DETECTION OF PERI-URBAN AND AGRICULTURAL EXPANSION 1990-2015 IN PAKSE, LAOS, USING DENSE TIME STACKS OF LANDSAT IMAGERY

by

Evan Applegate

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Abstract

Built-up areas in Southeast Asia have been expanding rapidly in the export-oriented economies of Vietnam, China, and Thailand, but less attention has been paid to cities in more rural nations such as Laos. The Laotian landscape has been shaped by both internal migration to burgeoning urban areas and large-scale foreign agricultural investment, but these trends have never been assessed together using remotely sensed satellite data. This study presents results from efforts to characterize and quantify expansion of built-up and agricultural land over a 35 km radius surrounding Pakse, the third largest city in Laos, using a multi-date composite change detection approach applied to dense time stacks of Landsat imagery. The method relies on a supervised, boosted decision tree classification that exploits training data of stable/changed areas interpreted from Google Earth and Landsat images spanning 1990 to 2015. The results show that the decision tree approach provides a land cover change map with an overall accuracy of 92%, despite noisy and missing data, frequent cloud cover, and high land cover heterogeneity across small areas. The results also show that, while built-up areas in greater Pakse expanded 28% over 25 years, agricultural lands expanded 48% over the same period. This work provides the most up-to-date land cover map of greater Pakse at the highest spatial and temporal resolution available, and adds useful data to regional environmental monitoring and sustainability efforts.

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Chapter 1. Introduction

1.1: Land cover change in Southeast Asia: new urban and agricultural areas

Southeast Asia has witnessed massive land cover change over the past three decades as a result of increased urbanization and an expansion of plantation agriculture (Schneider 2003, Byerlee 2014). Driven by rapid economic growth beginning in the 1980s, East Asia's urban land surface increased 22% from 2000-2010, while urban populations grew 31% (Schneider et al. 2015). Most of this growth took place in the region's export manufacturing-oriented nations such as China and Vietnam, but even relatively poor and rural Laos has experienced increased urbanization: urban land grew 37% between 2000-2010 (Schneider et al. 2015). Built-up areas in Laos's two largest cities, Vientiane and Savannaket, expanded at least 30% since 2005 (Sharifi et al. 2014, Kimijiama et al. 2014). Today, 27% of Laotians live in urban areas and that figure is expected to reach 38% by 2030 (Asian Development Bank 2011). While Laos's rapid urbanization -- defined here as both an increase in urban population and the expansion of built-up areas -- is expected to continue, the country's largest land cover changes have resulted from agricultural concessions. Today, five percent of the nation's land surface area is leased to foreign businesses for agricultural, forestry, industrial, and mining development (Global Witness 2013). These investments are usually sited in rural areas but, as this study will show, they have greatly expanded in the peri-urban zone of a regional capital (Schönweger et al. 2012).

While Southeast Asia's enormous primary cities (e.g. Shanghai, Manila, Bangkok) attract massive industrial and infrastructure investment, the region's small and mid-size cities attract the majority of rural migrants and, because there are more of these cities, they affect a larger number of people and a greater proportion of land than their megacity counterparts (Webster et al. 2014). Pakse, Laos's third largest city and a budding tourism and commercial hub near the Thai border, offers a useful case study for urban land conversion in a heavily rural area that may be extensible to urban land cover change studies in Cambodia, Vietnam, and Thailand (Asian Development Bank 2011).

It is likely that much of the projected urban growth will take the form of converting formerly rural and agricultural land to residences, factories, or roads, a process called "peri-urbanization" that has been extensively documented in the growing metropolitan regions of Vietnam, Thailand, and China (Nguyen Thi et al. 2010, Gross et al. 2014). While most urban growth in the region has been contiguous expansion from urban cores, an increasing amount is taking place on the "peri-urban" fringe of cities (Legates and Hudalah 2014). "Peri-urbanization" has many definitions across the fields of urban planning and development studies, but broadly refers to the rapid, piecemeal, and unplanned process by which rural areas on the outskirts of cities become more "urban" socially, physically, and economically, often coincident with foreign direct investment (Webster et al. 2002). For the purposes of this study, peri-urbanization is defined as the unplanned and discontinuous growth of built-up areas up to 50 km from the urban core, usually involving the conversion of agricultural or naturally vegetated areas to roads, commercial structures, or residences (Simon 2008). Since 2000, Pakse's peri-urban zone has also hosted enormous forestry and agricultural projects, which converted massive amounts of smallholder croplands and natural areas to monoculture plantations (Global Witness 2013). Since peri-urban Pakse's land cover change trajectories cannot be adequately described by measuring urbanization or agricultural expansion alone, both are explored in this work.

By 2030, 40% of the urban population added to Southeast Asia, or 200 million people, will be in peri-urban areas (Webster 2002). Effective management can reduce the harmful environmental and socio-economic effects of peri-urbanization, and satellite-based assessments of East Asian peri-urbanization provide an invaluable tool to regional officials and planners to support efficient growth and monitor progress (Gross et al. 2014, Legates 2014). Recently, several remote sensing based studies of peri-urban areas have been carried out across China, Thailand, Vietnam, Indonesia and the Philippines, but no spatially and temporally detailed analyses have been conducted in Laos. This information can inform local urban planning efforts, previously attempted in 1997 and 2011 (Asian Development Bank 2011). Up-to-date land cover information is especially important in Laos where government offices exercise significant control over land use and commercial activity (Laungaramsri 2012).

In addition to peri-urbanization, large-scale agriculture is another major driver of land cover change in Southeast Asia. Multinational companies contract with local farmers in China, Vietnam, Thailand, Cambodia, and Laos, to produce cash crops, or they establish and run large monoculture plantations on leased plots. Since the mid-1990s, oil palm, rubber, cassava, eucalyptus, sugarcane, cashew, banana, and other forestry and agricultural products have been grown in large plantations across Southeast Asia, often established by multinational companies (Baird and Fox 2010, Global Witness 2013, Byerlee 2014, Latsaphao 2016). While this agricultural investment provides revenues and employment opportunities to host areas, it can have severe consequences for the local environment and the livelihoods of subsistence farmers (Kenney-Lazar 2012). Agricultural land cover change was also the primary driver of deforestation in the Southeast Asia between 1990-2010, contributing to an 11.8% decrease in forest cover that adversely affected biodiversity and carbon stocks (Stibig et al. 2014).

Since the mid 1990s official Laotian policies aimed at "turning land into capital" have promoted foreign investment in mining, hydropower, light industry, and especially agriculture (Manivong 2014). Provincial and national officials have leased vast tracts of land to Vietnamese, Thai, and Chinese companies to plant coffee, tea, palm, sugarcane, and rubber, with the latter representing the largest investments: 2,800 km^2 of rubber trees cover Laos, equivalent to 8% of the country's arable land (Global Witness 2013). Fully 23% of leased land is located on "protected" forest areas nominally off-limits to development, a contradiction to the Laotian government's stated goal of restoring the forest cover to 70% by 2020 (Lund 2010). Champasak province alone, of which Pakse is the capital, contains more than 100 30-year agricultural land leases (Latsaphao 2016). The true extent of the agricultural projects is unknown, as plantations regularly expand beyond their permitted boundaries into neighboring forests and smallholder croplands (Schönweger et al. 2012). Before the effect of Laotian plantation agriculture can be accurately assessed, it is necessary to know its true extent, and accurate land cover maps are a first step towards that goal.

1.2: Research questions and goals

Peri-urbanization and large-scale agricultural growth in Laos presents a unique set of planning and environmental challenges, requiring accurate land cover change assessments not only in the immediate surroundings of a city, but across the entire peri-urban zone. Recently, several remote sensing-based studies of peri-urban areas have been carried out across China, Thailand, and Vietnam, but no spatially- and temporally-detailed analyses have been conducted in Southern Laos. Presented here is a land cover change assessment of Laos's third-largest city, Pakse, measuring the extent and spatial pattern of new urban and agricultural land added in a 35 km radius from Pakse's core over three periods: 1990-2000, 2000-2006, and 2006-2015.

This work seeks to answer the following questions:

1) What was the amount of land converted to built-up and agricultural areas between 1990-2015 in greater Pakse?
2) Is there a relationship between land conversion and distance from Pakse's center, or distance from roads?

This work is organized as follows. Chapter 2 reviews existing studies and their conclusions. Chapter 3 describes the methods used to assess Pakse's land cover changes between 1990-2015. Chapter 4 presents the results and interpretation of the classification, as well as an analysis of the study area's spatial patterns of urban and agricultural growth. Chapter 5 synthesizes the findings of this study and offers future directions for study.

This work makes a valuable contribution to Southeast Asian land cover change studies by applying remotely sensed data and a semi-automated machine learning classifier to characterize the extent and pattern of urban and agricultural land additions in Pakse, Laos. The following methods and conclusions may be extensible to other nearby cities, making Pakse a useful case study and template for land cover change science in the region.

1.3: Study area

Pakse, Laos's third largest city and capital of Champasak province in the country's southwest, spreads along the banks of the Mekong River near the Thai border. Founded in 1908 as a French colonial outpost, its monsoon climate has a wet season spanning May through October and a dry season from November to April. Upland forests in the east reach elevations of 950m, hosting most of Laos's coffee production (Toro 2012). Lowlands (elevation ~100m) to the north and west of Pakse are covered with rice paddies and small croplands, fed by heavy rains that average 325mm a month during the wet season. Natural vegetation includes dry evergreen forests on the hills, and mixed deciduous forests, savannah, grasslands and the occasional wetland covering what has not been converted to paddies (FIPD 2002).

The built-up area of the urban core is approximately 5 km in diameter and surrounded by a patchwork of croplands composed of both smallholder plots and large monoculture plantations. The city's population grew from 20,000 residents in 1960 to approximately 72,000 today, and is growing 5-6% yearly; in all, Pakse's population is expected to grow 50% by 2030 (Sisoulath et al. 2016, Asian Development Bank 2011).

Today, accelerating road development and small but growing local industries including garment factories, construction, and agricultural processing give the region the second-highest per-capita GDP in Laos, only trailing the capital city of Vientiane (Sisoulath et al. 2016). Pakse is the only urban district in Champasak province and one of the few Laotian districts in general to experience net in-migration as populations from the southern regions move to Pakse for work and education (Nolintha 2011).

The central government is courting investment in the city to transform Pakse into a regional commercial hub, tourism destination, and a "bridge linking central and northern regions and neighboring countries" (Ministry of Planning and Investment 2011, Asian Development Bank 2011, Manivong 2014, Laine 2015). Investment in the area has been growing: in 2015 eight Japanese and Lao-Japanese companies paid $5 million to operate in a Pakse-Japan special economic zone, and another investment zone was established in May 2016 to host a tourist resort and trade complex totaling $80 million in investment (Vientiane Times 2015, 2016). The Laotian government's National Committee for Special and Specific Economic Zones has announced its intent to set up three additional investment-friendly areas in Champasak by 2020 (National Committee for Special and Specific Economic Zone Secretariat Office 2012).

This growth presents challenges to both the government's planning efforts and the financial and food security of its residents. As rice fields abutting the city are converted to residential areas, factories, or cash crop plantations, residents have abandoned farming for wage labor in Pakse or on plantation farms. As a result, agriculture's share of the regional economy has fallen from 40% in 2008 to 27.6% in 2014 (Asian Development

Bank 2011). While many welcome the new opportunities that urbanization brings, the loss of agricultural land has affected tens of thousands of residents (Sharifi et al. 2014). The city has an official urban plan to regulate development and prevent land degradation, but it was last revised in 1997 and has not been followed due to informal development and local officials granting building permits that contravene the plan (Asian Development Bank 2011).

The area surrounding Pakse hosts dozens of land concessions, where private companies lease government-owned land for business use (Figure 2) (Delang et al. 2013). Most of these plots host monoculture agricultural and forestry plantations, where rubber, eucalyptus, coffee, cassava, and rice are grown for export by Vietnamese, Thai, and Chinese companies; of 31 concessions in the area, 26 are for agricultural products and 21 are foreign-owned (Government of Laos 2010). These concessions are an important part of land cover change in the region, but their precise boundaries and extents are not public information (Global Witness 2013).

This study assesses the pattern and extent of both peri-urbanization and agricultural growth, as each affect the livelihoods of local residents; expanding built-up areas on the fringes of Pakse have a “pull” effect on nearby rural dwellers, while more and larger plantations displace villagers in a “push” towards the urban core (Kimijiama and Nagai 2014). An accurate land cover map is necessary to assess these trends and provide timely information towards the ends of inclusive, sustainable urban and agricultural development.

Chapter 2. Literature Review

2.1 Urbanization and peri-urbanization trends in Southeast Asia

Peri-urbanization in the region is not a new phenomenon. 11^{th} century Angkor Wat experienced the same type of fragmented growth appearing in Southeast Asia today, but it has accelerated since 1993 as the region's major cities began to host large-scale industry funded by foreign investment (Simon 2008). Indeed, growth in peri-urban zones comprises a major share of the urban land added to East Asia over the past two decades (Webster 2002, Legates and Hudalah 2014). In neighboring Vietnam, recent work has shown that one-third of urban land added to Ho Chi Minh City from 1990-2012 appeared more than 40 km from the urban core, and 57% of Hanoi's urban land added over the same period appeared 10-25 km from the city's center (Kontgis et al. 2014, Nong et al. 2015). In addition, regional analyses of East Asia have revealed that 71% of new urban surfaces 2000-2010 were added outside core municipal bounds (Schneider et al. 2015).

Peri-urban zones, containing both relatively rural and undeveloped land but high concentrations of potential workers, are attractive "blank slates" for foreign and local investors. The peri-urban regions of China's Pearl River Delta received 70% of foreign capital investment between 1980-1997, and 125 million jobs in peri-urban zones have been added in China alone since 1978 (Hudalah 2007, Webster et al. 2014). The 1990s brought foreign industrial and infrastructure investment that drove peri-urbanization in Hanoi, Vietnam, and Bangkok, Thailand, converting rural croplands and forests to factory complexes, railroads, expressways and residences (Keivani and Mattingly 2007).

Industrial peri-urbanization feeds economies but can hurt agricultural productivity, local livelihoods, and the environment. Unconstrained industrial growth around Bandung, Indonesia, caused farmland loss and lower yields, as well as increased air and water pollution (Hudalah 2007). In 2008, the peri-urban Map Ta Phut Industrial Estate on Thailand's eastern seaboard, which hosts metalworks and chemical refineries, damaged air quality and drew excessive water to the point that the government suspended 76 investment projects for one year (Webster et al. 2014). Industrial peri-urbanization in China's Hangzhou-Ningbo Corridor, which sprouted foreign-funded factories producing everything from apparel to fiber optic cables, demolished productive agricultural land, exacerbated acid rain and emitted large amounts of untreated wastewater into the surrounding area (Webster 2002). Similar patterns of farm destruction and environmental degradation began in the 1990s around Vietnam's Ho Chi Minh City, Hanoi and the greater Red River Delta (Kontgis et al. 2014, Nong et al. 2015). Laos, where agriculture employs 71% of the workforce, may be especially vulnerable to the negative environmental effects of peri-urban industrial growth (Simon 2008, World Bank 2010, Nguyen Thi et al. 2010, Kontgis et al. 2014).

This type of growth has raised populations as migrants are attracted by the opportunities and services that flow from new factories; on Thailand's eastern seaboard, which hosts dozens of factories and two high-capacity ports, the population has grown four times faster in the peri-urban regions than in urban cores (Webster 2002). Peri-urban growth can also follow informal residential growth on the boundaries between rural and urban areas, as urban residents seek space or rural migrants seek domestic jobs, housing, or education (Keivani and Mattingly 2007). Harm follows here as well; in Jakarta, Indonesia, peri-urban residential development exacerbated economic segregation and worsened flooding by encroaching onto a vital water catchment area (Firman 2004, Gross et al. 2014, Hudalah et al. 2007).

Whatever the driver, East Asian peri-urbanization is a consequence of unplanned development in areas of relatively weak land governance and high foreign investment, causing landscape fragmentation that exacerbates transport problems, increases pollution, and hurts agricultural productivity (Simon 2008). The negative effects of peri-urbanization can be ameliorated by effective planning mechanisms implemented by a centralized authority, but this is often impossible due to overlapping and/or weak regimes of planning and control (Webster et al. 2014, Legates and Hudalah 2014). Peri-urban informal growth, by definition outside urban core areas and thus also outside the bailiwick of city-level authorities, does not fit into governance structures or jurisdictions. This results in less attention from authorities, in turn causing uneven infrastructure investment and inconsistent land use permitting (Hudalah et al. 2007). Indeed peri-urbanization, by its very nature fragmented and discontinuous with existing services, resists planning. Recent urban and regional growth plans in Laos and the Philippines were unenforced by weak provincial and local authorities, and thus ignored by investors and residents (Hudalah et al. 2007, Kritsanaphan and Sajor 2011, Gross et al. 2014).

2.2: Urbanization and peri-urbanization trends in Laos

The U.N. projects that 39% of Laos's population lives in cities today, a figure that may reach 51% by 2030, below the Southeast Asian average of 56% (U.N. Population

Division 2014). A regional-scale study found that urban land in the entire country increased 37% from 2000 to 2010, giving Laos the largest annual growth rate in new urban areas among East and Southeast Asian nations, though starting from a relatively low base. Further study is needed, as that analysis used relatively coarse 250m resolution imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS), and much of the conversion to urban land takes place at scales far below 250m (Schneider 2015).

While Southeast Asian urban densities (defined here as the number of people per unit area of built-up land) are increasing, 40% of new growth is projected to take place on the peri-urban fringe of the region's cities (Webster 2002, Schneider 2015). Peri-urbanization's extent and effects have been documented across cities in Vietnam, Thailand, and China, but there are few urban land cover change studies for Laos and none focusing on Pakse (Kritsanaphan and Sajor 2011, Schneider et al. 2012, Kontgis et al. 2014, Sharifi et al. 2014). Laos's major urban areas have seen significant growth, but not on the scale of its industrializing neighbors: urban land increased 34% between 1995-2011 in the peri-urban zone of Laos's capital and largest city, Vientiane, and in the core areas of the second-largest city of Savannaket built-up areas jumped 165% from 2 km^2 to 5.3 km^2 between 1990-2013 (Kimijiama and Nagai 2014, Sharifi et al. 2014). Vientiane's peri-urban development followed four main patterns seen in other Southeast Asian cities: discontinuous deforestation, development along roads, expansion from the center, and annexation of surrounding villages into the core area (Sharifi et al. 2014).

Similar to its neighbors, a lack of enforcement and the fast pace of urban land cover change limit the effectiveness of Laotian urban planning regimes (Legates and

Hudalah 2014, Webster et al. 2014). Two successive master plans for the capital city of Vientiane, implemented in 2007 and 2010, were unsuccessful in either formalizing urban land expansion or creating frameworks for future development; the 2007 plan was created at too small a scale (1:60,000) for precise land use determinations, only included three land use classifications, and was not followed by private developers, while the 2010 plan was found to be "largely ignored" less than one year after approval (Lund 2010, Sharifi et al. 2014). Pakse's last master plan was implemented in 1997 and the results so far match those of the capital: unplanned, informal conversion of agricultural, forested, conservation, and drainage land has continued unabated (Asian Development Bank 2011, 2012).

Unlike urban areas in Thailand or Vietnam, Laos's two largest cities of Vientiane and Savannaket were not spurred into growth by export-oriented manufacturing; instead mining, service, electrification and tourist projects spawned new built-up areas. Most of this growth was largely fragmented, occurred irrespective of planning frameworks, tended to follow roads and very often happened at the expense of cropland (Sharifi et al. 2014, Kimijiama et al. 2014). Though the drivers differ, peri-urbanization at the rural-urban boundary has had similar effects in Laos as in neighboring countries: land conversion of former smallholder agriculture at the edge of existing urban land has accelerated deforestation, hurt agricultural productivity, and degraded natural resources. This creates a self-reinforcing trend where former rural residents, for lack of better options, move to cities for work after losing their subsistence farmland (Sharifi et al. 2014, Kimijiama and Nagai 2014).

2.3: Agricultural expansion trends in Southeast Asia

Between the late 1800s and mid 1960s, Southeast Asia's colonial rulers established large plantations to grow rubber, cassava, tea, oil palm, and other commodities. As the colonial powers retreated, the plantations were nationalized and most commodity production transitioned to smallholder systems. The late 20th century brought a shift back to large-scale plantation: rising commodity prices and governments' desire to exploit forest resources have driven a reduction in traditional agricultural practices and an increase in plantation area across Southeast Asia, especially after economic liberalization measures were carried out across the region in the 1990s. Today Southeast Asia hosts 64% of the world's oil palm plantations, 59% of all rubber plantations, and 58% of all cassava plantations (Byerlee 2014). Southeast Asia is the only region in the world where tree plantations make up a large portion of total agricultural land, and these plantations have had a significant impact on the region's forest cover, biodiversity, and carbon stocks, as well as the welfare of small farmers (Gibbs et al. 2010).

Rubber, oil palm, tea, coffee, sugarcane, cassava, and other cash crop plantations have been established at the expense of forest cover and protected areas: in Southeast Asia as a whole, 56% of all land conversions to agricultural land between 1980-2000 took place in intact forests, and cash crop plantations have been assessed as the largest driver of forest loss in the region (Gibbs et al. 2010, Stibig et al. 2014). In Malaysia, rubber, cacao and oil palm plantations covered 80% of the nation's cultivated land by

1990, threatening naturally forested and vegetated areas with adverse consequences for the local environment (Härdter 1997).

Large-scale plantations tend to be more profitable than smaller ones; timber plantations in Indonesia were found to be optimally profitable at 300-500 km^2. Contract farming agreements, where companies provide inputs and seeds to farmers in exchange for products, are common in Thailand for eucalyptus and rubber but are less productive. As a result, a large monoculture plantation run by a single entity is the preferred arrangement for multinational companies establishing an agricultural project in Southeast Asia (Hall 2003). These monoculture plantations are encouraged by the state as a more “efficient” land use alternative to smallholders’ shifting/swidden agricultural practices, i.e. when small fields are cleared with fire, cultivated for between one and three years, and then left fallow for a longer period (Ichikawa 2007). Monoculture plantations bring opportunities for local residents to clear land, care for crops and harvest and process products in exchange for wages, but plantation expansion has removed many residents from ancestral or traditional lands and has exacerbated poverty by cutting off access to forest products (Souphonphacdy et al. 2012, Global Witness 2013).

The increase in cash crop cultivation constitutes one of the major land cover change stories in Southeast Asia, with far-reaching consequences for environments and people. By 2010, rubber alone covered at least 10,000 km^2 across Laos, Thailand, Vietnam, Cambodia, Myanmar, and South China (Li and Fox 2012). In Thailand between 1990-2008, approximately 1,100 km^2 of forests were cleared for oil palm plantations, and Indonesia’s palm oil plantings nearly doubled between 2000-2008 (Gibbs et al. 2010, Thomas 2015). Today, Malaysia and Indonesia produce 85% of the world's palm oil and these plantations will likely expand; in 2015 the Indonesian president announced a plan to add 15,000 km^2 of new agricultural land by 2018 (Richards and Friess 2016).

2.4: Agricultural expansion trends in Laos

Due to the study area's lack of updated land cover data and the opaque operations of its industrial, mining, and agricultural land concessions, the precise extent and type of land cover change in Laos is not known. However a review of existing literature shows that land conversion to monoculture crops is the dominant land cover change trend in both Laos in general and greater Pakse in particular (Ministry of Industry and Commerce 2009, Baird and Fox 2015).

Over the past twenty years large industrial estates have appeared on the periphery of second-tier cities in Thailand, China, and Vietnam (Webster et al. 2014). Encouraged by all levels of government, foreign manufacturers of computer parts, cars, and other finished goods have converted a large amount of agricultural and forested land to urban and built-up areas (Simon 2008). Laos's relatively poor infrastructure and undeveloped secondary sector preclude large industrial investments, but companies mainly based in Thailand, China, and Vietnam have invested at least $1 billion since 2001 to produce minerals, forestry, and food products in Laos (Ministry of Industry and Commerce 2009, Vongkhamheng 2016). Rubber makes up the single largest product category produced under concession, occupying 8% of all arable land and 26% of the 10,661 km^2 leased to foreign companies (Schönweger 2012, Vientiane Times 2013). Concessions vary in size from 1.5 km^2 to more than 150 km^2, and the larger concessions have outsize effects: 9%

of leases cover 89% of total concession area. These massive investments have not been transparently documented. There is no publicly available up-to-date listing of land concessions or a map of their extents, and concession boundaries are often poorly defined or ignored altogether in the course of land clearing and planting operations (Schönweger et al. 2012).

Laotian officials view concessions as ways to attract investment, boost growth and formal employment, and in the case of agricultural concessions, reduce the "backwards" practice of shifting/swidden (Zurflueh 2013, Liao et al. 2015). Direct revenues from concessions are a major incentive for local officials to grant them: a 190 km^2 rubber project in Champasak was projected to yield $3.4 million in yearly taxes and fees for the provincial government, a considerable amount in a province where an agricultural laborer might earn $1,500 a year (Obein 2007, Portilla 2015).

French colonists first planted rubber in Laos in the early 1900s; eucalyptus and teak projects followed in the late 1960s and 1970s. These plantations were relatively small before the 1990s, but projects spanning dozens or hundreds of square kilometers followed as the Laotian government began to allow investment in large-scale forest and agricultural plantations (Phimmavong et al. 2009). Since Laos's 1986 implementation of the "New Economic Mechanism" to liberalize the economy and encourage trade, provincial and central government bodies have granted decades-long land concessions to private ventures (under Laotian law all land belongs to the state, so title is not transferred) (Schönweger 2012, Souphonphacdy et al. 2012). In northern Laos, foreign agricultural concessionaires often enter into contract arrangements with farmers, but in our study area of Champasak province this arrangement is not common and land is typically cleared all at once by the company (Portilla 2015).

During lease periods in southern Laos, investors clear forest, relocate villagers, install monoculture plantations, and build processing centers to refine products for export (Vongkhamheng et al. 2016). The provinces of Champasak and Salavan (comprising the study area of 35 km surrounding Pakse) host many of these projects; indeed, 5% of land (approximately 250 km^2 of 4,899 km^2) in the study area lies within one of approximately 30 concessions, and according to the most recent available data, 5% of Laos's land surface area is leased to businesses (Global Witness 2013, Messerli et al. 2015). Of the study area's documented land concessions as of 2010, 70% are foreign-owned plantations raising vast tracts of rubber, coffee, sugarcane, cassava, eucalyptus, and livestock (Ministry of Natural Resources and Environment 2011, Hirsch and Scurrah 2015). Recent information on the number and size of concessions in the study area is not publicly available, highlighting the importance of an up-to-date land cover assessment.

Large-scale agricultural projects have had a major impact on landscapes across Laos, and it is necessary to understand their relationship to peri-urbanization around Pakse. Concession-aires contribute to peri-urbanization directly by building roads, factories, and other infrastructure, and indirectly by forcing the migration of residents displaced by plantation agriculture (Baird 2010 and 2011, Dwyer 2007). While these concessions have added a small amount of built-up land in the form of factories and warehouses, the vast majority of land cover change in Laos has taken the form of converting forested areas and village-scale agriculture to plantations. However, the true extent of these plantations is not known (Zurflueh 2013).

The foreign projects in the study area have had negative effects on local residents, as illustrated by the following example: in one concession located 15 km east of Pakse, the Viet-Lao Rubber Joint Stock Company paid $65-$250 per planted hectare to households whose land was cleared for the plantation, but paid no compensation for fallow land, forest, or upland rice areas. Given that each household held 2-6 hectares of land, this was a one-time compensation of $130-$1,500 (note that the average household of eight consumes $900 of rice per year) (Portilla 2015). The plantations do offer jobs to local villagers, a significant opportunity to land-poor residents, and after the plantation was established most households sent at least one member to work there for $90-$125 per month. However, older residents were not offered the chance to work and many plantation employees complained of inconsistent pay and exposure to pesticides (Zurflueh 2013, Portilla 2015).

It is uncertain if plantation expansion and its accompanying land conversion will slow in coming years; in April 2016, the Champasak provincial government declared that no more land would be granted to cultivate rice, coffee, rubber, cassava, or maize because "there is no more land remaining" (Vientiane Times 2016). The existing concessions, however, are leased for periods of at least 30 years, and are therefore likely to affect the landscape and its residents for many years to come.

Smallholder coffee production in the Bolaven Plateau, 30 km east of Pakse, also drives conversion to agricultural land and indirectly urbanizes the area. This is a much more fragmented type of agricultural conversion than the large foreign-owned monoculture plantations, but still occupies a significant amount of land area (Toro 2012). The Bolaven Pleateau has some of the most ideal climatic, soil, and elevation conditions for coffee production in mainland Southeast Asia and currently hosts 55% of the country's planted coffee area. Laotian coffee had been grown and exported since its introduction in 1913, but a crash in the Brazilian coffee supply and the Laotian currency devaluation that followed the Asian Financial Crisis of 1997 (subsequently making coffee cheaper) made local coffee competitive in the global market. In 2015, Laos exported 20,700 metric tons of coffee, two and a half times more than in 1990. Coffee travels west from the upland fields of the Bolaven Plateau to Pakse's coffee processing centers before continuing further west to Thailand for export by sea. This trade accelerates land cover change as warehouses, roads, and processing centers are built to respond to demand, which in turn attract workers who move into nearby residences (Toro 2012, International Coffee Organization 2016). Coffee cultivation has been generally positive for the area, giving Bolaven Pleateau residents the lowest poverty rate of all similarly-developed regions in the country, though farmers often have to borrow capital at high interest rates to maintain sufficient yields (Toro 2012, Thomas 2015).

Chapter 3. Methods

3.1: Measuring land cover change using remotely sensed imagery

Remote sensing data offers a cost-effective method for assessing land cover change in general and peri-urbanization specifically. Satellite images assessed with machine learning classifiers provide an expedient tool for evaluating urbanization and land cover change patterns in Southeast Asia (Castrence et al. 2014, Nong et al. 2015). Medium-resolution (30-250m spatial resolution) sensors including MODIS, Landsat, and SPOT as well as high-resolution (1.5-5m) sensors such as RapidEye offer a relatively inexpensive way to study remote areas with poor infrastructure (Dewan et al. 2010). The United States' Landsat series of sensors, which have provided free and continuous medium-resolution global coverage since 1973 at a revisit rate of 16 days, have been effective at characterizing change at Southeast Asia's rural-urban interface. The area's small feature sizes, high variation in spectral response over agricultural lands, and frequent cloud cover requires high-revisit sensors with sufficient resolution to discriminate between agricultural, naturally vegetated, and urban land cover types (Castrance et al. 2014). Landsat has been extensively used to study Southeast Asian land cover change patterns (Dupuy 2012, Vongvisouk et al. 2016).

Satellite-derived land cover maps of Laos and Champasak province have been produced both by the Laotian government and by researchers. The Laotian Forest Inventory and Planning Division (FIPD) produced a nationwide vector-based land cover map in 2002 with 24 classes and a minimum mapping unit of 40,000m^2. However, the map is coarse, outdated, and since it was created for forest management purposes, does not focus on built-up areas or settlements (of which many are smaller than the minimum mapping unit). A 2010 update was finished in 2012 (Ministry of Natural Resources and Environment, 2012), but Thomas (2015) found that the map has too many quality issues to be useable for land cover change analysis, and lacks up-to-date information on forest extent and types. As part of a 2012 project assessing coffee production on the Bolaven Pleateau (east of the study area), Toro classified the area using Landsat and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data and a maximum likelihood classifier. He produced separate classifications for 1989, 2001, and 2008, but accuracy assessments were not provided and the maps only cover the eastern half of Pakse's core (Toro 2012). These maps do not provide sufficient spatial or temporal detail over the study area and lack detailed quality assurance metrics, highlighting the need for a Pakse-specific land cover change assessment.

Detecting land cover change in the region presents unique challenges; conversion to built-up land often happens at scales smaller than a sensor's detection threshold, and detection is further hampered by vegetation partially occluding structures that *themselves* may be constructed using materials that are difficult to distinguish from surrounding vegetation (Schneider et al. 2015). Peninsular Southeast Asia's tropical monsoon climate also significantly complicates remote sensing-based assessments: there are few cloud-free images available, and clouds often completely obscure the landscape during the May-October wet season (Sharifi et al. 2014, Kontgis 2014).

Dense time stacks, which combine several dozen or even hundreds of discrete scenes over the same area but acquired on successive dates, can help overcome the problem of endemic cloud cover by adding more data. Areas that are only seldom visible through cloud cover can be assessed by compositing many images together; an area consistently hidden by clouds will likely be obscured in any one image, but it is extremely likely that the area will be visible in at least a few out of a hundred images.

The additional images, which provide multi-season views of stable and changed regions, provide better results in complex landscapes than simpler change detection methods that make use of just one cloud-free image per change period (Kontgis et al. 2014).

To overcome map quality issues in official maps, recent studies of land cover change in Southeast Asia have used machine learning-based supervised classification algorithms such as support vector machines, artificial neural networks, and decision trees to determine land cover change trajectories. These classifiers make no a priori assumptions about the distribution of the data (i.e. they are non-parametric), tolerate noisy and/or incomplete data, and have been successfully applied to regional-scale remote sensing problems in general and urban/peri-urban land cover change studies in particular (Friedl et al. 2002, Schneider 2012, Castrence et al. 2014). Machine-learning based classifiers such as decision trees have been shown to yield higher accuracies than traditional statistical classification algorithms (e.g. maximum likelihood, minimum-distance-to-means) and are now the method of choice for remote sensing-based land change studies (Kontgis et al. 2014). They have been successfully deployed to study the complex landscapes of Southeast Asia, where they have been used to assess 20 years of land conversion across the peri-urban zones of Vietnam's Ho Chi Minh City, the Red River Delta, and the greater Mekong River Delta (Castrence et al. 2014, Kontgis et al. 2014, Nong et al. 2015, Schneider et al. 2015).

There are Laos-specific studies of land cover change using remotely sensed data, but none have used decision trees to assess peri-urbanization and agricultural expansion, none have focused on the greater Pakse area, and none reach the level of spatial and temporal detail needed for the study area's heterogeneous and fast-changing landscape. The existing studies of Laotian peri-urbanization focused on the two largest cities, the capital of Vientiane and the second-largest city of Savannaket, but neither used a machine learning classification algorithm. They found that since the late 1970s, urban land cover has expanded rapidly in these two cities, with already-developed Vientiane adding 34% more urban land 1995-2011 within 10 km of the urban core and central Savannaket's urban land growing 31% from 2001-2011. Much of the growth was spread across roads and isolated villages, not large industrial estates or residential areas as in Vietnam, China, Indonesia, or the Philippines. These studies were hampered by heterogeneous landscapes that include water, vegetation, and impervious surfaces commingled within Landsat's 30x30 m pixels. Endemic wet season cloud cover also hurt classification accuracies (Kimijiama and Nagai 2014, Sharifi et al. 2014).

Studies of agricultural land cover change have revealed the extent of cash crop plantings across the region. A remote sensing-based assessment of areas in Thailand, Cambodia, Vietnam and China using aerial photographs from the 1950s-1960s and an unsupervised classification of mid-1990s Landsat imagery found new rubber, palm oil, passion fruit, and Chinese cardamom plantations (Fox and Vogler 2005). 30m Landsat data, 5m RapidEye imagery and an object-oriented classifier (which segments images into spectrally-similar contiguous "objects" instead of classifying by each pixel) found nearly 3,400 km^2 of rubber plantations added between 1988-2010 in southwest China alone (Chen et al. 2016). Landsat imagery and a machine learning random forest classifier found large expansions of oil palm plantations between 2000-2012 across Indonesia and Malaysia (Richards and Friess 2016).

As for detecting agricultural expansion in Laos specifically, an assessment of Northern Laotian rubber plantations in the Luang Namtha province used 15m ASTER imagery and an object-oriented classifier to find increased growth in plantations 2001-2006, but difficulties in detecting immature plantations hindered accuracies (Hurni 2008). A study of Laotian rubber plantation expansion in the area around Pakse found 137.3 km^2 of potential rubber expansion between 2003-2012, but used only 10 Landsat 7 Enhanced Thematic Mapper (ETM+) scenes and was hindered by a lack of data in the imagery; the 2003 failure of the ETM+ scan-line corrector (SLC) caused its imagery to be affected by large striping artifacts, invalidating 22% of the data in each scene (Phompila et al. 2014). These studies have found agricultural expansion beyond rubber plantations: in Laos's upland Bolaven Plateau (just east of the study region), a Landsat-based land cover change assessment using a maximum likelihood classifier found 24.5% forest loss between 1989-2008, of which most was attributable to new coffee fields (Toro 2012).

3.2: Using dense time stacks of Landsat imagery and a decision tree classifier to assess greater Pakse

Building on past land cover change studies in Southeast Asia, this work relies on a decision tree classifier to assess dense time stacks of Landsat imagery using a multi-date composite change detection approach (Schneider 2012, Castrence et al. 2014, Kontgis et al. 2014). Dense time stacks, in which dozens or even hundreds of successive Landsat images are merged and assessed together, allow for long-term land cover change measurement over wide regions (Huang et al. 2010). Dense time stacks ease discrimination of land cover change by taking advantage of phenological (plant growth cycle) patterns: agricultural, urban, and naturally vegetated areas have distinct cycles of rising and falling reflectance in the near-infrared (NIR) and visible parts of the spectrum, or, in the case of urban land, a conspicuous absence of this signal (Rogan and Chen 2004). Active croplands reflect a large amount of NIR energy to the sensor as the plants grow and mature, then much less after they are harvested and the fields are cleared back to bare soil. Healthy, well-watered natural vegetation also reflects NIR energy, but since plants in the forest or grasslands are not harvested and replanted in a distinct cycle, they are relatively easy to distinguish from agriculture by their temporal signature (Figure 3).

Surface reflectance data is the preferred input for remote sensing studies as it partially corrects for atmospheric distortions that would introduce errors into downstream analyses (Feng et al. 2012). Scenes spanning 1990-2015, each including three visible and three infrared bands, were acquired from the USGS Earth Resources Observation and Science Center Science Processing Architecture (ESPA). The data provided by ESPA were processed using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), which corrected image distortions caused by the atmosphere (Masek et al. 2006). Although this radiometric correction was unnecessary as scenes were assessed together and not individually, analysis of LEDAPS-corrected images provides less noisy phenological signals that can boost change detection accuracies (Song et al. 2001, Kontgis 2014). 102 scenes covering path/row 126/49 and 95 scenes covering path/row 126/50 were acquired; some 126/50 scenes had to be discarded due to data errors (Table

1). The scenes were assessed in their native projection of Universal Transverse Mercator (UTM) Zone 48 based on the World Geodetic System 1984 datum (WGS84).

Any data collected after May 31, 2003, by the Landsat Enhanced Thematic Mapper (ETM+) sensor is affected by striping artifacts due to the failure of the instrument's scan line corrector. The artifacts in affected scenes were masked and excluded from the analysis. Though the scenes were generally un-obscured by clouds, ESPA's cloud mask was applied for each scene to set cloudy pixels to "no data," excluding them from analysis. The scenes were cropped to the study area of 35 km around Pakse's city center and combined into dense time stacks by footprint, yielding two image stacks covering the two path/row footprints, 126/49 and 126/50 (Figure 1).

A classification scheme was chosen following the International Geosphere-Biosphere Programme (IGBP) land cover criteria. Training samples were collected for both "stable" land cover classes (i.e. areas that did not change over the study period) and three change periods: 1990-2000, 2000-2006, 2006-2015. These periods were selected for the availability of cloud-free imagery, to capture long-term land cover trajectories from the beginning of Laos's development spurt to the present day, and to align with the change periods used in an ongoing NASA study of peri-urban change across mid-size Southeast Asian cities. These uneven change periods were originally selected to coincide with the latest available commune-level Vietnamese census data, and were retained in this work for the sake of consistency and comparability (Asian Development Bank 2011, Baird 2010, Kontgis et al. 2014, Hirsch and Scurrah 2015, Nong 2015).

Training pixels were selected in the ENVI software package by visual interpretation of NIR composites for fall, spring, and summer Landsat scenes circa 1990, 2000, 2006, and 2015, as well as high resolution Google Earth imagery collected 2006-2015. Sites were selected following the class criteria outlined in Table 2. Specifically, "urban" pixels were selected based on the predominance of structures, roads, and other impervious surfaces within the boundary of a single pixel; if more than half of a pixel contained these features it was considered built-ip (Schneider 2009). 41 ground truth sites collected in Laos during Toro 2012's fieldwork were used to improve classification of the vegetation-dominated change classes. Toro's points included natural vegetation and several different agricultural classes: cardamom, coffee, fruit trees, rubber, and rice. Since these contained planting dates obtained from farmers, these were used to select additional training sites for the agricultural change classes.

The classification was performed using the C5I implementation of Quinlan's decision tree algorithm (Figure 4) (Quinlan 1993, 1996). Support vector machines, maximum likelihood, and artificial neural network classification algorithms were initially considered for this project, but decision trees were likely to yield the best initial results in Southeast Asia's cloudy and heterogeneous landscape (Schneider 2012). A decision tree iteratively splits a set of training data into increasingly homogenous groups using decision rules (statistical tests), which are generated using a set of training data and refined as the algorithm repeats its splits. After sufficiently homogenous groups are generated using the training data (resulting in class labels at the terminal leaf nodes), the decision rules are applied to the whole image to produce a classified map. "Boosting" is used to enhance classification accuracy among nodes the algorithm had trouble with on the first pass: on each successive run the classifier focuses on ambiguously-classified nodes and adjusts its decision rules until final classes are maximally “pure” and separable (Pal and Mather 20023, Schneider 2003). Like other machine learning classifiers (artificial neural networks, support vector machines) decision trees are able to handle noisy inputs, make no assumptions about the distribution of the data, and can handle complex relationships between feature reflectance and final classes. They are also more intuitive to use, transparent in the training data they make use of, and can arrive at the same final classification from many different starting nodes (Schneider 2003).

Each iteration of the decision tree provides a probability estimate for each class at each pixel, and a weighted vote is taken across all iterations to determine the final classification. For this work the 1,493 training sites were separated by Landsat footprint and given to the decision tree, which was “boosted" ten times (i.e. ten iterations of the tree were generated) to produce a classification for each of the two dense time stacks. The classification step was an iterative process: the fragmented landscape of southern Laos landscape made it necessary to repeatedly assess the accuracy of the output, edit and add training sites, then run the decision tree again before a satisfactory result was achieved (S. Dupuy 2012, Liao et al. 2015).

The two resulting classifications were mosaicked together, and a series of post-classification steps was performed to improve the accuracy of the final product. First, a “sieve” spatial processing operation was used to remove “salt and pepper” artifacts common to Landsat classifications (i.e. isolated, misclassified pixels). An eightconnected sieve operation was performed in QGIS to remove areas below the minimum mapping unit of 1,800m^2 (2 pixels) (Dewan et al. 2010). Next, water areas were masked to further refine the final output map. During the wet season the Mekong and Xe Dong rivers inundate land that the classifier recognized as changed land as it switched from vegetated to water and back again. Since measurement of this seasonal flooding was not part of the study objectives, a water mask was manually digitized from the first cloud-free image that followed the maximum water extent of the 2015 monsoon. This mask was merged with the final output to label seasonally flooded areas as “stable water” regions (Nong et al. 2015).

The third post-processing step included adding roads from non-imagery sources. Since roads are an important cause and consequence of peri-urbanization in Southeast Asia but their detection can be hampered by overhanging canopy and small feature sizes, non-footpath dirt and paved roads were added from OpenStreetMap (OSM) and data provided by the Laotian government (Hudalah et al. 2007, Ministry of Planning and Construction 2010, Manivong 2014, Lainé 2015). The vector roads were projected to the proper coordinate system, rasterized to one-pixel width (consistent with their appearance on Landsat composites) and merged with the final output. These roads were added to the stable urban class if they were visible on 1990 Landsat imagery, and added to one of the three conversion-to-urban classes if they appeared on post-1990, post-2000, and post-2006 imagery respectively. Roads that appeared in the vector data but not in Landsat or Google imagery were discarded.

Finally, manual editing was performed to correct large, obvious errors and increase the accuracy of the final classification. Since large portions of the final output image were composed of monoculture plantations added after 2000, most of this editing took place within these areas. As a starting point, agricultural concession point data consisting of date, extent and type were acquired from the LaoDECIDE spatial information project, a joint Lao-Swiss project to disseminate sociocultural and geographic data in an online GIS (Messerli 2014). These data were used with Landsat and Google Earth imagery to confirm the existence of concessions within the study area and provide context for manual editing. Additional, more detailed concession boundaries were digitized from a Global Witness report on rubber expansion, and land within those boundaries was assigned to an agricultural change class coinciding with the date closest to plantation establishment (Global Witness 2013).

3.3: Assessment of map accuracy

A stratified random accuracy assessment was performed by comparing the final map to independently labeled “ground truth” sites. To prevent under-sampling of the relatively sparse change classes, masks for each class were created and used separately as boundaries for random truth site selection. Truth sites were randomly generated within each class’s boundaries to reach 30-60 sites per class (Nong et al. 2015). Ground truth sites were labeled based on visual interpretation of Landsat and very high resolution Google Earth imagery. This process was repeated for the raw decision tree output until classification accuracies reached 85%, and then after hand editing and road addition was complete an assessment was performed on the final map using approximately 60 truth sites per class. A confusion matrix was produced from these results to evaluate total map accuracy and to document per-class omission and commission errors.

3.4: Post-classification analyses

Adapting techniques from existing studies of Southeast Asian land cover change, a ring buffer and a road buffer analysis were performed to measure the distribution of land conversion in the study area. To assess land cover change as a function of distance from Pakse's core (defined as the geographic center of the contiguous, higher-density region visible on official maps and high-resolution satellite imagery), circular ring buffers were generated at 5 km intervals from Pakse's center and the share of developable surface within each buffer that was converted to built-up or agricultural land was calculated (Kontgis 2014). A separate road buffer study was conducted at several interval distances from the OSM-derived roads to determine if there was a relationship between road location and land cover change, similar to studies conducted in Vientiane, Laos, and Taipei, Taiwan (Sharifi et al. 2014, Huang, Wang, Budd 2009). Buffers were created at 30m intervals up to 270m from the roads, and the share of developable surface within each buffer that was converted to built-up or agricultural land was calculated. A summary of the preceding steps can be seen in Figure 5.

Chapter 4. Results

4.1: Assessment of map accuracy

Figure 6 shows the classified map and Table 4 shows the full confusion matrix, indicating which classes were confused with one another and the type of error. Note that errors of omission for each class can be read in the columns, and the errors of omission in the rows. Producer's accuracy, which corresponds to the chance of an error of omission, was 91.63%. The user's accuracy, corresponding to the chance of an error of commission, was about the same at 91.62%. The map's overall accuracy was 91.63% and the kappa coefficient was 0.90, indicating the classification was approximately 90% better than one resulting from random chance. Stable classes had a minimum of 92% accuracy, while 87% accuracy was the minimum for the change classes. Among change classes the map most reliably classified land conversions to water and agriculture, followed by conversions to built-up land.

Stable croplands were confused with other classes with similar spectral profiles, e.g. dense, well-watered natural vegetation and lands converted to agriculture between 1990-2000. Stable water areas were easily distinguished due to water's unique and consistent low-reflectance signature. Stable urban and stable barren classes were confused as they have a similar lack of phenological cycles and high overall reflectance. Stable urban areas were confused with stable barren areas and early (1990-2000) conversions to urban land, as these areas shared a high overall reflectance and were especially mixed between vegetated and non-vegetated surfaces (e.g. bare soil, rock, impervious surfaces, or structures). Stable agricultural areas, which often include bare-soil fallow fields and flooded paddies, were confused with barren and early conversion-to-water change classes with similar spectral signatures.

Trees, grasses, shrubs and crops closely commingled with structures and roads caused relatively low accuracies for all urban change classes. Built-up areas in rural Southeast Asia are difficult to distinguish from their surroundings; building materials often match neighboring land cover types, and structures and roads are often too small to distinguish using medium-resolution imagery such as Landsat (Castrence et al. 2014, Schneider 2015). Classes with high NIR reflectance, i.e. natural vegetation, stable agriculture, and conversions to agriculture, were confused with each other, likely because of the similar spectral signatures of tropical vegetation and intensely cultivated rubber plantations (Torbick et al. 2016). Conversion-to-water change class accuracies were affected by the small size of most man-made ponds and co-location with woody vegetation, which makes them harder to discriminate at 30m resolution.

There was mutual confusion between the 1990-2000 and 2000-2006 change classes, but the 2006-2015 changes were more easily discriminated due to the availability of high-resolution imagery and Toro 2012's verification sites. The 1990-2000 and 2000-2006 vegetation-to-urban change classes were consistently over-classified, i.e. they included urban change pixels from other periods. These temporal errors were likely caused by inconsistent training data, as built-up areas in the region have small feature sizes and high-resolution imagery was not available before 2006. 1990-2000 conversions to agriculture were consistently missed (i.e. under-classified) possibly due to land that was cleared and not planted, but could be picked up as croplands converted in later periods when the vegetation had grown enough to register as active agriculture to the decision tree.

The well-documented challenges of finding built-up areas in Southeast Asia's heterogeneous and complex landscapes hurt classification accuracies for urban change classes, but overall accuracy was good and the output accurately characterized the area's major land cover change story: new agricultural areas.

4.2: Land cover change results

The results show that naturally vegetated areas and stable agricultural areas dominate the map, covering 65% and 18.5% of the area, respectively (Table 3, Figure 6). Land conversion in the form of natural vegetation being replaced with built-up areas, human-made ponds, or agricultural land covered 9.8% of the total study area, with the majority of those changes being conversions to agricultural land (Figure 7). Agricultural areas grew 435.3 km^2 over 25 years, increasing the total cropland area by 48%. 27.2 km^2 of built-up land was added between 1990-2015, bringing the study area's urban land cover to 124.7 km^2 in 2015, a 28% increase (covering a total of 2.5% of the study area). 15.3 km^2, or 0.3% of the total area, was converted from agriculture or vegetation to artificial ponds or drainages. Change accelerated in the later periods, as average annual additions of each type of land conversion increased successively from 1990-2000, 2000-2006, and 2006-2015. For example, 65.9 km^2, 132.8 km^2, and 236.6 km^2 of new agricultural land was added during the three successive change periods, respectively (Table 3, Figure 7a).

New agriculture comprised 90% of detected land cover change. Based on information from local experts and visual interpretation of high resolution imagery, it is likely that new agricultural areas (~50 km^2) in the eastern highlands in the study area were coffee cultivation that occurred during the 1990-2000 period. From 2000-2006, agricultural change consisted of hundreds of square kilometers of rubber plantations planted to the northeast, east, and southeast of Pakse; these areas effectively converted naturally vegetated areas and small fields to monocultures (Figure 6). During 2006-2015 existing rubber plantations expanded into neighboring forest and village land, and expert assessment of high-resolution satellite imagery shows that smallholder coconut palm, cassava, sugarcane, and other plantings grew rapidly around villages in the northeast corner of the study region (Foppes 2016).

Built-up areas increased 28% from 1990-2015, adding 27.2 km^2 of urban land to bring greater Pakse area's 2015 total to 124.7 km^2. This constitutes only a small portion of the total study area, and is to be expected given the small size of the city and the area's low population. Pakse's urbanization, while modest, appears to be accelerating: an annual average of 0.9 km^2 of urban land was added each year between 1990-2000, 1.1 km^2 per year from 2000-2006, and 1.3 km^2 per year during 2006-2015.

Conversions to water were also small, as the results indicate that 15.3 km^2 of ponds were dug from natural vegetated areas and paddies between 1990-2015; these hold irrigation water and can also be used to raise fish for sale or household consumption (Nguyen Thi et al. 2010). These made up the smallest change class, covering 0.3% of the study area.

4.3: Spatial analyses to assess patterns of change

The circular buffer analysis around Pakse's center showed that 16% of all urban areas as of 2015 were located within central Pakse, a region occupying only 2% of the total study area. Urban land conversion steadily decreased as a function of distance from Pakse, similar to the pattern seen in a previous study of Vientiane (Figure 8b, Sharifi et al. 2014). The imagery and results suggest that a few industrial estates and agricultural processing centers appeared after 2000 but most of the growth consisted of residences added to tiny villages and roads cleared or expanded between them. Most agricultural land was added between 15-25 km of Pakse's center, likely due to rubber planting, as most of the plantations added after 2000 fall within that range (Figure 8c). This may be because cash crops generally require the transport and trade infrastructure of a city; a plantation close enough to Pakse for convenient services but far enough to take advantage of large contiguous tracts of land may be more efficiently sited than one closer or farther from the city (Nahuelhual et al. 2012). The spike in agricultural land added 1990-2000 35 km from central Pakse coincides with a coffee plantation established after 2000 (Figure 8c).

Most built-up land was added within 60m of a road; urban land conversion across all change periods tapered off as distance from a road increased, a common peri-urban development pattern in Laos (Figure 8e, Kimijiama and Nagai 2014). Agricultural conversion did not have a strong relationship to distance from a road: between 1990-2000 cropland conversion was unrelated to road distance, between 2000-2006 it was slightly negatively correlated, and from 2006-2015 was slightly positively correlated (Figure 8f).

The degree of developable surface within each buffer converted to agriculture matched the class shares over the entire study area: more was converted to agriculture between 2006-2015 than from 2000-2006 or 1990-2000.

Chapter 5. Discussion

5.1: Overview of classification results and spatial analysis

This work aims to provide a spatially and temporally-detailed assessment of the land cover changes that occurred over the last three decades in the peri-urban region of Pakse, Laos. The results show that built-up areas and agricultural lands grew 28% and 48%, respectively. The boosted decision tree approach using Landsat dense time stacks detected 478 km^2 of land conversion over 25 years, providing detailed class information over four time points (1990, 2000, 2006, and 2015) with 91.6% overall accuracy. This suggests the method was effective at capturing two important landscape changes in Laos: development of built-up areas in peri-urban zones, and large-scale conversion of land to agriculture, with the latter comprising 90% of the total land cover change in the study area. The land cover change patterns explored in the previous section reinforce existing studies: Laotian urban areas are small, rapidly growing, and tend to stick close to roads. However, large agricultural and forest plantations take up much more land and are the major land cover change story in Laos in general and the study area in particular (Global Witness 2013, Hirsch and Scurrah 2015).

5.2: Discussion of peri-urbanization results

Pakse's peri-urban growth of 28% over the 1990-2015 period is comparable to the one other Laotian city with peri-urbanization data: built-up areas within 40 km of the capital of Vientiane increased by 34% between 1995-2011 (Sharifi et al. 2014). Vientiane and Pakse experienced similar in-fill urban growth in their core areas (e.g. structures appearing in naturally vegetated areas between roads) while adding significant land along roads, but Pakse did not undergo the patchy expansion and annexation of neighboring villages that occurred in Vientiane (Sharifi et al. 2014). This is to be expected given that Vientiane has more than five times as many residents as Pakse. Pakse's core did not greatly expand in the "spreading pancake" model of urban growth, but instead settlements and commercial structures (agricultural processing centers, large buildings on plantations) grew along roads; 38% of new built-up areas 1990-2015 appeared within 30m of a road. This is an established pattern in Champasak province, where an Asian Development Bank study of road infrastructure projects showed that villagers tended to build homes close to newly established roads, i.e. roads attracted built-up areas (Fujimura and Ramesh 2010). In the aggregate, loss of natural vegetation was mostly due to agricultural expansion, not urban growth as in Vientiane (Sharifi et al. 2014).

Within Laos, a review of primary and secondary sources reveals little of the manufacturing investment that coincided with accelerating peri-urbanization in China's Pearl River Delta, Thailand's eastern seaboard, and Vietnam's Red River Delta. From 1989-2014, most of the $23.5 billion invested in Laos from abroad was in electricity generation, mining and agriculture; only 8% was invested in industry (Ministry of

Planning and Investment Promotion Department 2015). While Laotian industrial production has grown rapidly since the mid 1990s, recent data shows that industry comprises only 31% of Laotian GDP, compared to 37% in Thailand and 43% in China (World Bank 2014). Foreign investment may have driven land cover changes in the study area, but it was investment in the primary sectors of agriculture, forestry, and hydropower, not manufacturing capacity or residential development.

5.3: Discussion of agricultural expansion results

The results of this study confirm reports of rapidly increasing plantation development by foreign companies, but at much finer scales than previous studies (Figure 9). Since 2000 Laotian, Vietnamese, Chinese, and Thai companies have leased large tracts of land in greater Pakse; these concessions (totaling ~250 km^2 in 2015) have been planted primarily with rubber, cassava, coffee, eucalyptus, and rice (Figure 10, Kenney-Lazar 2012, Delang et al. 2013, Vongvisouk et al. 2016). Between 2000-2015, 58.9% of the agricultural land added to the study area appeared in large plantations first established in 2004. The individual change classes reveal finer distinctions: 122.9 km^2 of the agricultural land added 2000-2006 (93% of the class total) lies inside land concessions granted to Vietnam's Dak-Lak Rubber Company and the Dau Tieng Viet-Lao Rubber Joint Stock Company (Global Witness 2013).

The largest of the individual rubber concessions, belonging to the Viet-Lao Rubber Joint Stock Company, covers more than 100 km^2 of former forest, grassland, and smallholder fields. These results highlight the intensity of plantation investment in the region since 2000. After the first plantings, these plantations expanded further: 133.4 km^2

were added to these plantations between 2006-2015, representing 56% of the total agricultural land added within the study area during that period.

The 1990-2000 agricultural expansion results reveal a markedly different story: 75.7% of the period's new cropland appeared in the Bolaven Plateau, the highland eastern portion of the study area considered suitable for coffee. High-resolution Google Earth imagery and Toro's (2012) ground truth data point to extensive and mature shade-grown coffee cultivation. Since Laotian coffee exports jumped 159% over the same period and 58% of Laotian coffee is grown in this region, it is possible that coffee planting increased rapidly in the eastern uplands of the study area from 1990-2000 (Lao Coffee Association 2013, International Coffee Organization 2015). However, since shade-grown coffee grows under the canopies of larger trees (effectively "hidden" from satellite sensors) it is difficult to distinguish coffee plantings from natural forest cover and thus plantation age cannot be confirmed using medium-resolution imagery alone (Cordero-Sancho and Sader 2007). Further study is needed to isolate detailed crop information (e.g. finer-grained coffee production figures, land use surveys) from each change period to determine exactly when coffee plantings expanded in the region.

Unlike the post-2000 agricultural expansion that took the form of plantation expansion, most of the agricultural expansion 1990-2000 occurred as new smallholder plots 0.03-0.08 km^2 in size. There are two large coffee plantations in the study area totaling 4 km^2 and several more plantations east of the study area's boundary, but within the study area coffee cultivation is much less consolidated than the plantations (Figure 6).

It is not possible to use this work to estimate forest loss due to agricultural conversion. The pre-conversion land cover type for agricultural change classes lumped together forests, savannahs, grasslands, wetlands, and shifting agricultural areas (the latter certainly captured by mistake due to their spectral and temporal similarity to naturally vegetated areas). In addition, since the agricultural change included only naturally vegetated areas as initial land cover, this work does not measure the conversion of smallholder croplands to plantation agriculture, i.e. agricultural consolidation.

5.4: Factors affecting map accuracy

Though map accuracy was high overall, the results were adversely affected by a range of factors: few wet-season Landsat scenes, less information available to the classifier when Landsat 7 SLC-off imagery comprised much of the available data, less temporal coverage for high-resolution imagery, a paucity of "on the ground" information, and issues related to training and verification site collection.

There was very little cloud-free Landsat data available during the wet seasons, a problem endemic to land cover change analysis in tropical regions (Nong et al. 2015, Kontgis et al. 2015). More wet season (May-October) data would help the decision tree separate seasonal changes from permanent land conversion, especially for paddy rice; wet-season flooding creates a very distinct drop in overall reflectance over those areas that is paired with a rebound in NIR reflectance as the water drains from the paddies (Kontgis et al. 2015). Also across the study area's two footprints, 58% of the 2003-2013 scenes were recorded by Landsat 7 after the SLC failure; this led to "no data" gaps in 20% of the pixels in each affected image. While the Landsat SLC-off data is still useful for characterizing land cover change in this period, there is definitely a lower signal to noise ratio, making it more difficult for the classifier to effectively locate areas similar to the training sites.

High-resolution imagery was not available prior to 2006, hampering training and verification site selection for the 1990 and 2000 periods. For those years, sites had to be picked using only the spectral and temporal information available at 30m resolution. At that scale, the area's complex landscape and small feature sizes make it difficult to distinguish stable from changed areas. In addition, the only "ground truth" information used in this study came from Toro (2012), which was limited to agricultural conversions and did not confirm new built-up areas.

Training and verification site selection was hampered by additional factors, as well. No detailed cadastral, planning, or land use data was available to confirm historical land cover types. Spectral confusion was common across classes: land cover types in the region often include a variety of materials with unique signatures, e.g. urban land cover in Southeast Asia includes both dirt and asphalt roads (Jensen 2006). It was impossible to distinguish crop intensities (e.g. single- vs. double-cropped rice) for agricultural training sites due to the lack of agricultural census data, high-resolution imagery, and field surveys (Nong et al. 2015). These factors hindering training and verification site selection are not unique to Pakse; rural Southeast Asia's difficult terrain, relative inaccessibility, and monsoon climate have affected almost all previous studies of land cover change in the region (Nong et al. 2015). The preceding factors and the well-documented challenges of using Landsat to distinguish small croplands and built-up areas harmed the accuracy of this work's land cover assessment (Pham and Yamaguchi 2011, Schneider 2012).

Many of the errors in the maps occurred across areas that changed (Table 4). Often the classifier was able to capture land conversion, but the timing of the conversion was incorrect (e.g. confusion between the conversion to urban 2000-2006 and conversion to urban 2006-2015 classes). This result was likely caused by inconsistent spectral and temporal profiles of the classified areas: nearby vegetation rapidly occluded roads, homes, and other built-up surfaces soon after land was cleared for construction, creating pixels with such inconsistent temporal signals that even "stable" pixels appeared changed and changed pixels were sorted into the wrong time periods. Mixed pixels, exacerbated by the region's small feature sizes, are a common source of error in land cover change studies in tropical regions (Kontgis et al. 2014, Nong et al. 2015). This is clearly the case in this study, as shown in the confusion between the 1990-2000 and 2000-2006 conversion to agriculture classes.

Finally, one-way transitions were assumed for all change classes in this study. For urban pixels this is almost always the case and is likely a reasonable assumption for Pakse (Lambin and Geist 2008). However, the presence of shifting (swidden) agriculture in the area, where naturally vegetated areas are cleared for planting and then allowed to regrow naturally after harvest, presents a major challenge for change detection: tropical swidden plots are often irregularly-shaped, only occupy a few Landsat pixels, and have highly variable and complex land cover change patterns that may cycle between forest, soil, burned areas, and planted crops from year to year. This yields unpredictable temporal and spectral signals that significantly complicate remote sensing-based assessments. Landsat imagery has been used to measure the expansion of shifting agriculture in Vietnam and northern Laos, but the studies required hundreds of field survey samples and high-resolution imagery for validation (Schmidt-Vogt et al. 2009, Liao et al. 2015).

Chapter 6. Conclusion

6.1: Overview of research questions

This work characterized land cover change trajectories between 1990-2015 in the peri-urban region of Pakse, Laos. The first research question focused on "…the amount of land converted to built-up and agricultural areas in greater Pakse"; this work showed that 27.2 km^2 of urban land and 435.3 km^2 of agricultural land were added over the study period. In all, the amount of new urban land was dwarfed by the amount of new cropland, with the bulk of the latter established by foreign agribusiness enterprises. While urban areas grew 28% in the 4,900 km^2 study area comprising greater Pakse, agricultural areas grew 48%; today, fully 5% of the land surface area in Pakse's peri-urban zone consists of monoculture plantations growing rubber, cassava, palm, coffee, and other agricultural products. Agricultural land conversion was the major land cover change story in the region.

Two Vietnamese rubber companies, The Dak Lak Rubber Company and Dau Tieng Viet-Lao Rubber Joint Stock Company, were responsible for 52% of all land conversion in the study area. While the plantations operated by these companies have been documented before, detailed information on their extent is not available. This creates a need for accurate and expedient monitoring of land use and land cover change, a need that this work shows can be met by remotely sensed imagery and semi-automated classifiers (Fan et al. 2015, Chen et al. 2016).

Turning to the second research question, “is there a relationship between land conversion and distance from Pakse’s center, or distance from roads?”, this work showed that new built-up areas tend to appear closer to Pakse’s core and along roads. This aligns with current studies on peri-urbanization patterns in Southeast Asia in general and Laos in particular (Kontigs et al. 2014, Sharifi et al. 2014, Nong et al. 2015). As for new agricultural areas, there was no evidence of a strong relationship between distance from central Pakse and the degree of expansion. Agricultural areas tended to grow at a middle distance 15-25km from Pakse’s core, but it’s not possible to separate “proximity to city” from the multitude of factors that affect plantation siting (soil quality, labor availability, land tenure regime, elevation, etc.). There was also no strong relationship between the location of new croplands and their distance from roads, though this requires further study; research has found that roads (or often, one main road) are correlated with increased oil palm and rubber plantation development across Malaysia and China, though the causal direction has not been established (Ichikawa 2007, Zhou and Thomson 2014).

6.2: Significance of research

This work adds an important spatial-quantitative aspect to land use studies in Southern Laos, updating existing work on Pakse’s urban land extent. Accurate assessments of regional land cover trajectories are necessary for sustainable urbanization that preserves productive forests, farmland, local biodiversity, and water quality (Kontgis 2014). The work may also be useful for development; the Laotian government's goal of turning Pakse into a regional commercial and tourism hub depends on adding structures and roads in a way that eases the movement of goods and people while preserving the local environment, a process that can be aided by accurate land cover maps (Rabe et al. 2007, Asian Development Bank 2011). This type of work is also necessary for planning and assessment towards the government's goal of restoring the country to 70% forest cover by 2020 (Lund 2010).

Further study is needed to assess the long-term biophysical effects of the region's monoculture plantations on local biodiversity, carbon stocks, and soil quality, as well as their impacts on local populations (Baird 2010). Harm can follow when these projects fail or overextend, making knowledge of their true extents even more valuable. Over the past decade in Laos, for example, low yields in eucalyptus plantations and large coffee projects caused poverty to increase as contract farmers had to repay loans taken out to plant cash crops (Asian Development Bank 2005, Schönweger and Messerli 2015). Swings in commodity demand (especially for rubber) have caused Laotian state economists to caution against expanding plantation capacity beyond what the export market can support (Asian Development Bank 2012, Schönweger and Messerli 2015, Vientiane Times 2013).

Large-scale plantation agriculture is likely to continue even though Champasak's government declared in April 2016 that no new concessions would be granted (Vientiane Times 2016). Existing concessions are under decades-long leases and there is precedent for ignoring these kinds of bans: in 2007 the Lao Prime Minister announced an indefinite moratorium on tree plantations and mining, but it was never fully enforced and land deals have continued apace. It is also likely that rubber, which makes up the largest plantation crop in the study area, will continue to be a lucrative export: global rubber demand is projected to increase 30% by 2020, incentivizing more production (Zurflueh 2013). This trend highlights the importance of remote sensing-based assessments of Laotian plantation agriculture, since it provides an open, public, spatially- and temporally-detailed record of their expansion where official records are opaque and/or incomplete.

6.3: Future directions

Future work should exploit additional medium-resolution imagery, e.g. from the ASTER or Sentinel-2 sensors, or apply other machine learning algorithms such as support vector machines or neural networks; support vector machines especially have been successfully used in Southeast Asian land cover change assessments and would be extensible to southern Laos (Kontgis et al. 2014, Castrence et al. 2014, Nong et al. 2015). In addition, medium resolution RADAR sensors such as PALSAR and Sentinel-1 can peer through clouds to detect land cover change and have been used to measure rubber plantation extent in Myanmar (Torbick et al. 2016). Though it is difficult to differentiate forest crops such as rubber from other trees using medium-resolution imagery, high-resolution data (e.g. RapidEye) and object-based classification can help make more precise land use determinations by distinguishing between types of plantation crops (S. Dupuy 2012, Avtar et al. 2012, Toro 2012). Since forest loss and subsistence farmer displacement are important topics in Southeast Asian land cover change science, future studies should exploit higher-resolution imagery and land use surveys to create finer divisions of land cover classes; this would make it possible to quantify forest loss, smallholder displacement, and land consolidation to monoculture plantations (Kenney-Lazar 2012).

Fusing survey, census, cadastral, and other sub-district level information with satellite data has enhanced land cover change studies in Vietnam by providing more detailed trend assessment and land use information, but the most recent demographic and land use information in Laos is only available at the coarser district level. Village-level agricultural data is available, but was last collected in 2011 (Nong et al. 2015, Sisoulath et al. 2016). Field surveys and household questionnaires are highly desirable adjuncts to remotely sensed data that increase accuracy and strengthen the findings of land cover change studies, but they are expensive and time consuming (Vongvisouk et al. 2016). Future studies could include more extensive spatial analysis of peri-urban and agricultural expansion patterns, e.g. measuring new road additions vs. distance from city, a temporal study of road additions by change period vs. when plantations were established, or a point-to-point distance analysis of road networks vs. new urban areas.

Peri-urbanization and plantation development present unique challenges in Southeast Asia, spurring economic growth while displacing villagers, accelerating environmental degradation, and destroying carbon stocks (Baird 2010, Fox and Castella 2013, Gross et al. 2014). Accurate and expediently-produced land cover trajectories offer a powerful tool to researchers and environmental advocates to measure these trends, and may be potentially used by local stakeholders to minimize the impacts of land conversion while maximizing economic gains to a broad strata of residents (Hudalah et al. 2007, Sharifi et al. 2014). More of this work is needed in Laos, where few urbanization studies have been conducted and where land cover change is projected to accelerate in the coming decades as cities grow and more land is cleared for export-oriented agriculture. Sustainable development in Southeast Asia in general and Laos in particular depends on timely and precise land cover assessments. This study, characterizing Pakse's land cover change trajectories at the highest spatial and temporal resolution yet, takes a step in that direction.

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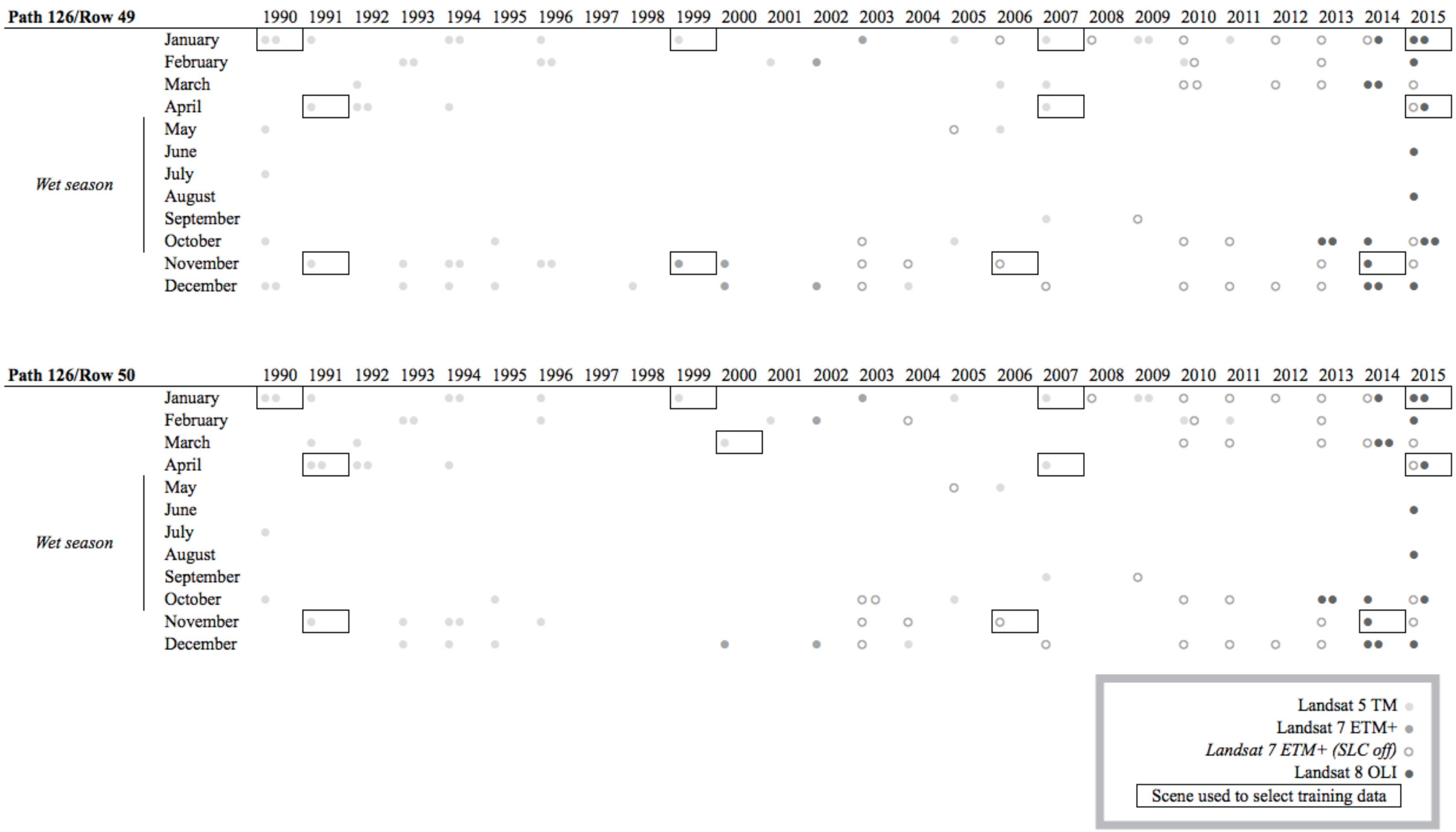


Table 1: Landsat TM, ETM+ and OLI surface reflectance scenes used as inputs to the decision tree. 102 scenes from path/row 126/49 and 95 scenes from path/row 126/50 were used.

	Class	Definition	Training sites per class Path 126/49	Path 126/50
Stable	Barren	Low vegetation signal. No human habitats or impervious surfaces, vegetation comprises less than 25% of 900m^2 pixel.	55	54
	Natural vegetation	High vegetation signal. Low-intensity phenological signal. Woody vegetation, grassland or wetland comprise >50% of pixel.	69	65
	Urban	Low vegetation signal. Built environment, human habitats, structures, roads and/or other impervious surfaces comprise >50% of pixel.	71	69
	Water	Low reflectance in all bands. Includes natural water features, man-made irrigation ponds and drainages, fishponds.	62	59
	Agriculture	High vegetation signal with high-intensity phenological signal. Fallow and active agriculture comprises >50% of pixel.	67	61
Change	1990 to 2000: vegetation/agriculture to water	Active and fallow cropland, forest or grassland converted to man-made ponds or drainages.	56	51
	1990 to 2000: vegetation/agriculture to urban	Active and fallow cropland, forest or grassland converted to human habitats, structures, roads and/or other impervious surfaces comprising >50% of pixel	62	55
	1990 to 2000: vegetation to agriculture	Woody vegetation or grassland converted to fallow or active cropland comprising >50% of pixel	53	47
	2000 to 2006: vegetation/agriculture to water	See above	53	49
	2000 to 2006: vegetation/agriculture to urban		57	51
	2000 to 2006: vegetation to agriculture		60	57
	2006 to 2015: vegetation/agriculture to water		48	41
	2006 to 2015: vegetation/agriculture to urban		62	55
	2006 to 2015: vegetation to agriculture		59	54
		Totals:	**779**	**768**

Table 2: The 14 land cover and land cover change classes (based on Seto 2002, Schneider 2012), criteria for class inclusion, and number of training exemplars used during the supervised classification procedure.

	Class	Share of study area	Total class size, sq. km	
Stable	Natural vegetation	65.0%	3,184.3	*Stable total: 4,420.8 km²*
	Agriculture	18.5%	906.8	
	Water	3.7%	179.8	
	Urban	2.0%	97.6	
	Barren	1.1%	52.4	
Change	1990 to 2000: vegetation/agriculture to water	0.1%	3.0	*1990-2000 total: 78.0 km²*
	1990 to 2000: vegetation/agriculture to urban	0.2%	9.1	
	1990 to 2000: vegetation to agriculture	1.3%	65.9	
	2000 to 2006: vegetation/agriculture to water	0.1%	4.2	*2000-2006 total: 143.4 km²*
	2000 to 2006: vegetation/agriculture to urban	0.1%	6.3	
	2000 to 2006: vegetation to agriculture	2.7%	132.8	
	2006 to 2015: vegetation/agriculture to water	0.2%	8.1	*2006-2015 total: 256.4 km²*
	2006 to 2015: vegetation/agriculture to urban	0.2%	11.7	
	2006 to 2015: vegetation to agriculture	4.8%	236.6	

Table 3: Results of the decision tree classification for each stable and changed land cover class. Conversion to agriculture made up the largest change class: 435 km^2 of agricultural land was added 1990-2015, most of it large-scale plantation agriculture. 27 km^2 of urban land was added, which includes residential areas, roads and commercial structures.

Reference data

Decision tree output

	Stable natural vegetation	Stable agriculture	Stable water	Stable urban	Stable barren	1990 to 2000: natural vegetation / agriculture to water	1990 to 2000: natural vegetation/ agriculture to urban	1990 to 2000: vegetation to agriculture	2000 to 2006: natural vegetation/ agriculture to water	2000 to 2006: natural vegetation/ agriculture to urban	2000 to 2006: vegetation to agriculture	2006 to 2015: natural vegetation/ agriculture to water	2006 to 2015: natural vegetation/ agriculture to urban	2006 to 2015: vegetation to agriculture	Total	User's accuracy (commission error)
Stable natural vegetation	*54*	1	1		1			1							**58**	**93%**
Stable agriculture	1	*55*						1							**57**	**96%**
Stable water	1		*55*						1			1			**58**	**95%**
Stable urban				*54*	2		1			1			**1**		**59**	**92%**
Stable barren	1			2	*55*					1			**1**		**60**	**92%**
1990 to 2000: natural vegetation/agriculture to water	1		1			*50*			2						**54**	**93%**
1990 to 2000: natural vegetation/agriculture to urban				3	1		*52*			2			1		**59**	**88%**
1990 to 2000: vegetation to agriculture		3					1	*55*			1			2	**62**	**89%**
2000 to 2006: natural vegetation/agriculture to water			1			1			*52*			1			**55**	**95%**
2000 to 2006: natural vegetation/agriculture to urban							4			*52*			3		**59**	**88%**
2000 to 2006: vegetation to agriculture								2			*57*		**1**	**2**	**62**	**92%**
2006 to 2015: natural vegetation/agriculture to water						2			2			**52**			**56**	**91%**
2006 to 2015: natural vegetation/agriculture to urban							2			3			**53**	1	**59**	**90%**
2006 to 2015: vegetation to agriculture								2			4			**55**	**61**	**90%**
Total	**58**	**59**	**58**	**59**	**59**	**53**	**60**	**61**	**57**	**59**	**62**	**54**	**60**	**60**	**819**	
Producer's accuracy (omission error)	**93%**	**93%**	**95%**	**92%**	**93%**	**94%**	**87%**	**90%**	**91%**	**88%**	**92%**	**94%**	**88%**	**92%**		**91.6%**

Reading this table left to right:
The "stable natural vegetation" mistakenly included four pixels belonging to the "stable agriculture," "stable water," "stable barren" and "1990 to 2000: vegetation to agriculture" classes. That's an error of commission

Reading this table top to bottom:
"Stable agriculture" should have included four more pixels of stable agricultural areas, but these were left out, instead assigned to "stable natural vegetation" and "1990 to 2000: natural vegetation to agriculture." That's an error of omission.

Overall accuracy ↑

Producer's accuracy average: 91.6%
User's accuracy average: 91.6%
Kappa coefficient: 0.9024

Table 4: Confusion matrix comparing a sample of test sites to the final map of land cover change to assess map accuracy. Producer's, user's and overall accuracies were all approximately 92%. The map had a kappa coefficient of 0.9024, indicating the classification was 90% better than one resulting from random chance.

Figure 1: The Pakse study area and the Landsat scene footprints used in this analysis.

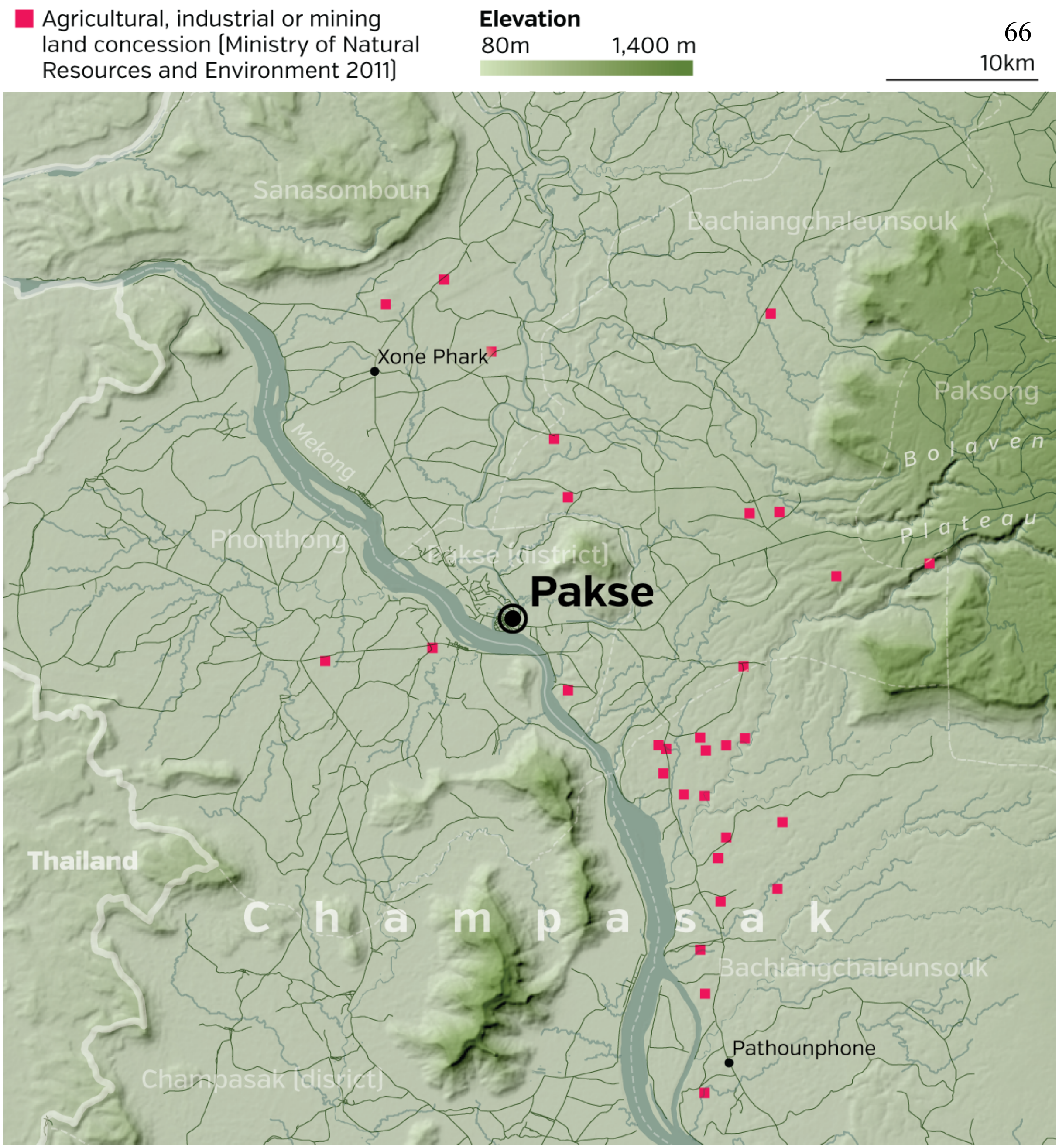


Figure 2: The extent of the study area, encompassing a 35km radius around central Pakse. Elevation, roads, drainages, and available information on land concessions are also indicated.

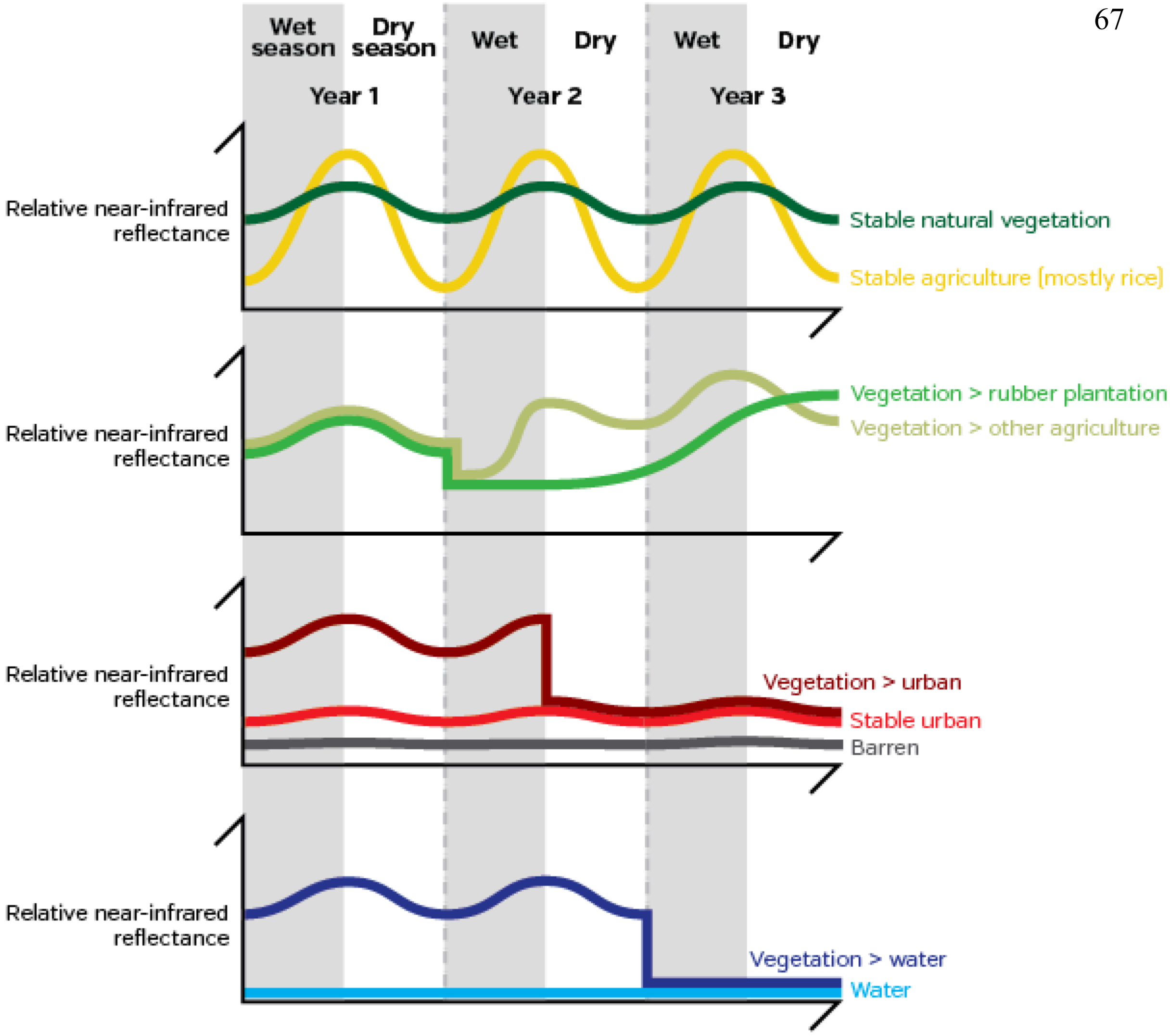


Figure 3: Simplified NIR reflectance trends for different land cover types and conversions. Croplands have a distinct cycle of rising and falling near-infrared reflectance as plants are sown and harvested. Urban cover still shows a slight cycle as vegetation is commingled among the structures, roads, and other impervious surfaces that comprise an urban area. Conversions to urban or water show a large drop in overall reflectance, with water losing the phenological signal altogether. Most of the paddies in the study area contain single-cropped rain-fed rice (Manivong 2014). The illustrative reflectance trends pictured here were adapted and simplified from Son et al (2013).

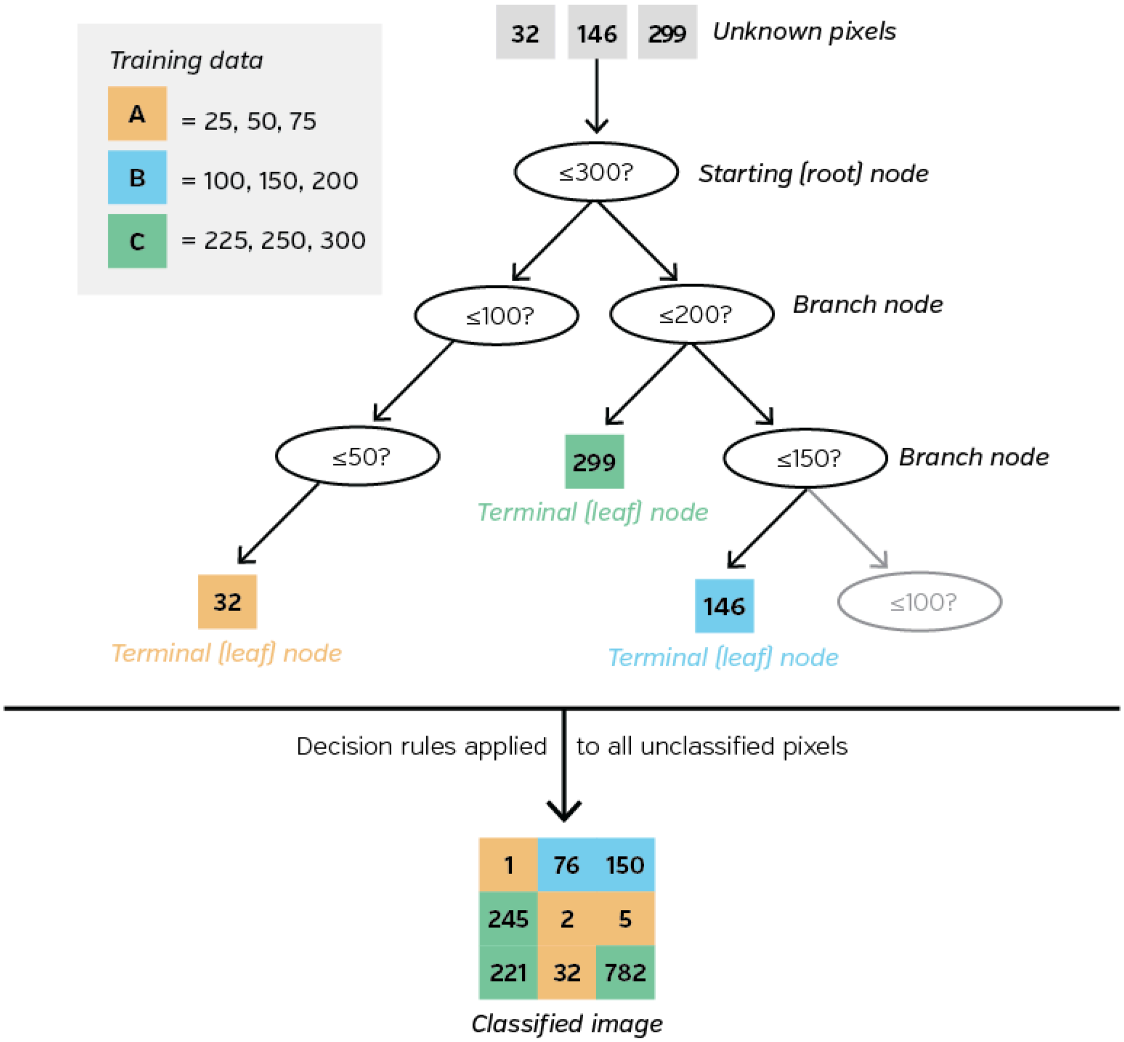


Figure 4: Schematic decision tree. Training data is used to generate a series of tests that are applied to the dataset, recursively splitting it into increasingly homogeneous classes. After the classes are satisfactorily homogenous and separable, the rules are applied to the entire image.

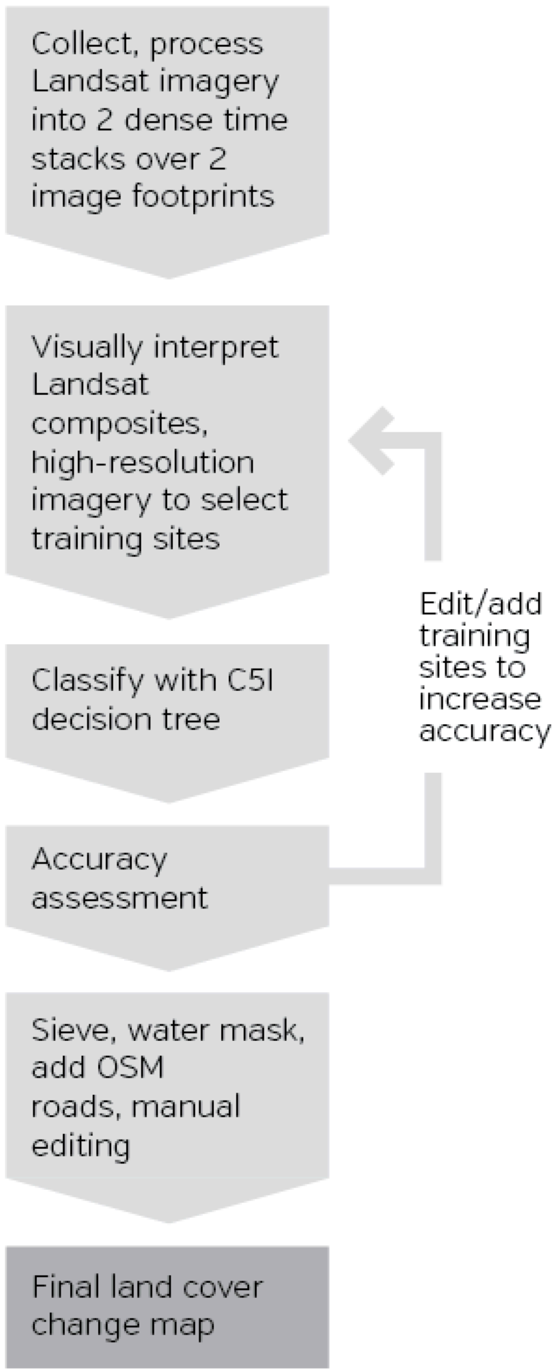


Figure 5: Work flow used to generate the land cover map.

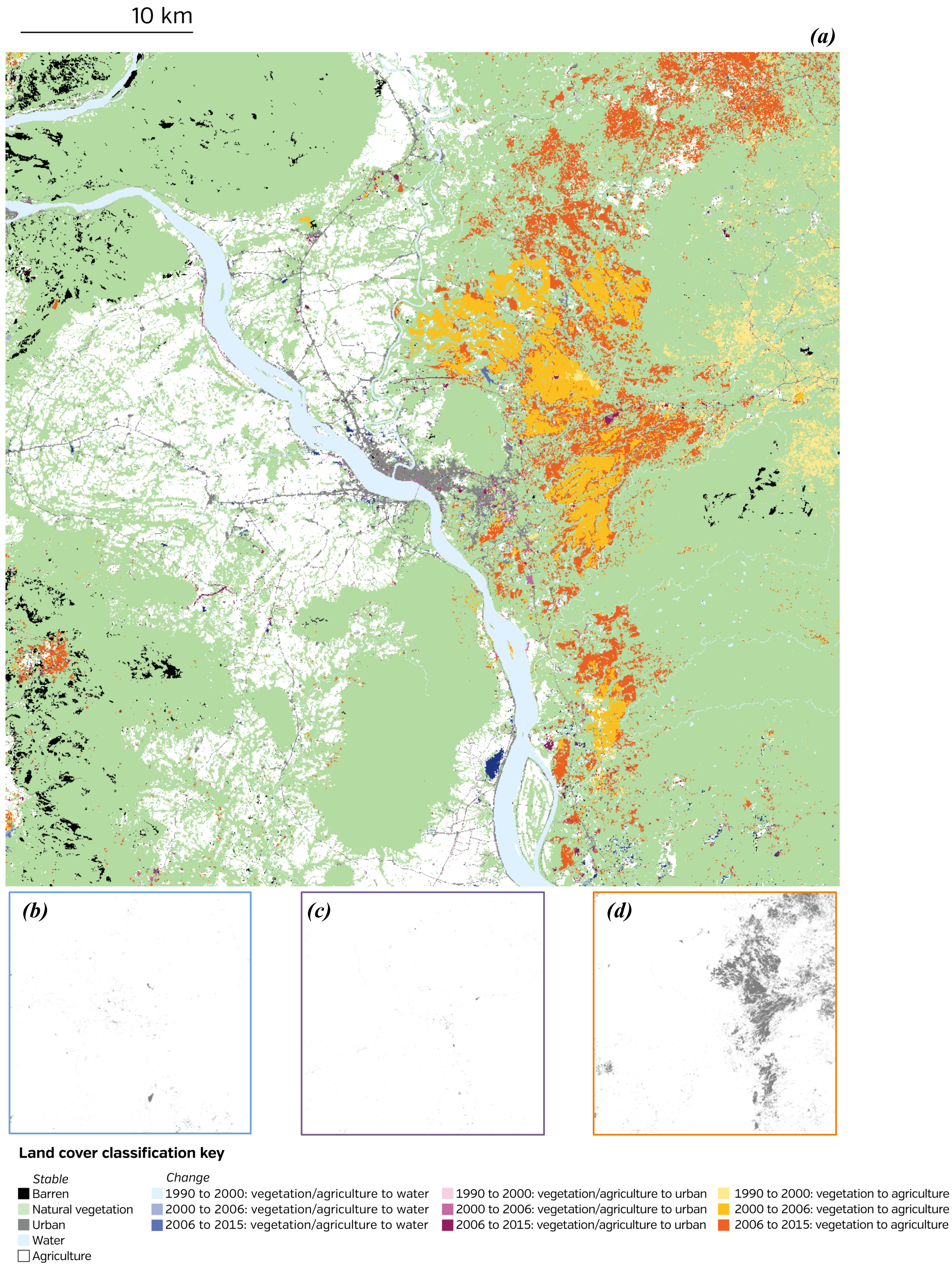


Figure 6: The final land cover map 1990-2015 for the greater Pakse area for (a) the full study area, as well as zoom boxes illustrating (b) areas that changed to water, (c) areas converted to urban and built-up areas, and (d) areas converted to agriculture.

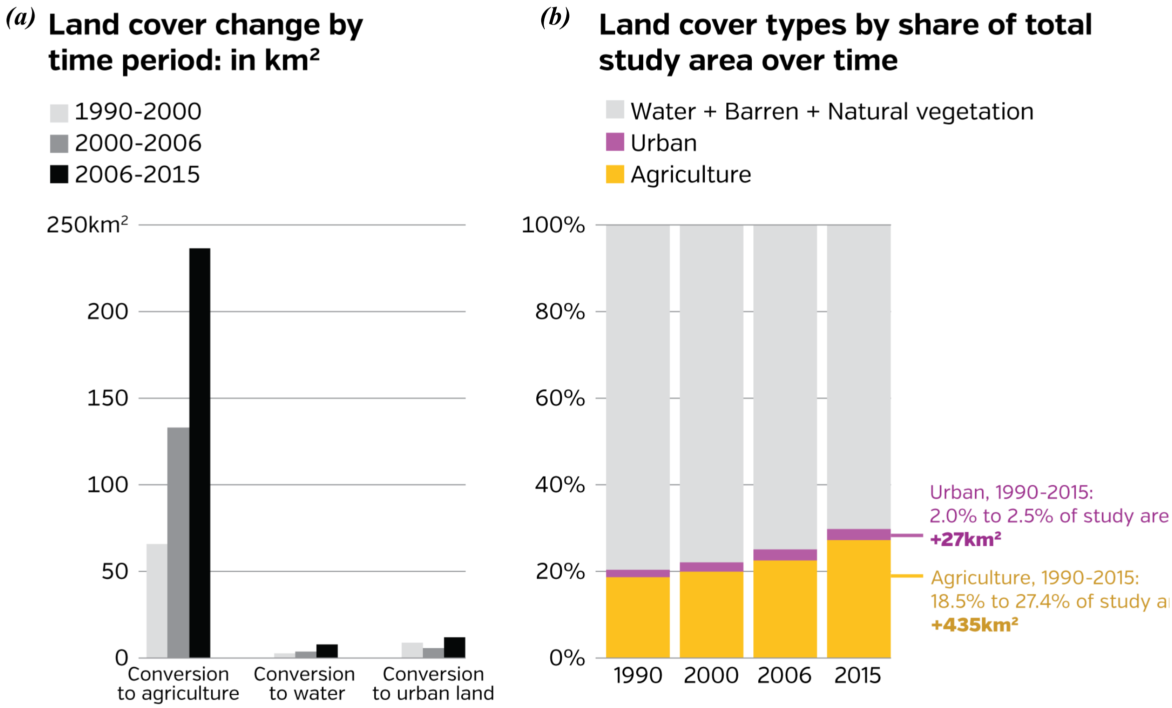


Figure 7: Summary of results showing (a) land cover change by time period and (b) land cover types by total share of study region. Note that natural vegetation and barren land cover types (66% of the study area) were excluded to better highlight the change classes.

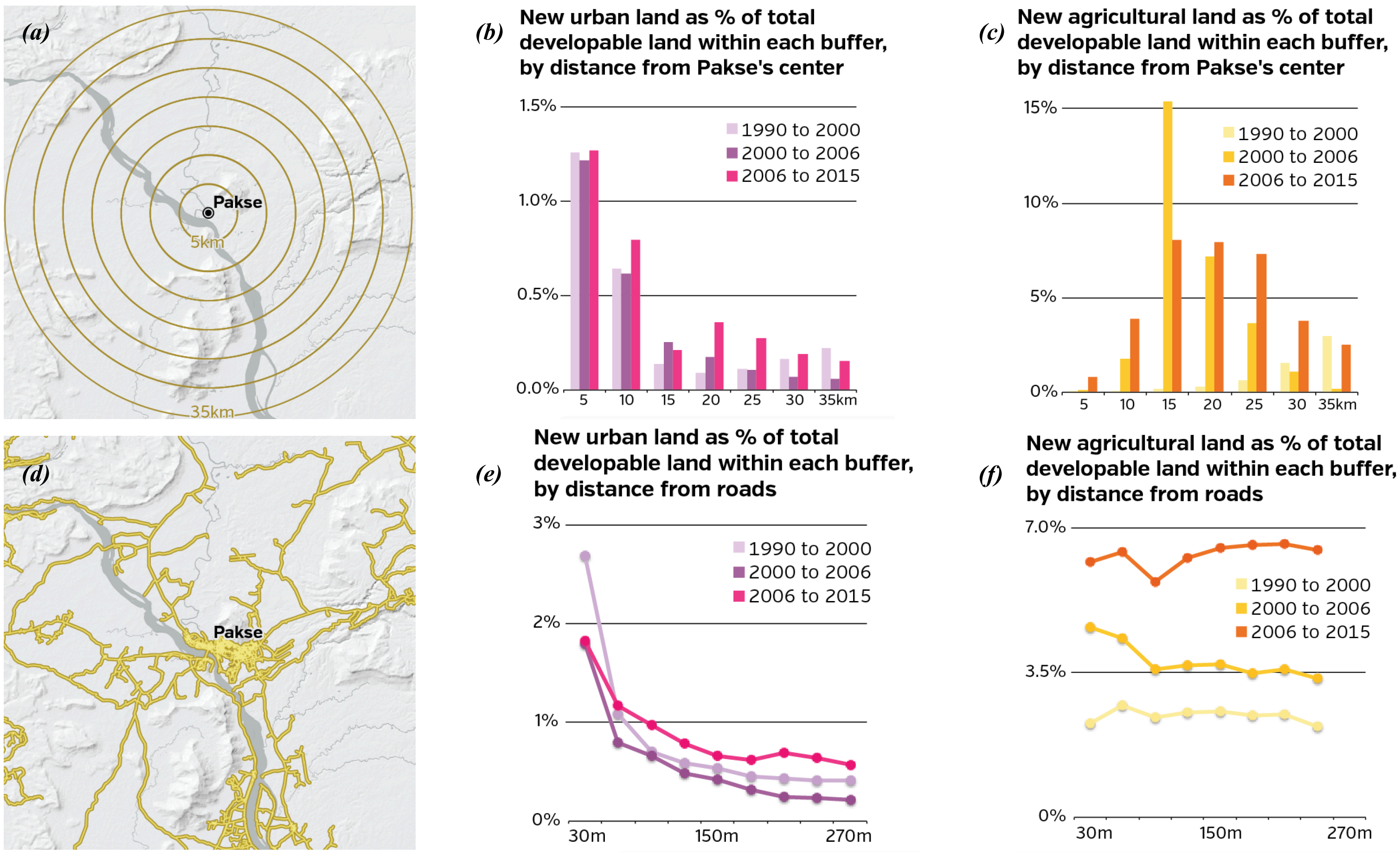


Figure 8: Results of the buffer analyses measuring land cover conversion vs. distance from the Pakse core (a) and from roads (d). The results are shown for new urban land (b, e) and for new agricultural land (c, f). Note that developable land refers to any land that is not in a water or stable urban class.

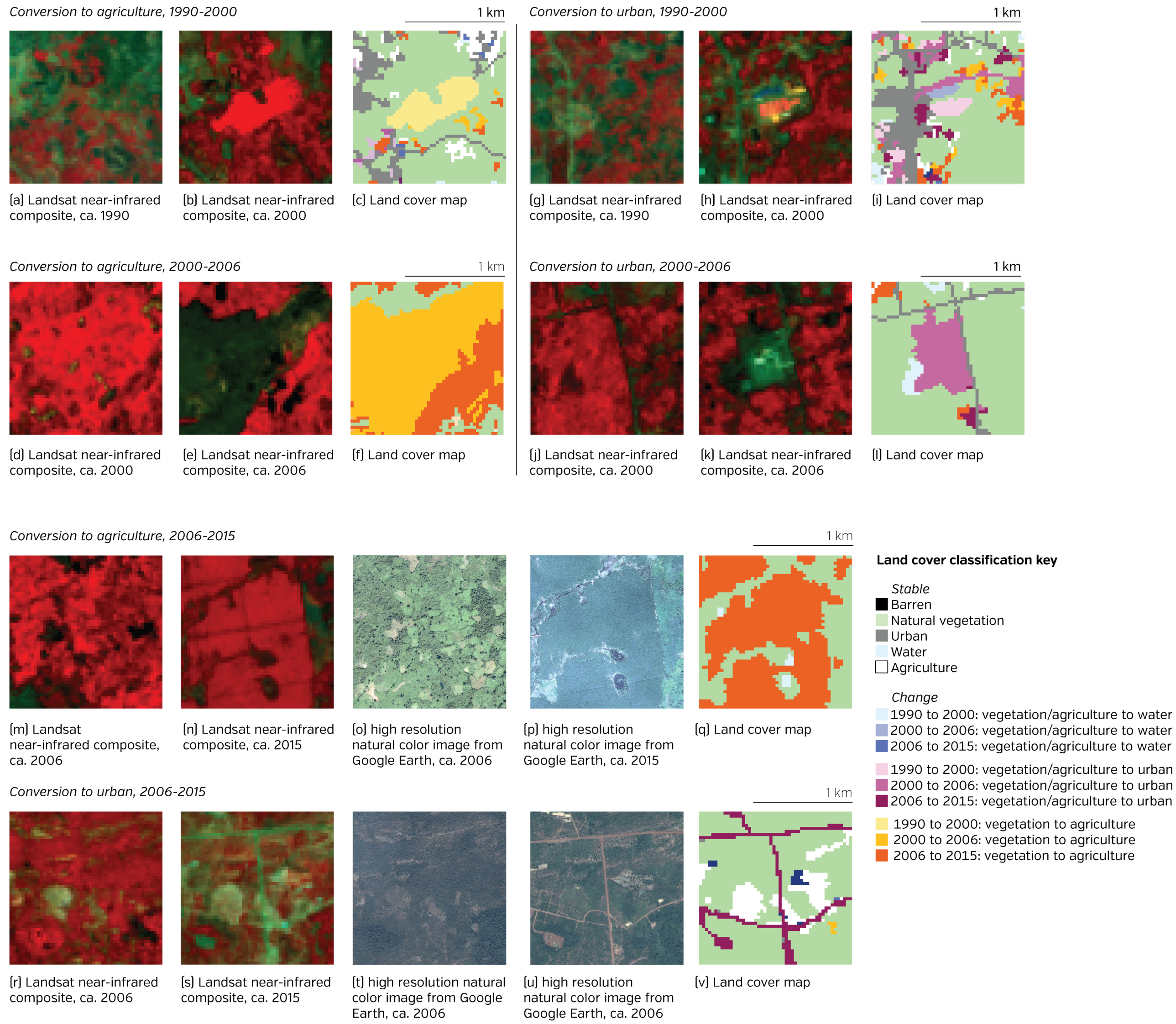
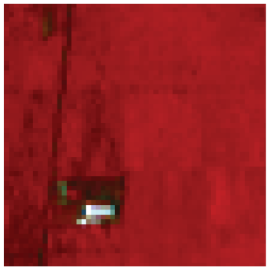


Figure 9: Land cover comparisons between Landsat near-infrared composites (bright red means high near-infrared reflectance), high-resolution imagery from Google Earth, and the classification result. All images are at the same scale. (a-f) shows conversions to agriculture 1990-2006, (g-l) shows conversions to urban land 1990-2006, (m-q) shows conversions to agriculture 2006-2015 with additional high-resolution imagery, and (r-v) shows conversions to urban land 2006-2015 with additional high-resolution imagery.

Figure 10: Views of plantations in the greater Pakse area captured from Landsat, Google Earth, and on the ground. Photos are representative only and were not taken at the sites imaged by the satellite.

Rubber plantation

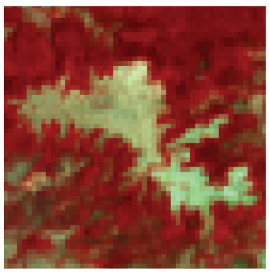


[a] Landsat near-infrared composite, ca. 2015

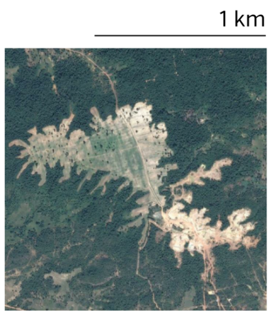
[b] high resolution Google Earth image, ca. 2015

[c] rubber plantation as seen on the ground [Toro 2012]

Cassava plantation



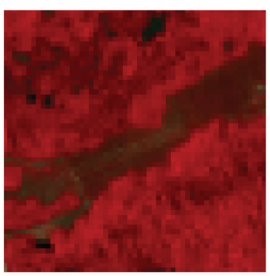
[d] Landsat near-infrared composite, ca. 2015



[e] high resolution Google Earth image, ca. 2015

[f] cassava plantation as seen on the ground [Chris Lang 2006].

Coffee plantation



[g] Landsat near-infrared composite, ca. 2015

[h] high resolution Google Earth image, ca. 2015

[i] coffee plantation as seen on the ground [Schoenweger et al 2012]