the CO, $PM_{2.5}$, PM_{10}, and SO_2 emissions from crop residue burning accounted for approximately 6% of total emissions of all burning activity reported in the 2002 NEI. In addition, crop residue burning emissions were equal to or exceeded emissions from the sectors of solvent utilization, storage and transport, chemical manufacturing, petroleum and related industries, and metals processing. Given these results, the EPA may need to revise current air pollution regulation and mitigation strategies to include crop residue burning. The 2011 NEI would be more accurate if it included both results from this research (and other analyses using independent approaches for emission calculations) and explicit reporting of different categories of biomass burning to allow comparison between crop residue burning and wildland burning emissions.

Current CH_4 and CO emissions reported by the EPA Greenhouse Gas Inventory of the U.S. are calculated using expert knowledge on burned area, fuel load, combustion completeness, and emission factors as well as state government statistics on cropland burning extent (EPA, 2008). Crop residue burning emissions from this analysis accounted for an average of 22% of reported CH_4 and 27% of reported CO emissions. As this is the first remote sensing-based study to quantify crop residue burning for the CONUS, and thus not limited to 23 states as were previously reported by the EPA, results from this research could be used to refine the 2009 Greenhouse Gas Inventory in order to include estimates that are independent of state government reporting.

At the state-level, crop residue burning is increasingly an important issue concerning trans-boundary air pollution (Personal communication with Mr. Scott Weir, Kansas Department of Health and Environment, 7 August 2008) and localized health impacts which have led to lawsuits (SAFE, 2007). All states in the U.S. must compose SIPs as mandated by the 1990 Clean Air Act. The SIPs outline the permitted usages of prescribed burning as well as proposed restrictions if pyrogenic emissions exceed national air quality standards. This research found that most states in the CONUS, except for the New England states of Connecticut, Maine, Massachusetts, New Hampshire, and Rhode Island, were sources of air quality emissions from crop residue burning. Given these results, it would be advisable for most states in the CONUS to revisit their respective SIPs in order to clarify or prohibit the use of prescribed burning for crop residue removal.

The results of this analysis did not demonstrate an indirect relationship between state-level policies which restricted burning or required permitting or burn management training with crop residue burned area and related air quality emissions. Three states that currently require permits for burning, i.e., California, Florida, and Washington, are three of the six source states for air quality and carbon emissions. California and Florida did show a net decrease in cropland burned area between 2003 and 2007, with both positive and negative interannual variability of cropland burning and related emissions. Washington had an average percent increase in burning between 2003 and 2007 of 5%. The state policies requiring burn permits, restricting burned fields, or mandating burn management education may be decreasing crop residue burning and related emissions.

The results of this analysis are useful to federal and state-level decision makers and farmers. Federal decision makers must not conclude from this research that all emissions from crop residue burning are minor. While greenhouse gas emissions from crop residue burning are less than other agricultural and industrial sources, emissions that impact air quality are important for areas that experience cropland burning. Federal decision makers should take note of the number (approximately 15.5 million people) and percentage of citizens (approximately 5.2%) in the CONUS who live in or near source areas of crop residue burning emissions. The majority of crop residue burning and related emissions are concentrated in source states (Arkansas, California, Florida, Idaho, Texas, and Washington) and EPA regions (regions 4, 6, 7, 8, and 10). Within the rural communities of these states and regions, emissions from crop residue burning will impact health and general air quality. Transport of air pollution, including trans-boundary pollution from one state to the next, from crop residue burning will continue to impact neighboring suburban and urban communities. Most of the source states, including California, Florida, Idaho, Texas, and Washington, are densely populated and/or are experiencing high rates of population growth and increased development in rural areas (U.S. Census Bureau, 2008). Federal efforts and monies for air quality monitoring, in developing state and/or local level fire weather forecasting, and in assisting farmers in sensible burn plans based on local atmospheric and wind conditions must be the focus for these source areas and/or any other area concerned with the level of crop residue burning emissions.

At the state-level, crop residue burning is a balancing act between the negative impacts on air quality (and human health) from the emissions and the benefits (i.e., pest and weed control, inexpensive residue removal, ash fertilization effect) that farmers receive by having fire as a tool. In addition, eliminating crop residue burning as a tool for farmers may be in conflict with many state-level freedom-to-farm laws (Wulfhorst et al., 2006). State-level decision-makers must be aware that considerable percentages of the population will be impacted by these emissions. For example, results from this analysis show that at the very least one in ten people in the states of Arkansas, California, Florida, Idaho, Texas, and Washington live near source areas of emissions from crop residue burning.

State-level decision makers can also base future approaches to limiting crop residue burning from current examples of state-level policies. Three of the states with the highest levels of emissions, California, Florida, and Washington, have already instituted some form of burn permitting for crop residue burning. California has taken a further step by restricting the amount of rice acres that can be burned during a given harvest with a state law (CARB, 2003). This analysis showed that California and Florida have experienced decreasing crop residue burning between the years of 2003 and 2007. It is possible that state-level restrictions and/or permitting systems are effective tools for gradually reducing crop residue burning and related emissions while still allowing farmers to burn when fire is considered the best management practice.

The results of this research are also valuable at the field-level. Farmers and their families often reside in the same communities that experience impaired air quality due to residue burning. The U.S. Census Bureau predicts expanding development into exurban and rural communities in much of the southern and western U.S. (Campbell, 1996; Wang, 2002). If this is the case, emissions from crop residue burning in the southern and western U.S. will affect a growing number of people. As populations increase, fire will become less viable as the most common tool for residue removal due to the negative impact on air quality demonstrated in this analysis. Farmers should seek new alternatives to burning for residue removal. In doing so, fire can remain a tool that can be used when burning is the best management practice for pest and weed control and/or residue removal while still reducing the overall contribution of emissions from crop residue burning at the local and regional scale.

6.5. Future Directions of Crop Residue Burning Emissions Research

Future CONUS and global emission inventories of crop residue burning in the will include estimates of mercury emissions. Air quality standards for mercury are currently at the center of policy debates, highlighted by the recent filing of an appeal to the U.S. Supreme Court by the EPA to allow the removal of power plants from a list of mercury air pollution source categories (EPA, 2008). Mercury emissions from biomass burning have also become an important research direction as wildland fires, especially boreal forests, have been shown to be an important source of mercury emissions (Sigler et al., 2003; Biswas et al., 2004; Cinnirella et al., 2006; Engle et al., 2006; Turetsky et al., 2006). Previous studies have concluded that mercury emissions from agricultural burning are important regionally, like in the southeastern U.S. (Wiedinmyer and Friedli, 2007), and may be important to the global atmospheric cycling of mercury, as crop residue burning is a global activity (Friedli et al., 2003).

Improved land cover and land use products will be needed to improve emissions estimates and to develop operational crop residue burning monitoring systems. Crop type mapping is essential to both emissions calculations and identification of illegal burning for enforcing state and local laws (WA DOE, 2003; CDFA, 2007b; ODA, 2007; KDHE, 2008). The author is involved in a current research project to increase the accuracy and expand the spatial and temporal coverage of the USDA NASS Cropland Data Layer product. The results of this NASA-funded project, entitled "Integrating Earth-Sun Science results with state-of-the-art agricultural survey data to improve the accuracy and timeliness of national crop acreage forecasts provided by the operational USDA/NASS Decision Support," will be a moderate resolution (56 m) CONUS-scale crop type map that can be used to reduce current uncertainties in crop type assignment of burned area for emissions calculations. Additionally, the fire modeling community has noted that a CONUS-scale crop type map is necessary to accurately quantify emissions occurring at the interface between cropland and wildland areas as well as between cropland and residential areas (LANDFIRE, 2008). A global-scale crop type map is also needed to complete a remote sensing-based inventory of global crop residue burning emissions.

To improve crop residue burned area mapping, future research will focus on refining the existing dNBR thresholds for all MODIS tiles using coincident high resolution satellite data and newly available state government data of crop residue burning sites. The existing dNBR approach has limitations in quantifying burned areas in the Pacific Northwest and northern Great Plains. Two new data sets, including burned field locations in central Washington from the Washington Department of Ecology and burned field locations in western South Dakota from the South Dakota Association of Fire Departments, will be used to refine the dNBR thresholds that have shown confusion with irrigated fields (Washington) and plowed fields (South Dakota). In addition, future analyses will expand on this research by associating crop residue burned area from the hybrid MODIS 500 m dNBR and the

MODIS 1 km active fire approach with Geostationary Operational Environmental Satellites Automated Biomass Burning Algorithm (GOES ABBA) instantaneous area, simultaneous GOES and MODIS active fire detections, and high resolution ASTER burn scar maps. This comparison will quantify the utility of the GOES ABBA algorithm for calibrating the area of crop residue burning. Such an effort is needed to determine the usefulness of GOES ABBA for crop residue burning emissions estimates and the inclusion of GOES ABBA or other coarse geostationary fire products into operational crop residue burning monitoring systems.

Modeling future air quality emissions will further advance this research through projections of regional air quality emissions from crop residue burning given varying scenarios of change. In order to create modeled emissions that would be informative to national, state, and local level agencies and/or non-profit organizations, predictions of burned area, crop type, and burning rates will have to be spatially explicit as well as have fine to moderate temporal resolutions. Modeling which does not predict the spatial distribution of crop residue burning would reduce the ability to quantify distance of human populations to the predicted emission sites as well as eliminate the possibilities of modeling dispersion of the pollutants through existing agriculture smoke dispersion models like ClearSky (Jain et al., 2007). Similarly, fine (i.e., daily) to moderate (i.e., monthly) temporal resolutions of predicted emissions from remotely sensed fire data would be needed both for dispersion modeling and other impact analyses. Preliminary modeling of emissions has been completed which relates economic variables and trends to crop residue burned area and associated crop types in monthly time steps. Future research will expand this modeling approach to include scenarios of policy change and near-term climate change to predict spatially and temporally explicit future emissions.

Future modeling of crop residue burning emission concentrations (mg/m^3) could be achieved by employing existing air quality models, such as the CALPUFF Model (EPA, 2007c) favored by the EPA or the ClearSky Model (Jain et al., 2007) developed specifically for agricultural burning in the Pacific Northwest by the USFS and Washington State University, which are currently used to predict agricultural burning concentrations. CALPUFF and/or ClearSky would be able to predict both the dispersion of pollutants over time and space given changing atmospheric conditions like wind speed, relative air quality at the site of burning over a larger temporal scale, and the impact of including multiple burning fields in the modeling process to model emission concentrations at the site and the local- and regional-scale.

Crop residue burning and related emissions will continue to be an important scientific and policy issue for the CONUS and globally. The remote sensing approaches developed in this study can be continued to produce a long term record of crop residue burning using MODIS and potentially adapted for production using the Visible/Infrared Imager Radiometer Suite (VIIRS) on-board the National Polar-Orbiting Operational Environmental Satellite System (NPOESS) Preparatory Project (NPP) or NPOESS. A long term data record of crop residue burning would be useful for further analyses of effects of policy on burning rates and for developing decadal or longer temporal scale emission estimates. Future research will include continued work with state and local governments for the development of operational crop residue burning systems as well as expanding the scope of crop residue burning emissions to the global scale.

Appendices

A.1. Appendix A: Statistical equations

All accuracy statistics for remote sensing products developed during this analysis were calculated using the error matrix approach. Error matrices evaluate the relationship between actual classes (i.e., ground truth or reference data) and predicted classes derived from a classification. This comparison is performed on a category-by-category basis, so that rows (predicted classes) are compared with corresponding columns (actual classes). The following statistics were used in the accuracy calculations.

The Kappa statistic is an index which compares the agreement between observed accuracy in an error matrix versus the accuracy that is expected through chance. The Kappa statistic is defined as:

$$\hat{K} = \frac{n\sum_{k=1}^{q} n_{kk} - \sum_{k=1}^{q} n_{k+}n_{+k}}{n^2 - \sum_{k=1}^{q} n_{k+}n_{+k}} \qquad \text{(A-1)}$$

where n is the total number of observations, q is the number of rows in the error matrix, n_{kk} is the number of observations in row k and column k, n_{k+} is the total observations in row k, and n_{+k} is the total number of observations in column k.

The user's accuracy indicates the probability that a classified pixel accurately represents the pixels value from the corresponding validation data set.

The user's accuracy statistic is computed as:

$$\text{User's accuracy} = \frac{n_{ii}}{n_{i+}} \tag{A-2}$$

where n_{ii} is the total number of correctly classified pixels in a class and n_{i+} is the sum of pixel values in the row.

The producer's accuracy statistic indicates the probability that class *i*, the reference data, is mapped as class *i*. The producer's accuracy is computed as:

$$\text{Producer's accuracy} = \frac{n_{ii}}{n_{+i}} \tag{A-3}$$

where n_{ii} is the total number of correctly classified pixels in a class and $n_{+}i$ is the sum of pixel values in the column.

Percent of correctly classified pixels was computed as:

$$\text{Percentage correct} = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100 \tag{A-4}$$

where n is the total number of observations, q is the number of rows in the error matrix, and n_{kk} is the number of observations in row k and column k.

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