# ABSTRACT

Title of Dissertation: LAND USE AND LAND COVER CHANGE AS A DRIVER OF ECOSYSTEM DEGRADATION ACROSS BIOMES



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The expansion and intensification of agricultural production in human-dominated landscapes threaten efforts to sustain natural ecosystems and maintain agricultural production in a changing climate. Long-term use of agricultural lands, combined with conversion of natural ecosystems for agricultural production, can rapidly degrade the health of remaining natural ecosystems. The fundamental goal of this dissertation was to assess the impacts of anthropogenic degradation on stocks and sequestration of carbon. Although degradation alters a range of ecosystem services, case studies of ecosystem degradation in this dissertation focus on reductions in vegetation productivity, carbon stocks, and the extent of natural forest cover as a result of human activity. Time series of satellite remote sensing data were used to track forest and rangeland degradation in the southwestern United States, forest carbon emissions from cropland expansion in the Brazilian Cerrado, and fire-driven

forest conversion for oil palm plantations in Southeast Asia. Three major themes link the regional case studies: expansion and intensification of agricultural production, market demand and certification, and agricultural management in response to climate variability. Conclusions from the dissertation underscore the widespread influence of land management on vegetation productivity and forest carbon stocks. In the Southwest United States, reductions in net primary production on managed lands were higher in forested landscapes than other cover types. In contrast, Native American Indian Reservations, often considered to be more degraded, actually had smaller absolute reductions in net primary productivity during 2000-2011. Multi-year droughts in the southwest present new challenges for managing forests and rangelands, and climate projections suggest dry conditions will intensify in the coming century. In Southeast Asia, industry-led efforts to certify sustainable palm oil production were evaluated using satellite data on fires and forest loss. Rates of fire-driven deforestation and total fire activity declined following certification, highlighting the potential for certification to reduce ignitions during El Niño years and protect remaining fragments of lowland and peat forest. Aligning certification criteria for sustainable palm oil with satellite monitoring capabilities may help accelerate compliance with environmental legislation and market demands for deforestation-free products. In Brazil, government and industry actions to limit Amazon deforestation have largely overlooked the neighboring Cerrado biome. Forest carbon emissions from deforestation for soy expansion in the Cerrado increased substantially after the implementation of the Soy Moratorium in the Brazilian Amazon, partially offsetting recent reductions in Amazon deforestation carbon emissions. The success of policies to support sustainable agricultural production therefore depends on efforts to minimize cross-biome leakage and the ability to monitor compliance and unintended consequences. Solutions for management must also confront the growing influence of climate variability. Time series of satellite data may allow early detection of degradation impacts and support efforts to mitigate the influence of sustained agricultural production on natural systems.

Changes in vegetation carbon stocks from ecosystem degradation varied across case studies, underscoring the diverse nature of direct and indirect drivers of degradation across different land use systems. Direct human drivers of ecosystem degradation in the southwest United States from management of livestock grazing resulted in gradual changes in vegetation productivity, whereas mining and oil extraction areas showed large and permanent reductions. Forest carbon emissions from agriculture expansion in the Cerrado were a one-time process, as native vegetation is cleared for cropland expansion. In contrast, the carbon emissions from Southeast Asia's forest and peatland conversion involve both sudden and gradual processes, as carbon accumulation in oil palm plantations partially compensates for emissions from forest conversion. Overall, this research made contributions to understanding of the regional impacts of human activity and the potential for climate change mitigation from sustainable land use practices in human-dominated landscapes.

LAND USE AND LAND COVER CHANGE AS DRIVER OF ECOSYSTEM DEGRADATION ACROSS BIOMES

by

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Dissertation submitted to the Faculty of the Graduate School of the
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# Chapter 1: Introduction

## *1.1 Background*

Over the last century, the cumulative impact of human activity has resulted in unprecedented changes in the terrestrial ecosystems (Vitousek *et al.*, 1997; Steffen *et al.*, 2004). Human impacts on the Earth system occur at all scales, from local to global (Foley *et al.*, 2005). At the local scale, changes are widespread, with a high degree of variability across regional biomes (MEA, 2005). Indicators of global change, such as changes to world's climate system (Houghton *et al.*, 2001; Schimel *et al.*, 2001), ozone concentrations (Hauglustaine & Brasseur, 2001), and patterns of atmospheric particles and pollutants (Steffen *et al.*, 2004) confirm the growing influence human activities as direct drivers of changes in the Earth system. In many cases, the rise in per-capita resource consumption has amplified the impacts of population growth and economic activity, leading to degradation of both human and natural systems.

Global population is projected to reach 7 billion by 2020 (USCB, 2016), adding to demand for food, fiber, and fuel. The growing footprint of human activity has a profound impact on the Earth system, as agricultural expansion threatens remaining natural ecosystems and intensification of existing production concentrates water, nutrient, and agrochemical use for crop production (DeFries *et al.*, 2004, Lambin *et al.*, 2003, Foley *et al.*, 2005, Turner *et al.*, 2007). Land use and land cover change has emerged as a critical area of study to evaluate and monitor direct human impacts from land management (Turner *et al.*, 1995; Lambin *et al.*, 1999). Tracking land areas at different points along the path from natural to managed ecosystems provides a conceptual framework for the degree of human appropriation of ecosystem services (Figure 1.1).

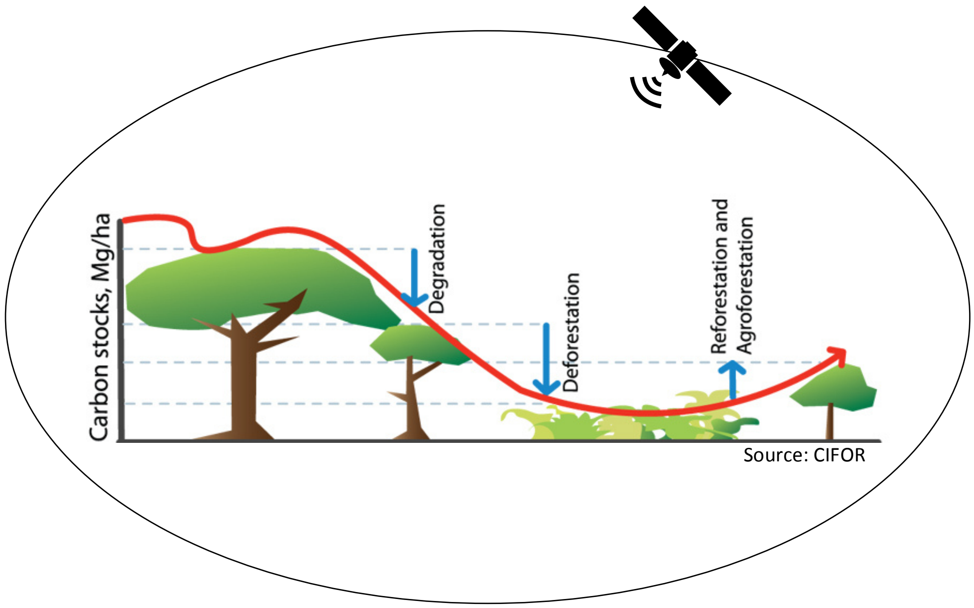


Figure 1.1 Forest and land use transition curve.

The forest transition model captures the sequence of land cover and land use changes that often at the agricultural frontier (Steffen *et al.*, 2004; Morton *et al.*, 2006; Foley *et al.*, 2011; Macedo *et al.*, 2012; Lambin *et al.*, 2013; Morton *et al.*, 2016). The forest transition framework emerged in the early 1990s to describe patterns of forest cover change together with the process of development (Mather, 1992; Grainger, 1995). The forest transition defines the sequence of forest conversion in five stages (Figure 1.1): a) intact forest, b) forest degradation, c) forest loss/deforestation, d) forest stabilization, and e) forest regeneration. Forest transitions occur at different spatial and temporal scales; the amount of land in these categories may be in steady flux, based on the duration of land use following forest conversion.

Satellite data have been instrumental to track transitions between cover types and characterize the ecosystem impacts of fragmentation and agricultural production.

However, the trajectory of land cover and land use changes outlined in Figure 1.1 involves a range of socioeconomic and development stages. For example, Lambin and Meyfroidt (2010) suggest that forest transitions are only part of the larger picture of land use transitions. The drivers of land use transitions can be divided into two groups: a) socio-ecological (endogenous)—i.e., negative feedbacks associated with depletion of key resources or declining provision of key ecosystem services, or b) socio-economic (exogenous)—i.e., changes driven by economic development or globalization. The studies in this dissertation consider both ecological and socio-economic drivers of land use transitions. The endogenous nature of land use transitions is explored for dryland ecosystems in the southwest United States—i.e., growth under resource constraints, mainly from land management (i.e., livestock grazing, soils, water, etc.). Exogenous drivers of land use transitions play out across Southeast Asia and the Cerrado biome in Brazil, where international commodity markets drive land use transitions for expanded production of oil palm and soya. The ecosystem impacts of land use transitions are often substantial, and there is a pressing need for objective, repeatable, systematic, and spatially explicit measures of these impacts. Time series of satellite remote sensing data offer a consistent and objective manner to characterize ecosystem degradation from human activity.

In dryland ecosystems, human-induced degradation is one of the major global environmental problems of our generation (UNCED, 1992; UNCCD, 1994; Reynolds *et al.*, 2007b). Loss of productivity in dryland ecosystems affects over 250 million people, and the human impacts are projected to increase in future years from population growth and climate change (Reynolds *et al.*, 2007b). The term "land" refers to "the terrestrial bio-productive system that comprises soil, vegetation, other biota, and the ecological and hydrological processes that operate within the system" (UNCCD, 1994). In dryland studies, land degradation results in a reduction of biological productivity from intensive use (Thomas & Middleton, 1994; UNCCD, 1994; Reynolds, 2001; Prince *et al.*, 2007; Reynolds *et al.*, 2007b; Prince *et al.*, 2009), and may arise from a diversity of processes including changes in plant species composition or soil erosion.

In the tropical ecosystems, the global demand for agriculture commodity products has led to large scale land use transitions in recent decades (Lambin & Meyfroidt, 2011;Nepstad *et al.*, 2014; Gibbs *et al.*, 2015; Morton, 2016). The *forest-soy* (i.e., in Brazilian Cerrado) and *forest-oil palm* (i.e., in Southeast Asia) transitions are simultaneously extensive and intensive, causing widespread deforestation and degradation. While deforestation is complete removal of forests, forest degradation has multiple definitions, complicating science and policy efforts to reduce or mitigate impacts from human activity on tropical forests (IPCC, 2003). Two proposed definitions of forest degradation are, *"a direct human-induced loss of forest values (particularly carbon), likely to be characterized by a reduction of tree crown cover"* (IPCC, 2003), and "*changes within the forest which negatively affect the structure or function of the stand and site, and thereby lower the capacity to supply products and/or services*" (FAO, 2002). "Degradation" in this dissertation refers to reductions in carbon sequestration, including vegetation productivity and forest carbon emissions, explored in distinct case studies across three biomes (Figure 1.2).

There is general consensus within the framework of Reducing Emissions from Deforestation and forest Degradation (REDD+) that forest degradation specifically refers to reduction in forest carbon stocks (IPCC, 2003; Angelsen *et al.*, 2009; Gibbs *et al.*, 2007). Logging, burning, and fragmentation of forest landscapes reduce carbon stocks in aboveground biomass. These degradation processes may alter forest structure and function, or signal the start of a land cover conversion process for agricultural expansion (Figure 1.1).


Figure 1.2: Study sites (dark grey) across, A) southwest United States, B) Cerrado biome in Brazil, C) Southeast Asia, including Indonesia, Malaysia, and Papua New Guinea.

The three regional case studies in this dissertation consider a diversity of land use and land cover transitions, yet the drivers of ecosystem degradation are similar across systems (Table 1.1). Drought impacts on vegetation productivity are common

Table 1.1: Common degradation factors across case studies

| Key factors in degradation | Case Study A | Case Study B | Case Study C |
|---|---|---|---|
| Predisposed to degradation by climate | Drought/ENSO | Drought | ENSO |
| Periodic fire | Grassland, forest | Savanna, woodland | Forest and peatland loss |
| Agriculture | Livestock production | Cropland expansion | Plantation forest |
| Export-driven | Beef | Soy | Palm oil |
| Legal controls | Federal agencies | Industry/Govenment policies | Industry/Govenment policies |

across the study regions.  However, severe droughts associated with the El Niño Southern Oscillation (ENSO) specifically affect the southwest United States and Southeast Asia, although from opposite phases of ENSO cycle. Fires, both natural and human-caused, are widespread in all three regions, burning large areas of grassland and forest ecosystems in the southwest United States, savanna ecosystems in the Cerrado, and forest and peatland ecosystems in the Southeast Asia. Agriculture production is the primary driver of the land use transitions across the case study regions, and market forces link regional production to global demand for beef, soy, and palm oil. Finally, all three regions are managed under legal frameworks of land management for sustainable agriculture production that aim to maintain ecosystem services and reduce carbon emissions in support of climate mitigation goals .

In this context, this dissertation explores case studies of ecosystem degradation from land use and land cover change across three biomes (Figure 1.2), with a focus on reductions in vegetation productivity, carbon stocks, and the extent of natural forest cover. Dryland degradation is quantified in the southwest United States based on reductions in vegetation productivity. Tropical forest conversion is estimated based on reductions in carbon density, including losses of aboveground and below ground biomass in the Cerrado and fire-driven deforestation in Southeast Asia. Drivers of forest degradation were assessed using time series of remotely sensed data. The regional case studies in this dissertation highlight the influence of land management, policy interventions, and climate on ecosystem degradation over decadal time scales.

*1.2 Rangelands of Southwest United States*

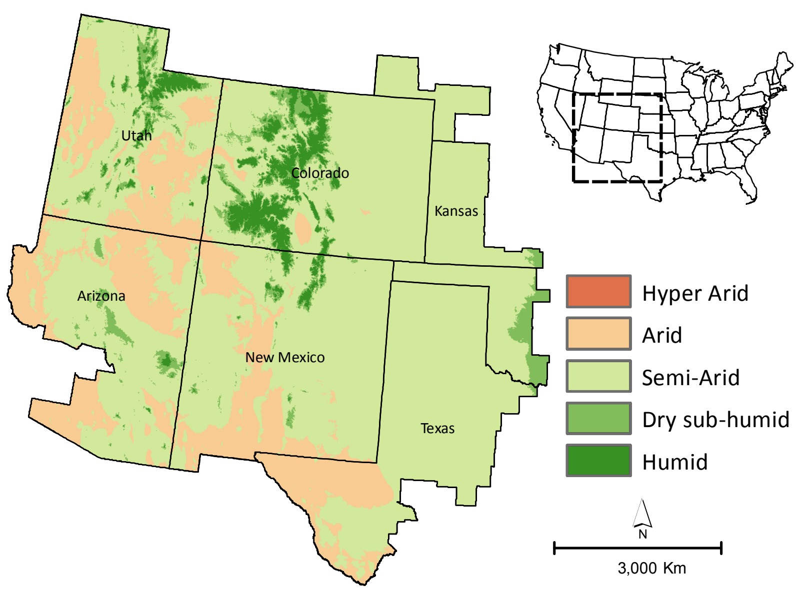


Figure 1.3: Southwest United States study region and aridity index.

Rangelands in the western United States are arid and semi-arid regions with a mixture of grasses, forbs, and shrubs (Havstad *et al.*, 2009). The southwest region consists of New Mexico (NM), Utah (UT), Colorado (CO), and parts of Arizona

(AZ), west Texas (TX), Oklahoma (OK), Kansas (KS), and Nebraska (NE) (Figure 1.3). The southwestern rangelands are often characterized by limited water and nutrients, mainly influenced by gradients of winter and summer rainfall, and winter temperatures that range from cold to warm based on latitude and elevation.

The southwest United States is susceptible to periodic droughts, often during La Nina conditions of the El Nino Southern Oscillation (ENSO) in tropical Pacific sea surface temperatures (Herweijer *et al.*, 2006; Cook *et al.*, 2008). The "Dust Bowl" drought of the 1930s was a significant disaster for the United States that caused widespread economic and agricultural losses, farm abandonment, and human migration. The effects of drought on vegetation can be severe; recent droughts have compounded regional warming trends, leading to vegetation die-back in the southwest United States, particularly in forested ecosystems (Breshears *et al.*, 2005; Shaw *et al.*, 2005; Floyd *et al.*, 2009; Anderegg *et al.*, 2013). Droughts may become more common and more severe in the southwest United States, as climate projections suggest further declines in surface-water availability in future decades (Seager *et al.*, 2013; Cook *et al.*, 2014). The period between 2000-2011 was characterized by moderate drought years, including La Niña events in 2007-2008 and 2010-2011, and provides valuable insight into the vegetation response to variability in precipitation under different management conditions.

Vast areas of public land in the southwest United States are managed by the Bureau of Land Management (BLM) and US Forest Service (USFS), and both agencies permit commercial livestock grazing. The region also has sizeable reservations under Native American land management. The combined impacts of drought and intensive management include reduction in vegetation productivity, habitat fragmentation, non-native species invasion, and alterations to the hydrologic cycle.

### *1.3 Cropland expansion in Cerrado biome*

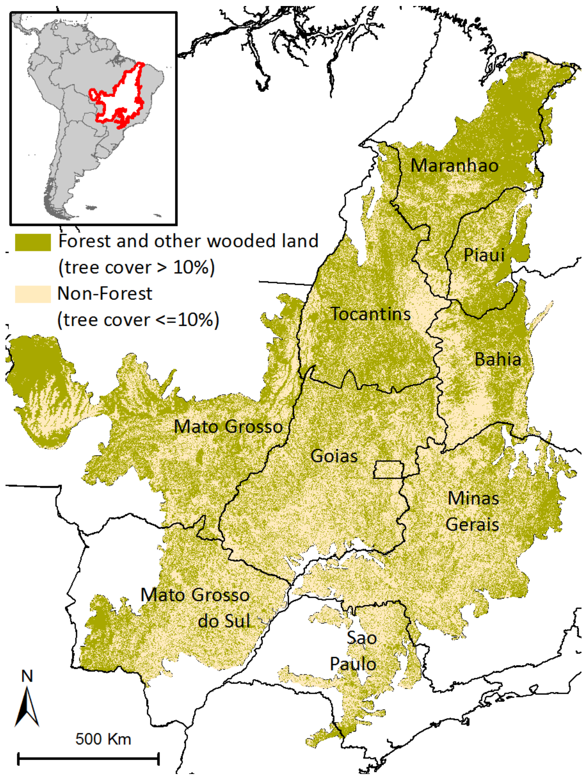


Figure 1.4: The Cerrado biome and the cover types defined as forest and other wooded land (tree cover > 10%) and non-forest (tree cover ≤ 10%) based on the percent tree cover in 2000 (Hansen *et al.*, 2013).

The Cerrado is the second largest biome in South America (Figure 1.4)—a vast neotropical savanna that spans over 2 million square kilometers of the Brazilian plateau (Hunke *et al.*, 2015). The average annual rainfall ranges between 750 mm $yr^{-1}$

and 2000 mm $yr^{-1}$. The Cerrado biome has an extended dry season between May and September when the region receives little or no rainfall (Oliveira *et al.*, 2005). The Cerrado is also considered a biodiversity hotspot, as the diverse mix of grassland, shrublands, and woodlands supports a large number of endemic species (Felfili & Silva Júnior, 2005; Klink & Machado, 2005). Rainfall and topographic variability contributes to differences among Cerrado physiognomies, commonly divided into five formations: a) *Cerrado denso,* an open-canopy formation with forest and woodland trees reaching 25 m in height and a dense understory layers with shrubs and grasses, b) *Cerrado ralo* (open scrub) or *Cerrado sensu stricto* (closed scrub), formations dominated by shrub and grass cover with few trees; c) *Campo limpo* and *campo sujo,* both dominated by C4 grasses, with increasing shrub abundance between *campo limpo* and *campo sujo* formations (Eiten, 1972; Ottmar *et al.*, 2001). Cerrado vegetation occurs across a wide range of topographic features, from flatlands to hilly areas and high plateaus (Silva *et al.*, 2006). Cerrado soils have low fertility and high acidity—factors that limit crop production without additions of lime and fertilizer (Lopes *et al.*, 2004; Hunke *et al.*, 2015).

Historically, the Cerrado region had low population density, primarily for cattle ranching and subsistence farming (Jepson *et al.*, 2010), but development of new crop varieties for Cerrado soils opened the region to large-scale grain production in recent decades. In the 1970s, the Brazilian government also encouraged settlement of the Cerrado, leading to deforestation of savanna and woodland areas for agriculture production and cattle grazing (Marris, 2005; Jepson *et al.*, 2010). Expansion of crop production in the Cerrado (IBGE, 2013) spurred Brazil's rise as a global leader of soy production and shifted the landscape of commodity crop production towards South America (Aide *et al.*, 2013; Lambin *et al.*, 2013).

Over the past two decades, contributions from soy expansion to Amazon deforestation (Morton *et al.*, 2006) resulted in an industry moratorium on soy production from new Amazon deforestation (Macedo *et al.*, 2012; Nepstad *et al.*, 2014; Gibbs *et al.*, 2015). Together with stringent environmental legislation (Soares-Filho *et al.*, 2014), the potential land available for further soy expansion in the Amazon is limited (Morton *et al.*, 2016), forcing soy producers to neighboring Cerrado biome. The industry's Soy Moratorium does not apply in the Cerrado (Gibbs *et al.*, 2015), and with less stringent environmental regulations, new frontiers of agricultural production have been developed through large-scale soy expansion into forest and non-forest Cerrado formations in Brazil.

### *1.4 Oil palm in Southeast Asia*

Oil palm (*Elaeis guineensis*) is native to West and Central Africa and was introduced to Southeast Asia in 1848 (Sheil *et al.*, 2009). The palm fruit kernel produces more oil on a per-hectare basis than any other tropical or temperate oil seed (Henderson & Osborne, 2000; Sheil *et al.*, 2009). Palm oil is used in wide array of products, from cooking oil to processed foods and non-edible products such as detergents, cosmetics, industrial chemicals, and biodiesel (Wahid *et al.*, 2005). By 1966, Indonesia and Malaysia dominated the palm oil trade, surpassing African nations in palm oil production (Poku, 2002). Southeast Asia remains the center of

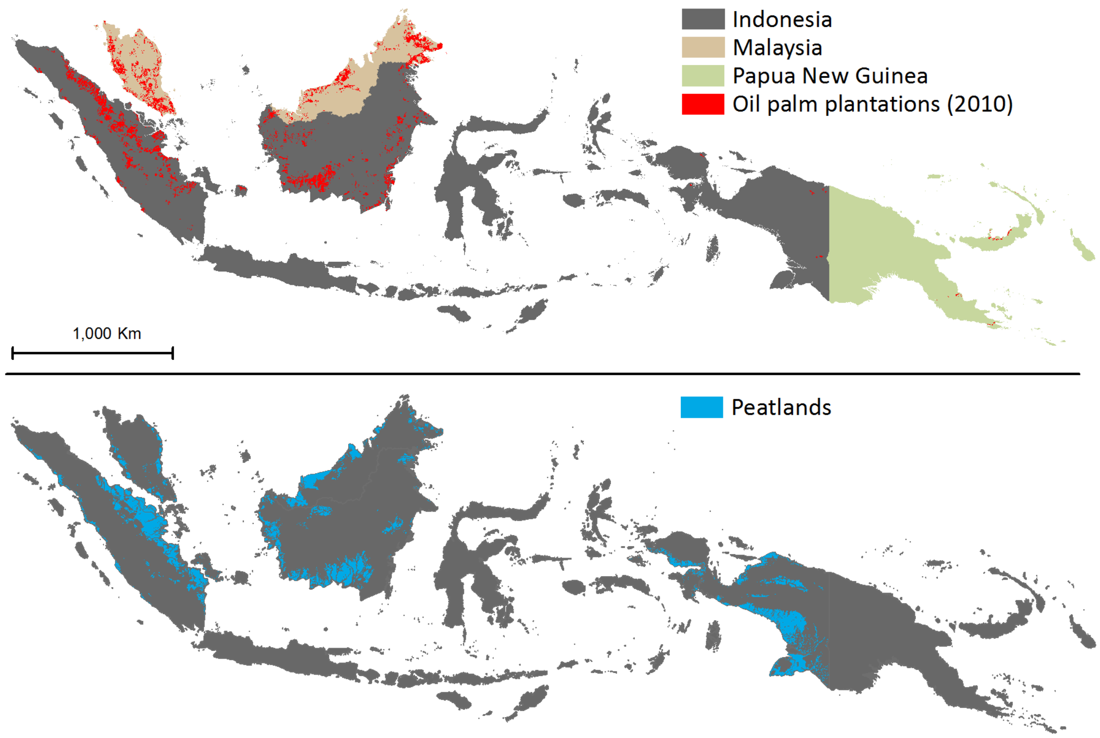


Figure 1.5: Extent of oil palm plantations (top panel) in Indonesia, Malaysia, and Papua New Guinea and peatland extent (bottom panel) in Indonesia and Malaysia.

global palm oil production with large-scale oil palm plantations in Indonesia, Malaysia, and Papua New Guinea (Figure 1.5).

Oil palm production in Southeast Asia has grown by expanding into lowland rainforest and peat areas—regions with high carbon stocks in vegetation and soils. Conversion of lowland rainforest and peat forests has released globally-significant greenhouse gas (GHG) emissions (Siegert *et al.*, 2001; Page *et al.*, 2002; van der Werf *et al.*, 2008; Hooijer *et al.*, 2012, Hooijer *et al.*, 2010; Koh *et al.*, 2011; Abood *et al.*, 2015; Field *et al.*, 2016). Oil palm certification, led by the Roundtable on Sustainable Palm Oil (RSPO), is one pathway for reducing emissions from palm oil production that is in alignment with industry set zero deforestation goals.

## *1.5 Drivers of degradation & potential mitigating policies*

Land degradation can result from direct impacts of anthropogenic activity or climate, indirect drivers such as governance or culture, or interactions among multiple drivers. Direct human drivers of ecosystem degradation include biomass extraction through logging or fuel wood collection, use of fertilizers and pesticides, and unsustainable management practices that reduce productivity on managed lands. Natural drivers of land degradation include climate (e.g., wind, drought, temperature, snowpack) and biotic factors (e.g., insect outbreaks, invasive species). Indirect drivers of land degradation are related to institutions and governance systems, as well as cultural, technological, socioeconomic factors, which underlie other direct drivers at multiple scales, including poverty. The extent and severity of different drivers may vary within and across biomes, regions, and land use systems around the world.

### 1.5.1 Southwest United States

Climate variability in southwest United States is particularly influenced by ENSO (Chen *et al.*, 2016). Drought conditions in the southwest United States are often associated with the La Nina phase of the ENSO cycle (Seager *et al.*, 2005; Cook *et al.*, 2008; Hoerling *et al.*, 2009; Woodhouse *et al.*, 2010; Cook *et al.*, 2014). The effects of drought on vegetation can be severe; leading to vegetation die-back in the southwest United States, particularly in forested ecosystems (Breshears *et al.*, 2005; Shaw *et al.*, 2005; Floyd *et al.*, 2009; Anderegg *et al.*, 2013). The recent drought years of 2011 and 2012 were severe causing significant damage from reductions to crop yields and mortality (Hoerling *et al.*, 2014; NCDC, 2016a), including the record area burned(NCDC, 2016b). The 2012 drought year was claimed as second most expensive natural disaster after Hurricane Sandy (Cook *et al.*, 2014; NCDC, 2016a). The significant management challenges associated with drought event range across broad regions and communities with different water resource constraints and ecosystems.

Apart from climate drivers, other direct drivers of degradation such as livestock grazing, invasive species, fires, and biotic disturbances clearly contribute to the risk of degradation in the southwest United States. Demand for rangelands goods and services has increased, adding to pressure on natural systems and generating conflict among competing land uses: extraction of minerals, oil, and natural gas; recreation and wildlife habitat; and management of forage for grazers and browsers. Balancing the tradeoffs among land uses and diversity of impacts from climate and human activity falls to a range of regional land management agencies.

Livestock grazing is the major land use in the southwest United States, and over grazing is one of the key drivers of land degradation and changes in ecosystem structure (Asner *et al.*, 2004). Although grazing under managed conditions can be sustainable (Holechek *et al.*, 1999; Wylie *et al.*, 2012), over grazing is common, leading to soil erosion and steep decline in forage production (Pellant *et al.*, 2005). Leases for commercial livestock ranching are managed by a number of management agencies in the Southwest United states, including the Bureau of Land Management (BLM), United States Forest Service (USFS), and Bureau of India Affairs (BIA) (GAO, 2005). The BLM and USFS use a grazing permit system within its allotments and administer primarily through issuance of 10-year term permits. The BIA helps

Native Americans to manage grazing on tribal lands and private ranchers can lease these lands for grazing at a fee. Management of livestock grazing must also respond to natural fire occurrences in the region. Combined, overgrazing and severe fire disturbances have changed the vegetation dynamics and forage consumption in the region through introduction of two different non-native species such as honey mesquite (*Prosopis glandulosa*) and cheatgrass (*Bromus tectorum*). The honey mesquite is non-palatable species (i.e., for livestock consumption) and cheatgrass is an invasive annual grass that increases landscape connectivity, eliminating natural fire breaks in barren areas, leading to greater fire spread potential. Biotic disturbances such as bark beetles have also reduced forest productivity in tree stands, contributing to regional forest die-backs in the region (Hicke *et al.*, 2012). The combined impacts of climate and human activity in the southwest United States have widespread impacts on land productivity potential and fire regime.

### 1.5.2 Southeast Asia

Seasonal fires are common in Southeast Asia, and often practiced for land clearing purposes (Stolle *et al.*, 2003; Herawati & Santoso, 2011; Medrilzam *et al.*, 2014). The interannual variability of Southeast Asia's fire frequency is largely influenced by the El Niño events of the ENSO phases (Ropelewski & Halpert, 1987; Chen *et al.*, 2016). During El Niño years, drought conditions render Southeast Asia's carbon rich forests and peat areas are susceptible to extensive burning (Page *et al.*, 2002; van der Werf *et al.*, 2008; Field *et al.*, 2016; Chen *et al.*, 2016). Climate anomalies from ENSO have predictable impacts on vegetation productivity, particularly from fire events. Efforts to predict ENSO variability may ultimately alter management strategies for agriculture and drought impacts in these regions (Chen *et al.*, 2016).

Fire also plays a significant role in reducing the forest carbon stocks in the humid tropics of Southeast Asia, chiefly in Indonesia. Fire is illegal in Indonesia (Tacconi, 2003; Edwards & Heiduk, 2015), yet use of fire for forest and peatland conversion is widespread. Human modified landscapes are typically associated with fire related processes, especially the seasonal fires in Southeast Asia for land clearing (Herawati & Santoso, 2011; Medrilzam *et al.*, 2014). However, during the extended drought periods in a stronger El Niño (for e.x. 1997, 2006, 2015), the seasonal fires gets greatly inflated burning large areas of forests and peatland and causing significant GHG emissions (Siegert *et al.*, 2001; Page *et al.*, 2002; van der Werf *et al.*, 2008; Field *et al.*, 2016), and health impacts (Marlier *et al.*, 2015; Johnston *et al.*, 2015).

Southeast Asia represent world's third largest tropical forests and contains forests with high carbon content and rich biodiversity (Saatchi *et al.*, 2011; Pimm *et al.*, 2014). Southeast Asia countries of Indonesia, Malaysia, and Papua New Guinea contribute significantly to deforestation (Hansen *et al.*, 2013). Among them, Indonesia alone account for large fraction of forest loss and contribute substantially towards global carbon emissions (Siegert *et al.*, 2001; Hansen *et al.*, 2013; Harris *et al.*, 2012). The rising demands for food, fiber, timber, and other natural resources are driving extensive forest loss and forest degradation in the region (DeFries *et al.*, 2010; Foley *et al.*, 2011; Wilcove *et al.*, 2013). In Indonesia alone, three major industrial plantations, mainly timber, fiber, and oil palm are driving the forest conversion process (Abood *et al.*, 2015), taking advantage of decentralized policies and weak institutions that protect forests (Jepson *et al.*, 2001; Edwards & Heiduk, 2015).

Palm oil from Southeast Asia is used worldwide in large number of products (Wahid *et al.*, 2005). In the oil palm sector, the Roundtable on Sustainable Palm Oil (RSPO) certification is the most widely adopted certification standard, promoting sustainable production and simultaneously reducing the environmental impact of palm oil production (RSPO, 2004; RSPO, 2015b; Rachael *et al.*, 2016). Worldwide, RSPO has certified 2.83 Mha in oil palm concessions, with Indonesia alone representing >50% of certified areas as of 2016 (Potts *et al.*, 2014; RSPO, 2016).

### 1.5.3 Brazilian Cerrado

In the 1970s, the Brazilian government introduced various state programmes encouraging occupation of Cerrado and lead to deforestation of the region for agriculture production and cattle grazing (Marris, 2005; Jepson *et al.*, 2010). In the last decade, Amazon forest protection through implementation of soy moratorium and stringent environmental regulation has also shifted soy expansion to the Cerrado. Today, the Cerrado is the breadbasket of Brazil and is one of the top soy producers in the world (IBGE, 2013; IBGE, 2016), following extensive research and experimentation to adapt temperature crop varieties for Cerrado soils and climate. Recent deforestation rates in the Cerrado biome have reached more than twice as high as those in the Amazon basin (Lambin *et al.*, 2013), and soy production is one of the major driver of deforestation (Gibbs *et al.*, 2015; Morton, 2016).

In the Brazilian Cerrado, landscape changes in recent decades reflect market forces, environmental legislation, and industry-led efforts to promote sustainable agriculture. Demand for Brazilian soy has risen steadily in the European (Nepstad *et al.*, 2011; Garrett *et al.*, 2013) and Asian markets (Godar *et al.*, 2015; Lambin & Meyfroidt, 2011; Lathuillière *et al.*, 2014). Besides, conservation efforts in the Cerrado biome have received less attention over the years (Marris, 2005; Barreto *et al.*, 2013), and with recent rise in cropland expansion (Gibbs *et al.*, 2015), Cerrado's tropical savanna ecosystem is under pressure from both extensification (i.e., large scale forest conversion) and intensification of land for agriculture production and cattle grazing. Industry-led efforts promote forest protection in alongside soy production (Macedo *et al.*, 2012; Nepstad *et al.*, 2014; Gibbs *et al.*, 2015).

In Brazil, both Soy Moratorium and Forest Code are geared towards reducing deforestation in the region (Soares-Filho *et al.*, 2014; Gibbs *et al.*, 2015). The Soy Moratorium is an industry-led effort and do not extend beyond Brazilian Amazon, whereas the Forest Code is the Brazil's environmental legislation with specific guidelines for legal reserves of natural vegetation on private properties in the Amazon and Cerrado.

### *1.6 Quantifying degradation using remotely sensed data*

Satellite data support routine monitoring of changes in vegetation productivity from land cover and land use change.  Time series of satellite data capture changes in land cover, land use, and vegetation productivity in a consistent and repeatable manner. Today, the broad availability of global satellite data products has lowered the barriers to effective assessment and conservation of ecosystems, including satellite-derived estimates of global vegetation productivity (Running *et al.*, 2004b), cropland expansion (Gibbs *et al.*, 2015; Morton *et al.*, 2016), fire activity (Giglio *et al.*, 2003; Schroeder *et al.*, 2014), and forest loss (Hansen *et al.*, 2013). In general, satellite remote sensing alleviates some of the inconsistency and subjectivity in the assessment of ecosystem services, as regional or global analyses can target the timing, extent, and magnitude of ecosystem changes from human activity.

Several studies have used temporal Normalized Difference Vegetation Index (NDVI) data to assess desertification or land degradation (Prince & Justice, 1991; Tucker *et al.*, 1991; Nicholson *et al.*, 1998; Prince *et al.*, 1998; Anyamba & Tucker, 2005; Olsson *et al.*, 2005; Wessels *et al.*, 2004; Prince *et al.*, 2009). The term "land degradation" is preferred over "desertification" as degradation focuses on human impacts and avoid any confusion from drought effects (Wessels, 2005). In arid and semi-arid regions, annually or seasonally summed NDVI (ΣNDVI) is linearly related to NPP (Tucker *et al.*, 1983; Prince, 1991; Tucker *et al.*, 1991; Rasmussen, 1992; Fensholt *et al.*, 2006). Changes in NDVI derived from time series of remote sensing data could therefore provide the basis for detecting degradation in vegetation productivity.

The underlying challenge to use NDVI (or derived estimates of net primary production, NPP) to detect degradation lies in distinguishing human-induced degradation from variability caused by the climate. Several methods have been developed to identify human-induced degradation based on persistent reductions in primary production relative to potential productivity under reference environmental conditions, such as rainfall, temperature, soil moisture, radiation, etc. (Evans & Geerken, 2004; Hirata *et al.*, 2005; Wessels *et al.*, 2007; Prince *et al.*, 2009). These methods compare potential NPP—the NPP that would be expected in the absence of land utilization by humans—with actual NPP estimated from diagnostic models that utilize satellite remote sensing data (Prince, 2002).

Remote sensing data also provide information on vegetation carbon stocks needed to estimate emissions from deforestation and degradation. Benchmark estimates of forest carbon stocks are available for the pan-tropics (Saatchi *et al.*, 2011; Baccini *et al.*, 2012), based on field measurements and multiple sources of remotely sensed data. Satellite-derived estimates of vegetation carbon stocks can be combined with satellite data on forest loss, cropland expansion, and active fire detections to characterize human driven reductions in forest carbon stocks from degradation.

The combination of satellite remote sensing data is often helpful to capture the timing, extent, and transition type (e.g., forest to cropland) needed to attribute carbon emissions to specific drivers, such as agricultural expansion. The use of multiple satellite data products can also overcome some of the inherent limitations of moderate resolution sensors for land cover and land use change detection. For example, active fire detections from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on NASA's Terra and Aqua satellites provide a long time series of fire data at 1 km resolution. Higher resolution active fire detections from the Visible Infrared Imaging Radiometer Suite (VIIRS) I-band (375m) on the Suomi-National

Polar orbiting Partnership (S-NPP) satellite (Schroeder *et al.*, 2014) and 30-m fire detections from the Landsat-8 Operational Land Imager (OLI, Schroeder *et al.*, 2015) offer a unique way to constrain fire activities within specific management types.

### *1.7 Research Objectives*

Human modified landscapes amplified by population rise and economic drivers are changing the earth's ecosystem. In last few decades, the intensity of land use and land cover change have increased substantially to meet the global demand for food, fiber, and fuel. The fundamental goal of this dissertation is to examine ecosystem degradation from human activity and land management on carbon stocks and sequestration. Each case study considers the influence of land management and specific policy interventions intended to reduce the impact of agricultural use on natural systems.

This dissertation targeted three research objectives, with specific research questions regarding changes in carbon stocks and sequestration and policy options for climate mitigation:

A. Estimate the reductions in vegetation productivity due to land degradation in the southwest United States (Chapter 2)
    1. What are the extent and severity of land degradation in the Southwest region of the United States of America (USA)?
    2. Does land ownership and management contribute to differences in satellite-based estimates of declining net primary production (NPP)?

B. Estimate forest carbon emissions due to cropland expansion in the Brazilian Cerrado (Chapter 3)

    3. Do gross forest carbon emissions from cropland expansion in the Cerrado biome offset recent reductions in emissions from Amazon deforestation?
    4. How do policy interventions in the Brazilian Amazon, including Brazil's Forest Code and the industry's Soy Moratorium, influence cross-biome leakage of cropland expansion in the Cerrado?

C. Assess fire related forest and peatland conversion for oil palm expansion (Chapter 4)

    5. What fraction of forest and peat forest conversion for oil palm in Southeast Asia involves the use of fire?
    6. Does certification of oil palm production halt forest conversion and fire activity on certified concessions, including during El Niño drought conditions?

## *1.8 Outline of Dissertation*

This dissertation consists of five chapters. Chapter 1 presents a brief overview and conceptual framework to consider the interactions among land cover transitions, various drivers of land use and land cover change, and consequences of ecosystem degradation as a foundation for the work presented in this dissertation.

Chapter 2 considers the role of management for ecosystem degradation in the southwest United States, a region predominantly utilized for grazing, given a diversity of land management strategies by federal agencies, state agencies, native American tribes, and private landholders. Degraded and non-degraded areas were compared within the same biophysical strata, or land capability units, to understand the resilience and stability of ecosystem under different land management conditions. Changes in vegetation productivity were assessed using twelve years (2000 to 2011) of Normalized Difference Vegetation Index (NDVI) data derived from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS; 250m). This chapter highlights the importance of long time series of satellite data to characterize the productive potential of land under different land-use and land management conditions.

Chapter 3 estimates forest carbon emissions from expanding agricultural production in the Brazilian Cerrado. Satellite-derived estimates of forest cover and vegetation carbon stocks were combined with cropland expansion data to quantify gross forest carbon emissions from cropland expansion. This chapter explores the role of policy interventions, market demands, and national circumstances for changing land use dynamics in the Cerrado biome.

Chapter 4 considers the role of certification for changing dynamics of deforestation and fire use in and around oil palm concessions in Southeast Asia. Satellite-based estimates of forest cover, forest loss, planted oil palm, and active fires were used to estimate the spatial and temporal patterns of fire-driven deforestation and total fire activity. Comparisons among certified, non-certified, and adjacent agricultural regions were used to identify the influence of certification on fire-driven deforestation dynamics and total fire activity during El Niño drought years.

Finally, Chapter 5 summarizes the key findings from Chapters 2-4 and outlines potential directions for future research using ecosystem models, new satellite data products, and policy and certification approaches that leverage satellite monitoring capabilities.

# Chapter 2: Reductions in productivity due to land degradation in the drylands of the southwest United States

## *2.1 Summary*

Dryland degradation has long been recognized at regional, national and global scales, yet there are no objective assessments of its location and severity. An assessment of reductions in net primary production (NPP) due to dryland degradation in the southwest (SW) U.S.A is reported. The Local NPP Scaling (LNS) approach was applied to map the extent and magnitude of degradation. LNS seeks to identify reference sites in which there is no degradation that can be used as a standard for comparison with other sites that share the same environment, except for degradation. Twelve years were analyzed (2000 to 2011), using Normalized Difference Vegetation Index (NDVI) data (250 m) from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite-borne multispectral sensor. The results indicated that the total NPP reductions in the study area were about 35.9±4.7 Tg C $yr^{-1}$, which equates to 0.31±0.04 Mg C $ha^{-1}$ $yr^{-1}$. The NPP reductions in grassland-savanna and livestock grazing areas were large and mostly consistent between years in spite of large variations in overall NPP caused by differences in land-use, interannual variations in rainfall and other aspects of weather. In comparison with other cover types, forested land generally had higher NPP reduction per unit area. The maps also enable attribution of degradation from the finest management units to entire agencies - such as the Bureau of Land Management which had 50% less production per unit area than U.S. Forest Service. The degradation within Native American Land was low with total NPP reduction of about 2.41±0.24 Tg $Cyr^{-1}$ and

unit area reduction of productivity of just 0.21±0.02 Mg C $ha^{-1}yr^{-1}$, yet the percent reduction from potential was in equivalence with other land management agencies.

## *2.2 Introduction*

Drylands cover 41% of the global terrestrial surface (UNCEDSafriel and Adeel (2005)) and nearly 40% of land area in the USA (White & Nackoney, 2003). While vegetation in drylands has low biomass and low carbon (C) sequestration per unit area, they still store approximately twice the amount of organic C stored in temperate forest ecosystems due to their large extent and to their high soil organic carbon (SOC) pool (Safriel & Adeel, 2005; Eswaran, 2000). Lal (2004) and Eswaran (2000) estimated that global drylands store about 15% (241 Pg) of the Earth's total SOC. Waltman and Bliss (1997) estimated that about 5% (75-90 Pg C) of the global SOC pool is stored in US soils, with 15.3-16.5 Pg alone in grazing lands. Thus, dryland ecosystems are potentially large sinks for atmospheric $CO_2$ and play an important role in the terrestrial C balance with feedbacks to climate change (Lal, 2004; Wohlfahrt *et al.*, 2008).

Degradation is considered to be one of the major environmental problems in drylands (UNCED, 1992; UNCCD, 1994; Goetz *et al.*, 1999; Reynolds *et al.*, 2007a). It involves adverse changes in one or more aspects of the biota and their environment, loss of species diversity including palatable species, soil erosion and reduced biological productivity (Schlesinger *et al.*, 1990; Milchunas & Lauenroth, 1993). SOC is a key indicator of soil quality (Brady & Weil, 2010) and reduction is often associated with degradation (Lal, 2004, Ardö & Olsson, 2003). Large portions of US drylands are rangelands and management to reduce degradation has been estimated to be able to increase SOC by 0.1 - 0.6 Mg C $ha^{-1}year^{-1}$ (Schuman *et al.*, 2002). When the vast areas of rangelands are considered, these rates translate into 43 MMg C $yr^{-1}$ (Schuman *et al.*, 2002) addition to the total for USA.

Despite its significance, the extent and severity of all forms of rangeland degradation are still unknown (Lund, 2007), mainly due to the lack of objective, practical methods of measurement (Verstraete, 1986; Prince, 2002). The few, existing, global maps of desertification (dryland degradation) are based on coarse resolution soil maps (Middleton & Thomas, 1997; Eswaran & Reich, 2003) from which vulnerability is assessed, but not the actual occurrence of degradation. The absence of quantitative maps of the degree of degradation of the world's drylands is universally agreed to be a major hindrance to critical science questions, several associated with global change, and for mitigation and prevention of future degradation (Chasek *et al.*, 2015).

Several measurable indicators have been proposed to monitor land degradation such as: accelerated soil erosion rates (Stroosnijder 2007) deteriorating soil fertility (Batterbury *et al.*, 2002) and long-term and irreversible reductions in vegetation cover or production efficiency (Nicholson *et al.*, 1998; Prince *et al.*, 1998; Prince, 2002; Batterbury *et al.*, 2002). Changes in vegetation NPP, which are inherently linked to the major processes that lead to degradation (Prince, 2002; Safriel, 2007; Nicholson, 2011), can be monitored using repeated satellite observations (e.g. Hansen *et al.*, 2003, Myneni *et al.*, 2002, Prince & Goward, 1995, Running *et al.*, 2004a). The underlying challenge to the use of NPP to detect degradation lies in distinguishing human induced degradation from the variability caused by the climate and other environmental factors, such as soils, climate, vegetation type, rainfall, temperature, and others (Prince, 2015), all of which can also reduce NPP. Several studies have attempted to identify land degradation by long term and persistent reductions in NPP below the potential set by the environmental conditions, in the absence of land degradation caused by humans (Prince *et al.*, 1998; Prince, 2002; Evans & Geerken, 2004; Hirata *et al.*, 2005; Wessels *et al.*, 2007; Wylie *et al.*, 2012; Prince *et al.*, 2009; Reeves & Baggett, 2014). In the present study, a reference NPP was estimated using the LNS method (Prince, 2004; Prince *et al.*, 2009).

The objectives were to quantify and map the extent and severity of loss of production in the SW of the USA, having first normalized the effects of long and short-term natural environmental factors. The basis of LNS is to stratify the land into homogeneous regions, called land capability classes (LCCs), within which, in the absence of degradation, productivity can be expected to be the same throughout. The potential NPP is estimated for each LCC using the maximum NPP, which is then compared with all other parts of the LCC. Any deficits of NPP are regarded as possible cases of anthropogenic degradation.

## *2.3 Materials and Methods*

### 2.3.1 Study area

The study was conducted in the SW US based on the Southwest Regional Sequestration Partnership (SWRP) and the Regional Sequestration Partnership

Program of the U.S Department of Energy (US-DOE, 2003) (Figure 2.1). It consisted of New Mexico (NM), Utah (UT), Colorado (CO), parts of Arizona (AZ), west Texas (TX), Oklahoma (OK), Kansas (KS), and Nebraska (NE). The vegetation is diverse, ranging from desert in the west, changing successively to bush, grassland, savanna, and short grass prairie eastwards as summer rainfall increases. Land uses include extensive ranching on public land principally managed by the Bureau of Land Management and the U.S Forest Service, large areas of Native American reserves, large preserves of various types, some irrigated and dryland farming and small areas of exurban development.

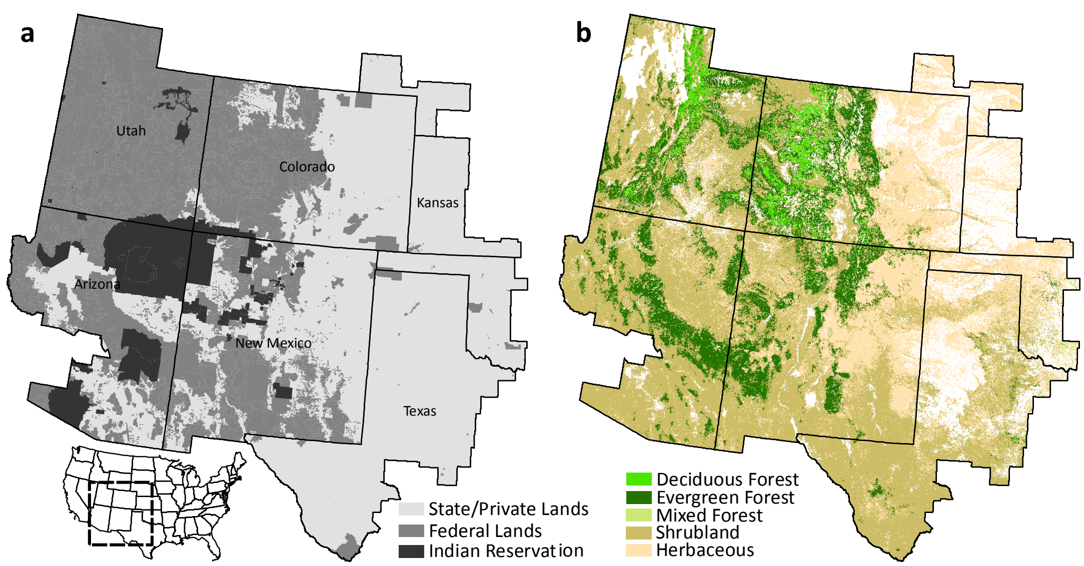


Figure 2.1: (a) Study region and (b) National Land Cover Database (2006) land

*Land cover*: The National Land Cover Database (NLCD; Fry *et al.*, 2011) was used to provide land cover information at 30m resolution to identify areas belonging to the NLCD classes: Evergreen forest, Deciduous forest, Mixed forest, Shrubland,

and Herbaceous, for the year 2006. Ideally, yearly land cover data would be used, but these were not available. All other land cover classes such as water, developed, barren, planted/cultivated, and wetlands were excluded from the analyses.

*Soils*: Eight interpretive soil land capability classes from the U.S. Department of Agriculture (USDA) Natural Resources Conservation Services (NRCS) State Soil Geographic (STATSGO) soil database (NRCS, 2007) based on use limitation (e.g., soil depth, SOC, texture, erosion risk, slope, porosity, etc.) were used.

*Meteorology*: Meteorological information of annualized precipitation totals, yearly average maximum and minimum temperatures and the dew point at 4km resolution were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly *et al.*, 2002) data sets.

*Elevation* : The United States Geological Survey (USGS) Shuttle Radar Topography Mission (SRTM; Farr et al. 2007) 90m digital elevation model (DEM) was used to provide topographic information.

*Slope*: The slope was calculated from the USGS SRTM 90m DEM and areas having slopes > 15% were excluded to minimize the presence of natural erosion which is more common on steeper slopes.

*Aspect*: Slope and azimuth were combined in "southness" (Franklin *et al.*, 2000) in order to represent different exposure to the sun in one index.

*Riparian vegetation:* Riparian land, although small compared to the typical LCC, is usually very different from the neighboring land. These were excluded using a stream map and a buffer, the width of which was adjusted to the flow-accumulation of the waterway, as available in HydroSHEDS (Lehner *et al.*, 2008). Pixels with >450 upstream contributing pixels were buffered using an exponential relationship based on number of contributing streams. The width was varied from 200m (at 450 contributing pixels) to 1500m maximum. In addition, the National Wetland Inventory (NWI; Cowardin *et al.*, 1979; Cowardin & Golet, 1995) dataset was used to mask the wetlands and surface water bodies.

*Land use and land management*: Croplands were masked using 2012 USDA National Agricultural Statistical Statistics Service (USDA-NASS, 2012) cultivated data layer (CDL). The Terrestrial Protected Areas of North America dataset (CEC, 2010) was used to identify areas managed by the Bureau of Land Management (BLM), U.S. Forest Service (USFS), Native American Land (NAL), National Park Service (NPS), Department of Defense and Energy (DOD-DOE), and State Land Board (SLB).

*Roads*: Roads and other paved areas were identified from the National Atlas dataset (USGS, 2004) and masked, together with one pixel on each side to create a 750m-wide buffer to exclude verges and disturbed land associated with roads.

*NDVI*: It is now generally accepted that light use efficiency models (LUE) forced with multi-temporal NDVI data can be used to map terrestrial gross primary production (Tucker *et al.*, 1985; Prince, 1991; Rasmussen, 1992; Running *et al.*, 1999; Running *et al.*, 2004a). However, in arid and semi-arid regions, annually or seasonally summed vegetation indices (e.g. NDVI, Enhanced Vegetation Index; EVI) themselves, without the added complexity of light use efficiency, have also been found to be adequate since they are linearly related to primary production (Fensholt *et al.*, 2006; Sjöström *et al.*, 2011). This simplification has the advantage of eliminating the additional errors in the variables needed for a full LUE models. Thus NDVI was used as a proxy for NPP (Prince & Justice, 1991; Tucker *et al.*, 1991; Nicholson *et al.*, 1998). Yearly averages of MODIS NDVI (MOD13Q1), 250m, 16-day data for 2000-2011 were used to calibrate the NDVI values in NPP units.

#### 2.3.2 Land capability classification

Every dataset used, including the annualized precipitation totals, the yearly averages of maximum and minimum temperature and dew point were geographically registered to match the resolution and grid of the MOD13Q1, 250m x 250m data. The following steps were used to define the LCCs. *i.* Potential errors caused by inadequate classification were minimized by removing small patches with extreme low or high NPP that were unrepresentative of their LCC: these included areas such as riparian strips, small wetlands, cropland, roads and settlements. A very conservative approach was used, by adding buffers around such features. The excluded areas were combined to a single mask and applied to all input datasets. *ii.* The digital elevation and meteorological datasets were normalized to zero mean and unit variance before unsupervised classification of the pixels using ISODATA clustering algorithm (Ball & Hall, 1967). Unsupervised classes were derived with a stopping criterion of one hundred iterations and a convergence factor of 0.975. The class numbers were chosen to be arbitrarily large to maintain spatial heterogeneity and also to constrain the influence of residual environmental factors on productivity. *iii.* The unsupervised classes were intersected with land cover, soil, and land management maps. The final number of classes after intersection was between 3000 and 5000. *iv.* For each year, two LCC maps were generated, one based on unsupervised classes, soil, and land cover (UMD) and the other (UMDLM) with the land management agency added (federal public lands only). Both LCC maps were different for each year because of the differences in annual meteorological variables, but the land cover, land management, and soil information were assumed to be the same for all years. *v.* The LCCs were assessed by estimating the extent to which they reduced the correlation between the environmental factors that were used in their creation.

In addition to UMD and UMDLM maps, two existing land stratifications were analyzed and compared with the UMD LCCs: *i.* USDA common resource area (USDA-CRA, 2004). *ii.* USGS-GAP National Land Cover data (USGS, 2011), which shows both vegetation and land use.

### 2.3.3 Local NPP Scaling

A reference or maximum NDVI of each LCC was estimated by finding the $85^{th}$ percentile of the frequency distribution of yearly average NDVI (Figure 2.2). The effect of unrepresentative, highly productive pixels was thus reduced (Prince *et al.*, 2009). The $85^{th}$ percentile was an arbitrary cut-off. Reductions were quantified by subtracting the actual NDVI from the reference value. The reduction in productivity, therefore, was relative to a reference or standard against which degradation within its LCC was assessed (Prince *et al.*, 2009). The yearly LNS maps of the differences between actual and reference NDVI were expressed in terms of the reduction of NPP (in Mg C $ha^{-1}$ $yr^{-1}$) compared with the reference. The reference NDVI identified using

85th percentile threshold within each LCC was matched with the yearly MODIS NPP product (MOD17A3; Running *et al.*, 2004a), resampled at 250m resolution, to calibrate the NDVI data with NPP. The relative NPP reductions within a LCC were therefore in NPP units.

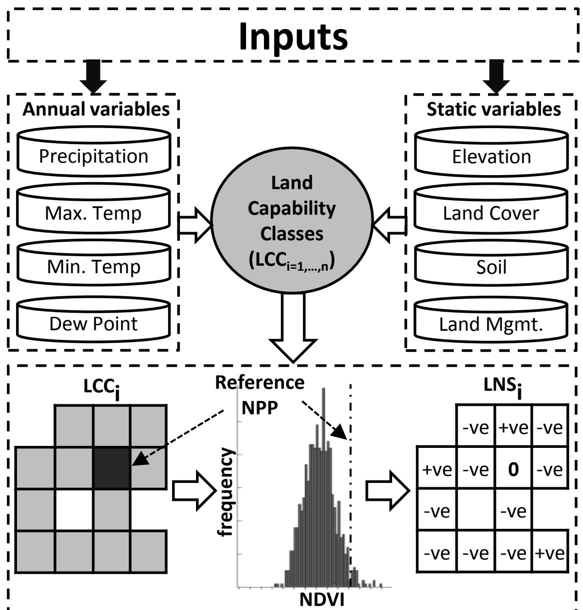


Figure 2.2: Schematic diagram of the procedures used to define LCCs and create LNS maps

LNS maps were made for each year using the appropriate annual UMD and UMDLM LCC classifications and also from the USDA-CRA and USGS-GAP maps. Thus there were 12 UMD LNS maps, taking account of weather differences between years; however the USDA-CRA and USGS-GAP LCCs maps were the same for all years.

2.3.4 Assessment of reference NDVI and LNS

It is important that the reference NDVI pixels are representative of the LCC for which they were selected. The extent to which this was achieved was determined by. *i.* Visual comparison with Google Earth (GE, 2014), high resolution (<4m), true color imagery. Although visual interpretation is subjective, the GE images were adequate to detect differences between the detailed land cover of the reference pixels and their LCC. 100 reference locations were selected using a stratified random sampling in each NLCD land cover type, and a binary decision of good/bad reference was made. *ii.* Very low LNS values were checked with GE to eliminate land cover that was not typical of the LCC (e.g. unmasked wetland, unmapped settlements). *iii.* The relationships of reference NDVI and environmental variables used to create the LCCs were analyzed in a one-way ANOVA to determine by how much the within LC variance had been reduced in the classification. *iv.* To determine the efficiency of classification to group separate classes, the variability in reference NDVI across the full range of LCCs was analyzed by calculating the increments of NDVI between pairs of LCCs ranked by NDVI.

The UMD, USDA-CRA and USGS-GAP LNS maps were compared numerically. The comparison used a "fuzzy numerical" extension (Hagen-Zanker *et al.*, 2006) of the simple, binary, pixel-by-pixel kappa ($\kappa$) test (Cohen, 1960) by using continuous LNS data and weighted values for spatially close mismatches, which often arise in map comparisons. Kappa was calculated for both entire maps ($\overline{\kappa}$) and, in order to visualize the spatial distribution of differences, for individual pixels ($\kappa$).

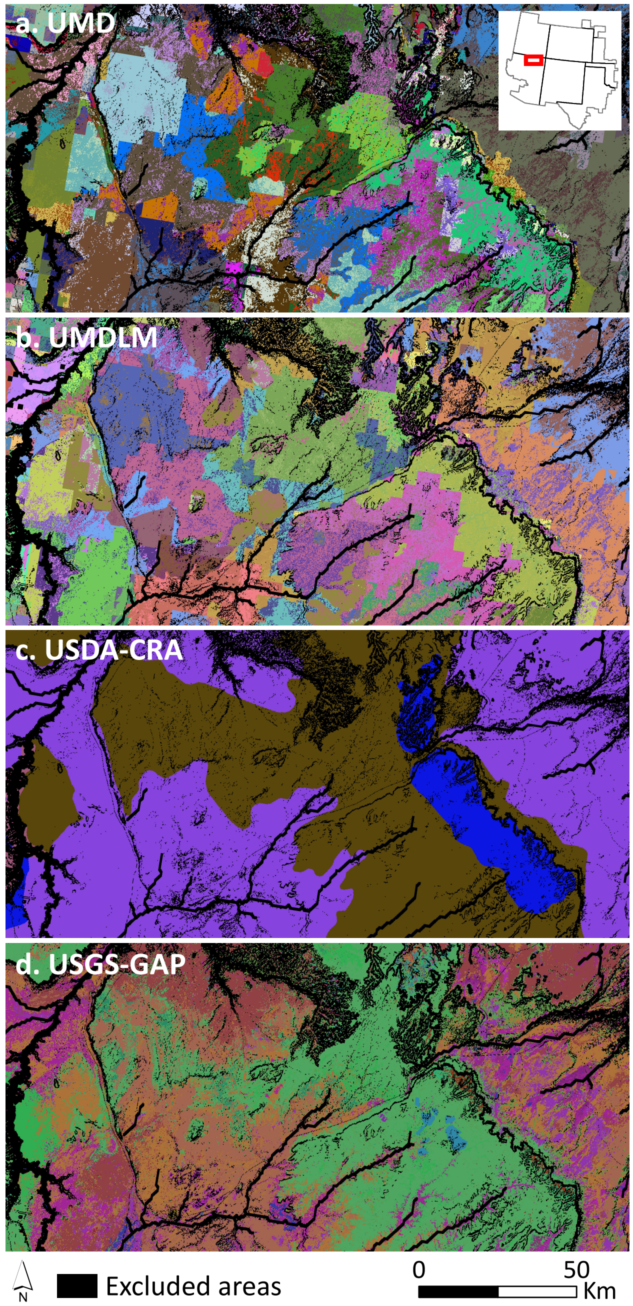


Figure 2.3: The UMD, UMDLM, CRA and GAP LCC maps. For UMD and UMNLM there were 12 LCC maps, one each year. The 2010 maps are shown. (a) UMD LCCs created from the intersection of unsupervised classes, soil, and land cover. (b) UMDLM which added land management to the UMD classification. (c) USDA-CRA. (d) USGS-GAP. The black areas are excluded land cover and land management types. Owing to the large number of classes in UMD and UMDLM, only a representative subset illustrating the spatial heterogeneity is presented. Colors were assigned arbitrarily and do not indicate the same classes across all four maps.

## *2.4 Results*

### 2.4.1 Land Capability Classification

UMD and UMDLM classifications were made for each year. Examples of one year are shown in Figures 2.3-a & 2.3-b. The number of classes varied between years: in the UMD the average was approximately 5000 and, for UMDLM, 3000. The CRA and GAP maps (Figures 2.3-c & 2.3-d) differed from the two UMD LCC maps in two respects: *i*. CRA had 89 and GAP 152 LCCs - many fewer than UMD classifications and therefore less able to discriminate differences in land capability; *ii*. the classifications were created without consideration of interannual changes. Few of the CRA or GAP LCCs coincided with either of the UMD classifications.

The majority of the UMD LCCs were in the NLCD Shrubland, Herbaceous, and Evergreen Forest vegetation classes, since these cover about 97% of the study region. The UMD LCCs were distributed across most of the elevation, precipitation, temperature, and dew point gradients. However, at higher elevations, some LCCs consisted of pixels with a wide range of "southness" values while, at lower elevation, about 10% were confined to narrower ranges of values. The frequency distributions of numbers of LCCs along the environmental variables used to derive the two UMD classifications all had strong central tendencies, varying degrees of skewness, and some slight irregularities in the numbers of LCCs in adjacent classes, reflecting unevenness of the occurrence of different environments in the study area.

### 2.4.2 Local NPP Scaling

Using the high resolution GE imagery, the assessment of the extent to which the reference pixels were the same as the rest of the pixels in its LCC showed that, of the 100 reference pixels examined in each land cover type, the agreement was >94% (95% confidence limits 82 & 95). The agreement in LCCs for three of the major land cover types (Evergreen Forest, Shrubland, and Herbaceous) was higher, >98% (95% confidence limits 96 & 100). Therefore, the reference pixels were judged, albeit visually, to be adequately representative of their respective LCCs.

The reference NDVI values of UMD LCCs were positively correlated with precipitation ($r > 0.8$) and dew point ($r < 0.4$) across all LCCs. Correlations with precipitation were even higher ($r > 0.8$) within individual land cover types than for all types together, except for Deciduous ($r < 0.3$). The correlations with dew point were higher in Shrubland and Herbaceous ($r > 0.7$) than across all cover types ($r < 0.4$). The one-way ANOVA found differences in reference NDVI and their environmental variables: the relationships of reference NDVI and the environmental variables were significantly different ($p < 0.001$) between land cover types; surprisingly, the reference NDVI and the environment variables in the land managed by different agencies (BLM, USFS, NAL, NPS, DOD-DOE, and SLB) were also significantly different ($p < 0.0001$). There were strong correlations between two groups of environmental variables: elevation with all three temperature variables; and among the three temperature variables.

A LCC classification is successful if the classes have different potential NDVI values and is most efficient when the reference NDVI values are equally spread over the full range. For the two UMD classifications, the increments in reference NDVI across the entire range of values were almost equal except for the extreme low and high classes, but were highly variable in the CRA and GAP classifications. However, it should be recalled that the UMD LCCs were derived from a set of environmental variables that could be expected to be good predictors of potential NDVI, unlike the CRA and GAP classification.

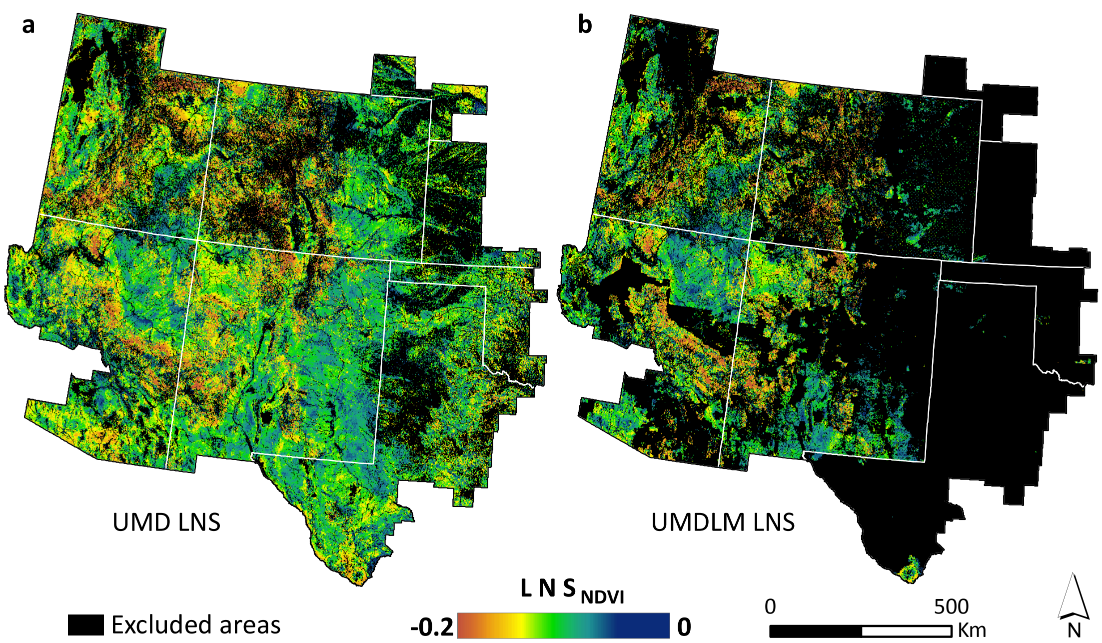


Figure 2.4: LNS maps for (a) UMD and (b) UMDLM expressed as NDVI units. Blue areas (0) are at their reference condition and therefore interpreted as not degraded while other colors show reductions below the reference condition. Black areas are masked land cover, land use types, roads, riparian buffers and slope >15% that were excluded from the study. Note, the panel b is for federal public lands only.

The LNS maps derived from the UMD and UMDLM LCCs were nearly identical (Figure 2.4), but the USDA-CRA and USGS-GAP maps were noticeably different from both the UMD maps and each other. The average similarity for the entire UMD vs. USDA-CRA, UMD vs USGS-GAP, and USDA-CRA vs. USGS-

GAP map comparisons were low ($\overline{\kappa}$ = 0.521, 0.495, and 0.484 respectively). The maps of differences in individual pixels between each pair of classifications (UMD, USDA-CRA, and USGS-GAP LNS), measured by $\kappa$, showed that the two UMD maps were similar, but both comparisons of UMD with USDA-CRA and USGS-GAP LNS maps were very different. Since the UMD LNS maps were different from USDA-CRA and USGS-GAP LNS maps, we used the UMD LNS maps to summarize the NPP reductions within the CRA and GAP classes (Tables 2.3 & 2.4).

The mean LNS and interannual variations differed between land cover types (Figure 2.5). Comparisons of the 12-year average UMD LNS maps with high spatial resolution imagery showed many examples of correspondence of LNS with obvious ground conditions that can be expected to cause differences in LNS. Furthermore, the visual assessments showed that all the maps had some generally coherent groups of similar LNS values, mostly related to mountainous areas, rather than a speckle of pixels with different LNS.

The average LNS values in active and abandoned mining areas were very low (i.e. large deficits from reference, low –ve LNS values) and had low interannual variability (i.e. low coefficient of variation; CV) showing clear signs of permanent reduction. The interannual average LNS values of grassland and savanna were high (i.e. small negative deficits from reference), and their CVs was high (Figure 2.5-c2), indicating strong interannual variability in absolute LNS (g C $ha^{-1}$ $yr^{-1}$), which is expected since precipitation plays an important role in these ecosystems (e.g. Figure 2.5-b3) and annual precipitation totals are high variable. High variability in LNS was also observed around the watering points within the grazing allotments (Figure 2.5-c4), however, the average LNS values in these areas remained high (Figure 2.5-b4).

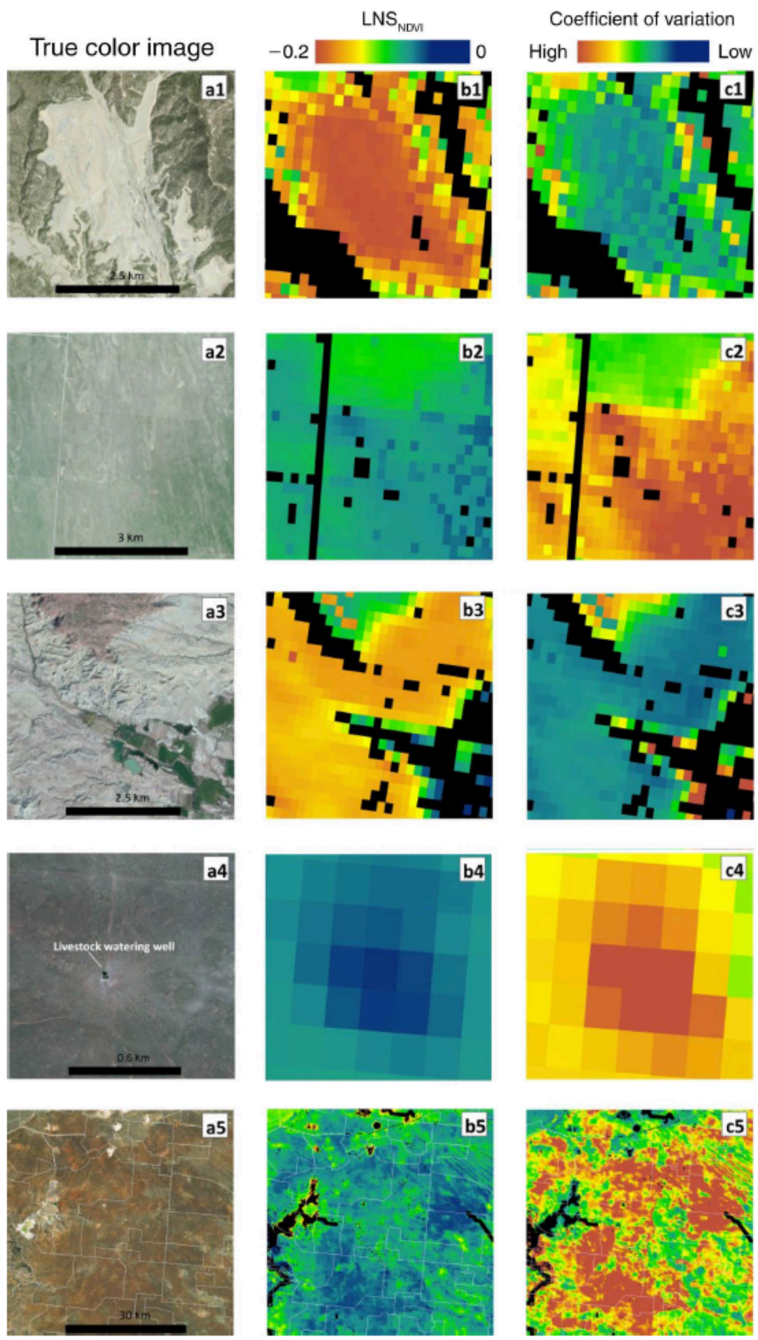


Figure 2.5: Examples of LNS calculated using UMD LCCs representing different levels of degradation. a1 – 5 high spatial resolution true-color image (ESRI 2014); b1–5 the LNS map (average of 2000-2011); and c1 – 5 the interannual coefficient of variation (12-years). Black pixels in LNS and CV maps are areas excluded from the analyses.

### 2.4.3 Reduction in net primary production in degraded areas

The twelve year (2000-2011) average reduction of productivity varied between cover types (Table 2.1). The total reduction of 35.88±4.72 Tg C $yr^{-1}$ (11.80% below potential) and per unit area reduction of 0.31±0.04 Mg C $ha^{-1}$ $yr^{-1}$ among land cover types was largely due to reductions in Shrubland and Herbaceous cover types (17.20±2.02 and 10.02±1.88 Tg C $yr^{-1}$).

Table 2.1: Average (2000-2011) NPP reductions in land cover types

| **Land Cover Type (NLCD)** | **NPP reduction per unit area (Mg C $ha^{-1}$ $yr^{-1}$)** | **Land Area (%)** | **Total NPP reduction (Tg C $yr^{-1}$)** | **Percent reduction from potential** (%) |
|---|---|---|---|---|
| Shrublands | 0.27±0.03 | 54.96 | 17.20±2.02 | 12.30 |
| Herbaceous | 0.28±0.05 | 30.46 | 10.02±1.88 | 9.93 |
| Evergreen Forest | 0.51±0.07 | 12.66 | 7.53±0.99 | 12.78 |
| Deciduous Forest | 0.50±0.08 | 1.7 | 0.98±0.15 | 11.01 |
| Mixed Forest | 0.56±0.10 | 0.22 | 0.14±0.03 | 13.00 |
| Total | 0.31±0.04 | 100 | 35.88±4.72 | |

*Notes:* Reductions are the summed differences between each pixel and its reference, averaged across the twelve years with ± one standard deviation

The results were also tabulated for the six agencies with the largest land holdings in the study area (Table 2.2). Each agency has a different mix of land cover types and size, so direct comparisons between them is only useful, for example, to inform policies and capacities for changes in C sequestration for an overall agency. The total reduction of productivity among land management types was 15.25±1.61 Tg C $yr^{-1}$, 12.53% below potential. Three agencies (BLM, USFS, and NAL) together occupy about 91% of the land which accounted for a reduction of 14.38±1.5 Tg C $yr^{-1}$. The USFS area (24.98%) contributed 6.69 Tg C $yr^{-1}$, much higher than BLM even though the land managed by BLM is approximately twice the USFS. The unit area reduction of productivity was highest for USFS (0.56±0.07 Mg C $ha^{-1}$ $yr^{-1}$) and lowest for DOD-DOE (0.15±0.03 Mg C $ha^{-1}$ $yr^{-1}$). NAL with similar land area (23.62%) as USFS accounted for just 2.41 Tg C $yr^{-1}$ reductions, clearly indicating lower productive potential. Although, the reduction expressed as a percentage of the potential was similar to the other agency lands (Table 2.2).

Table 2.2: Average (2000-2011) NPP reductions in federal agencies with largest holdings

| **Land Management Agency** | **NPP reduction per unit area (Mg C $ha^{-1}$ $yr^{-1}$)** | **Land Area (%)** | **Total NPP reduction (Tg C $yr^{-1}$)** | **Percent reduction from potential** (%) |
|---|---|---|---|---|
| Bureau of Land Management (BLM) | 0.26±0.03 | 42.48 | 5.30±0.54 | 11.06 |
| Forest Service (USFS) | 0.56±0.07 | 24.98 | 6.67±0.82 | 12.41 |
| Native American Land (NAL) | 0.21±0.02 | 23.62 | 2.41±0.24 | 9.60 |
| National Park Service (NPS) | 0.18±0.02 | 3.19 | 0.27±0.03 | 8.51 |
| Department of Defense (DOD) and Department of Energy (DOE) | 0.15±0.03 | 3.17 | 0.23±0.04 | 7.71 |
| State Land Board (SLB) | 0.31±0.05 | 2.57 | 0.37±0.06 | 9.90 |
| Total | 0.32±0.03 | 100 | 15.25±1.61 | |

*Notes:* Reductions are the summed differences between each pixel and its reference, averaged across the twelve years with ± one standard deviation

Forested land had the highest NPP per unit area and hence capacity for reduction by degradation, so the high reference NDVI and the large area of USFS land explains its high total reduction. In comparison with USFS, BLM had 50% less production per unit area, probably because of the small forest component (13%) and the rest occupied by Shrublands (87%), which had lower reference productivity. NAL had similar land cover as BLM but a slightly lower NPP reduction per unit area. The NPS and DOD-DOE lands had the lowest per unit area reduction.

Of the 89 CRAs in the study region, only 36 occupy more than 1% of land area (Table 2.3). Shrubland and Herbaceous account for about 85%. Five CRAs (codes 35.60, 36.10, 39.10, 47.20, 48A.1) were >50% forested and the rest were dominated by Shrubland-Herbaceous. The average annual reduction of NPP in the 36 CRAs was 30.68±3.97 Tg C $yr^{-1}$, the highest being in CRA code 48A.1 with a reduction of 3.75±0.56 Tg C $yr^{-1}$. The CRAs that are predominantly coniferous tree had the highest per unit area reduction of all the CRAs.

The Colorado Plateau CRAs occupied the largest land area (14.86%) in the study region. Although their combined NPP reduction was large (4.64±0.54 Tg C $yr^{-1}$), the unit area reduction of productivity in each CRA was relatively small. The Chihuahuan Desert Shrubs (42.20) and Grassland (42.30) together accounted for the second largest area (10.73%). They also had small NPP reduction (about 0.21±0.06 Mg C $ha^{-1}$ $yr^{-1}$). Another small NPP reduction per unit area was in the Central Rolling Red Plains, Eastern (78C.1) and Western parts (78B.1), areas that have distinctive rangeland vegetation and are widely used for livestock grazing.

There are 152 GAP land cover types in the study region, of which only 26 occupy >1% land area (Table 2.4). The NPP reduction per unit area was generally smaller than for the CRA classification, except for a few coniferous woodland areas, but their differences in area made up for the difference. The largest area (13.37%) is occupied by Western Great Plains Shortgrass Prairie (code 7310) which had the highest total NPP reductions (4.10±0.78 Tg C $yr^{-1}$), followed by the Colorado Plateau Pinyon

Table 2.3: Average (2000-2011) NPP reductions in the USDA-Common Resource Areas

| **Common Resource Area (CRA)** | **CRA Code** | **NPP reduction per unit area ($Mg\ C\ ha^{-1}\ yr^{-1}$)** | **Land Area (%)** | **Total NPP reduction ($Tg\ C\ yr^{-1}$)** |
|---|---|---|---|---|
| Colorado Plateau | | | | |
| - Irrigated Cropland | 35.10 | 0.32±0.04 | 5.73 | 2.16±0.28 |
| - Shrub - Grasslands | 35.20 | 0.22±0.03 | 4.89 | 1.27±0.15 |
| - Sagebrush - Grasslands | 35.30 | 0.24±0.05 | 3.24 | 0.89±0.20 |
| - Pinyon - Juniper - Sagebrush | 35.60 | 0.27±0.05 | 1.00 | 0.32±0.06 |
| Southwestern Plateaus, Mesas, and Foothills | | | | |
| - Cool Subhumid Mesas and Foothills | 36.10 | 0.51±0.08 | 1.03 | 0.61±0.09 |
| - Warm Semiarid Mesas and Plateaus | 36.20 | 0.38±0.06 | 2.70 | 1.19±0.18 |
| Mogollon Transition | | | | |
| - Lower Interior Chaparral | 38.10 | 0.17±0.03 | 1.88 | 0.36±0.06 |
| - Interior Chaparral - Woodlands | 38.20 | 0.28±0.05 | 1.36 | 0.45±0.08 |
| Mogollon Plateau Coniferous Forests | 39.10 | 0.44±0.08 | 2.33 | 1.19±0.21 |
| Sonoran Desert | | | | |
| - Upper | 40.10 | 0.17±0.06 | 1.34 | 0.27±0.09 |
| - Middle | 40.20 | 0.17±0.05 | 1.20 | 0.23±0.07 |
| Chihuahuan | | | | |
| - Sonoran Semidesert Grasslands | 41.30 | 0.20±0.05 | 1.64 | 0.38±0.10 |
| Chihuahuan Desert | | | | |
| - Shrubs | 42.20 | 0.22±0.06 | 4.98 | 1.27±0.33 |
| - Grassland | 42.30 | 0.21±0.06 | 5.75 | 1.38±0.37 |
| Wasatch and Uinta Mountains | | | | |
| - Low Mountains and Foothills | 47.10 | 0.53±0.09 | 1.13 | 0.69±0.12 |
| - High Mountains | 47.20 | 0.74±0.14 | 2.10 | 1.81±0.34 |
| Southern Rocky Mountain Foothills | 49.10 | 0.38±0.06 | 1.65 | 0.73±0.11 |
| Upper Arkansas Valley Rolling Plains | 69.10 | 0.30±0.07 | 2.75 | 0.96±0.21 |
| Central High Tableland | 72.10 | 0.33±0.10 | 2.38 | 0.90±0.26 |
| Great Salt Lake Area | | | | |
| - Sagebrush Basins and Slopes | 28A.1 | 0.26±0.05 | 2.78 | 0.84±0.15 |
| - Shadscale - Dominated Saline Basins | 28A.3 | 0.24±0.07 | 1.53 | 0.42±0.13 |
| Cool Central Desertic Basins and Plateaus | | | | |
| - Green River Basin | 34A.1 | 0.46±0.06 | 1.12 | 0.60±0.08 |
| Warm Central Desertic Basins and Plateaus | | | | |
| - Semiarid Plateaus and Low Mountains | 34B.1 | 0.35±0.04 | 1.46 | 0.60±0.06 |
| - Uncompahgre and Grand Valleys | 34B.2 | 0.39±0.06 | 1.07 | 0.49±0.08 |
| Southern Rocky Mountains | | | | |
| - High Mountains and Valleys | 48A.1 | 0.68±0.10 | 4.73 | 3.75±0.56 |

| | | | | |
|---|---|---|---|---|
| Central Great Plains, Southern Part | 67B.1 | 0.29±0.07 | 2.66 | 0.89±0.20 |
| Northern New Mexico Highlands | 70A.1 | 0.26±0.06 | 2.67 | 0.81±0.19 |
| Central Pecos Valleys and Plains | 70B.1 | 0.21±0.05 | 2.38 | 0.59±0.15 |
| Central New Mexico Highlands | 70C.1 | 0.25±0.05 | 2.90 | 0.85±0.16 |
| High Plains | | | | |
| - Northern Part | 77A.1 | 0.25±0.08 | 1.07 | 0.31±0.10 |
| - Cotton Belt | 77C.1 | 0.22±0.09 | 1.07 | 0.28±0.11 |
| - Southwestern Part | 77D.1 | 0.16±0.05 | 1.70 | 0.32±0.10 |
| - Northeastern Part | 77E.1 | 0.24±0.08 | 2.21 | 0.61±0.19 |
| Rolling Red Plains | | | | |
| - Western Part | 78B.1 | 0.25±0.08 | 3.31 | 0.96±0.31 |
| - Eastern Part | 78C.1 | 0.29±0.09 | 2.89 | 0.97±0.29 |
| Western Edwards Plateau | 81A.1 | 0.23±0.06 | 1.38 | 0.36±0.10 |

*Notes:* 36 USDA-CRAs that occupy more than 1% of the study area are reported. Average reductions with ± one standard deviation were calculated using the UMD LNS, expressed in NPP units.

Juniper Woodland (code 4512) with a reduction of 3.28±0.45 Tg C $yr^{-1}$. While this land cover type occupies nearly 40% less area than Western Great Plains Shortgrass Prairie (code 7310), it still had large NPP reductions. Furthermore, in comparison with Western Great Plains Shortgrass Prairie, the Colorado Plateau Pinyon-Juniper Woodland had higher NPP reductions per unit area (0.35±0.05 Mg C $ha^{-1}$ $yr^{-1}$), largely due to the dominance of Pinyon-juniper woodlands. Similarly, the Ponderosa Pine Woodland and Pinyon-Juniper Woodland in the Southern Rocky Mountain range, mostly with coniferous vegetation, exhibited relatively high NPP reduction per unit area (0.40±0.07 Tg C $ha^{-1}$ $yr^{-1}$). Among the 26 GAP land cover types, the Inter-Mountain Basins Montane Sagebrush Steppe, had higher unit area reduction of productivity (0.72±0.11 Mg C $ha^{-1}$ $yr^{-1}$) than land cover types dominated by coniferous vegetation. Interestingly, the Sonoran Paloverde-Mixed Cacti Desert Scrub had low NPP reduction per unit area (0.16±0.05 Mg C $ha^{-1}$ $yr^{-1}$).

Table 2.4: Average (2000-2011) NPP reductions in the USGS-GAP land cover classes

| **Land Cover (USGS-GAP)** | **Class Code** | **NPP reduction per unit area (Mg C ha$^{-1}$ yr$^{-1}$)** | **Land Area (%)** | **Total NPP reduction (Tg C yr$^{-1}$)** |
|---|---|---|---|---|
| Western Great Plains Shortgrass Prairie | 7310 | 0.26±0.05 | 13.37 | 4.10±0.78 |
| Western Great Plains Sandhill Steppe | 5301 | 0.25±0.08 | 3.17 | 0.91±0.28 |
| Western Great Plains Mesquite Woodland and Shrubland | 5810 | 0.26±0.08 | 3.80 | 1.17±0.35 |
| Southern Rocky Mountain Ponderosa Pine Woodland | 4530 | 0.40±0.07 | 3.77 | 1.76±0.31 |
| Southern Rocky Mountain Pinyon-Juniper Woodland | 4534 | 0.42±0.07 | 1.28 | 0.62±0.10 |
| Southern Rocky Mountain Juniper Woodland and Savanna | 5606 | 0.25±0.05 | 1.08 | 0.31±0.07 |
| Sonoran Paloverde-Mixed Cacti Desert Scrub | 5213 | 0.16±0.05 | 1.94 | 0.35±0.10 |
| Sonora-Mojave Creosotebush-White Bursage Desert Scrub | 5207 | 0.22±0.05 | 1.35 | 0.34±0.08 |
| Madrean Pinyon-Juniper Woodland | 4518 | 0.26±0.04 | 1.61 | 0.49±0.07 |
| Introduced Upland Vegetation - Perennial Grassland and Forbland | 8407 | 0.22±0.05 | 1.23 | 0.31±0.08 |
| Introduced Upland Vegetation - Annual Grassland | 8404 | 0.22±0.05 | 1.11 | 0.28±0.06 |
| Inter-Mountain Basins Semi-Desert Shrub Steppe | 5309 | 0.33±0.03 | 4.08 | 1.57±0.14 |
| Inter-Mountain Basins Semi-Desert Grassland | 7305 | 0.31±0.04 | 2.94 | 1.06±0.13 |
| Inter-Mountain Basins Montane Sagebrush Steppe | 5308 | 0.72±0.11 | 1.55 | 1.29±0.19 |
| Inter-Mountain Basins Mixed Salt Desert Scrub | 5205 | 0.29±0.04 | 2.69 | 0.91±0.11 |
| Inter-Mountain Basins Greasewood Flat | 9810 | 0.29±0.03 | 1.12 | 0.37±0.03 |
| Inter-Mountain Basins Big Sagebrush Shrubland | 5706 | 0.38±0.04 | 3.86 | 1.71±0.18 |
| Great Basin Pinyon-Juniper Woodland | 4514 | 0.33±0.11 | 1.05 | 0.40±0.13 |
| Colorado Plateau Pinyon-Juniper Woodland | 4512 | 0.35±0.05 | 7.99 | 3.28±0.45 |
| Colorado Plateau Mixed Bedrock Canyon and Tableland | 3218 | 0.28±0.05 | 1.02 | 0.33±0.05 |
| Colorado Plateau Blackbrush-Mormon-tea Shrubland | 5803 | 0.16±0.04 | 1.12 | 0.21±0.05 |
| Chihuahuan Mixed Desert and Thorn Scrub | 5212 | 0.21±0.06 | 2.15 | 0.53±0.15 |
| Chihuahuan Creosotebush, Mixed Desert and Thorn Scrub | 5201 | 0.23±0.05 | 4.27 | 1.16±0.25 |
| Central Mixedgrass Prairie | 7302 | 0.26±0.08 | 3.50 | 1.07±0.34 |
| Apacherian-Chihuahuan Semi-Desert Grassland and Steppe | 5303 | 0.23±0.05 | 4.89 | 1.32±0.26 |
| Apacherian-Chihuahuan Mesquite Upland Scrub | 5211 | 0.18±0.05 | 4.09 | 0.85±0.22 |

*Notes:* 26 USGS-GAP land cover classes that occupy more than 1% of the study area are reported. Average reductions with ± one standard deviation were calculated using the UMD LNS, expressed in NPP units.

## *2.5 Discussion*

In general, the twelve-year average UMD LNS map (Figure 2.4) indicated widespread, large reductions in productivity compared with their reference conditions. NPP reductions also varied between different land cover and land management types. NPP reduction per unit area was high for all areas of forest cover, possibly due to insect damage, diseases, fire and managed clearing (Floyd *et al.*, 2009; Heath *et al.*, 2011; Hicke *et al.*, 2012; Anderegg *et al.*, 2013). In the Shrubland and Herbaceous NLCD vegetation classes, the NPP reduction per unit area was relatively low, but they occupy nearly 85% of the study region and therefore, in total, contribute large reduction of potential NPP.

Livestock grazing allotments showed similar patterns to grassland-savanna with large areas of small reductions below potential, but with high interannual variability. Overgrazing is often stated to be one of the key drivers of land degradation, associated with alterations in ecosystem structure (Asner *et al.*, 2004) and soil erosion, both of which may lead to steep decline in forage production (Pellant *et al.*, 2005). In addition, Holechek *et al.* (1995) and Ganskopp (2001) have demonstrated strong association between water availability and forage utilization. Higher utilization can be observed around the cattle drinking locations within the grazing allotments as noted elsewhere (Pickup *et al.*, 1998; DelCurto *et al.*, 2005), including utilization by livestock in riparian areas (Bear *et al.*, 2012; Dalldorf *et al.*, 2013) which are, however, generally masked in the LNS procedure. The high interannual variability in the LNS around the watering points may be indicative of deliberate management of livestock access to water.

The LNS maps have some sharp boundaries between degraded and less-degraded land associated with human activities (Figure 2.5) especially at the edges of active and abandoned mining and oil extraction facilities, across fences between neighboring grazing allotments and at the edges of forest clearings. Such abrupt differences across boundaries are not surprising given the role of human management in degradation. While many LNS values were low each year, interannual variability in LNS could be caused by changes in land-use, such as livestock grazing and fire which were not used in the creation of LCCs.

The classification into LCCs with uniform environmental variables is a critical step since they are a basis for comparisons between degraded and non-degraded, reference sites. Without such reference sites, any statement of degradation can simply be differences, for example, in rainfall, soil or other irrelevant factors and therefore have little meaning. A good example is the Native American reserves in the Four Corners district which are generally considered to be extreme cases of degradation, attributed to poor management. On the contrary, the LNS results reported here found that the reserves have a low reference potential and are therefore not degraded in the sense that it is used here.

There is a long history of conceptually similar land evaluation (FAO, 1976; McRae & Burnham, 1981), however, these are developed for specific purposes, such as evaluation of land for new forest plantations or suitability for the passage of heavy vehicles. In the case of LNS, the criterion for an LCC is an area in which productivity would be equal throughout, unless there is some other factor such as degradation present. The environmental variables used were selected to represent the chief controlling factors of NPP in the study region and that were available in maps with adequate spatial and temporal resolutions. Precipitation is the major environmental factor that controls productivity in the arid and semi-arid regions (Noy-Meir, 1973; Graetz *et al.*, 1988) but the effects of precipitation can be significantly more complex than the annual totals used here can specify. Changes in the frequency and seasonal distribution of precipitation may alter the vegetation response at critical times in the life-cycle (Knapp *et al.*, 2008) and could influence the vegetation more strongly than annual totals (Ojima *et al.*, 1993; Graetz *et al.*, 1988).

While more functional metrics could be included in the creation of the LCCs, the selection depends on having the necessary data. Naturally, the more variables relevant to NPP that are included in the creation of LCCs, the better their homogeneity. Process models that convolve the controlling factors in a more mechanistic representation of NPP than a statistical model, as used here, could yield better LCCs, but most process models need more data and parametrizations than were available at the scale of this study. Nevertheless, progress in LCC development using mechanistic NPP models is an obvious way forward.

There are various reasons why LNS may not indicate land degradation. For example, if important factors that affect the potential NPP are not included in the LCC step, differences in LNS may be a reflection of the differences in potential rather than degradation. Another is if any areas that are not representative of the LCC, such as wetlands and riparian areas are inadvertently included. Yet another is, if there are no pixels in an LCC at their potential production, the LNS values will indicate less degradation than is the case. However, in spite of these shortcomings, the only other methods available at present involve direct field measurement of NPP, which is impossible for areas larger than a few $km^2$, or a mechanistic productivity model. However, adequate parameterization and forcing data to resolve differences in NPP at a scale that is relevant to the typical areas of anthropogenic degradation is not possible. Given these circumstances, LNS is used here, in the knowledge of its limitations.

The reductions of the potential NPP that are revealed by LNS can have many causes in addition to degradation. These include any natural conditions (e.g. natural erosion) or management (e.g. application of fertilizers) that affect NPP but are not normalized in the classification into LCCs. Since these factors are difficult to normalize, the role of LNS is to identify, map and assess the severity of reductions in LNS, but the causes require further interpretation. This may involve further remote sensing or field reconnaissance. Once sites that are affected by degradation are identified, then actions can be taken to better understand the causes and develop sustainable utilization avoiding irreversible degradation and to increase the capacity of land to sequester $CO_2$. Identification of the causes of low LNS may not be possible if low values occur in the first year of study, which indicates degradation was caused prior to the study period.

Errors in LNS can be caused if reference pixels have different potential NPP owing to factors other than those accounted for in the classification: for example small run-on patches can have a high NPP that is unrelated to the rest of the LCC.

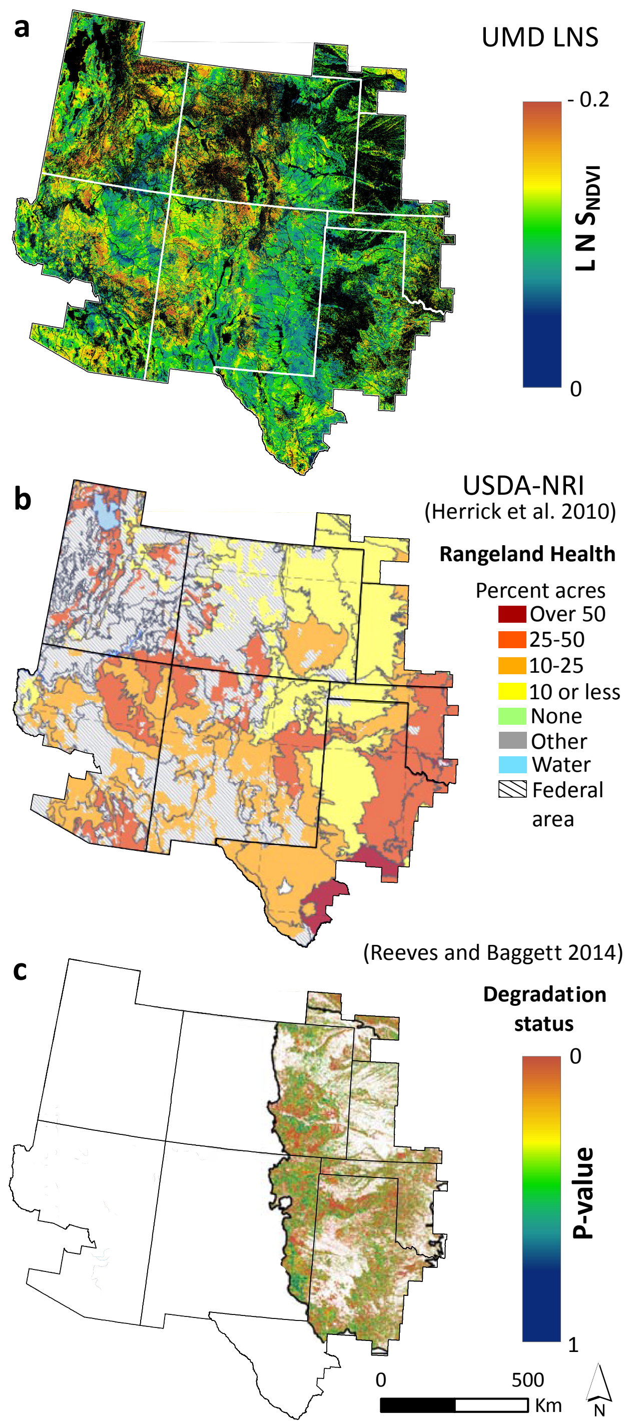


Figure 2.6: Comparison of (a) UMD LNS, (b) USDA-NRI map of non-Federal rangelands where biotic integrity shows at least moderate departure from reference condition (Herrick *et al.*, 2010), and (c) overlapping parts of Reeves and Baggett (2014) map of degradation represented as p-values from t-tests between the mean response of each pixel and reference conditions. Except USDA-NRI map, both UMD LNS and Reeves and Baggett (2014) maps of degradation were satellite based.

Similarly, overly conservative masking may eliminate some of the most degraded areas, such as livestock trampling near water. Even unrepresentative areas that are smaller than the pixel sized used could bias the classification. Finer spatial resolution data, such as Landsat 30m, would reduce this problem, but usually such finer spatial resolution data have low repeat frequency that reduces the accuracy of estimation of the total, seasonal NPP. Moreover, if data for environmental variables at this scale are not available, nothing would be gained.

In a recent study, Reeves & Baggett, 2014 reported rangeland degradation relative to reference condition in the northern and southern Great Plains of the U.S. (Figure 2.6-c). Their method created reference areas using the NDVI of each individual pixel relative to the mean maximum NDVI of the ecological unit in which it occurred. There are three differences with LNS: *i.* the ecological units were the same in each year, irrespective of any differences in interannual environmental variation such as rainfall; *ii*. the mean maximum was influenced by the NDVI of all the pixels in the unit, some of which may themselves be degraded, thus the measure of degradation could be biased in a heavily degraded ecological unit; *iii*. since the pixel data were the mean of the maxima of NDVI across the entire study period (13 years), any interannual variation could not be detected. Nevertheless, Reeves and Baggett (2014) results have some broad similarities to LNS, for example in the areas of eastern New Mexico and Colorado and northwestern Texas. There were, however, large differences in the degree of degradation, even in some known areas of degradation (Figure 2. 6).

The USDA NRCS-NRI rangeland degradation assessment maps (Figure 2b)

(Herrick *et al.*, 2010) differ from LNS to a much greater extent than Reeves and Baggett (2014). For example, the NRI map of "biotic integrity" shows intense degradation in areas where LNS has only moderate departure from the reference condition, such as in the region at the intersection of state lines of UT, CO, NM, AZ ("four corners") also western TX and OK (Figure 2.6). Changes in species composition may reduce the "rangeland health" through reduction in biotic integrity and palatability but, at the same time, may increase the NPP (Knapp *et al.*, 2008). For example, several studies (Asner *et al.*, 2003; Laliberte *et al.*, 2004; Liu *et al.*, 2013) have found woody encroachment into grassland-savanna ecosystem by honey mesquite (*Prosopis glandulosa Torr.)* in the southwest US (Goslee *et al.*, 2003) that changes species composition and simultaneously increases NPP. Thus, there are some fundamental differences in LNS and NRI's methods that contribute to the differences. However, NRI was based on non-federal lands alone, while LNS included federal lands as well; also the NRI maps use ecosystem metrics such as "hydrologic function" and "soil and site stability" in addition to "biotic integrity", and not NPP. Aside from these legitimate differences, the NRI maps are an interpolation between data from field samples ("sections") that were between 16 and 259 ha, giving a spatial sampling rate of between 0.063% and 1%, but without an explicit method to allow for variations between point samples, whereas LNS uses satellite data with complete coverage.

*2.6 Conclusions*

With growing population and increased human consumption of primary production (Rojstaczer *et al.*, 2001; Haberl *et al.*, 2007; Krausmann *et al.*, 2013), land degradation is increasing. While there are broad changes that increase the risks of degradation, such as anthropogenic climate change, pollution and governmental policies, human-induced degradation is characterized by strong local spatial patterns caused by local differences in management. Thus the complete coverage and high spatial resolution of satellite-based monitoring systems are needed, coupled with field interpretation (Herrick *et al.*, 2010). The elaborated methodology and the reduction assessments reported here will not only help local sustainable management, but also influence policies intended to enhance US as well as global carbon sequestration. Currently, policies for carbon sequestration often use the findings of "potential" primary production models. However, such models do not take into account of human modifications of land and its processes. The differences between potential production and actual can be very large, to the extent that potential models can be irrelevant.

This study provides an assessment of dryland degradation and estimates of reductions of productivity in the SW U.S study area. It also identifies areas where remediation efforts would have the greatest effects on regional C sequestration if applied to areas with higher productive potential and vice versa. The total NPP reductions were 35.9±4.7 Tg C $yr^{-1}$. The reductions were large and mostly consistent between years in spite of large variations in overall NPP caused by interannual differences in rainfall and other aspects of weather. The results indicate the overall difference between potential and actual NPP in the SW USA was 11.8%.

# Chapter 3: Forest Carbon Emissions from Cropland Expansion in the Brazilian Cerrado Biome


## *3.1 Summary*

Land use, land use change, and forestry accounted for two-thirds of Brazil's greenhouse gas emissions profile in 2005. Amazon deforestation has declined by more than 80% over the past decade, yet Brazil's forests extend beyond the Amazon biome. Understanding forest dynamics across all biomes is critical to avoid cross-biome leakage that undermines climate change mitigation efforts such as Reducing Emissions from Deforestation and forest Degradation (REDD+). Satellite data on cropland expansion, forest cover, and vegetation carbon stocks were used to estimate annual gross forest carbon emissions from cropland expansion in the Cerrado biome. Nearly half of the Cerrado met Brazil's definition of forest cover in 2000 (≥0.5 ha with ≥10% canopy cover). In areas of established crop production, conversion of both forest and non-forest Cerrado formations for cropland declined during 2003-2013. However, forest carbon emissions from cropland expansion increased over the past decade in Matopiba, a new frontier of agricultural production that includes portions of Maranhão, Tocantins, Piauí, and Bahia states. Gross carbon emissions from cropland expansion in the Cerrado averaged 16.28 Tg C $yr^{-1}$ between 2003 and 2013, with forest-to-cropland conversion accounting for 29% of emissions. However, the fraction of forest carbon emissions from Matopiba was much higher; between 2010-2013, large-scale cropland conversion in Matopiba contributed 45% of the total Cerrado forest carbon emissions. Carbon emissions from Cerrado-to-cropland transitions partially offset emissions reductions (1.9% - 5%) from declining rates of

Amazon during 2011-2013. Comprehensive national estimates of forest carbon fluxes, including all biomes, are critical to detect cross-biome leakage within countries and achieve climate mitigation targets to reduce emissions from land use, land use change, and forestry.

### *3.2 Introduction*

Deforestation is an important source of global greenhouse gas emissions from human activity (van der Werf *et al.*, 2009a; van der Werf *et al.*, 2009b; Le Quéré *et al.*, 2015). For tropical forest countries such as Brazil, carbon emissions from deforestation account for a large proportion of total greenhouse gas emissions (42% of $CO_2$ emissions in 2010; BRAZIL, 2016). Efforts to Reduce Emissions from Deforestation and Forest Degradation (REDD+) are therefore a critical component of climate mitigation activities (UNFCCC, 2015; Morton, 2016). Over the past decade, deforestation in the Brazilian Amazon declined by 80% (BRAZIL, 2014), highlighting the potential for government, industry, and non-governmental organizations to achieve emissions reductions from forest regions (e.g., Soares-Filho *et al.*, 2014; Gibbs *et al.*, 2015). However, forest cover in Brazil extends beyond the Amazon biome. The success of REDD+ efforts therefore depends on complete national accounting of forest cover changes, including emissions from Cerrado forest conversion processes.

The Cerrado biome is a vast neotropical savanna ecosystem covering more than 2 million $km^2$, second only to the Amazon in terms of size. A biodiversity hotspot, the Cerrado comprises a diverse mix of grasslands, shrublands, and woodlands (Felfili & Silva Júnior, 2005; Klink & Machado, 2005). Aboveground biomass varies by Cerrado physiognomy and fractional tree cover (Ottmar *et al.*, 2001; Saatchi *et al.*, 2011; de Miranda *et al.*, 2014). Large carbon stores are also found in belowground biomass and soil carbon because Cerrado vegetation allocates substantial resources to root production (de Miranda *et al.*, 2014). The combined above and belowground carbon stocks in Cerrado vegetation likely represent an important source term in Brazil's national greenhouse gas emissions. Yet, current reporting either excludes forest conversion in the Cerrado (BRAZIL, 2014) or provides aggregated, multi-year estimates for all cover types and land uses (Lapola *et al.*, 2014; BRAZIL, 2016), complicating efforts to track regional dynamics with satellite observations of land use change or greenhouse gas emissions.

Nearly half of the Cerrado has been converted to pasture (29.5%) or cropland (11.7%) (MMA, 2015), and only a small portion (8.2%) of the biome is formally protected by parks or indigenous reserves (BRAZIL, 2016). Since 1990, the Cerrado region has emerged as the leading producer of major export crops, and by 2014 it accounted for the majority of Brazil's planted area in soy (61%), maize (61%), and cotton (99%) (IBGE, 2013). As in the Brazilian Amazon (Morton *et al.*, 2006; Macedo *et al.*, 2012), soy production is an important driver of deforestation in the Cerrado (Gibbs *et al.*, 2015; Morton *et al.*, 2016), motivated primarily by international market demand for animal ration (Nepstad *et al.*, 2011; Lambin & Meyfroidt, 2011; Garrett *et al.*, 2013; Lathuillière *et al.*, 2014; Godar *et al.*, 2015). From 2008-2012, annual deforestation rates in the Cerrado were more than double that of the Brazilian Amazon (Lambin *et al.*, 2013). Recent expansion has been concentrated in new agricultural frontiers, including the Matopiba region that encompasses portions of Maranhão, Tocantins, Piauí, and Bahia states (BRAZIL, 2016; Gibbs *et al.*, 2015; MMA, 2015; Spera *et al.*, 2016). The Brazilian government's Matopiba Development Plan outlines a strategy for continued agricultural expansion in the region as part of a broader initiative on low-carbon agriculture.

Recent cropland expansion in the Cerrado region also reflects important changes in environmental legislation and industry efforts to reduce Amazon deforestation. The Forest Code (FC) is a key component of Brazil's environmental legislation (Soares-Filho *et al.*, 2014), with specific guidelines for legal reserves of natural vegetation on private properties in the Amazon (80%) and Cerrado (35% within the Legal Amazon, 20% for Cerrado outside the Legal Amazon). Changes to the FC legislation in 2012 removed permanent protection of "hill top" areas, opening large areas of the Matopiba region for potential land use (Soares-Filho *et al.*, 2014; Hunke *et al.*, 2015). The Soy Moratorium (SoyM), an industry-led effort to reduce Amazon deforestation for soy production, contributed to marked reductions in Amazon deforestation (Macedo *et al.*, 2012; Gibbs *et al.*, 2015), but did not address forest conversion in the neighboring Cerrado biome. Together, the SoyM and the new FC legislation altered the dynamics of soy expansion in the Brazilian Amazon, incentivizing production in other regions, including the Cerrado, where the SoyM is not implemented and the FC allows a larger fraction of individual properties to be converted for agriculture (i.e. "cross-biome leakage"). In addition to these legal constraints, older frontiers of soy expansion (e.g., Mato Grosso) have few remaining flat lands suitable for large-scale grain production (Morton *et al.*, 2016), driving soy producers to alternative frontiers.

In this study, satellite remote sensing data on recent cropland expansion and vegetation carbon stocks was combined to estimate gross forest carbon emissions from cropland expansion in the Cerrado. This study addresses two primary questions in the context of complete carbon accounting for REDD+ (Bustamante *et al.*, 2016; Morton et al., 2011) and global carbon emissions from land use change (Le Quéré *et al.*, 2015): (1) Is cropland expansion an important driver of forest conversion in the Cerrado? (2) To what extent do carbon emissions from forest conversion in the Cerrado offset emissions reductions from declining Amazon deforestation? Satellite-based estimates of annual cropland expansion provide critical insights into the spatial and temporal dynamics of land use emissions in the Cerrado. Expanding estimates of tropical forest carbon emissions beyond the Amazon biome is a critical step to improve regional and global carbon budgets, as Cerrado emissions contribute directly to fire carbon losses observed by regional atmospheric inversion studies (Gatti *et al.*, 2014; Alden *et al.*, 2016) and global observing networks (e.g., Keppel-Aleks *et al.*, 2014).

## *3.3 Materials and methods*

### 3.3.1 Cropland expansion 2003-2013

Annual estimates of cropland expansion in the Cerrado were developed using time series of Moderate Resolution Imaging Spectroradiometer (MODIS) data at 250m resolution from NASA's Terra satellite (Gibbs *et al.*, 2015; Morton *et al.*, 2016).  Although soy is an important driver of recent agricultural expansion in the Cerrado (IBGE, 2013), mapped cropland in this study included all mechanized agriculture based on phenology metrics associated with planting and harvesting row crops, similar to previous studies of cropland dynamics in Brazil (Morton *et al.*, 2006; Galford *et al.*, 2008; Rudorff *et al.*, 2011; Macedo *et al.*, 2012).  A detailed description of the land cover change analysis can be found in Gibbs *et al.* (2015).

### 3.3.2 Cropland expansion and carbon emissions

Annual estimates of cropland expansion with data on percent tree cover and vegetation carbon stocks were combined to estimate gross carbon emissions.  Forest and non-forest emissions were separated using fractional tree cover data (Hansen *et al.*, 2013). For reporting purposes, Brazil defines 'forest' as land spanning more than 0.5 hectares, with trees higher than 5 meters and a canopy cover of more than 10 percent  (BRAZIL, 2014). Based on this definition, a threshold of 10% canopy cover was used to separate forests and other wooded land areas (>10%) from non-forest areas (≤10%) in the Cerrado.

Vegetation carbon stocks for Cerrado vegetation were estimated using data from Saatchi *et al.* (2011) in areas of cropland expansion. Saatchi *et al.* (2011) used satellite data to model pantropical vegetation carbon stocks through 2005, including radar data with specific sensitivity to lower aboveground carbon stocks in savanna and woodland cover types.  For cropland expansion after 2005, emissions were calculated using spatially-explicit estimates of vegetation carbon stocks from Saatchi *et al.* (2011).  For cropland expansion prior to 2005, the relationship between 2000

Landsat fractional tree cover estimates (Hansen *et al.*, 2013) and Saatchi *et al.* (2011) biomass estimates were used for remaining areas of natural Cerrado vegetation (MMA, 2015) to develop a look-up table of pre-conversion vegetation carbon stocks based on fractional tree cover in 2000. Uncertainties in vegetation carbon stocks (Saatchi *et al.*, 2011) were propagated into carbon loss estimates, scaling the total emissions estimates using the annual average carbon stock uncertainty from cropland expansion pixels each year.

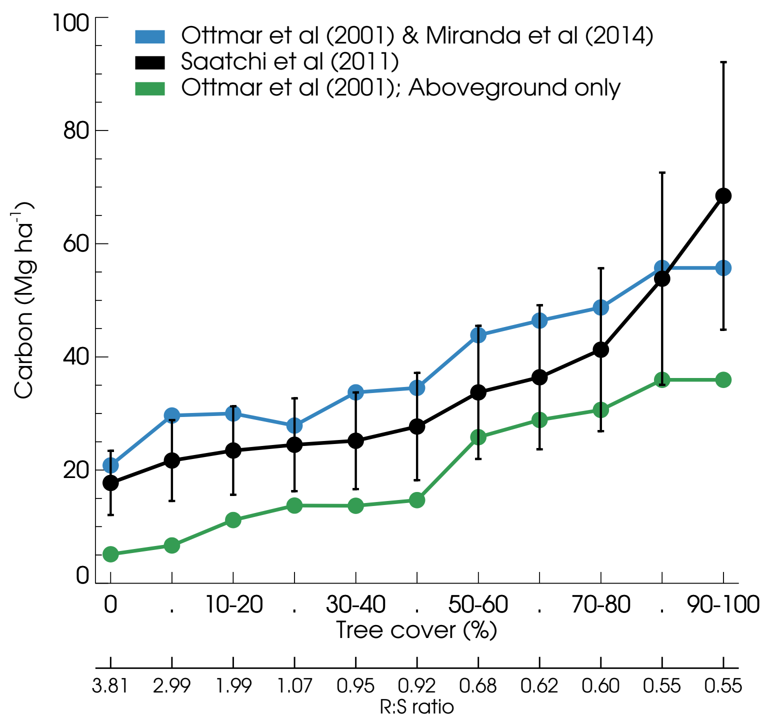


Figure 3.1: Estimated carbon stocks in Cerrado vegetation, summarized by fractional tree cover intervals. Satellite-derived estimates represent above and below ground vegetation carbon stocks (Saatchi *et al.*, 2011), while in-situ measurements represent aboveground carbon stocks in Cerrado vegetation (Ottmar *et al.*, 2001) or total carbon stocks based on aboveground (Ottmar *et al.*, 2001)and below ground carbon (de Miranda *et al.*, 2014). Error bars indicate the average uncertainty in estimated total carbon stocks for each tree cover decile.

Carbon stock estimates from Saatchi *et al.* (2011) was compared to field measurements for each tree cover interval. Satellite-based estimates of aboveground biomass compared favorably to field estimates from Ottmar *et al.* (2001), binned by fractional tree cover (Figure 3.1). Saatchi *et al.* (2011) used a root:shoot ratio that scales with aboveground biomass (AGB) to estimate belowground biomass (BGB) and total vegetation carbon stocks:

$$BGB = 0.489AGB^{0.89}$$

For low-biomass cover types (1-5 Mg $ha^{-1}$), this relationship yields a root:shoot ratio over 40%, while the root:shoot ratio ranges from 25-30% for high-biomass cover types (75-300 Mg $ha^{-1}$). A recent synthesis of Cerrado field data suggests that average root:shoot ratios could be much higher for grasslands (334%) and shrublands (166%) with intermediate tree cover (de Miranda *et al.*, 2014). For comparison, a look-up table based on aboveground biomass (Ottmar et al 2001) and root:shoot ratios (de Miranda *et al.*, 2014) was developed for different fractional tree cover intervals to estimate gross carbon emissions from cropland expansion in the Cerrado (Figure 3.1).

Estimated gross carbon emissions from cropland expansion included both above and belowground biomass. Mechanized crop production requires the complete removal of above and belowground woody biomass, typically through repeated burning of piled woody debris (DeFries *et al.*, 2008; Morton *et al.*, 2008; van der Werf *et al.*, 2009a). Gross and net carbon emissions from deforestation for cropland are therefore similar, as long-term carbon storage in annual crops is small (DeFries *et al.*, 2008). Gross carbon emissions estimates excluded changes in soil carbon pools. Soil carbon stocks in Cerrado cover types are large, but recent studies suggest small net carbon losses following agricultural conversion (Cerri *et al.*, 2009; Batlle-Bayer *et al.*, 2010; Mello *et al.*, 2014; Bustamante *et al.*, 2012; Bustamante *et al.*, 2016), in part due to the widespread practice of no-till agriculture.

Gross carbon emissions from cropland expansion in the Cerrado were compared to gross (committed) carbon emissions from deforestation in the Brazilian Amazon. For 2003-2010, data from Brazil's forest reference emissions level (FREL) report to the United Nations Framework Convention on Climate Change (UNFFCCC; BRAZIL, 2014) was used. For 2011-2013, deforestation carbon emissions were estimated using the average vegetation carbon stocks from deforestation in 2003-2010 (153 Mg ha$^{-1}$) and annual deforestation estimates from PRODES (BRAZIL, 2014). Forest carbon emissions from 2011-2013 Amazon deforestation declined relative to the 2011-2015 baseline (247.63 Tg C yr$^{-1}$, BRAZIL, 2014). Gross carbon emissions from cropland expansion in the Cerrado offset some of these declines, estimated as the difference between deforestation carbon emissions and the 2011-2015 baseline.

## *3.4 Results*

### 3.4.1 Cropland expansion

Cropland expansion in the Cerrado biome was widespread over the decade from 2003-2013, totaling more than 9 Mha, of which 1.72 Mha replaced forests and other wooded lands. In the first half of the decade, cropland expansion was concentrated in areas of established production in the south and west (Figure 3.2). Since 2008, however, the Matopiba region accounted for 14% of all cropland expansion, including 30% of all cropland expansion into forest. MODIS-based estimates of total cropland area in 2013 were 15% lower than estimates from TerraClass, a Landsat-based land cover classification. These differences were attributable to the coarser spatial resolution of MODIS data (250 m versus 30 m) and conservative spatio-temporal filtering used in the MODIS approach (Gibbs *et al.*, 2015).

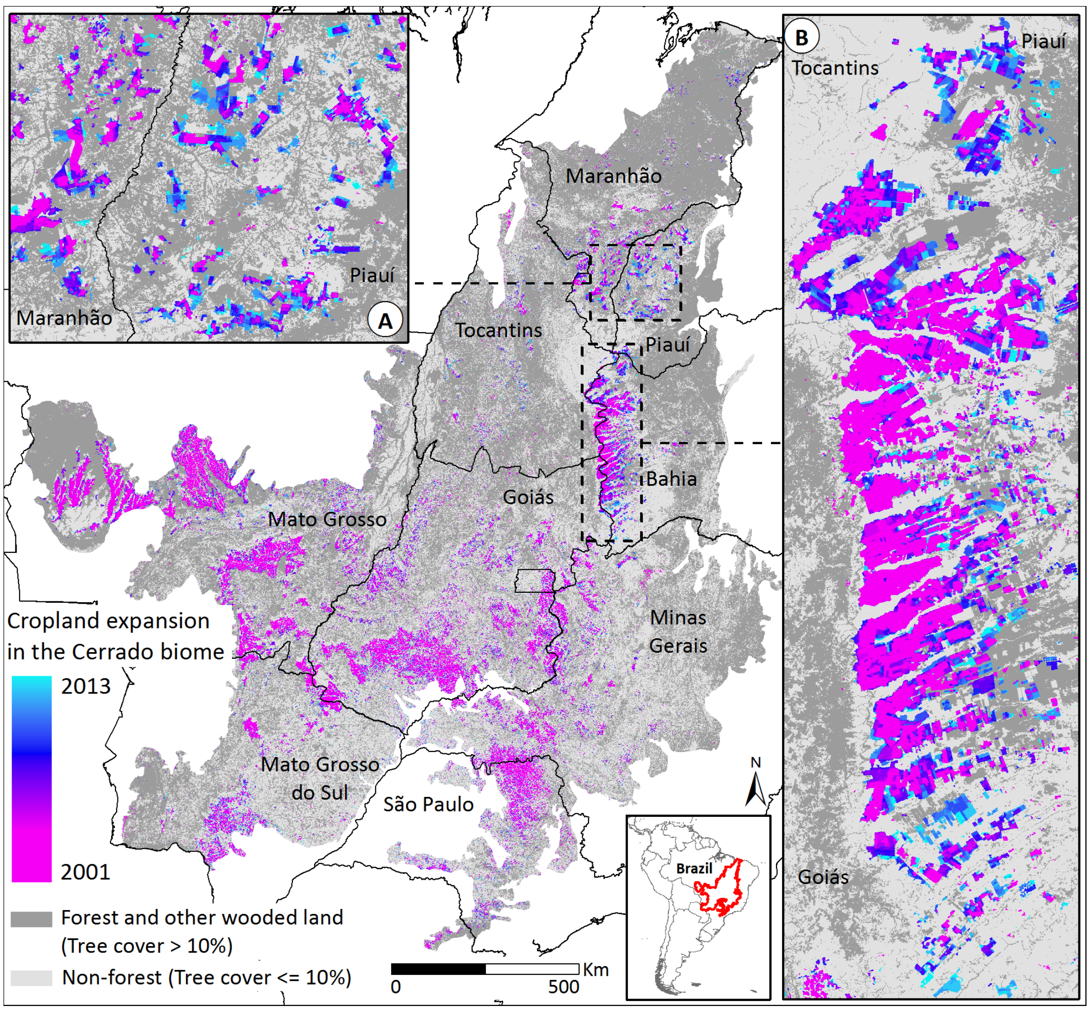


Figure 3.2: Cropland extent and annual cropland expansion in the Cerrado biome between 2001 and 2013. Panels A & B (inset) highlight cropland expansion in the Matopiba region into forest and other wooded land (dark grey, tree cover > 10%) and non-forest land (light grey, tree cover ≤10%).

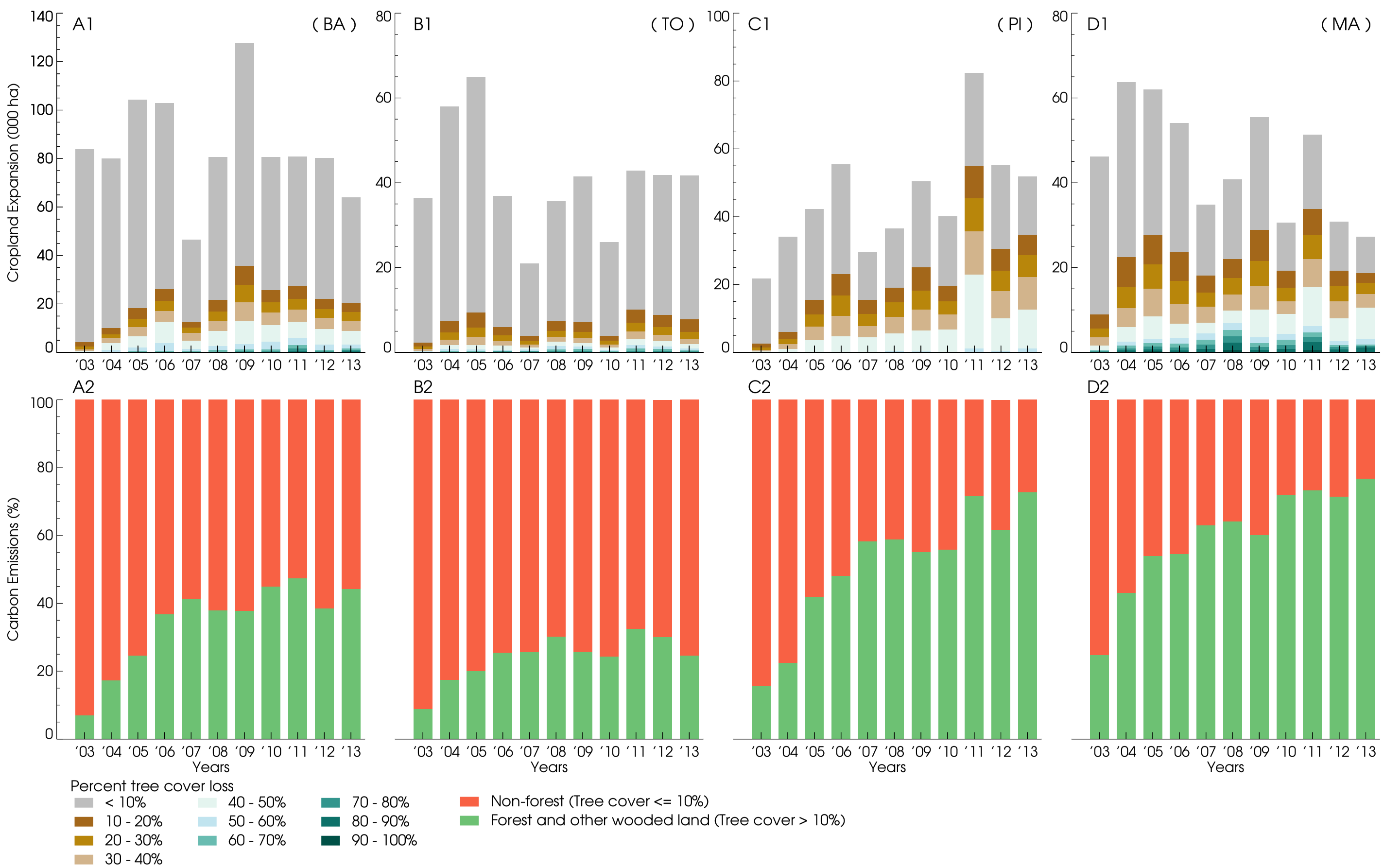


Figure 3.3: Cropland expansion and related carbon emissions in the Matopiba region between 2003-2013. A1-D1) Annual cropland expansion and associated fractional tree cover loss; A2-D2) Breakdown of estimated annual gross carbon emissions from cropland expansion into non-forest (tree cover ≤10%) and forest and other wooded land (tree cover > 10%). States are labeled as Bahia (BA), Tocantins (TO), Piauí (PI), and Maranhão (MA).

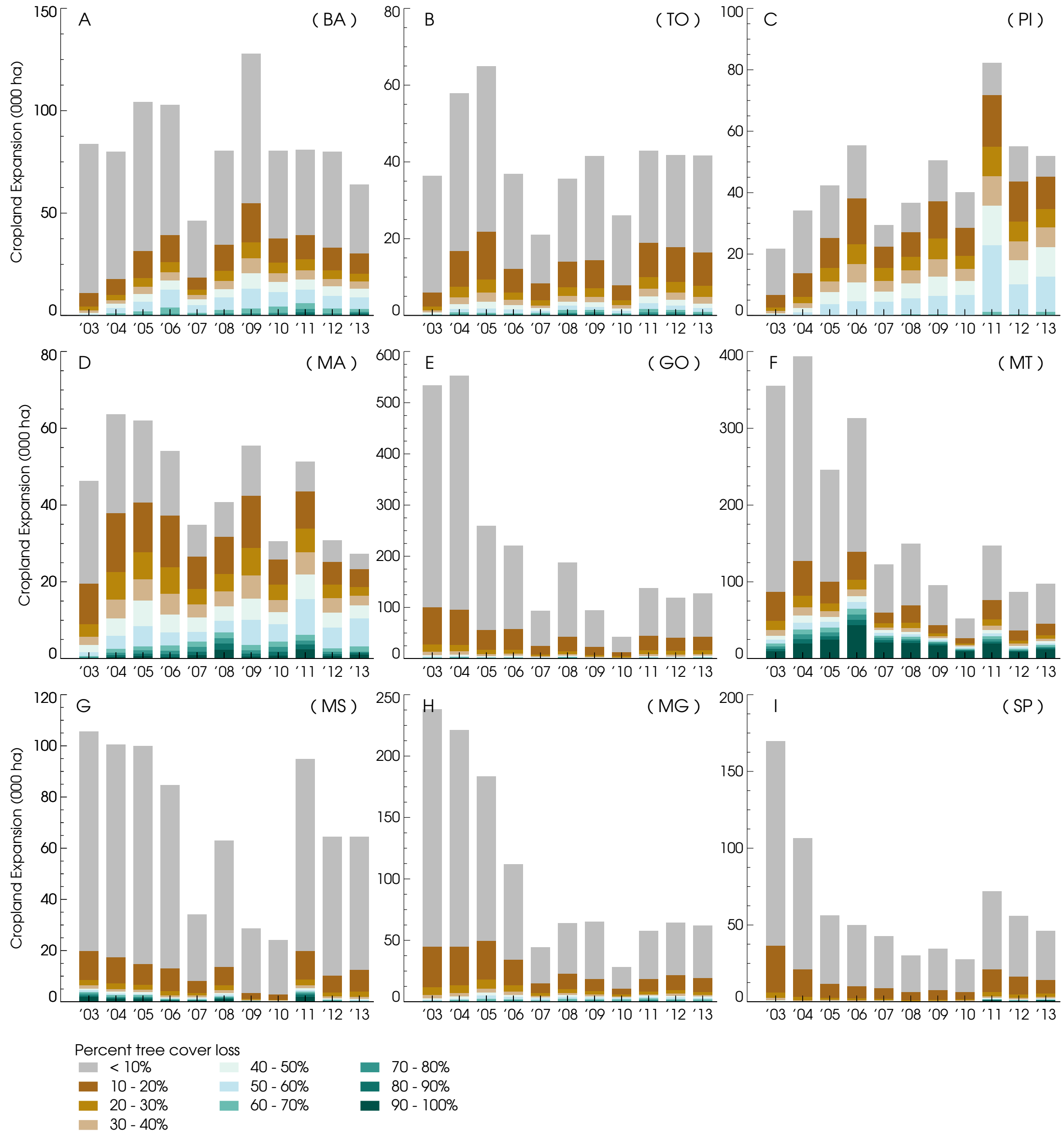


Figure 3.4: Annual cropland expansion into forest and non-forest Cerrado cover types for Brazilian states in the Cerrado biome. States are labeled as Bahia (BA), Tocantins (TO), Piauí (PI), Maranhão (MA), Goiás (GO), Mato Grosso (MT), Mato Grosso do Sul (MS), Minas Gerais (MG), and São Paulo (SP).

Overall, woody cover was not a strong barrier to cropland expansion in the Cerrado. On average, approximately 21% of the annual cropland expansion replaced forests and woodlands. In Matopiba, however, forest conversion accounted for a larger fraction of new cropland (Figure 3.3), especially in the states of Maranhão (51%) and Piauí (46%). Annual rates of cropland expansion in Matopiba remained consistent during this period, with steady increases in forest conversion for cropland expansion even as cropland expansion declined in other Cerrado regions (Figure 3.4).

### 3.4.2 Gross carbon emissions from cropland expansion

Conversion of forest and non-forest Cerrado formations for cropland expansion was an important source of carbon emissions during 2003-2013. Over the study period, conversion of forest and other wooded lands accounted for 29% (52 Tg C) of estimated total carbon emissions from cropland expansion in the Cerrado biome, with 127 Tg C (71%) from non-forest Cerrado physiognomies. Annual emissions from forest and non-forest conversion averaged 16.3 Tg C $yr^{-1}$, with considerable interannual variability due to changes in rates of cropland expansion and the proportion of forest cover types converted (Figure 3.5). Average annual emissions from forest conversion for cropland were 4.69 Tg C $yr^{-1}$.

Emissions estimates using the look-up table approach (Figure 3.6) were somewhat higher than using total vegetation carbon stock data from Saatchi *et al.* (see Figure 3.5). Field data suggest a greater allocation to belowground biomass by Cerrado vegetation than estimated by Saatchi *et al.*, leading to higher vegetation carbon stocks for each fractional tree cover bin (Figure 3.1). Average carbon emissions from conversion of forest and non-forest Cerrado areas to cropland were higher in the look-up table approach by 1.09 Tg C $yr^{-1}$ (18.9%) and 4.22 Tg C $yr^{-1}$ (29.3%), respectively.

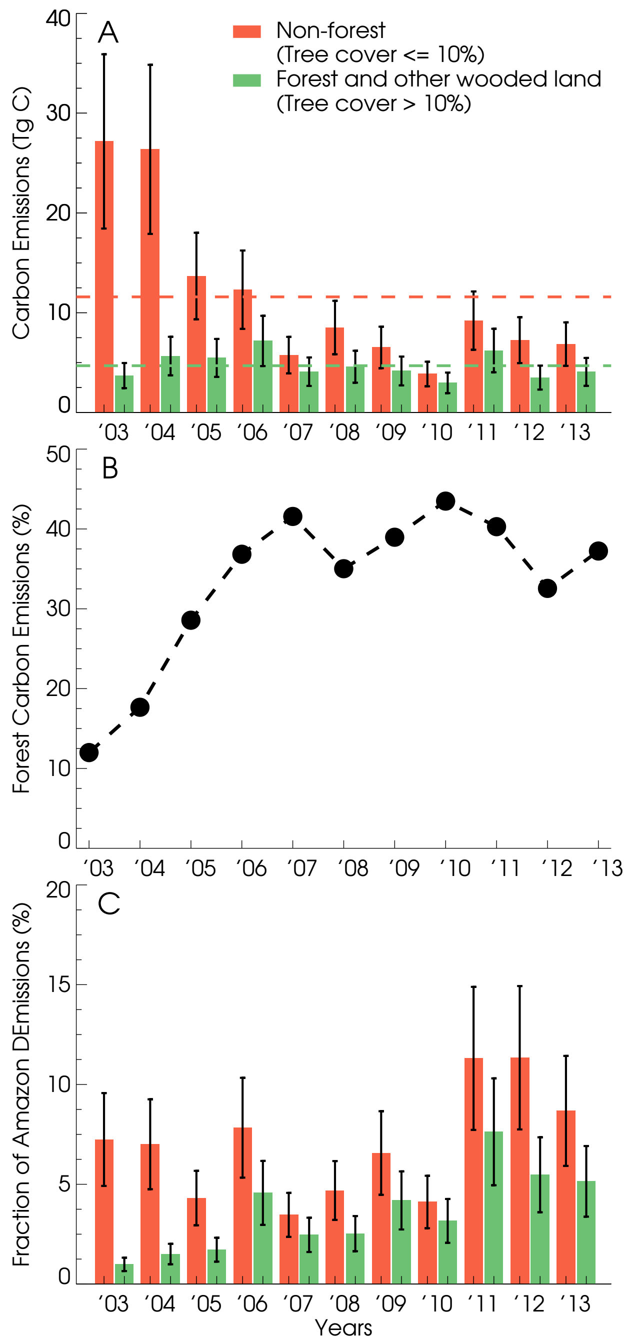


Figure 3.5: A) Estimated annual gross carbon emissions from cropland expansion into non-forest (orange) and forested Cerrado cover types (green) between 2003 and 2013. Error bars indicate ± average uncertainty in vegetation carbon stocks within cropland expansion areas. B) Fractional contribution from forest conversion to gross carbon emissions from cropland expansion in Cerrado. C) Comparison between gross carbon emissions from cropland expansion in the Cerrado to emissions from deforestation in the Amazon between 2003 and 2013.

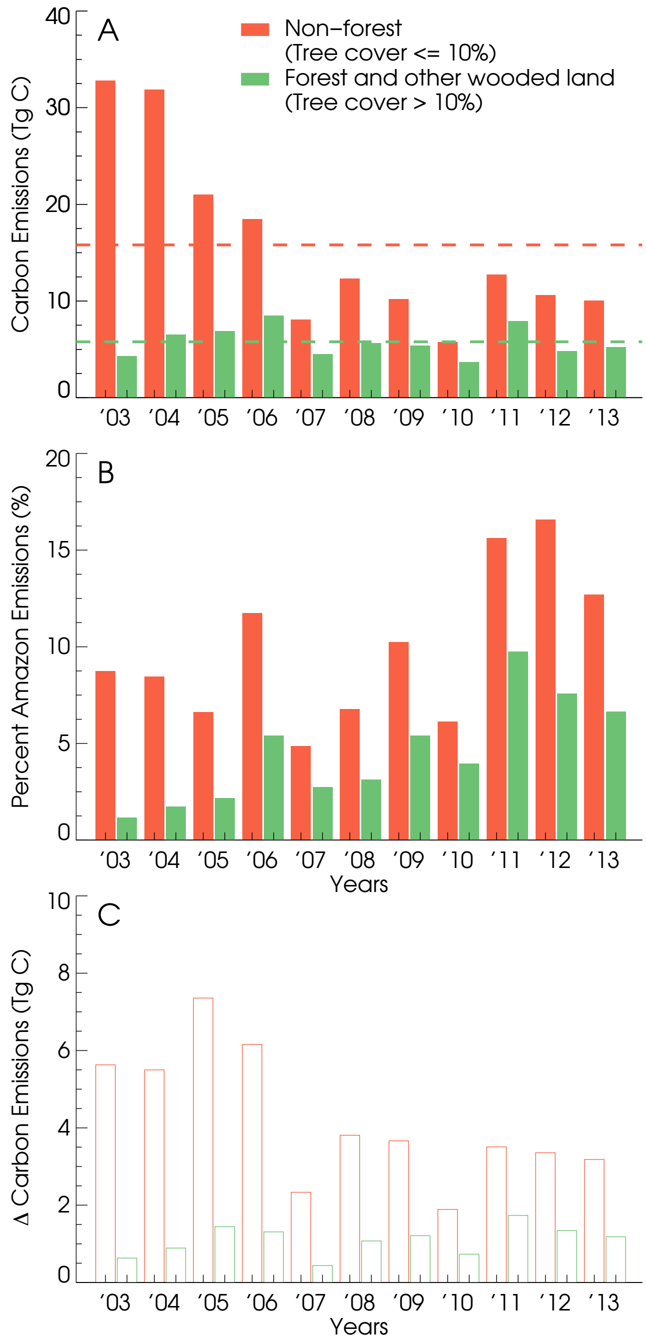


Figure 3.6: Annual gross carbon emission estimates using the look-up table approach. A) Annual gross carbon emissions from cropland expansion into non-forest (orange) and forested Cerrado cover types (green) between 2003 and 2013. B) Comparison between gross carbon emissions from cropland expansion in the Cerrado and Amazon deforestation between 2003 and 2013. C) Difference in estimated gross carbon emissions, calculated as look-up table - satellite.

The Matopiba region accounted for 33% of forest carbon emissions from cropland expansion in the Cerrado during 2003-2013 (17 Tg C, Table 3.1). Between 2010-2013, Matopiba forest carbon emissions accounted for a greater proportion of forest carbon emissions (45%), with the largest contributions from Maranhão (14.42%) – a state with higher biomass, spanning the transition between the Cerrado and Amazon biomes.

Forest-to-cropland transitions in the Cerrado biome partially offset reductions in Amazon deforestation emissions over the past decade. From 2011 to 2013, annual forest carbon emissions from cropland expansion in the Cerrado were more than 6% of estimated carbon emissions from Amazon deforestation (Figure 3.5). Low and high estimates of Cerrado forest carbon stocks, including above and belowground biomass (Figure 3.1), bound the emissions range for 2011-2013 at between 4% and 8.3% of carbon emissions from Amazon deforestation. Total cropland expansion into Cerrado vegetation, including forest and non-forest cover types, has added 16% to estimated carbon emissions from Amazon deforestation since 2011.

Gross carbon emissions from cropland expansion in the Cerrado also offset emissions reductions from declining Amazon deforestation. Compared to Brazil's baseline deforestation emissions for 2011-2015 (247.63 Tg $yr^{-1}$; BRAZIL, 2014), declines in Amazon deforestation reduced gross carbon emissions in 2011-2013 by an average of 74.82 Tg C $yr^{-1}$. Forest carbon emissions from cropland expansion in the Cerrado offset 1.9% of these emissions reductions during 2011-2013, and combined emissions from all Cerrado-to-cropland transitions offset 5% of emissions reductions in the Brazilian Amazon in these years.

Table 3.1: Annual gross carbon emissions (Tg C $yr^{-1}$) from cropland expansion in forest and other wooded lands (F, Tree cover > 10%) and non-forest Cerrado formations (NF, tree cover ≤10%) for Brazilian states in the Cerrado biome.

| | **Goiás** | | **Bahia** | | **Tocantins** | |
|---|---|---|---|---|---|---|
| Years | F | NF | F | NF | F | NF |
| 2003 | 0.72±0.24 | 9.26±2.97 | 0.11±0.04 | 1.44±0.46 | 0.06±0.02 | 0.62±0.20 |
| 2004 | 0.72±0.24 | 9.59±3.08 | 0.27±0.09 | 1.27±0.41 | 0.20±0.07 | 0.93±0.30 |
| 2005 | 0.30±0.10 | 3.33±1.04 | 0.29±0.10 | 0.88±0.28 | 0.20±0.07 | 0.79±0.25 |
| 2006 | 0.31±0.10 | 2.85±0.90 | 0.46±0.17 | 0.80±0.26 | 0.15±0.05 | 0.43±0.14 |
| 2007 | 0.16±0.05 | 1.22±0.38 | 0.27±0.10 | 0.38±0.12 | 0.09±0.03 | 0.25±0.08 |
| 2008 | 0.31±0.10 | 2.60±0.80 | 0.40±0.15 | 0.66±0.21 | 0.18±0.06 | 0.42±0.13 |
| 2009 | 0.14±0.05 | 1.19±0.37 | 0.61±0.22 | 1.00±0.32 | 0.17±0.06 | 0.50±0.16 |
| 2010 | 0.09±0.03 | 0.55±0.17 | 0.49±0.18 | 0.61±0.20 | 0.10±0.03 | 0.30±0.10 |
| 2011 | 0.31±0.10 | 1.79±0.56 | 0.53±0.19 | 0.59±0.19 | 0.24±0.08 | 0.50±0.16 |
| 2012 | 0.27±0.09 | 1.50±0.47 | 0.39±0.14 | 0.63±0.20 | 0.21±0.07 | 0.48±0.15 |
| 2013 | 0.30±0.10 | 1.62±0.50 | 0.38±0.13 | 0.47±0.15 | 0.17±0.06 | 0.51±0.16 |

| | **Piauí** | | **Maranhão** | | **Mato Grosso** | |
|---|---|---|---|---|---|---|
| Years | F | NF | F | NF | F | NF |
| 2003 | 0.07±0.02 | 0.35±0.11 | 0.23±0.08 | 0.70±0.23 | 1.73±0.59 | 5.57±1.79 |
| 2004 | 0.15±0.05 | 0.53±0.17 | 0.60±0.20 | 0.79±0.26 | 3.04±1.04 | 5.70±1.83 |
| 2005 | 0.25±0.09 | 0.35±0.12 | 0.64±0.22 | 0.55±0.18 | 3.18±1.12 | 2.65±0.85 |
| 2006 | 0.40±0.14 | 0.43±0.14 | 0.59±0.20 | 0.49±0.16 | 4.84±1.72 | 3.31±1.06 |
| 2007 | 0.28±0.10 | 0.20±0.07 | 0.57±0.20 | 0.33±0.11 | 2.41±0.84 | 1.22±0.39 |
| 2008 | 0.35±0.12 | 0.24±0.08 | 0.68±0.23 | 0.38±0.12 | 2.26±0.80 | 1.67±0.53 |
| 2009 | 0.44±0.15 | 0.36±0.12 | 0.70±0.24 | 0.46±0.15 | 1.86±0.65 | 1.01±0.32 |
| 2010 | 0.36±0.13 | 0.29±0.10 | 0.55±0.19 | 0.22±0.07 | 1.15±0.40 | 0.52±0.17 |
| 2011 | 1.08±0.37 | 0.43±0.14 | 0.93±0.32 | 0.34±0.11 | 2.28±0.80 | 1.63±0.52 |
| 2012 | 0.59±0.21 | 0.37±0.12 | 0.52±0.18 | 0.21±0.07 | 1.07±0.37 | 1.00±0.32 |
| 2013 | 0.68±0.24 | 0.26±0.08 | 0.53±0.19 | 0.16±0.05 | 1.55±0.54 | 1.05±0.33 |

| | **Mato Grosso do Sul** | | **Minas Gerais** | | **São Paulo** | |
|---|---|---|---|---|---|---|
| Years | F | NF | F | NF | F | NF |
| 2003 | 0.31±0.11 | 1.76±0.57 | 0.29±0.10 | 4.15±1.33 | 0.15±0.05 | 3.02±0.97 |
| 2004 | 0.24±0.08 | 1.70±0.54 | 0.35±0.12 | 3.81±1.23 | 0.08±0.03 | 1.90±0.61 |
| 2005 | 0.22±0.08 | 1.68±0.53 | 0.29±0.10 | 2.10±0.66 | 0.07±0.02 | 1.18±0.38 |
| 2006 | 0.12±0.04 | 1.50±0.48 | 0.23±0.08 | 1.26±0.40 | 0.06±0.02 | 1.13±0.37 |
| 2007 | 0.11±0.04 | 0.60±0.20 | 0.13±0.05 | 0.50±0.16 | 0.06±0.02 | 0.96±0.30 |
| 2008 | 0.17±0.06 | 1.05±0.33 | 0.19±0.07 | 0.74±0.23 | 0.04±0.01 | 0.68±0.21 |
| 2009 | 0.03±0.01 | 0.48±0.15 | 0.16±0.05 | 0.70±0.22 | 0.04±0.02 | 0.78±0.25 |
| 2010 | 0.02±0.01 | 0.42±0.13 | 0.14±0.05 | 0.30±0.09 | 0.05±0.02 | 0.63±0.20 |
| 2011 | 0.38±0.15 | 1.65±0.52 | 0.19±0.07 | 0.67±0.21 | 0.26±0.10 | 1.56±0.49 |
| 2012 | 0.09±0.03 | 1.12±0.35 | 0.19±0.06 | 0.71±0.22 | 0.15±0.05 | 1.19±0.38 |
| 2013 | 0.10±0.03 | 1.14±0.36 | 0.16±0.05 | 0.69±0.21 | 0.19±0.06 | 0.92±0.30 |

Forest conversion for cropland is only one pathway of forest loss in the Cerrado biome. Estimated forest carbon emissions from cropland expansion between 2003-2013 (179 ± 58.6 Tg C) are therefore a substantial underestimate of total forest carbon emissions from all agricultural expansion in the Cerrado biome. Cropland expansion in this study accounted for 21% of the total forest loss identified by Hansen *et al.* (2013) (Figure 3.7). Nearly two-thirds (67%) of forest loss was associated with pasture conversion and a small proportion (12%) was related to other agricultural activities. However, not all forest-to-cropland transitions were mapped as forest loss. Differences between cropland expansion and forest loss estimates may reflect limitations of the annual Landsat approach to detect phenology differences during the rapid change from forest to cropland. Some of the difference may also be attributed to the coarser spatial resolution of MODIS (250m) relative to Landsat (30m).

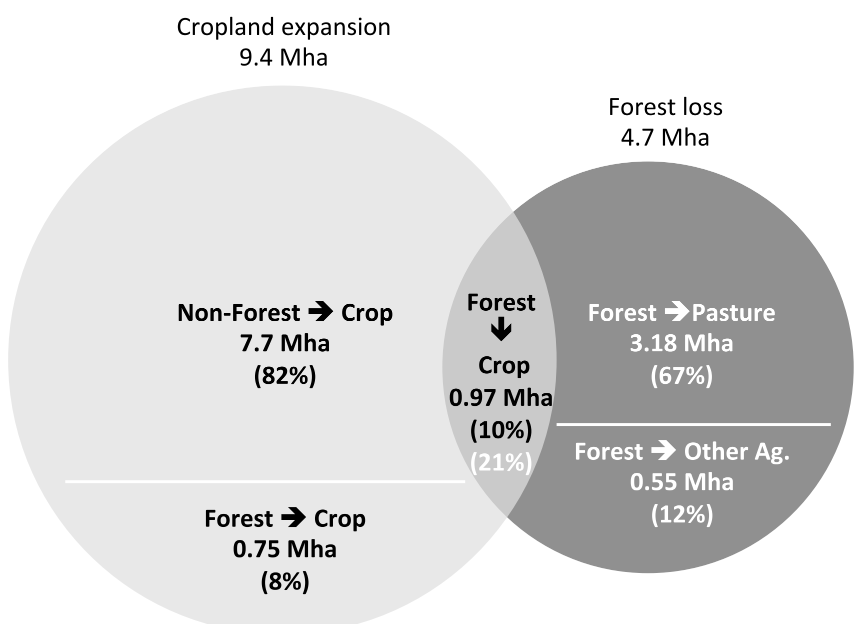


Figure 3.7: Relationship between cropland expansion (this study), TerraClass (MMA, 2015), and forest loss (Hansen *et al.*, 2013), highlighting the proportional overlap between cropland expansion and other forest loss pathways.

*3.5 Discussion*

Complete carbon accounting is essential for national reporting of greenhouse gas sources and sinks and global carbon cycle studies to support climate mitigation. The Amazon and other tropical rainforest regions have been the primary target for REDD+, given high carbon stocks in tropical forests (Saatchi *et al.*, 2011; Baccini *et al.*, 2012) and rapid deforestation for agricultural expansion in recent decades (Hansen *et al.*, 2013; Kim *et al.*, 2015; Morton *et al.*, 2016). Forest conversion in other tropical biomes has received less national and international attention, despite growing evidence for concentrated cropland expansion in dry tropical forest regions (e.g., Aide *et al.*, 2013; Lambin *et al.*, 2013).

In the Cerrado, emissions from large-scale cropland expansion totaled 179 Tg C between 2003-2013. During the study period, the fraction of emissions from forest conversion increased from 12% to 37%, driven by a shift in cropland expansion to the Matopiba region and a steady increase in the proportion of forest conversion for cropland expansion. Over the same period, the fraction of emissions from forest conversion in the Matopiba region increased from 13% to 56%. A decline in Amazon deforestation since 2005 underscores the importance of Cerrado emissions; Cerrado cropland expansion during 2011-2013 added an estimated 6% (forest) and 16% (combined forest and non-forest transitions) to total Amazon carbon emissions, offsetting 1.9-5% of the reductions in Amazon deforestation emissions relative to the 2011-2015 baseline. Given that cropland expansion only accounted for one-fifth of forest loss between 2003-2013, total forest carbon emissions from the Cerrado are likely a substantial and growing part of Brazil's national greenhouse gas budget and should be included in regional estimates of deforestation and fire emissions (e.g., DeFries *et al.*, 2008; van der Werf *et al.*, 2009b; Gatti *et al.*, 2014; Alden *et al.*, 2016).

Emissions estimates in this study are similar to official reporting in Brazil's Third National Communication to the UNFCCC (BRAZIL, 2016), yet several issues prevent a direct comparison of the results. Brazil's Third National Communication suggests that net emissions from agricultural expansion in the Cerrado totaled 575.2 Tg $CO_2$ (156.9 Tg C) between 2002-2010, with the majority of net carbon emissions from forest conversion to cropland (82%, 129 Tg C). Estimated gross carbon emissions from cropland expansion in this study from 2003-2010 totaled 142 ± 46.41 Tg C (see Figure 3.5), but with only 27% of emissions from forest conversion. Satellite data on fractional tree cover suggest a lower proportion of forest conversion for cropland expansion than Brazil's Third National Communication, potentially due to differences in land cover classifications or deforestation information.

Our analysis developed annual estimates of cropland expansion from satellite data, while the UNFCCC submission used periodic land cover information to generalize emissions over multi-year intervals. Ultimately, sub-annual information on the timing and magnitude of land use change emissions is critical to link bottom-up accounting with measurements of atmospheric trace gases from aircraft (e.g., Gatti *et al.*, 2014) or satellite observations (Edwards *et al.*, 2006; van der Laan-Luijkx *et al.*, 2015). Only gross carbon fluxes (rather than net carbon emissions) were reported and did not further disaggregate carbon emissions using information on fire emissions ratios (van Leeuwen & van der Werf, 2011) or combustion completeness (e.g., van der Werf *et al.*, 2009a). Accounting for non-carbon greenhouse gas emissions, including nitrous oxide from fertilizer use (Galford *et al.*, 2010), is also critical to capture the full range of impacts from cropland expansion.

To date, commodity industry commitments to zero deforestation have overlooked forest losses in dry forest regions such as the Cerrado. In Brazil, the government, civil society, and industry have primarily focused on reducing deforestation in the Amazon region (e.g., the SoyM) while ignoring the Cerrado. More recent efforts, including the Action Plan for Prevention and Control of Deforestation and Burning in the Cerrado (PPCerrado) and Low Carbon Agriculture Program (ABC), have been implemented to reduce land use and agricultural emissions within the biome. Existing legislation, including Brazil's FC, offers a mechanism to restrict Cerrado conversion in legal reserve areas with the full implementation of Brazil's Rural Environmental Registry (Cadastro Ambiental Rural; CAR) of private properties (Soares-Filho *et al.*, 2014; Gibbs *et al.*, 2015).

There are several barriers to effective monitoring and conservation in the Cerrado. First, the tools for effective satellite monitoring of private properties developed for the Amazon region (e.g., PRODES, DETER, and DEGRAD) are not operational for the Cerrado biome, with the notable exception of the recent TerraClass Cerrado product (MMA, 2015). Monitoring is critical to ensure compliance with environmental legislation; in 2014, nearly half of the Amazon deforestation in the states of Pará and Mato Grosso occurred within designated legal reserve areas (Gibbs *et al.*, 2015). Policies such as PPCerrado are also counterbalanced by government efforts to promote agricultural development in the

Matopiba region (Matopiba plan; BRAZIL, 2016). Satellite monitoring offers an objective perspective in the search for balance between Brazil's goals to increase agricultural production, reduce greenhouse gas emissions, and adhere to commitments for forest restoration as part of the New York Declaration on Forests (UNCS, 2014). Overall, the government strategy to expand agricultural production in the Matopiba region is a low carbon development pathway. However, other ecosystem services are important to consider, such as biodiversity conservation, water recycling (Spera *et al.*, 2016), and regional climate impacts (Pongratz *et al.*, 2006; Loarie *et al.*, 2011). Efforts that focus on deforestation area (as opposed to carbon emissions), consistent with industry commitments to zero deforestation, could help balance land use pressures among biomes, regardless of carbon stocks.

Satellite-based estimates of annual cropland expansion and vegetation carbon stocks provide an important benchmark in support of complete national accounting of carbon emissions from land use change. Higher resolution data may help future studies improve upon these estimates. MODIS resolution is suitable for mapping and monitoring cropland expansion in the Cerrado region, but Landsat (30 m) data allows for more precise delineation of management areas and deforestation. Existing satellite products in Brazil, including TerraClass, PRODES, and MAPBIOMAS (MAPBIOMAS, 2016), offer a blueprint for regular monitoring of land use changes in the Cerrado at Landsat resolution.

This study estimated gross carbon emissions from cropland expansion, since complete removal of above and belowground biomass for mechanized crop production simplified the emissions calculation. A comprehensive assessment of carbon emissions and uncertainty remains a challenge (Houghton *et al.*, 2012), in part due to the broad range of land management practices for establishment and maintenance of pastures and croplands in the Cerrado region (e.g., van der Werf *et al.*, 2009a). Second-generation biomass products, developed from upcoming lidar and radar satellite missions (Morton, 2016), will map aboveground biomass at higher resolution, consistent with the spatial scales of vegetation heterogeneity and land management. Efforts to track the reduction in forest and shrub biomass from expansion of grazing lands will also benefit from new remote sensing data, particularly from radar sensors with the ability to map carbon stocks in low-biomass vegetation types. Field estimates of above and belowground carbon stocks in Cerrado vegetation remain critical for improving estimates of vegetation carbon stocks.

### *3.6 Conclusions*

First estimate of annual forest carbon emissions from cropland expansion in the Cerrado biome was generated. Forest conversion accounts for a growing proportion of recent cropland expansion, particularly in newer agricultural frontiers such as the Matopiba region. Although soy and other mechanized crop production are not the major drivers of deforestation in the Amazon or Cerrado, cropland expansion has larger gross and net carbon emissions per unit area than pasture expansion, based on the need for complete removal of above and below-ground biomass (van der Werf *et al.*, 2009a). Cropland expansion partially offset recent declines in Amazon deforestation emissions, highlighting the critical need for national scale accounting for successful climate mitigation through REDD+.

# Chapter 4: Fire-driven forest conversion for oil palm in Southeast Asia: the role of certification

## *4.1 Summary*

Indonesia and Malaysia have emerged as leading producers of palm oil in the past several decades, expanding production through the conversion of tropical forests to industrial plantations. Growing efforts to certify palm oil production, led by the Roundtable on Sustainable Palm Oil (RSPO), have implemented policies to reduce the environmental impact of palm oil production. Fire-driven deforestation is prohibited by law in both countries and therefore a stipulation of RSPO certification, yet the degree of environmental compliance is unclear, especially during El Niño events when drought conditions increase fire risk. Here, time series of satellite data were used to estimate the spatial and temporal patterns of fire-driven deforestation in and around oil palm concessions (OPCs). In Indonesia, fire-driven deforestation accounted for one quarter of total forest losses in both certified and non-certified OPCs. Following RSPO certification in 2009, forest loss and fire-driven deforestation declined in certified OPCs but did stop altogether. Oil palm expansion in Malaysia rarely involved fire; only 6% of forest loss in certified OPCs had coincident active fire detections. Interannual variability in fire detections was strongly influenced by El Niño and the timing of certification. Fire activity during the 2002 and 2006 El Niño event was similar (0.11 $km^{-2}$ $yr^{-1}$) among OPCs in Indonesia that would later become certified, non-certified OPCs, and surrounding areas. However, rates of fire activity were 70% lower in certified OPCs than non-certified OPCs during the 2009 and 2015 El Niño events. The decline in fire activity on certified OPCs, including

during drought periods, highlights the potential for RSPO certification to safeguard carbon stocks in peatlands and remaining forests and support legislation banning fires. However, aligning certification standards with satellite monitoring capabilities will be critical to realize sustainable palm oil production and meet industry commitments to zero deforestation.

## *4.2 Introduction*

Global production of agricultural commodities such as palm oil has risen steadily in recent decades, driven by market demand and high economic value (USDA, 2009; USDA, 2010; USDA, 2016). Southeast Asia's palm oil sector has growth through expansion of oil palm plantations in Malaysia, Indonesia, and more recently, Papua New Guinea (Gunarso *et al.*, 2013; Carlson *et al.*, 2013; Miettinen *et al.*, 2016a; Vijay *et al.*, 2016). By 2014, Indonesia accounted for nearly 40% of the global oil palm harvested area (FAO, 2016).

In the past decade, Indonesia had the highest rate of forest loss of any country in Southeast Asia (Hansen *et al.*, 2013; Margono *et al.*, 2014; Kim *et al.*, 2015), spurred by rapid forest conversion for oil palm and other industrial plantations (Carlson *et al.*, 2012; Gunarso *et al.*, 2013; Abood *et al.*, 2015). Between 1990-2010, more than one third of oil palm plantations replaced forested landscapes in Southeast Asia (Gunarso *et al.*, 2013), with rates as high as 90% in regional hotspots such as the Indonesian province of Kalimantan (Carlson *et al.*, 2013). Conversion of primary and secondary forests for oil palm, including vast areas with deep peatland soils, contributed to significant greenhouse gas (GHG) emissions from decomposition, fire, and peat oxidation (Page *et al.*, 2002; van der Werf *et al.*, 2008; Hooijer *et al.*, 2012; Ramdani & Hino, 2013; Field *et al.*, 2016; Huijnen *et al.*, 2016). Concerns with palm oil production extend beyond GHG emissions, however, as forest loss threatens biodiversity (Pimm *et al.*, 2014; Vijay *et al.*, 2016) and particulate emissions from fires are a major public health concern in Indonesia and downwind population centers such as Singapore (Murdiyarso *et al.*, 2004; Gaveau *et al.*, 2014; Kunii *et al.*, 2002; Reddington *et al.*, 2014; Marlier *et al.*, 2015; Chisholm *et al.*, 2016; Johnston *et al.*, 2015).

Palm oil is the fastest growing certified agriculture commodity, and Indonesia accounted for >50% of certified production areas in 2016 (Potts *et al.*, 2014; RSPO, 2016). The push for certification within the palm oil industry reflects a growing consumer awareness of GHG emissions from palm oil expansion and peat oxidation and an overall rise in consumer demand for deforestation-free products (UNCS, 2014; Butler, 2015; McCarthy *et al.*, 2016). The Roundtable on Sustainable Palm Oil (RSPO) certification is the most widely adopted certification standard; specific principles and criteria of RSPO certification promote sustainable palm oil production and processing (Garrett *et al.*, 2016; RSPO, 2004; RSPO, 2015b). Among other provisions, RSPO certification prohibits conversion of primary and high conservation value (HCV) forests and bans fire use for land clearing in compliance with the Indonesian moratorium on fire (RSPO, 2007; Edwards & Heiduk, 2015). RSPO does not independently monitor fire activity within member concessions, despite freely available data from NASA satellites, and the use of fire for forest conversion on OPCs has not previously been quantified.

Improving estimates of fire-driven deforestation is critical to assess environmental compliance by OPCs, reduce uncertainties in deforestation carbon emissions (Le Quéré *et al.*, 2015; Houghton *et al.*, 2012; van der Werf *et al.*, 2009b), and characterize ignition sources that may give rise to uncontrolled burning during drought periods (Carlson *et al.*, 2012; Cattau *et al.*, 2016). The timing of GHG emissions from forest conversion to oil palm depends on the degree of fire use for deforestation (DeFries *et al.*, 2008; Houghton *et al.*, 2012), including the proportion of clearing activity through fire and the combustion completeness of initial or repeated burning (van der Werf *et al.*, 2009a). Fires for forest conversion are illegal in both Indonesia and Malaysia (Tacconi, 2003; Edwards & Heiduk, 2015) and prohibited under RSPO certification (RSPO, 2007), yet fires are common in industrial plantations and smallholder properties (Stolle *et al.*, 2003; Austin *et al.*, 2015; Marlier *et al.*, 2015; Miettinen *et al.*, 2016b). Many estimates of carbon emissions from tropical forest conversion report committed fluxes without separating fire and decomposition (Koh *et al.*, 2011; Carlson *et al.*, 2012; Austin *et al.*, 2015). Previous studies with biogeochemical or bookkeeping models suggest that fire accounts for 30% (Houghton & Hackler, 1999) to 50% (van der Werf *et al.*, 2009a) of carbon emissions from forest conversion in southeast Asia—a broad range that applies to all forest conversion, not strictly to oil palm expansion. Fires are not restricted to forested areas; El Niño conditions suppress precipitation over large parts of Southeast Asia, leading to widespread fire activity during drought periods, particularly in carbon-rich peatlands (Page *et al.*, 2002; van der Werf *et al.*, 2008; Field *et al.*, 2009, , 2016). Understanding the contribution from fire-driven deforestation to total fire activity is therefore a critical part of mitigating fire risk during drought years (e.g., Chen *et al.*, 2016).

Here, time series of satellite data on forest loss and active fire detections were combined to assess fire-driven forest and peatland conversion in and around OPCs. The combination of land management, forest loss, and active fire data provides an opportunity to evaluate the relative contributions from different fire types to spatial and temporal variability in satellite fire detections. This study addresses three primary questions regarding oil palm expansion: 1) What fraction of forest and peat forest conversion for oil palm involves fire? 2) Does certification alter fire use for forest conversion or management of concession areas? and 3) During El Niño years, does certification reduce fire activity compared to non-certified OPCs and surrounding lands? Characterizing fire-driven deforestation is critical to evaluate the influence of RSPO certification on fire activity and improve estimates of GHG emissions from oil palm expansion.

## *4.3 Material and methods*

### 4.3.1 Oil Palm Concessions (OPCs)

The government of Indonesia allocates land for oil palm production to companies for a limited period of time. Oil palm leases were separated into two categories, certified and non-certified oil palm concessions (OPCs). Certified OPCs are properties certified by the RSPO between 2009-2015; non-certified OPCs are properties allocated by the Indonesian government to companies but have not yet been certified, even if other properties held by the company have been certified by RSPO (Carlson *et al* in review). Worldwide, RSPO has certified 2.83 Mha in oil

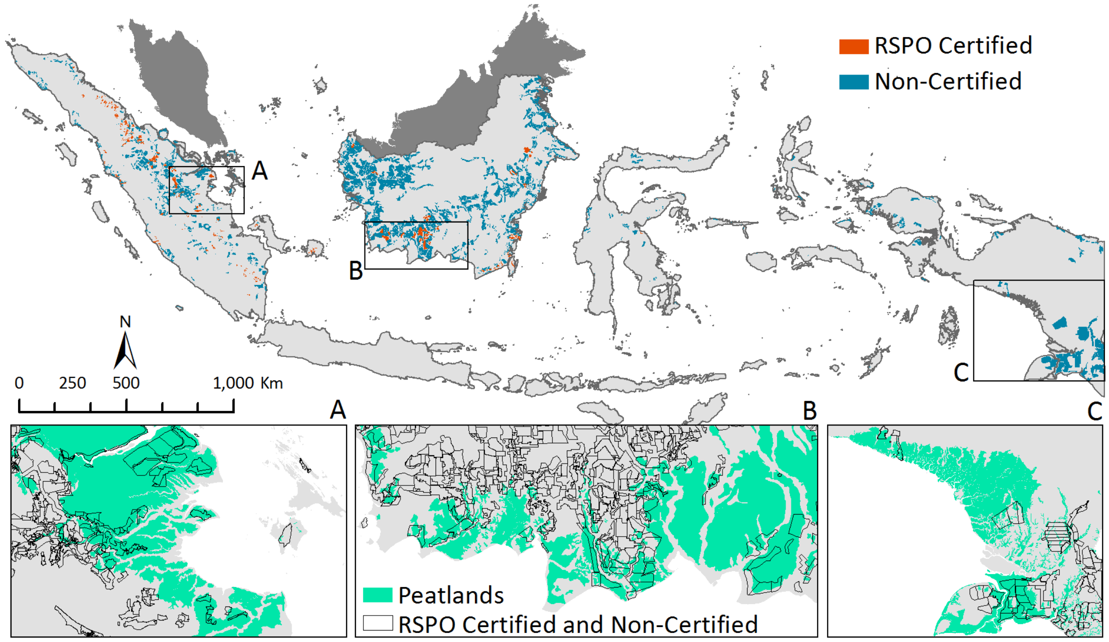


Figure 4.1: Extent of RSPO certified and non-certified oil palm concessions in Indonesia. Regional subsets highlight oil palm concessions (black polygons) on peatlands (green) in lowlands of Sumatra (A), Kalimantan (B), and Papua (C).

palm concessions (OPCs) that produce 10.8 million tons of palm oil, or approximately 17% of global palm oil production (RSPO, 2016). Boundaries of certified OPCs were compiled from several sources, including boundary polygons provided by RSPO, digitized boundaries from RSPO audit reports (RSPO, 2004), and spatial data on plantation boundaries from companies (RSPO, 2015a). Boundaries of non-certified OPCs were obtained from a database of OPCs published by Greenpeace (Greenpeace, 2016b) and non-certified OPCs held by RSPO members (RSPO, 2015a). In total, 140 certified and 1750 non-certified OPC boundaries for Indonesia were analyzed (Figure 4.1). Data on certified OPCs were also available for Malaysia (n =121) and Papua New Guinea (n = 10), but boundaries of non-certified OPCs were not available.  See Carlson *et al* (in review) for a detailed description of the palm oil lease compilation.

Maps of planted oil palm were used to identify established plantations within certified and non-certified OPCs in Indonesia, Malaysia, and Papua New Guinea. Data on planted oil palm were available from Gunarso *et al.* (2013) for three years (2000, 2005, and 2010) and supplemented with additional planted oil palm information from Carlson *et al.* (2013).

### 4.3.2 Forest definition, cover, and loss

Estimates of forested areas and forest loss fundamentally depend on the definition of forest cover (Sexton *et al.*, 2016).  The Indonesian government uses the definition of forest from the United Nations Food and Agriculture Organization (FAO) Forest Resource Assessment (FRA), i.e., canopy cover > 10% (FAO, 2010). Countries may use canopy cover thresholds between 10-30% for reporting under the United Nations Framework Convention on Climate Change (UNFCCC) REDD+ framework (UNFCCC, 2002). In this study, canopy cover at the top of REDD+ range (> 30%) were chosen as a conservative threshold for forest cover based on difficulties associated with discriminating tropical forests from other land cover types using remote sensing data for regions with little rainfall seasonality, such as Southeast Asia.

Forest and non-forest areas were separated using Landsat-based estimates of fractional tree cover in 2000 (Hansen *et al.*, 2013). Estimates of annual forest loss between 2002-2014 (Hansen *et al.*, 2013) were used to identify the timing of forest conversion in and around OPCs.

### 4.3.3 Active fires

Active fire detections were used from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on NASA's Terra and Aqua satellites. The global monthly fire location product (MCD14ML) identifies the location of actively burning fires at the time of satellite overpass at 1km spatial resolution (Giglio *et al.*, 2003). Fire counts from Terra and Aqua MODIS sensors were combined using a 1km grid to evaluate monthly and annual fire activity from 2002 to 2015. The density of fire counts per $km^2$ was used to compare certified OPCs, non-certified OPCs, and a 5km buffer region surrounding both certified and non-certified OPCs.

For 2014 and 2015, higher resolution active fire detections were used to confirm patterns in 1 km MODIS fire data. Active fire detections were analyzed from the Visible Infrared Imaging Radiometer Suite (VIIRS) I-band (375m) on the Suomi-National Polar orbiting Partnership (S-NPP) satellite (Schroeder *et al.*, 2014) and 30-m fire detections from the Landsat-8 Operational Land Imager (OLI; Schroeder *et al.*, 2015). Finer spatial resolution fire data capture heterogeneity in fire activity that can be lost in coarse resolution data products such as MODIS. VIIRS and Landsat fire detections help to identify the location of active fire fronts, separate areas of flaming and smoldering fires (Elvidge *et al.*, 2015), and improve the detection of small fires (Schroeder *et al.*, 2015)—an important component of fire activity in agricultural landscapes (Randerson *et al.*, 2012). In this study, the improved spatial resolution of

VIIRS and Landsat 8 fire detections aided the attribution of active fires to specific land management areas.

#### 4.3.4 Fire-driven forest conversion for oil palm expansion

Satellite remote sensing data on forest cover (2000; Hansen *et al.*, 2013), forest cover change (2002-2014; Hansen *et al.*, 2013), and active fire detections (2001-2014; Giglio *et al.*, 2003) were combined to identify fire-driven forest conversion in certified and non-certified OPCs. The assessment in this study excluded forested areas identified as oil palm from Gunarso *et al.* (2013) and Carlson *et al.* (2013). Deforestation within OPCs was therefore limited to Hansen *et al.* (2013) tree cover loss in forested areas (tree cover >30%) outside of planted palm. Oil palm expansion into peatswamp forests was assessed using peatland layers created by Wahyunto *et al.* (2003; 2004; 2006). Co-located forest loss and active fire detections were considered for fire-driven deforestation. Given the potential for fire activity to pre-date the detection of forest loss (Morton *et al.*, 2008), active fire data from the year of forest loss and one year before were combined to identify fire activity associated with forest conversion.

## *4.4 Results*

#### 4.4.1 Certification and Fire-driven Deforestation

In Indonesia, forest loss in and around OPCs reduced remaining forest cover by 18-28% between 2002-2014 (Figure 4.2). Gross forest loss outside of planted palm areas totaled 4.25 Mha (Table 4.1). Average annual rates of forest loss were similar (1.16 – 1.35% $yr^{-1}$) in certified and non-certified OPCs over this period. However, pre-certification rates of forest (1.66% $yr^{-1}$) and peatswamp forest conversion (0.34% $yr^{-1}$) were higher within certified OPCs than non-certified OPCs (1.09% and 0.29% $yr^{-1}$, respectively). Given the larger extent of non-certified OPCs, mean annual forest losses differed by more than order of magnitude between certified and non-certified OPCs (16,023 ha $yr^{-1}$ and 224,865 ha $yr^{-1}$, respectively). Patterns of forest loss for buffer areas within 5 km of OPCs were similar to non-certified concessions.

Table 4.1: Total and fire-driven forest loss for oil palm expansion in Indonesia from 2002-2014 within the certified and non-certified concessions.

| | Lease area | Planted palm by 2010 | Forest loss[a] | Peatswamp Forest loss | Fire-driven loss[b] |
|---|---|---|---|---|---|
| | ha | ha | ha | ha | ha |
| RSPO Certified | 1,489,003 | 1,125,846 | 224,326 | 43,107 | 71,659 (27%) |
| Non-Certified | 17,963,757 | 3,596,501 | 3,148,105 | 833,553 | 987,479 (25%) |
| 5km Buffer | 26,102,026 | 2,276,262 | 3,404,957 | 890,957 | 937,437 (22%) |

[a] Forest loss outside of peat areas
[b] Combined (peat and non-peat) forest loss related to fire

Although the use of fire for forest conversion is prohibited in Indonesia, satellite data suggest that nearly one quarter of forest clearing in both certified and non-certified OPCs involved fire. For certified OPCs in Indonesia, the fraction of fire-driven forest loss was higher before 2008 in both lowland and peatswamp forests (Figure 4.2). The proportion of fire-driven deforestation in non-certified OPCs and buffer areas was consistent in all years. Notably, the proportion of fire-driven deforestation in El Niño years (2002, 2006, 2009) was similar to fire use in other years for all three management classes.

The time series of fire-driven forest loss for oil palm expansion differed between certified and non-certified OPCs after the start of RSPO certification in 2009. Forest loss rates declined by 60% in RSPO certified OPCs from 2009-2014 compared to pre-certification levels. In contrast, mean annual forest loss increased in non-certified OPCs (180%) and buffer areas (154%) during this period relative to2002-2008 (Figure 4.2).

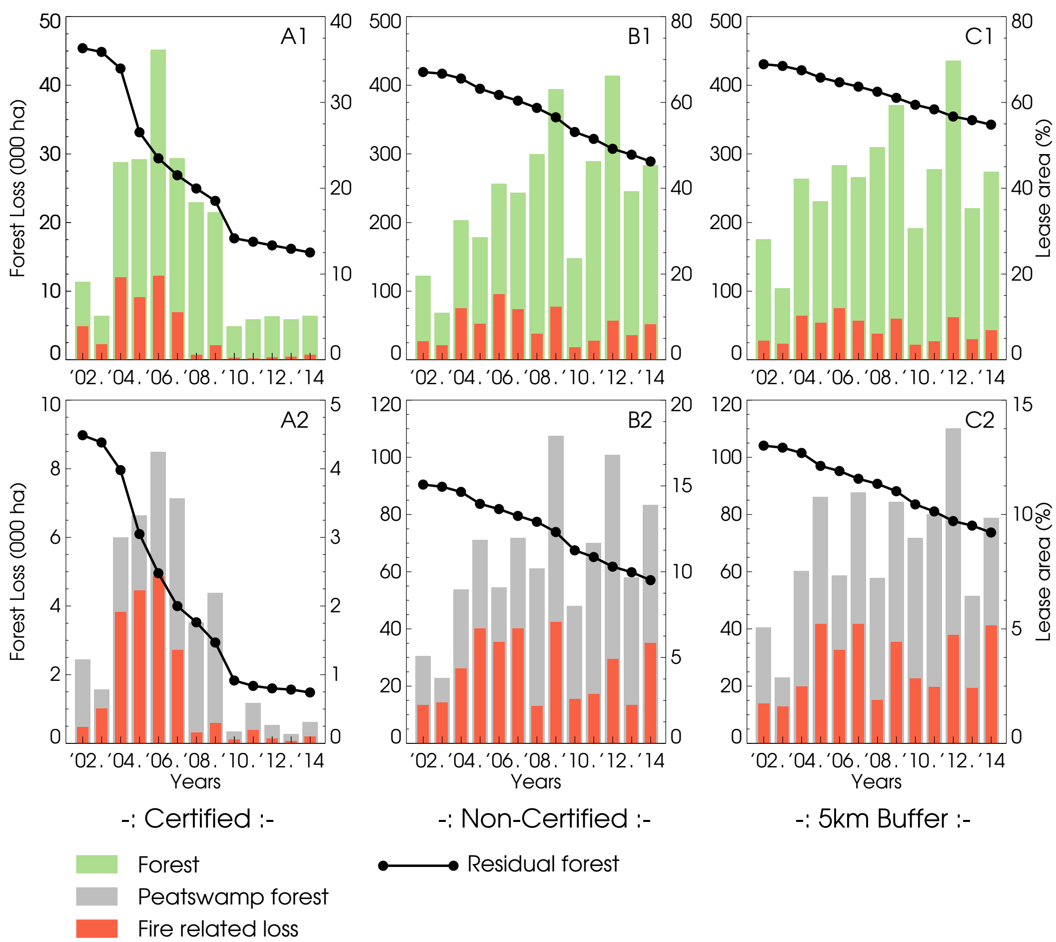


Figure 4.2: Forest loss within the boundaries of A) Certified OPCs, B) Non-Certified OPCs, and C) 5km Buffer region surrounding certified and non-certified plantations from 2001-2014. A1-C1) Fire (orange) and non-fire related (green) forest loss in non-peat areas; A2-C2) fire (orange) and non-fire related (grey) forest loss on peatswamp. Estimates of forest loss for all management classes excluded areas of planted palm (Carlson *et al.*, 2013; Gunarso *et al.*, 2013). The solid black line indicates residual forest cover within the certified, non-certified, and buffer region.

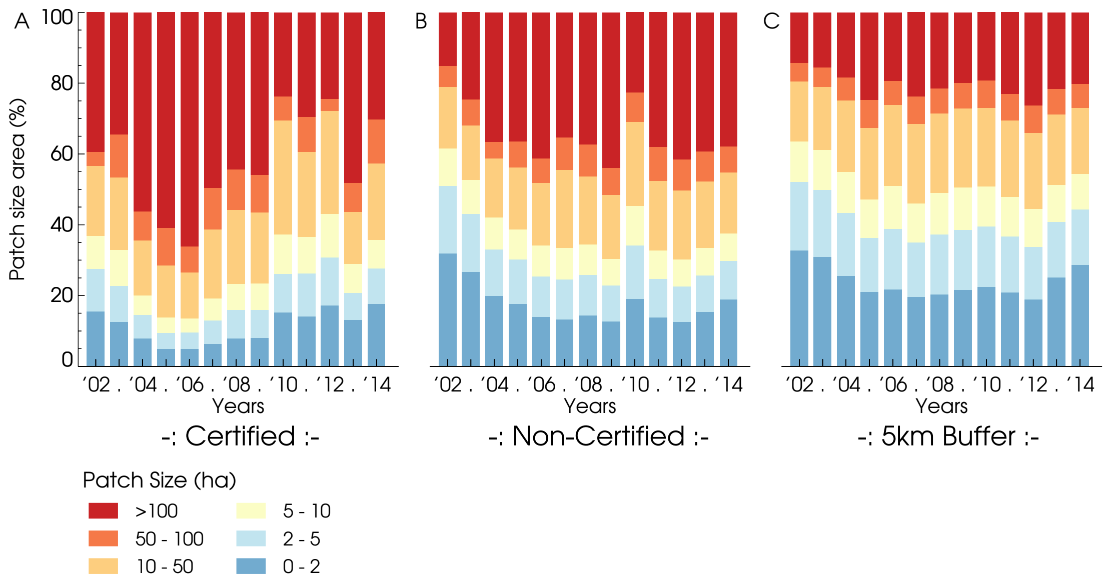


Figure 4.3: Forest loss patch size distribution in Indonesia within the boundaries of A) RSPO Certified OPCs, B) Non-Certified OPCs, and C) 5km Buffer region. Patch sizes were assessed at the plantation level and summarized yearly to report between 2002-2014.

However, certification did not halt forest conversion altogether. Forest loss continued on certified OPCs following certification, including fires for forest conversion, leading to an additional 6% loss of remaining forest cover. Lower rates of forest loss on certified OPCs are consistent with RSPO restrictions on clearing HCV forest areas and other lands deemed unsuitable for palm oil production. Declining rates of forest loss after 2009 may also reflect limited remaining forest cover on certified OPCs by 2014 (13%; Figure 4.2), leading to smaller clearing sizes that are more difficult to assess with remote sensing data on forest loss and fire activity (Figure 4.3). In contrast, the contribution from larger clearing sizes increased over time in non-certified OPCs and remained stable for buffer areas.

Table 4.2: Total and fire-driven forest loss for oil palm expansion in certified oil palm concessions (OPCs) in Indonesia, Malaysia, and Papua New Guinea during 2001-2014. All areas are given in hectares (ha).

| | Lease area<br>ha | Planted palm by 2010[a]<br>ha | Forest loss<br>ha | Peatswamp Forest loss<br>ha | Fire-driven loss[b]<br>ha |
|---|---|---|---|---|---|
| Indonesia (IDN) | 1,489,003 | 1,125,846 | 224,326 | 43,107 | 71,659 (27%) |
| Malaysia (MYS) | 1,147,495 | 903,546 | 125,218 | 8,273 | 7,816 (6%) |
| Papua New Guinea (PNG) | 174,444 | 94,002 | 21,491 | - | 3,860 (18%) |

[a] Forest loss outside of peat areas
[b] Combined (peat and non-peat) forest loss related to fire

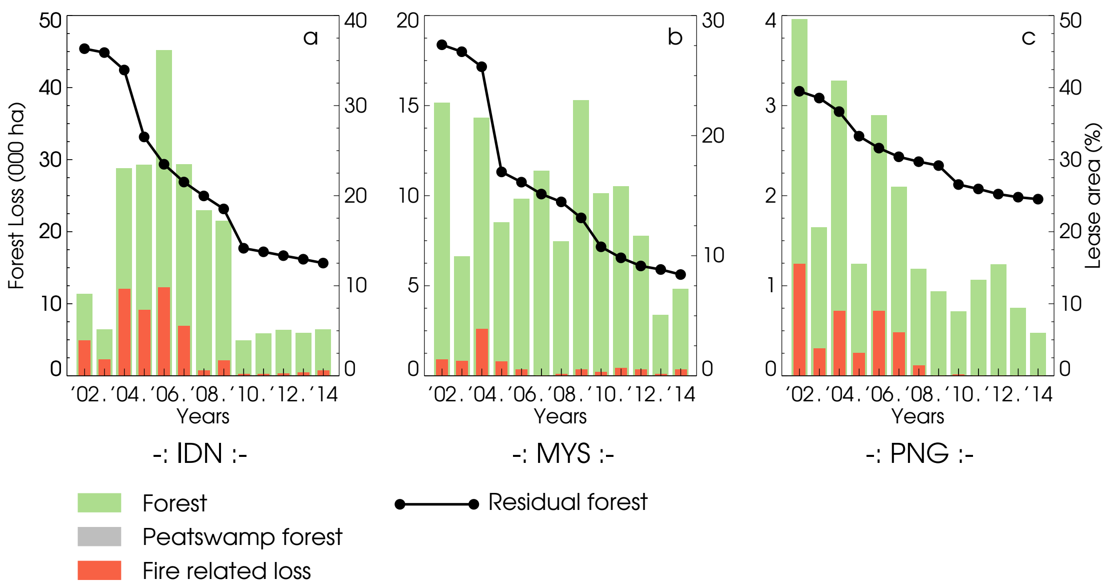


Figure 4.4: Total forest loss (green) and fire-driven deforestation (orange) in certified OPCs in a) Indonesia (IDN), b) Malaysia (MYS), and c) Papua New Guinea (PNG). Forest loss was estimated outside of planted palm (Carlson *et al.*, 2013; Gunarso *et al.*, 2013). The black line indicates residual forest as a fraction of the total lease area of certified OPCs in each country.

Patterns of fire-driven forest loss in certified OPCs differed across Indonesia, Malaysia, and Papua New Guinea (Table 4.2). Overall forest loss rates were higher in

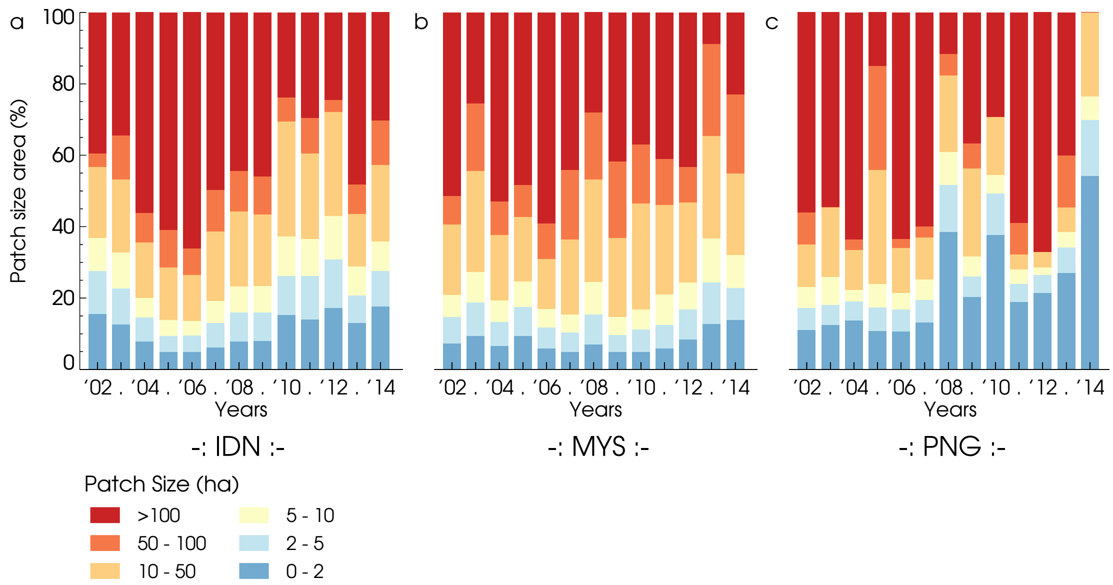


Figure 4.5: Forest loss patch size distribution in the RSPO Certified OPCs of a) Indonesia (IDN), b) Malaysia (MYS), and c) Papua New Guinea (PNG). Patch sizes were assessed at the plantation level and summarized yearly to report between 2001-2014.

Indonesia than Malaysia and Papua New Guinea. However, large forest clearing events were more common in certified OPCs in Malaysia and Papua New Guinea, with more than two-thirds of forest loss in patches > 10ha (Figure 4.5). Annual forest loss rates in Malaysia remained high following certification, with little change from pre-certification patterns (Figure 4.4). In Malaysia, oil palm expansion in certified OPCs rarely involved fire, and only 6% of total forest loss was identified as fire-driven deforestation. Fire detections associated with forest loss declined in all three countries following the start of certification in 2009.

Certification decoupled fire detections from ENSO-driven variability in fire risk. Interannual variability in regional fire activity is largely governed by the timing and magnitude of El Niño events (Figure 4.6; Chen *et al.*, 2015). Prior to certification,

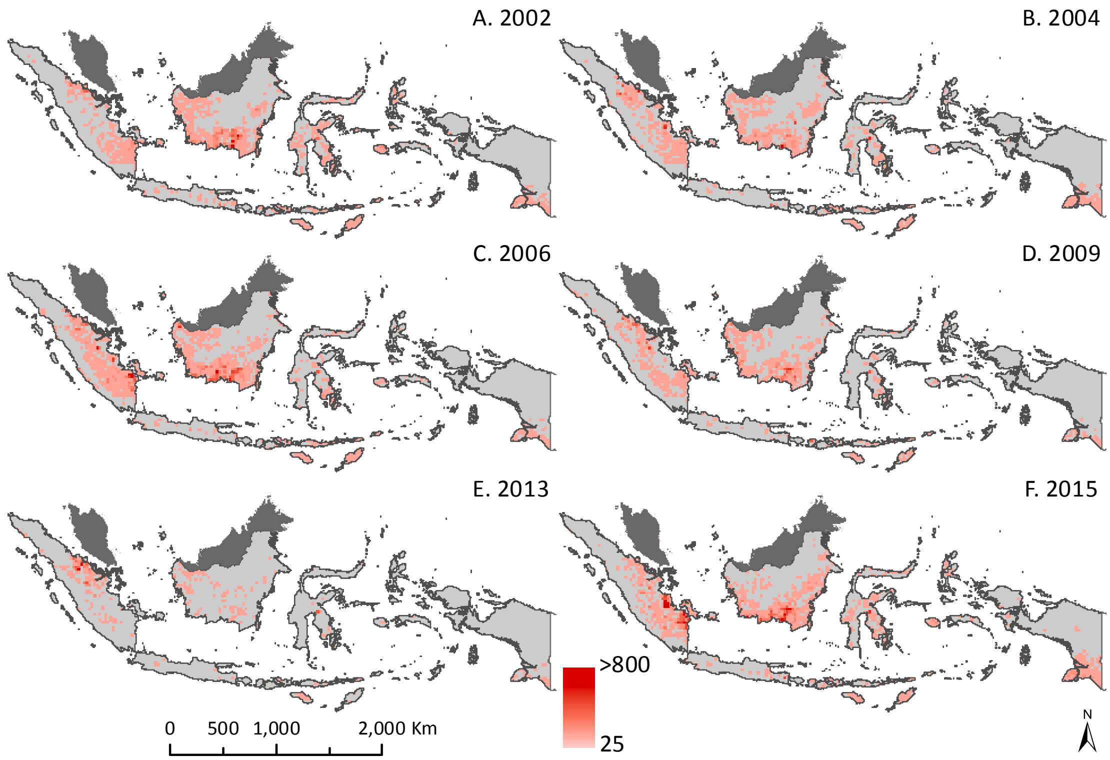


Figure 4.6: Density of MODIS active fire detections in Indonesia during El Niño years (A-D, F) and the June 2013 drought (E), when fires from Sumatra impacted air quality in Singapore (Gaveau *et al.*, 2014). The spatial distribution of fire activity was consistent during El Niño years, although fire densities were highest in 2006 and 2015. Maps show annual totals of Terra and Aqua MODIS fire detections at 0.25° resolution.

interannual variability in fire detections was similar for certified OPCs, non-certified OPCs, and buffer areas in Indonesia (Figure 4.7). Mean fire rates across land management classes were also consistent during El Niño events in 2002, 2004, and 2006 (0.09-0.11 $km^{-2}$ $yr^{-1}$), with important contributions from fire-driven deforestation to total fire detections in these years. Following certification, fire activity declined in certified OPCs in all years, with 67-78% fewer fires during the 2009 and 2015 El Niño events compared to non-certified OPCs. Monthly fire counts

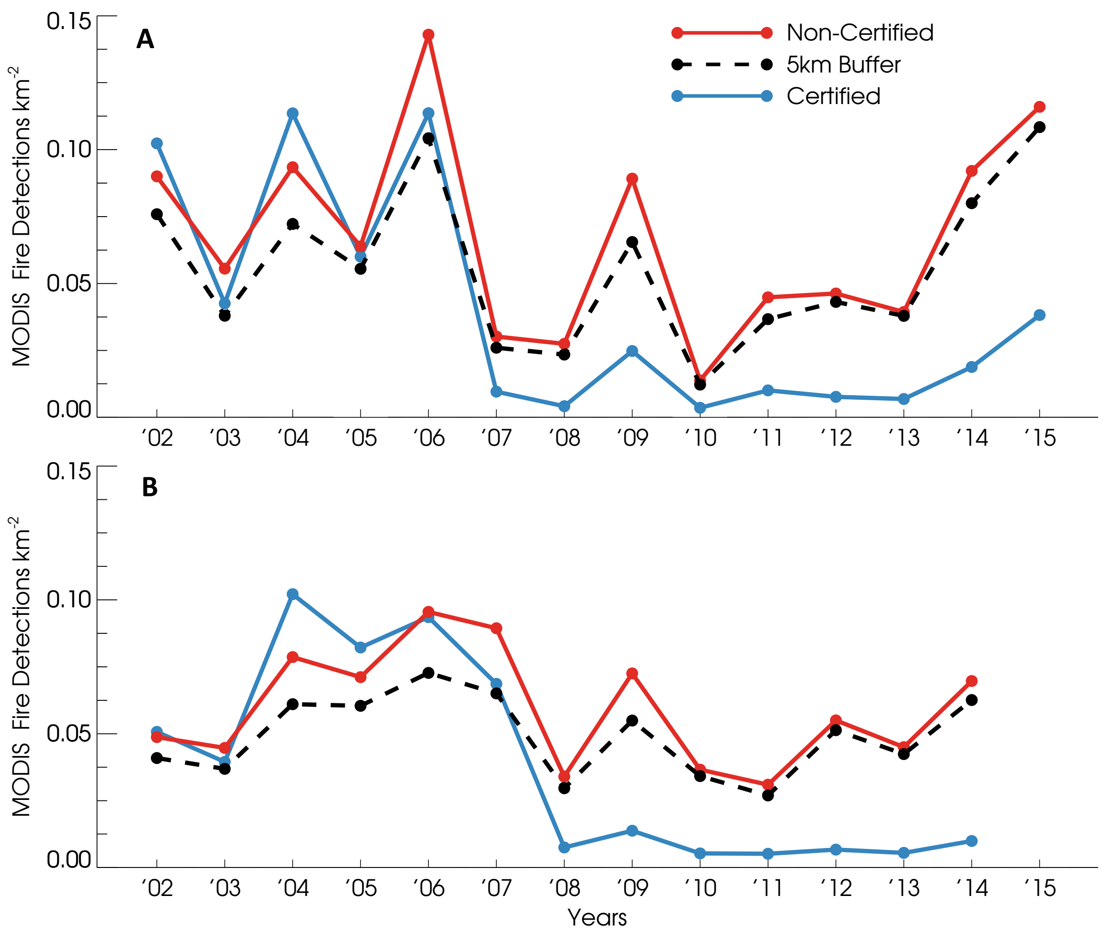


Figure 4.7: Density of MODIS active fire detections within certified OPCs, non-certified OPCs, and the 5-km buffer region around OPCs from 2002-2014. A) Time series of all MODIS active fire detections; B) Time series of MODIS active fire detections associated with fire-driven deforestation.

confirm the reduction in fire activity within certified OPCs during peak burning months of the 2009 and 2015 El Niño events (Figure 4.8). Evidence for reduced fire activity in certified OPCs highlights the potential for management of fire risk, even during strong El Niño drought conditions.

Attribution of fire activity is a critical component of satellite-based monitoring for environment compliance.  Higher resolution active fire data from VIIRS (375 m) and Landsat 8/OLI (30 m) confirm the decline in fire activity on certified OPCs compared to non-certified OPCs and buffer areas in both 2014 and 2015 (Figure 4.9).

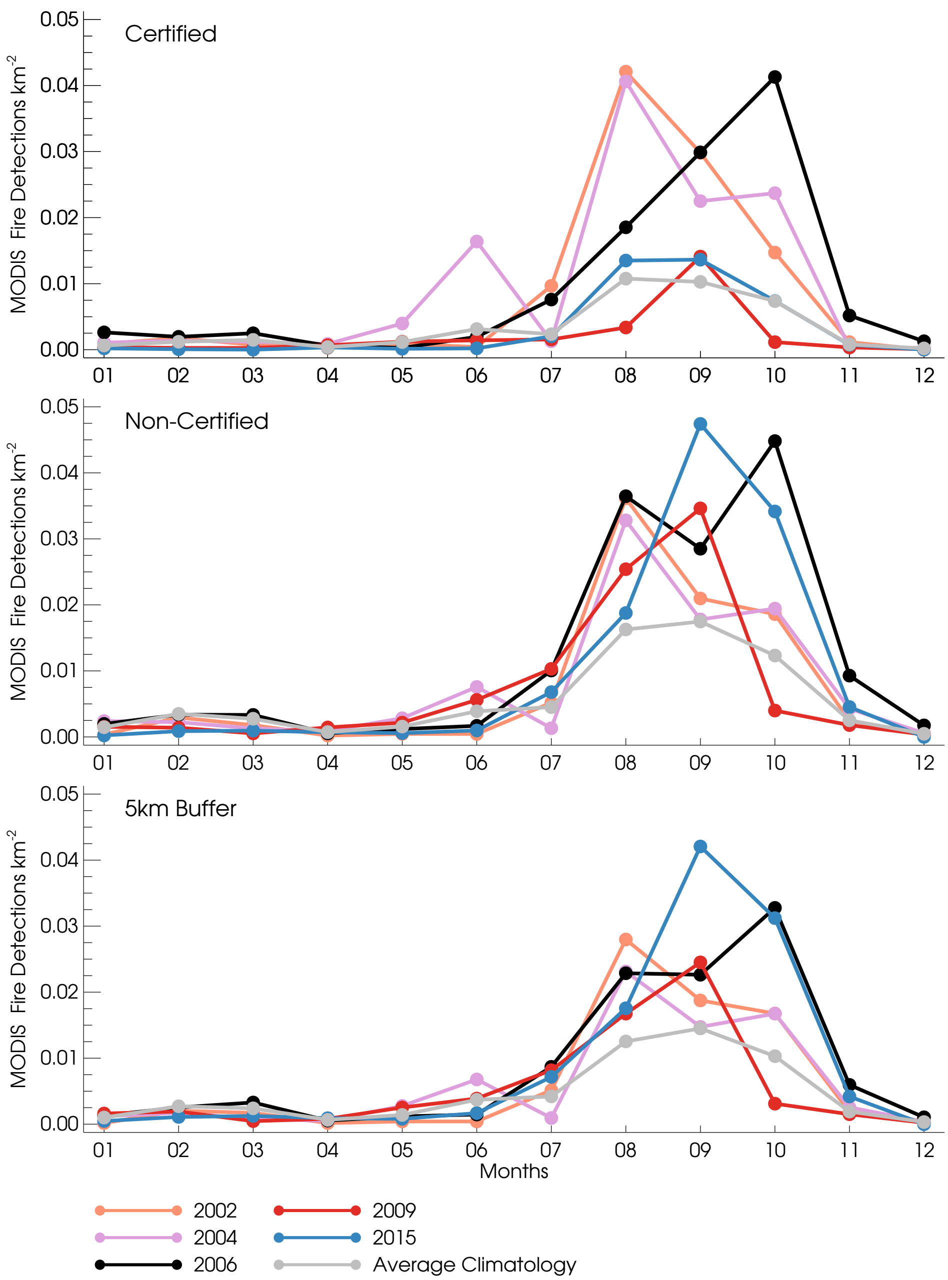


Figure 4.8: Monthly density of MODIS active fire detections (Terra and Aqua, combined) for certified OPCs, non-certified OPCs, and a 5-km buffer region surrounding OPCs in Indonesia during El Niño years. A climatology of average monthly fire detections from all years (2002-2015, grey) is shown for comparison.

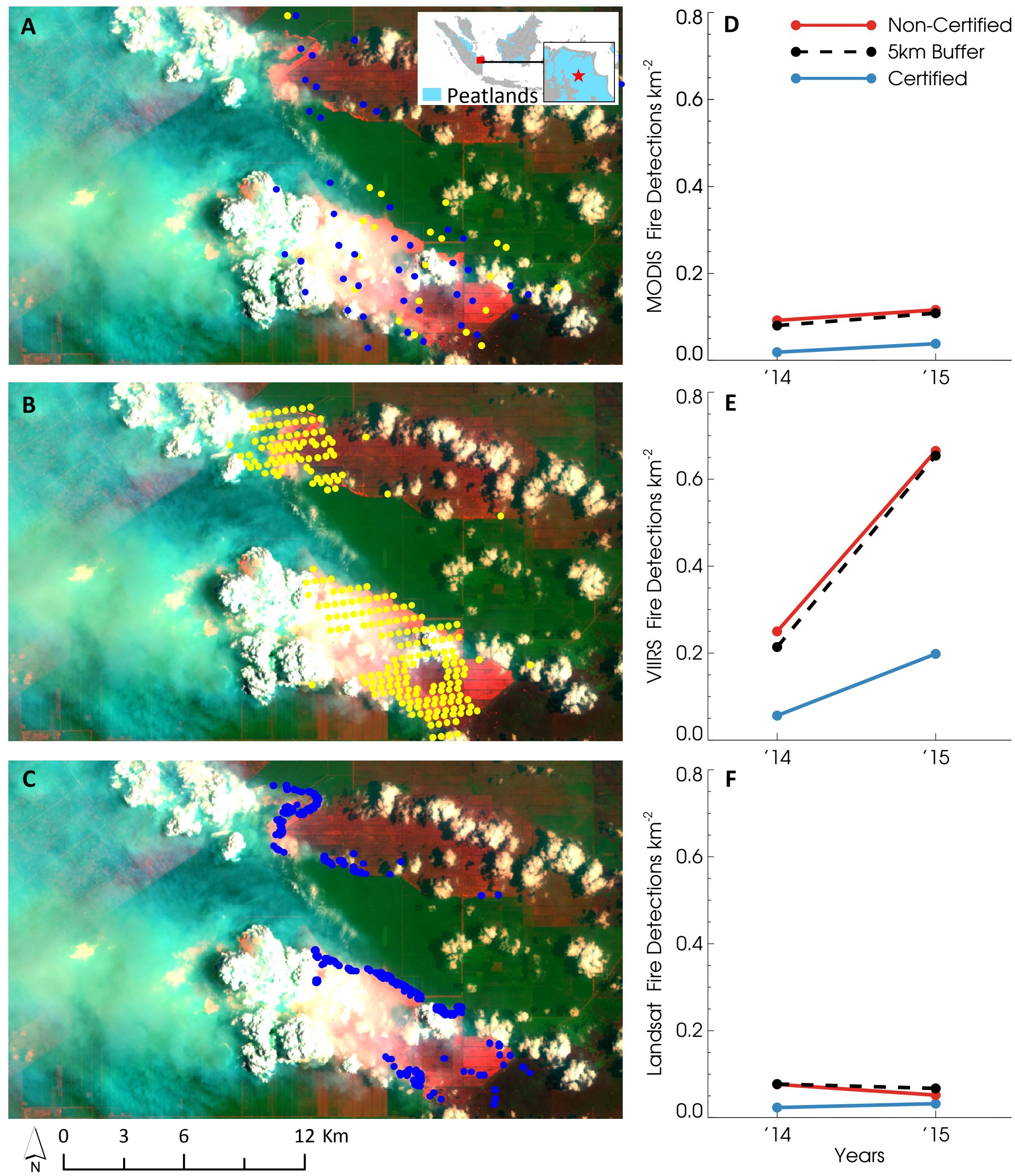


Figure 4.9: High-resolution active fire detections confirm lower fire activity in certified OPCs during the 2015 El Niño event. Map panels show active fire detections on Sep. 30, 2015 for peat fires in southern Sumatra from A) Terra (blue) and Aqua (yellow) MODIS (1 km), B) Visible Infrared Imaging Radiometer Suite (VIIRS) I-band (375m), and C) Landsat-8/OLI (30m). Background images in panels A-C are a false-color composite of Landsat 8/OLI bands 7-5-3 from the same date (Path/Row: 124/62). Adjacent panels show total annual fire detections in 2014 and 2015 for certified OPCs from D) MODIS, E) VIIRS, and F) Landsat 8/OLI.

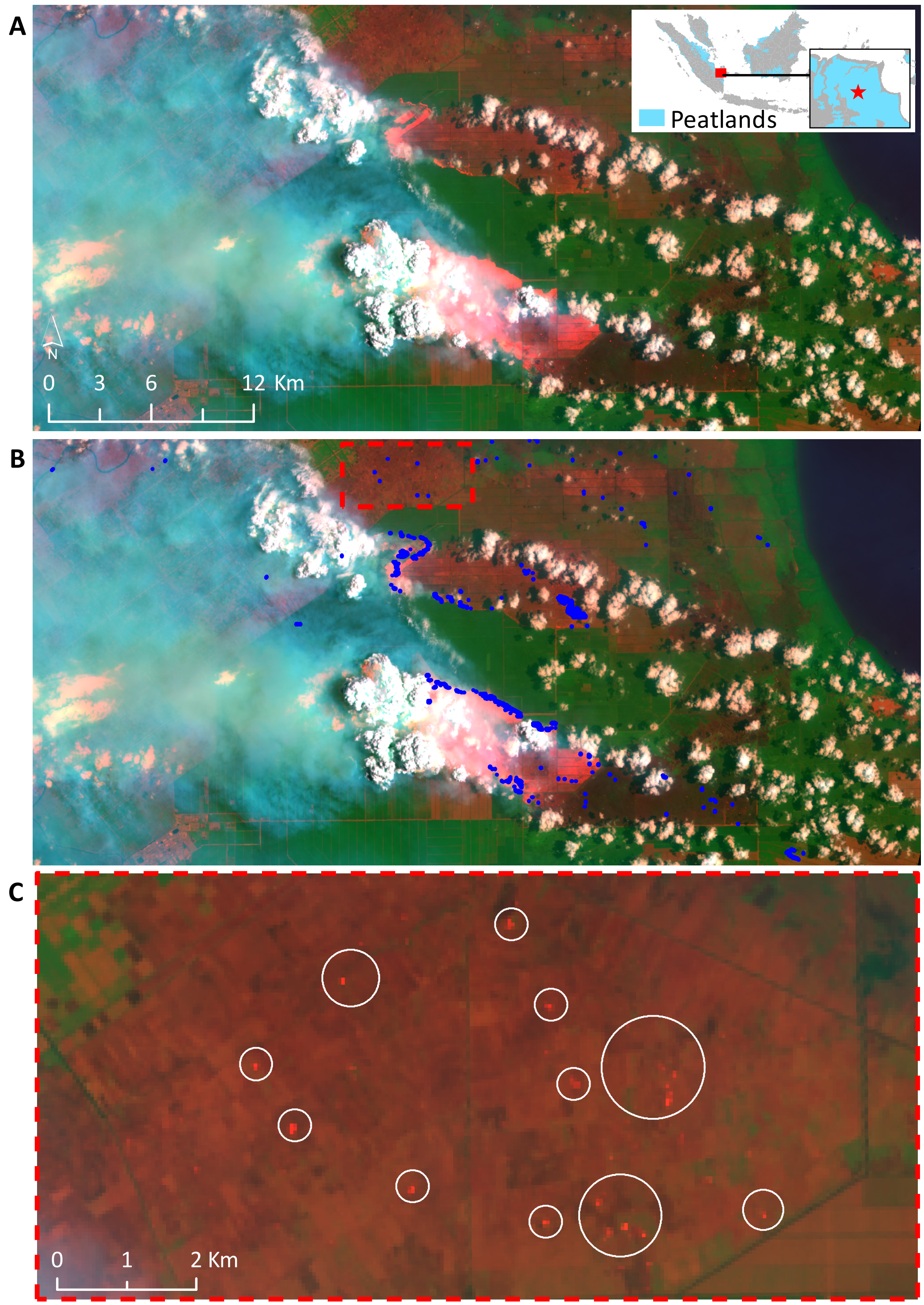


Figure 4.10: Landsat 8 active fire detections captured active fire fronts (B) and residual smoldering fires (C) in peatland areas of southern Sumatra on Sep. 30, 2015. White circles in panel C indicate smoldering for a subset of the image in panel B (dashed red outline). The regular grid of peatland drainage canals is visible in all panels.

The VIIRS 375 m fire data provide a more complete characterization of the fire perimeter than MODIS on a daily basis.  Although less frequent, Landsat 8 coverage every 16 days captures the precise location of active fire fronts, small fires, and persistent smoldering in peat areas that may last for many days (Figure 4.9 & Figure 4.10). High resolution fire data improve our understanding of fire use for deforestation and agricultural management, with detections that can be more definitively attributed to specific actors in support of monitoring, reporting, and verification.

### *4.5 Discussion*

Following certification, oil palm concessions had lower fire-driven deforestation and total fire activity during El Niño events.  These reductions point to the potential for RSPO to contribute to REDD+ and decrease fire ignitions during drought conditions.  However, certification did not halt forest losses or fire activity altogether.  In addition, certified OPCs currently account for a small fraction of total oil palm leases (e.g., 7% in Indonesia); non-certified OPCs maintained higher rates of fire-driven deforestation and fire activity in recent years, including the 2015 El Niño. The opportunity exists, therefore, to enhance the environmental benefits of RSPO certification through expansion of certified OPCs and strengthening of certification standards, including the use of satellite monitoring of fire activity and forest loss.

This study confirms the pervasive use of fire for forest conversion to oil palm in Indonesia, with one quarter of forest loss identified as fire-driven deforestation. Fire-driven deforestation was less common on certified OPCs in Malaysia and Papua New Guinea, and fire use for forest conversion declined to near zero after the start of certification in 2009. The fraction of fire-driven deforestation for different land management categories are likely conservative because satellite platforms underestimate of total fire activity. Satellite sensors do not sample at the peak of diurnal fire activity (Giglio *et al.*, 2000), and cloud cover (Giglio *et al.*, 2003) and orbital coverage (Schroeder *et al.*, 2005) reduce the probability of fire detections, particularly for low-latitude regions with a seasonal rainfall such as Southeast Asia. New satellite products partially overcome these limitations through improvements in orbital coverage (VIIRS; Schroeder *et al.*, 2014) and spatial resolution (VIIRS, Landsat), especially for detection of small and low-intensity fires in deforestation or peatland areas (Schroeder *et al.*, 2015; Elvidge *et al.*, 2015).

The proportion of fire-driven deforestation on OPCs in Indonesia (~25%) was similar to the estimate of combustion losses in bookkeeping models (30-40%, Houghton & Hackler, 1999), but fire use was much lower in Malaysia and Papua New Guinea. However, this study only confirms the coincident timing and locations of fires and forest losses, not the combustion completeness of fires for forest conversion. Removal of forest vegetation is critical to establish an oil palm plantation, but combustion completeness may be lower for these fires, given higher fuel moisture and less need for complete combustion of aboveground biomass than for expansion of row crop agriculture (Morton *et al.*, 2008). Fuel moisture also has a substantial influence on trace gas emissions from fire, including smoldering fires in peatlands (Miettinen *et al.*, 2012; Page & Hooijer, 2016).

Several factors may account for the reduction in fire activity on certified OPCs following certification. First, certification may reduce fire-driven deforestation by directly influencing land management practices. Collectively, all certified OPCs in Indonesia, Malaysia, and Papua New Guinea showed declines in fire-driven forest losses after 2009. Second, declining fire activity may simply be an artifact. If companies preferentially certify older plantations (Carlson *et al* in review), then the reduction in fire activity may indicate an end of the expansion process rather than a change in fire-driven deforestation. Remaining forest cover was only 9-13% on certified OPCs in Malaysia and Indonesia; remaining forest areas may not be suitable for oil palm or accessible based on RSPO restrictions. Regardless, the potential exists for RSPO to promote fire-free management of OPCs to protect high-value tree crops and remaining carbon stocks in forests and peatlands. Large labor forces needed for oil palm production (Lambin *et al.*, 2013) may aid regional fire suppression efforts, allowing established OPCs to maintain lower fire activity in and around plantations during El Niño years.

Aligning certification criteria with existing satellite monitoring capabilities could improve the transparency, accountability, and impact of RSPO and other certification efforts. RSPO certification prohibits specific categories of forest clearing that cannot be readily distinguished using satellite data. For example, total forest loss can be identified using freely available satellite data products, but high conservation value or primary forest types cannot be confirmed with Landsat or MODIS data. Changing RSPO criteria to more closely match existing products on forest cover would enable more rigorous monitoring of environmental compliance. Alternatively, public databases of set-aside areas on certified OPCs (e.g., stream buffers, areas deemed unsuitable for production, or HCV) could improve transparency and support monitoring efforts without the need to derive forest conditions directly from satellite data. New, higher resolution active fire data also complement the time series of MODIS active fire observations. Landsat and VIIRS active fire data offer sufficient spatial detail to unambiguously attribute fire activity to specific land owners—an important step forward in satellite monitoring by governments, non-governmental organizations, or certification bodies such as RSPO. Fire suppression is particularly important to safeguard carbon stocks in peatlands, and Landsat resolution is particularly beneficial to identify small, smoldering fires (Schroeder *et al.*, 2015; Elvidge *et al.*, 2015).

By 2020, Indonesia has pledged to double its palm oil production (Maulia, 2010), and expanding production threatens remaining rainforest and peatland areas. Certification offers a path for low-carbon development of additional oil palm production, provided that certification standards are consistent with capabilities for routine satellite monitoring. RSPO certification has reduced but not eliminated forest loss and fire use on certified OPCs. To realize the full potential of certification, requirements for RSPO certification must be updated to align environmental goals with objective measures of compliance.

# Chapter 5: Key Conclusions from the Dissertation, Lessons for Policy Makers, and Directions for Future Research

## *5.1 Summary*

The three case studies in this dissertation answer regional questions regarding human-induced degradation from land use and land cover change and offer lessons for agriculture management in response to climate variability, expansion and intensification of agriculture production, and market demand and certification. Three themes emerge from the regional studies regarding ecosystem degradation: climate variability and change, market demands, and carbon emissions.

First, climate variability and climate change have distinct impacts on managed and natural systems. The southwest United States and Southeast Asia are particularly influenced by ENSO, albeit by opposite phases of the ENSO cycle. In the southwest United States, La Niña conditions reduce rainfall and vegetation productivity. In the last decade, La Niña drought years (i.e., 2007-2008, 2010-2011, 2012) were superimposed on long-term declines in regional rainfall, leading to widespread reductions in vegetation productivity, forest dieback, and extensive fires. In Southeast Asia, El Niño conditions trigger drought across regions that otherwise experience aseasonal rainfall. During drought years, fires for agricultural expansion in forest and peat areas can get out of control, damaging large areas of forest and peatland and releasing globally-significant GHG emissions. In both regions, drought conditions from ENSO variability provides an indicator of challenges for agricultural management and conservation from climate change. Regional efforts to predict and respond to climate variability are therefore critical to sustain agricultural production and preserve ecosystem services.

Second, global market forces can have profound regional impacts for ecosystem degradation, based on the expansion and concentration of intensively managed croplands to satisfy global demand for commodity products. Industry-led efforts to achieve sustainable production of soy in the Brazilian Amazon (Soy Moratorium) and palm oil in Southeast Asia (RSPO certification) have had varying degrees of success in reducing the environmental impact of commodity production. In both regions, the sustainability efforts have unintended consequences. In Brazil, the Soy Moratorium only applies in the Amazon and not other biomes, including the Cerrado. In Southeast Asia, RSPO certification reduced but did not eliminate deforestation and fire from certified concessions. Industry-led efforts also must confront challenges from decentralized policies and weak governance. In the case of the Cerrado, government efforts to support environmental legislation are incomplete (e.g., satellite-based deforestation monitoring and complete land registries). In Indonesia, corruption and weak institutions compound the limitations of RSPO certification to protect forests. Both cases highlight the challenges for sustainable production, based on the need to balance competing interests of consumers, local and national governments, and private companies.

Third, carbon emissions from ecosystem degradation vary based on the patterns of human activity in different land use systems. In the southwest United States, management of livestock grazing results in a gradual changes in vegetation carbon stocks and soil carbon, whereas mining and oil extraction activities may generate a one-time pulse of carbon emissions from the complete removal of vegetation, especially if damages limit the recovery of vegetation following resource extraction. Carbon emissions from agricultural expansion in the Cerrado are predominantly a one-time process, as native vegetation is cleared and burned in order to plant soy and grains. In contrast, carbon emissions from oil palm expansion in Southeast Asia involve both rapid release of vegetation and soil carbon stocks and slower processes of loss and gain from land management (Carlson *et al.*, 2013). Forest conversion for oil palm expansion results in a rapid release of forest carbon through fire and decomposition. Oil palm expansion into peat areas, facilitated by draining and burning, releases carbon from peat oxidation in addition to burning. In both systems, carbon accumulation in oil palms partially compensates for the loss of initial forest carbon stocks (Carlson *et al.*, 2012). Overall, variability in the timing and magnitude of carbon emissions from different land use systems informs the need for specific strategies to counter carbon losses in these systems in support of global climate change mitigation.

## *5.2 Conclusions Related to Specific Research Questions*

1. **What is the extent and severity of loss of production in the southwest US?**

Time series of satellite data indicated widespread and large reductions in productivity in grassland ecosystems compared to reference conditions [Figure 2.4]. The local NPP scaling (LNS) maps highlighted sharp boundaries between degraded and less-degraded land, mainly associated with human activities. Sharp boundaries were observed at the edges of active and abandoned mining and oil extraction facilities, across fences between neighboring grazing allotments, and at the edges of forest clearings [Figure 2.5]. The time series signature from MODIS data suggests permanent losses of vegetation productivity in active and abandoned mining areas. The LNS maps also showed high degree of interannual variability in grassland and savanna areas, including in the grazing allotment areas and around the watering points.

2. **Does land ownership and management contribute to differences in satellite-based estimates of declining net primary production (NPP)?**

NPP Reductions differed across land cover and land management types [Table 2.1 and Table 2.2]. Among all land cover types, forested ecosystems had the largest NPP reductions per unit area, in part based on higher NPP in forests and hence a greater potential capacity for degradation. The US Forest Service manages many forest lands in the southwest United States, and therefore US Forest Service lands showed higher NPP reductions per unit area than other management types. The BLM manages more than 50% of the land area in southwest United States. Shrub-dominated landscapes on BLM lands showed low overall reductions in NPP, in part due to lower NPP in shrublands than forests. Native American Indian Reservations, often referred to as more degraded, actually had smaller reductions in NPP than other managed lands.

3. **Is cropland expansion an important driver of forest conversion in the Cerrado?**

Widespread cropland expansion in the Cerrado biome replaced grassland, shrublands, and forested Cerrado physiognomies with high carbon stocks [Figure 3.2]. From 2003-2013, the total cropland expansion in Cerrado was more than 9 Mha. On average, approximately 21% of the annual cropland expansion replaced forests and woodlands [Figure 3.5]. However, after the implementation of the Soy Moratorium in the Brazilian Amazon, forest conversion for cropland expansion accelerated in Matopiba, the northeastern region of the Cerrado. Since 2008, the Matopiba region accounted for one-third of all cropland expansion into forest and other wooded lands, including roughly half of all new cropland in Maranhão (51%) and Piauí (46%) [Figure 3.3]. Cropland expansion is one of the important drivers of recent forest conversion in the Cerrado biome. However, nearly two-thirds of forest loss was associated with expansion of pasture, as cattle ranching remains the major driver of forest conversion in the Cerrado.

**4. To what extent do carbon emissions from forest conversion in the Cerrado offset emissions reductions from declining Amazon deforestation?**

Cerrado carbon emissions partially offset Amazon deforestation emissions reductions. From 2003-2013, emissions from large-scale cropland expansion totaled 179 Tg, and 29% (52 Tg C) of estimated carbon emissions during this period came from forest conversion [Figure 3.5]. The fraction of forest carbon emissions from cropland expansion was higher in recent years based on the growing proportion of expansion in Matopiba [Figure 3.3 & Figure 3.4]. Between 2010-2013, annual forest carbon emissions from cropland expansion in the Cerrado were more than 6% of estimated carbon emissions from Amazon deforestation [Figure 3.5], partially offsetting the reductions in Amazon deforestation emissions from forest-to-cropland transitions. Total cropland expansion (including conversion of forest and non-forest cover types) added 16% to estimated carbon emissions from Amazon deforestation since 2011.

In the context of REDD+, gross carbon emissions from cropland expansion in the Cerrado can also be compared to the 2011-2015 baseline for Amazon deforestation emissions (247.63 Tg $yr^{-1}$; BRAZIL, 2014). Declining Amazon deforestation reduced emissions compared to the baseline. Cropland expansion in the Cerrado increased Brazil's forest carbon emissions, thereby reducing emissions reductions since 2011 by 1.9%. Combined forest and non-forest cropland transitions offset 5% of Amazon emissions reductions relative to the baseline. Given that cropland expansion only accounted for one-fifth of forest loss between 2003-2013, total forest carbon emissions from the Cerrado are likely a substantial and growing part of Brazil's national greenhouse gas budget, highlighting the need for national accounting to achieve climate mitigation targets with REDD+.

## 5. What fraction of forest and peat forest conversion for oil palm involves fire?

Satellite data suggest that nearly one quarter of forest clearing in both certified and non-certified oil palm concessions (OPCs) involved fire [Table 4.1]. The fraction of fire-driven forest loss was higher in both lowland and peatswamp forests prior to certification [Figure 4.2]. Following certification, fire-driven forest loss declined by 88% in RSPO certified OPCs in Indonesia compared to 2002-2008. At the same time, fire-driven forest conversion increased by 117% and 138% in non-certified OPCs and buffer areas, respectively. Patterns of fire-driven forest loss in certified OPCs differed across Indonesia, Malaysia, and Papua New Guinea [Figure 4.4], but certified OPCs in all three countries had lower fire activity following certification.

### 6. Does certification alter fire use for forest conversion or management of concession areas?

Certification reduced forest loss and fire activity, but did not halt deforestation altogether [Figure 4.2 & Figure 4.4]. Forest loss continued after certification on certified OPCs in Indonesia, Malaysia, and Papua New Guinea. In Indonesia alone, deforestation after certification led to an additional 6% loss of remaining forest cover. Forest loss rates declined by 60% in RSPO certified OPCs from 2009-2014 (i.e., post-certification time frame) compared to pre-certification levels, with larger declines in fire-driven deforestation (88.5%). During the same time, fire-driven forest conversion declined to near zero on certified OPCs in Malaysia and Papua New Guinea. Established oil palm plantations are less likely to burn under managed conditions and the reductions in post-certification fire activity on certified OPCs are likely influenced by land management practices. Likewise, reductions in forest clearing after 2009 may be an artifact, as remaining forest cover on certified OPCs in Malaysia and Indonesia were low at the start of certification and companies preferentially certified OPCs with low forest cover.

7. **During El Niño years, does certification reduce fire activity compared to non-certified OPCs and surrounding lands?**

Certification decoupled fire detections from ENSO-driven variability in fire risk. Interannual variability in regional fire activity is largely governed by the timing and magnitude of El Niño events [Figure 4.6] (Chen *et al.*, 2016). Prior to certification, interannual variability in fire detections was similar for certified OPCs, non-certified OPCs, and buffer areas in Indonesia, including during El Niño events in 2002, 2004, and 2006 [Figure 4.7]. Following certification, fire activity declined in certified OPCs in all years, with 67-78% fewer fires during the 2009 and 2015 El Niño events compared to non-certified OPCs. Monthly fire counts confirm the reduction in fire activity within certified OPCs during peak burning months of the 2009 and 2015 El Niño events [Figure 4.8]. Evidence for reduced fire activity in certified OPCs highlights the potential for management of fire risk, even during strong El Niño drought conditions.

### *5.3 Satellite monitoring in support of climate mitigation and sustainable agriculture management*

The use of time series of satellite remote sensing data in this dissertation improves our understanding of the patterns, processes, and consequences of ecosystem degradation across biomes. The findings in Chapters 2-4 underscore some of the opportunities to expand and improve satellite monitoring approaches in support of policy efforts to reduce deforestation and degradation and promote sustainable agriculture. In the context of growing human pressures on natural and managed ecosystems, satellite-based monitoring strategies may allow for early detection of degradation impacts and increase transparency for efforts to evaluate compliance with industry or government initiatives.

### 5.3.1 Rangeland monitoring in the southwest United States

Currently, there is no comprehensive assessment of rangeland conditions in the western United States based on satellite data. The NRCS-NRI has a monitoring program using field data (~ 800,000 locations) on private lands throughout the United States (Herrick *et al.*, 2010). The data from the NRI, however, are only available as national summaries, and access to field data is restricted to protect the privacy of private landowners on whose land the data was collected. In addition, NRI results are only for private lands; public lands (e.g. BLM, USFS) and Native American lands are not included. The BLM, the nation's largest public land manager and administrator of livestock grazing permits (i.e., nearly 155 million acres; BLM, 2016), is required to monitor the ecological impacts of grazing on western rangelands. At present, BLM's land health standards (LHS) evaluation has no formal approach to account for past or historic livestock damage, as the current approach uses field data to evaluate current grazing management. The NRI and LHS field inventories do have a wealth of information on soils and vegetation characteristics. Combining these field data with time series of satellite observations could provide a long-term, spatially-explicit perspective on changes in vegetation productivity from management of western rangelands.

### 5.3.2 Climate mitigation strategies for the Cerrado biome

The Soy Moratorium—a landmark agreement among industry, civil society, and government agencies to prevent Amazon deforestation for soy production—was renewed indefinitely in 2016 (GREENPEACE, 2016a). The Soy Moratorium is unique in many respects, including the explicit reliance on satellite monitoring programs to identify non-compliance and restrict market access for farms that violate the prohibition on deforestation for soy (Rudorff *et al.*, 2011; Macedo *et al.*, 2012; Gibbs *et al.*, 2015). Soy is grown in other parts of Brazil, including the Cerrado biome where Soy Moratorium does not apply. Incentivizing soy producers to reduce Amazon deforestation while allowing forest conversion for soy in the Cerrado does not fully realize the potential for the Soy Moratorium to protect forest landscapes of Brazil. Satellite monitoring programs in support of the Soy Moratorium include PRODES, an annual assessment of Amazon deforestation (BRAZIL, 2014), and routine monitoring of crop production using MODIS satellite data (Rudorff *et al.*, 2011). Expanding these efforts to consider forest conversion and soy cultivation in the Cerrado could directly support soy industry commitments to zero deforestation that have overlooked losses in dry forest regions such as the Cerrado.

### 5.3.3 Improving transparency, accountability, and impact of Palm Oil Certification

At present, the RSPO lacks the institutional and scientific capacity to implement satellite monitoring programs, despite freely-available products on forest loss, fires, and land cover from NASA satellites. The fact that current RSPO certification requirements are not compatible with satellite-based monitoring is also a major impediment for increasing transparency in RSPO using satellite data. For example, the RSPO prohibits conversion of primary and High Conservation Value (HCV) forests, yet these forest attributes cannot be unambiguously identified using current satellite remote sensing data and techniques. Aligning certification criteria with existing satellite monitoring capabilities is crucial to achieve transparency, accountability, and success of RSPO and other certification efforts. Alternatively, public databases of set-aside areas of stream buffers, including peat areas and HCV forest, could improve transparency and support community monitoring efforts without the need to derive forest conditions directly from satellite data. Currently, certified OPCs only account for 7% of the all OPCs in Indonesia; expanding certification will only increase the need to find an operational solution to routinely monitor OPCs using satellite data.

### *5.4 Future Research Directions*

Chapters 2-4 quantify the human impact on vegetation productivity and carbon stocks in drylands, tropical savannas, and humid forest ecosystems, yet land use and land cover change also impact other ecosystem services. Assessing the impacts of degradation on regional climate is one important direction for future research. Results from case studies in Brazil and Indonesia also highlight the role of influence of distant markets on local dynamics of land use and land cover change. Future research on the direct linkages between policies and decisions at the farm scale could inform efforts to reduce leakage within sectors or regions. Finally, new satellite monitoring capabilities offer the potential to develop monitoring efforts to safeguard carbon stocks in tropical peatlands.

### 5.4.1 Land degradation and regional climate

Land degradation alters water and energy fluxes and climate feedbacks through changes in surface roughness, albedo, and evapotranspiration (Charney, 1975). Interactions and feedbacks between rangeland vegetation and climate are complex and poorly understood (Izaurralde *et al.*, 2011). Soil-vegetation-atmosphere transfer (SVAT) models such as Simplified Simple Biosphere Model (SSiB-2) have been used in the past to study the impacts of land degradation on regional and global climate (Xue & Shukla, 1993; Xue *et al.*, 2001). Using models such as SSiB-2, simulations could evaluate the impact of changes in vegetation productivity from overgrazing on regional climate and carbon cycling. Given projected temperature increases across the western United States in coming decades (Seager *et al.*, 2007; Seager *et al.*, 2013; Cook *et al.*, 2014), assessing the direct role of management for amplifying regional climate change impacts is an important avenue for future research.

### 5.4.2 Soy "leakage" and Cerrado cropland monitoring

Tracking leakage is one of the most difficult tasks for international policy efforts such as REDD+. The Cerrado is the most active agriculture frontier in Brazil, and cropland expansion in the Cerrado has continued while expansion in the Amazon has slowed from industry and government interventions (Gibbs *et al.*, 2015; IBGE, 2013). Whether soy expansion in the Cerrado represents true "leakage" (i.e., producers avoiding more stringent environmental governance in the Brazilian Amazon) is an area of ongoing research. There are several barriers to definitely identify leakage of soy production from the Amazon to the Cerrado. First, satellite monitoring of deforestation developed for Amazon biome (e.g., PRODES, DETER, and DEGRAD) would need to be expanded to the Cerrado biome. Second, the satellite-based registry of private properties is more complete in the Amazon than the Cerrado biome. Completing land registries for both biomes, in combination with deforestation monitoring data, would support efforts to identify farmers that 1) leave the Amazon for the Cerrado and 2) expand production through deforestation.

### 5.4.3 Satellite-based monitoring for forest and peatland protection

Fire suppression is important to safeguard carbon stocks in Southeast Asia's peatlands. Terra and Aqua MODIS active fire detections offer near-daily information on fire activity at 1 km spatial resolution (MCD14ML; Giglio *et al.*, 2003). New, high-resolution fire detections from VIIRS (375 m) provide a more complete characterization of the fire perimeter than MODIS and improved daily coverage, since VIIRS does not have coverage gaps in the tropics like MODIS from swath width and sensor design issues. Additional data from Landsat 8/OLI (30m) fire detections captures the precise location of small fires, including fire use for smallholder agriculture or smoldering peat fires that may not be detected by MODIS/VIIRS [Chapter 4]. These new fire datasets offer an opportunity to improve our understanding of fire use for deforestation and agricultural management, with detections that can be more definitively attributed to specific actors in support of monitoring, reporting, and verification. Future research to support peat forest protection is particularly important, since monitoring of oil palm expansion will only cover a small portion of total peatswamp forest loss across Indonesia and Malaysia [Figure 5.1]. Safeguarding carbon stocks in peatlands is a priority for global greenhouse gas mitigation efforts (Hooijer *et al.*, 2010; Field *et al.*, 2016; Page & Hooijer, 2016) and Indonesia's intended nationally determined contribution (INDC) for the Paris Agreement (UNFCCC, 2015), and new satellite data can support these efforts through improved monitoring of fire activity in peatlands.

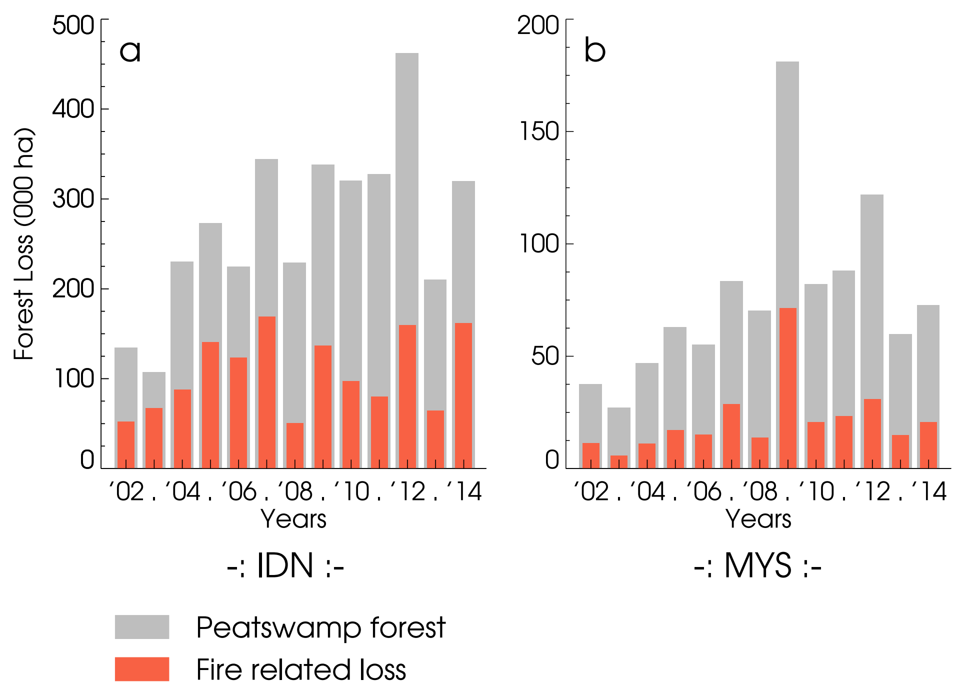


Figure 5.1: Total peat forest loss (grey) and fire-driven forest losses (orange) for all peat areas of Indonesia and Malaysia during 2002-2014. Forest loss from Hansen *et al.* (2013) was summed for all peat areas with tree cover > 0%. Peatland forest loss from fire was higher during the 2009 El Niño in Malaysia, but interannual variability in fire-driven forest loss did not track El Niño years in Indonesia.

*5.5 Conclusions*

Ecosystem degradation from human activity can reduce regional vegetation productivity, forest carbon stocks, and the extent of natural forest cover. Case studies of ecosystem degradation in this dissertation provide regional examples of the distribution and severity of human-induced degradation across biomes, based on objective measures of vegetation changes from satellite data. This dissertation underscores the pervasive impact of agriculture and land management for the transformation of vegetation carbon stocks in human-dominated landscapes, despite regional policies, and governance of land management, and certification systems for sustainable production.

Climate variability amplifies the impacts of human activity on natural systems. In this dissertation, both La Nina and El Niño phases of the ENSO cycle had widespread impacts on ecosystems and agricultural systems in the southwest United States and Southeast Asia. While the La Nina phase of ENSO cycle contributed to vegetation-die back in the southwest United States (Allen *et al.*, 2010), the El Niño phase in Southeast Asia led to extensive damage to forest and peatland ecosystems during 2006 and 2015 (Field *et al.*, 2016). In both case studies, climate variability and climate change are superimposed on top of continued human-induced land use changes in the region, elevating the levels of ecosystem degradation in drought years.

Large-scale and long-term changes in vegetation carbon stocks in all three regions were mediated by fires. Fire is the primary tool for land conversion in the Cerrado, and fire-driven deforestation accounted for at least 25% of forest conversion for oil palm in Indonesia. Human ignitions are an important source of fires in the southwest United States, as conditions during dry months routinely support fire activity. Fires impact more than just vegetation carbon stocks. Smoke plumes from peatland burning in Indonesia have far-reaching consequences; transboundary haze events reduce visibility, increase cases of respiratory illness, and contribute to higher mortality in Indonesia and major parts of Southeast Asia from poor air quality. Fire from human activity therefore degrades carbon sequestration potential and other ecosystem services.

Agriculture production is the single most important driver of large-scale ecosystem degradation, measured based on reductions in vegetation carbon stocks. Export-driven commodity agriculture production reduced forest carbon stocks in the Brazilian Cerrado and in Indonesia, where oil palm expansion replaced lowland rainforest and peat forest. Efforts to promote sustainable agriculture production have not achieved their potential benefits, but the potential exists to reduce ecosystem degradation from agricultural activity through more stringent regulations and more transparent monitoring mechanisms—including the use of satellite data.

Satellite remote sensing data offers an objective and repeatable pathway to assess ecosystem degradation across biomes in a consistent manner. Aligning sustainability standards with satellite-based monitoring approaches will improve transparency, needed to in support zero-deforestation goals. Certification, laws and improved management could also contribute to large and sustained reductions in carbon emissions from land use change.

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