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MAPPING AND MODELING TROPICAL DEFOLIATION:
A CASE STUDY ON THE EFFECTS OF PLAN COLOMBIA

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MAPPING AND MODELING TROPICAL DEFOLIATION: A CASE STUDY ON THE EFFECTS OF PLAN COLOMBIA

By

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ABSTRACT

MAPPING AND MODELING TROPICAL DEFOLIATION:
A CASE STUDY ON THE EFFECTS OF PLAN COLOMBIA

By

Paul Larry Delamater

This research explores the effects of aerial fumigation as part of the Drug War on Putumayo, Colombia. Green fractional coverage (***fc***) is examined in a time series of Landsat ETM+ images to quantify and describe the damage resulting from fumigation. No studies have attempted to quantify these effects.

I used remote sensing technology and fieldwork to build a direct parameterization of surface phenomena and a classification of landuse and landcover (LULC) types. This was accomplished by using ***fc*** as a biophysical variable that characterized the effects of defoliation and a hybrid classification method of LULC. I validating the use of ***fc*** by collecting ground truth data to show the linear relationship that exists between image ***fc*** and ground ***fc***. I proved that Plan Colombia spraying during 2002 was not discriminate over the landscape by relating LULC classes to changes in ***fc*** over space and time.

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Last, but certainly not least, I would like to thank my family and friends. To all of you… I love you and I thank you for the strength and confidence that you have bestowed in me throughout my life.

TABLE OF CONTENTS

LIST OF FIGURES

Images in this thesis are presented in color

LIST OF TABLES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

5S : Simulation of the Satellite Signal in the Solar Spectrum

AOI : Area Of Interest (in ERDAS Imagine)

AUC : *Autodefensas Unidas de Colombia* (United Self-Defense Groups of Colombia)

DEA : United States Drug Enforcement Agency

DN : Digital Number or Digital Pixel Value

DNE : *Direccion Nacional de Estupefacientes* (National Narcotic Direction)

DOS : Dark Object Subtraction (atmospheric correction)

ELN : *Ejercito de Liberacion Nacional* (National Liberation Army)

ETM+ : Enhanced Thematic Mapper +

FARC : *Fuerzas Armadas Revolucionarias de Colombia* (Revolutionary Armed Forces of Colombia)

fc : Green Fractional Coverage

GIS : Geographic Information System

GLA : Gap Light Analyzer

GPS : Geographic Positioning System

HDF : Hierarchical Data Format

IDL : Interactive Data Language

LAI : Leaf Area Index

MSAVI : Modified Soil Adjusted Vegetation Index

NDVI : Normalized Difference Vegetation Index

ONDCP : Office of National Drug Control Policy

PIF : Psuedo-Invariant Feature (atmospheric correction)

RSI : Research Systems Inc.

SAVI : Soil Adjusted Vegetation Index

TOA : Top of Atmosphere

UNDCP : United Nations Drug Control Program

UNODC : United Nations Office on Drugs and Crime

US : United States of America

USDS : United States Department of State

USGAO : United States General Accounting Office

Chapter 1 : INTRODUCTION

This research explores the effects of aerial fumigation as part of the Drug War on Putumayo, Colombia. More specifically, green fractional coverage (***fc***) change is calculated, validated, and examined in a time series of Landsat ETM+ images to explore the effects of aerial fumigation on a landscape. The location of this study is Colombia, in the Putumayo Department, where fumigation of coca fields has been and continues to occur as a part of Plan Colombia, a US funded program to combat drug production in Colombia. Fumigation is one method used by the Colombian government to eradicate the cultivation of coca in this region. The coca plant is a perennial shrub of the genus *Erythroxylum* and grows very well in poor, acidic soils that cannot support many other commercially cultivated crops (Peterson 2002). A coca plant can produce harvestable leaves within one year of being planted, can produce harvestable leaves up to 4 times per year, and can remain productive for up to twenty five years (Clawson and Lee 1996; Gardner 2001). The leaves of the coca plant are ground to a pulp that is one of the primary ingredients in the illegal narcotic, cocaine.

The Putumayo Department is located in the southwestern Colombia and shares borders with the Sucumbios canton of Ecuador and the Loreto department of Peru. The intensive study area is roughly 40 km x 60 km located in southwestern Putumayo, bordering Sucumbios (see study area box in Figure

1.1). Putumayo is just east of the Andes Mountains and is a part of the greater Amazon River Basin.

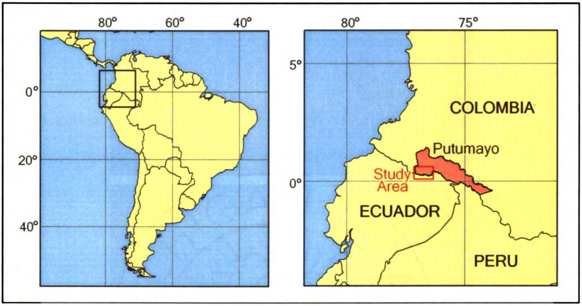


Figure 1.1 Study area maps

Located very near the Equator, Putumayo's geographic region has a Köppen-Geiger-Pohl Climate Classification of ***Af*** or Tropical rainforest climate. The average temperature of every month is above 18°C and annual precipitation generally is above 500cm and exceeds annual evaporation. This water surplus and the warm soil temperatures produce soils rich in iron oxides with a deep red color (see Figure 1.2); these soils belong to the Oxisols soil class (Strahler and Strahler 1992). The landscape can be characterized as a mix of agricultural (mostly subsistence) fields and lowland (Amazonian) tropical forest (see Figure 1.2). The province has a population of roughly 330,000 people who are mostly small-scale farmers and colonized the area through in-migration (Dudley 2000).

Figure 1.2 Photos showing Oxisols and tropical rainforest vegetation

Putumayo and the proximal regions in Colombia are considered only marginally controled by the Colombian government. The left-wing guerilla group, the *Fuerzas Armadas Revolucionarias de Colombia* (FARC) (Revolutionary Armed Forces of Colombia) and various other right-wing paramilitary groups such as the *Autodefensas Unidas de Colombia* (AUC) (United Self-Defense

Groups of Colombia) have a significant local presence, while the government has very little control. Due to its remote location and marginal governmental control, over the past 10-15 years, Putumayo (and especially southwestern Putumayo) has become one of the world's largest coca producing areas. Various reports estimate that Colombia produces the leaves for 80% of the world's cocaine (Bibes 2001) and Putumayo produces about 50% of the leaves in Colombia resulting in an astonishing 40% of the world's coca leaf production originating in Putumayo (Penhaul 2001). Because of these enormous levels of coca cultivation, Putumayo has become an area that is heavily targeted by the coca eradication efforts of Plan Colombia, the attempt by the Colombian and US governments to reduce the supply of coca for cocaine production. Putumayo has been referred to as "the ground zero" of Plan Colombia (LaFranchi 2001; Isacson and Vaicius 2001).

According to the United Nations Office on Drugs and Crime, over 400,000 ha of coca have been fumigated in Colombia since 1994, but, astonishingly, the amount of area in coca cultivation throughout the country has grown from 3,871 ha in 1994 to 102,071 ha in 2002 (however, the area in cultivation has dropped from a maximum of 163,289 ha in 2000) (UNODC 2003a). Many members of the media have spoken out against the fumigation efforts of Plan Colombia over these statistics, over reports of indiscriminate spraying of the landscape, over the amount of military equipment being supplied to Colombia, and over other social, political, and environmental issues (Alvarez 2003; Berger 2001; Brown 2000; Driver 2001; Isacson and Vaicius 2001; Kratz 2002; Penhaul 2001; Peterson

2002; Vaicius and Isacson 2003; Wilson 2003). The U.S. Department of State (2002) published Colombia's Environmental Auditor's parameters detailing conditions that must be met for spraying to be conducted, including thresholds for wind speed, temperature, and relative humidity. The USDS acknowledges that although they try to minimize mistakes in fumigation due to human and mechanical errors, occasional errors are unavoidable (USDS 2002).

Early fumigation efforts focused on large, "industrial" type coca fields, often ignoring smaller fields. However, between July and October of 2002, the push into Putumayo and Caqueta (a neighboring department, see Figure 1.3) commenced in which no differentiation between large and small coca fields was made and any field identified with coca became a target (Vaicius and Isacson 2003). Although Putumayo (and southwestern Colombia) was the focus of much of the fumigation in 2002 (over 50% of the total area fumigated in Colombia during 2002), the trend, more recently, has shifted away from these departments and to the departments of Guaviare and Nariño (see Figure 1.3) (UNODC 2003b).

Life for the people of southwestern Putumayo is not a life of luxury. Most of the farmers are very poor and are accustomed to violence associated with the presence of the FARC and other paramilitary groups and the results of cultivating an illegal crop. One local farmer remarked to Isacson and Viacius (2001) that, "life in Putumayo is not worth 1500 pesos ($0.75)." Unfortunately for the people in the Putumayo, there are few other alternatives for cash crops (Cooper 2001).

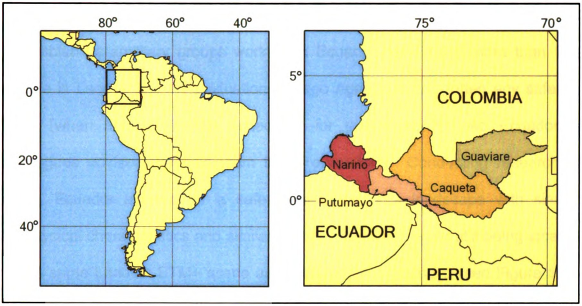


Figure 1.3 Colombia Departments

Because of the unrest of the people living in Putumayo and the presence of the FARC, conducting research in this region is far too dangerous for outsiders. This danger has also spread south from Colombia into northern Ecuador. Whereas, field teams from the University of North Carolina at Chapel Hill had previously conducted research in and around Lago Agrio, Ecuador (Messina and Walsh 2001), the base for field studies has been moved more south to Coca, Ecuador (see Figure 1.4). Lago Agrio has a population of around 24,000 people and the region was covered by primary forest 40 years ago. The population of Lago Agrio has risen greatly since the discovery of oil in 1967 by Texaco/Gulf and the agrarian reform laws that were passed in 1964 and 1973 (Perreault 2003). Although visiting Lago Agrio is safe, conducting research in the countryside is considered dangerous, as many believe that FARC members cross the border for rest and recovery in the Lago Agrio area. Farnam (2002) reported that from January to June of 2002, assassins of the FARC or the other Colombian paramilitary groups working in Ecuador have killed more than 100 people in Lago Agrio. The situation in Lago Agrio had not gotten any safer in 2003 (when field work was scheduled for this research) and Ecuadorian colleagues advised the field team to go elsewhere. Conducting research in Coca, Ecuador allowed for a safe observation of a landscape with similar biophysical characteristics and similar climatic conditions while still being located in the same Landsat ETM+ scene as southwestern Putumayo (see Figure 1.4). As mentioned previously, this region has a tropical rainforest climate. Although the distance between these two areas is roughly 100 km, there are no significant elevation changes between the coca growing areas of Putumayo and the areas surrounding Coca, Ecuador. Also, no geomorphical features exist between the areas that would significantly differentiate their respective biophysical or climatic conditions.

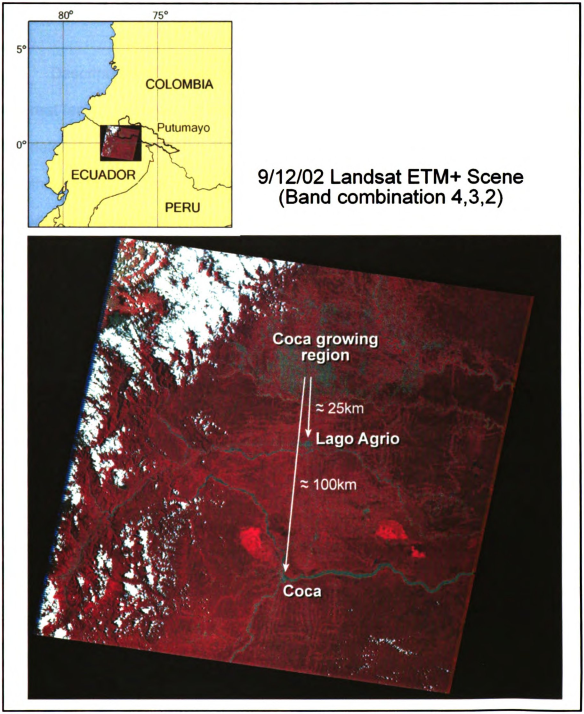


Figure 1.4 Coca, Ecuador; Lago Agrio, Ecuador; and coca growing region in Putumayo, Colombia

PROBLEM STATEMENT & RESEARCH OBJECTIVES

Descriptions of the visual damage from the spraying have been reported at great length, however no follow-up studies have been attempted that quantify the defoliation and subsequent regeneration of the coca fields, agricultural fields, or other vegetation types affected by fumigation in Putumayo. The UNODC has reported the amount of area in coca cultivation and the amount eradicated, but the methods used are questionable, particularly as the results do not explain exactly what is considered eradicated. There also have been reports of indiscriminate spraying on the landscape. These, however, have only been anecdotal reports from farmers and unsubstantiated stories by reporters. They also stand in conflict with the strict guidelines laid out by the Colombian Government's Environmental Auditor. Because of the paramilitary presence (FARC and AUC) and the unrest of the general population in Putumayo, such assessments of the effects of Plan Colombia cannot be safely completed in the field. Alternative methods of data collection and quantification must be employed.

The overall objective of this study is to quantitatively and qualitatively measure the defoliation and regeneration of the vegetation due to the Plan Colombia fumigation in Putumayo, Colombia. More specifically, the objectives of this research are to:

1. Use remote sensing techniques to detect the biophysical attribute changes that have occurred as a result of fumigation.
2. Verify and calibrate the detected biophysical attribute changes by conducting field measurements in Ecuador.

3. Quantify the amount of defoliation of vegetation using the field-calibrated data.
4. Identify the primary land cover classes affected by fumigation and attempt to identify whether the spraying is discriminate.

RESEARCH HYPOTHESES

I hypothesize that:

1. Green fractional coverage derived from ETM+ data accurately quantifies vegetation cover.
2. Hybrid classification techniques applied to ETM+ data identify LULC classes.
3. Changes in ***fc*** indicate changes due to defoliation.
4. Defoliation in Putumayo, Colombia occurs indiscriminately over the landscape affecting cover types other than coca.
5. Landsat ETM+ data provides the synoptic coverage with adequate resolution characteristics suitable for study.

Chapter 2 : LITERATURE REVIEW

THE UNITED STATES AND THE DRUG WAR IN SOUTH AMERICA

Reports of US government involvement with South American countries in battling illegal drug related activities go back about 30 years. In 1973, the US government began a four year, $6,000,000 training program for 600 law enforcement officials to fight marijuana cultivation in Colombia (Sharpe 1988). However, the US interdiction efforts in South American illegal drug trafficking escalated greatly with President Reagan's "war on drugs" of the early 1980's (Bagley 1988a). Many of the efforts resulting from this war have targeted the supply end of the drug chain. In the Anti-Drug Act passed by Congress and signed by President Reagan in 1986, approximately 75% of the $3.9 billion to be spent in 1987 were dedicated to supply end programs such as expanded enforcement, interdiction, and eradication/substitution versus the 25% dedicated to demand end programs such as education, prevention, treatment, and rehabilitation (Bagley 1988b). Over the last 20 years, narcotics control has become a foreign policy priority as the US has carried out massive drug interdiction operations in Colombia, Peru, and Bolivia (Vellinga 2000). The US military has also been very active in fighting the production and trafficking of drugs during this time period as spending increased from $0 in 1981 to $389 million in 1987. The Department of Defense (DOD) also loaned $303.5 million dollars worth of equipment to various authorities enforcing drug laws from 1981 to 1987 (Mabry 1988).

Some of the early interdiction efforts centered around attempts to target production at the source. During the early 1980's in Peru, local police carried out manual eradication of coca fields with logistical support provided by the US Drug Enforcement Agency (DEA), yet these programs showed only minor localized reductions while total cultivation in Peru rose. The program expanded to include spraying coca fields with herbicides in 1989, but demonstrations and a wave of guerrilla attacks prompted a return to the previously used manual procedures of eradication (Kay 1999).

No South American nation has received more US assistance in the drug war than Colombia. From the years 1986 to 1996 the US State Department estimated that over a half a billion dollars were spent in Colombia (Millett 1997).

COCA AND COLOMBIA

Colombia's recent history has been littered with violent and bloody clashes between people and the government and also between right-wing and left-wing political groups. These clashes have often left many people dead such as the period of *La Violencia* (from the late 1940's to early 1960's) which was characterized by extreme violence, cruelty, and wanton killing, and claimed an estimated 2-3% of the country's total population (Guzman et al. 1962 and Kalmanovitz 1988 as cited in Thoumi 1992). Colombia has also seen the rise to power of left-wing guerilla groups, such as the FARC, the oldest guerrilla force in the Americas (Browitt 2001), and the *Ejercito de Liberacion Nacional* (ELN) (National Liberation Army), the rise of right-wing paramilitary groups, such as the AUC, who attempt to combat the left-wing groups, and a very powerful emergence (and a later disappearance) by major drug-trafficking groups such as the Medellin and Cali cartels, all during the last 50 years. The FARC has garnered so much political power in Colombia that the Colombian government ceded a large portion of land in southern Colombia (roughly 40% of the total area of Colombia) to the group in 2002 (Nagle 2002). The Putumayo department is a stronghold of the FARC guerillas (Penhaul 2001) and is an underdeveloped area of very marginal governmental control with a long history of illegal activity (Marcella 2002).

Colombia also has a dubious and complex history of illegal narcotic production. The de-legitimization of its government system over the past 45 years has allowed the country to gain an "advantage" in terms of illegal drug production (Thoumi 1992). The Colombian government continues to struggle for legitimacy as it faces challenges such as questioning of the current peace process, corruption, weak institutions, and inability to provide basic public goods (Meltzer 2001).

During the 1970s, marijuana cultivation came to Colombia as eradication efforts were commencing in Mexico. Colombians then shifted to exporting cocaine during the late 1980s as marijuana cultivation shifted back to Mexico. During this time period, the raw materials (the coca leaves) were being imported from Bolivia and Peru and the coca paste was produced in Colombia. This changed again however in the early 1990s as Colombia began growing opium poppies, began producing and exporting heroin, and began growing much more coca (Vargas 2002). Poppy production has also been a target of Plan Colombia, however the small amount of area in poppy production (3,828 ha in 2002) and the sparse distribution throughout the mountainous areas of Colombia make it very difficult to study (UNODC 2003). The 1980s and 1990s also saw the rise and fall of the major drug cartels in Colombia. The Medellin and Cali cartels grew in power and during this time period owned over one twelfth of Colombia's land or roughly 9.5 million ha (Ehrenfeld 1990). The Medellin cartel, during the early 1980s, launched a brutal campaign of terrorism against Colombia's government and citizens (Dishman 2001). The emergence of groups, as powerful as the cartels, specifically the left-wing guerillas and paramilitaries, has been a major factor in the destabilization of Colombia. The coca growth has escalated since the early 1990s (as noted earlier) as Bolivia and Peru's production of coca has declined significantly. Much of the coca in Colombia is grown in regions located outside of the realm of control of the Colombian government (areas controlled by guerillas or paramilitaries). Although the numbers vary significantly, estimates place the 68% of Colombia's cocaine production in the departments of Putumayo, Guaviare, and Caqueta (DNE 2000) as reported in (Moreno-Sanchez et al. 2003) and 50% in Putumayo alone (Penhaul 2001). Coca came to Putumayo in the late 1970's, but was not a major factor until the mid-1990's when fumigation efforts by the Colombian government in Guaviare and Caqueta drove much of the coca production to the more remote

Putumayo department (Isacson and Vaicius 2001). The late 1990's also saw the demise of the Cali cartel, which had purchased their much of their coca leaves from Peru. This, along with Peruvian efforts to battle coca growth locally, led narcotics traffickers to promote the growth of coca in Colombia (Rojas 2003). Between 1990 and 1995, the area in coca cultivation more than doubled to 80,000 ha and that number swelled to between 120,000 and 150,000 ha in cultivation by 2000 (Thoumi 2002); (Uribe 1997), rose to 169,800 ha in 2002, before finally falling to 144,450 ha in 2003 (United States General Accounting Office (USGAO 2003) as reported by the Office of National Drug Control Policy [ONDCP]). However, as is often the case with many of the reports, there are discrepancies between one group's figures compared to others. The UNODC (2003a) estimates for area in coca cultivation are found in Figure 2.1.

In Colombia, much of the coca (estimates vary greatly) is grown on small plots by poor subsistence farmers who have few alternatives for the production of cash crops (Cooper 2001; Fratepietro 2001; Stauder 2001). The first step in the processing of the coca leaves usually occurs very near the fields in rudimentary laboratories (often nothing more than wooden shacks) as farmers use gasoline, bleach, and sulfuric acid to create the coca paste from the coca leaves (Dudley 2000). A farmer can sell a kilogram of coca paste for $900, which is enough to cover production costs, pay his workers, and feed his family (Stauder 2001).

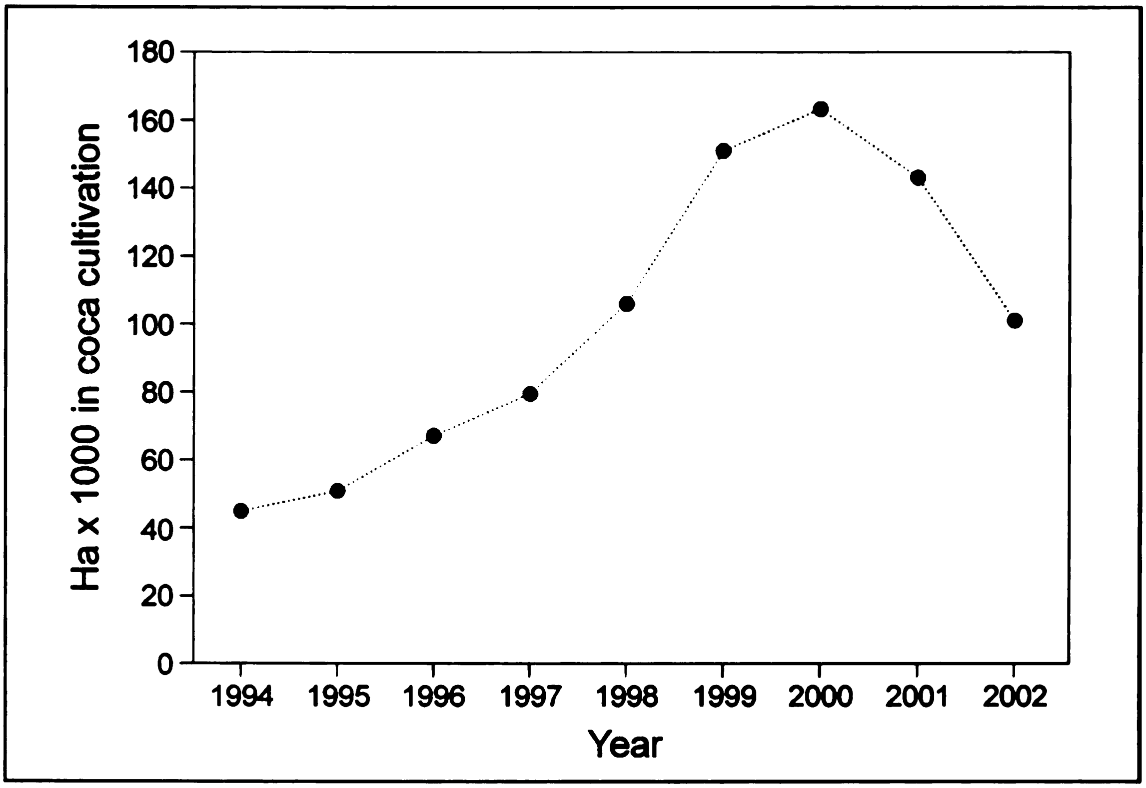


Figure 2.1 UNODC estimates of coca cultivation in Colombia

However, the paramilitary group or guerilla group who control the area often tax the money earned by the farmer from growing coca. The paramilitaries and guerilla groups use this tax to finance their wars against each other and the Colombian government. Colombian authorities have reported that the FARC makes nearly $500 million dollars per year in coca growing areas and the right-wing paramilitaries, with unofficial help of the Colombian military and police, make over $200 million per year via drug trafficking (Dudley 2000). These taxes, combined with farming expenses, often leave the farmer making only slightly more than the Colombian minimum wage of $150 per month ($1800 per year) (Fratepietro 2001; Isacson and Vaicius 2001). Although the farmers are surviving, they are not prospering. In some regions of Colombia, the guerilla groups are so involved in the drug production and trafficking that the distinction between fighting the drug war and fighting the guerilla war is blurred as the same equipment, intelligence, and personnel are used in both. US policy has been tough to implement as the focus is solely to combat drug trafficking, not the guerilla insurgency (Bibes 2001).

PLAN COLOMBIA

The US has a history of involvement in Colombian affairs that dates back to the early 1960s (Petras 2001). "Plan Colombia" was developed during the Clinton Administration as an attempt to reduce the impacts of drugs in the United States and was signed into law in 2000 (Crandall 2002). The specific goals of Plan Colombia are: a push into Southern Colombia; support for narcotics interdiction efforts; support for the Colombian National Police; support for developmental and particularly alternative development programs and approaches; support for justice and other social sector reform; and support for issues outside of Colombia, forward-operating locations, as well as several other counties that are affected by what happens in Colombia (USDS 2001). By 2002, Colombia had received over $2 billion for Plan Colombia with $1.7 billion coming from the United States and the rest contributed by various European countries, Canada, and Japan (Frechette 2003). Plan Colombia's support for narcotics interdiction efforts includes the use of aerial fumigation, which is employed in an effort to eradicate the cultivation of coca plants in Colombia, and voluntary manual eradication pacts with aid to help farmers make a living with legal crops (USDS 2002). Plan Colombia was renamed the Andean Regional Initiative by President George W. Bush and continues to be sold as the key component in the war on drugs (Driver 2001). (Although the program has been renamed, it is still generally referred to as "Plan Colombia" and will be referred to as such throughout the rest of this document)

The aerial fumigation program is carried out using crop dusters to spray a herbicide called RoundUp Ultra (a combination of glyphosate, Cosmo Flux-411f, and Cosmo-iN-D) onto the fields (Isacson and Vaicius 2001, many others have also covered this topic). Glyphosate, the main ingredient used in RoundUp Ultra, is the most widely used herbicide used in the United States and is generally not harmful to humans and animals (USDS 2002). The other ingredients in RoundUp Ultra are used to 1: more easily covert the liquid into a mist and 2: allow the substance to stick to the vegetation better (as RoundUp in its native form can be washed off with water, a concern in the humid tropics). The fumigation is carried out using a mixture of methods and equipment. The first stage is a reconnaissance flight where the aircraft is equipped with a digital imaging system that records multispectral information and identifies crop types. This device is connected to a Geographic Positioning System (GPS) receiver that records position information to be used with the crop type data. Mission planning for the actual spraying aircraft is carried out using this data, however the pilots use a visual identification method before spraying (USDS 2002). In 2000, with significant support from the US, the Colombian Government began this major aerial eradication program in Putumayo and promised support to farmers who willingly self-eradicated their own coca crops (Ernst 2002). Over the last few years, two major fumigation efforts have taken place in Putumayo. The first period of flights lasted from December 2000 to February 2001 covering 25,000 hectares and the second, from July to October of 2002, covered 60,500 hectares (Vaicius and Isacson 2003). Because of the different methods used, reports of the amount of area fumigated vary greatly (Ford 2003). The UNODC, using remotely sensed imagery, report slightly higher numbers in Putumayo with 32,506 ha fumigated in 2001 and 71,891 ha in 2002 (UNODC 2003). In a hearing before the US Senate, Colombian Vice President Santos-Calderon (US Senate 2003) reported that overall in Colombia, 130,000 ha were sprayed in 2002, 65,000 ha were sprayed between January 2003 and June 2003, and the goal was to spray 150,000 ha by the end of 2003. The UNODC estimates for the amount of area fumigated in Colombia from 1994-2002 are found in Figure 2.2.

Although spraying has occurred over large, industrial-type coca fields, much of the coca growing area in Putumayo is composed of small coca and agricultural fields interwoven together on the landscape. The complex layout of the Colombian landscape and the effects of wind drift and runoff have resulted in many non-coca fields being adversely affected by the fumigation. Many reports exist that detail how food and other subsistence crops have been sprayed and destroyed (Berger 2001; Cooper 2001; Fratepietro 2001; Isacson and Vaicius 2001; Kratz 2002; Penhaul 2001; Peterson 2002; Stauder 2001; Vaicius and Isacson 2003; Wilson 2003).

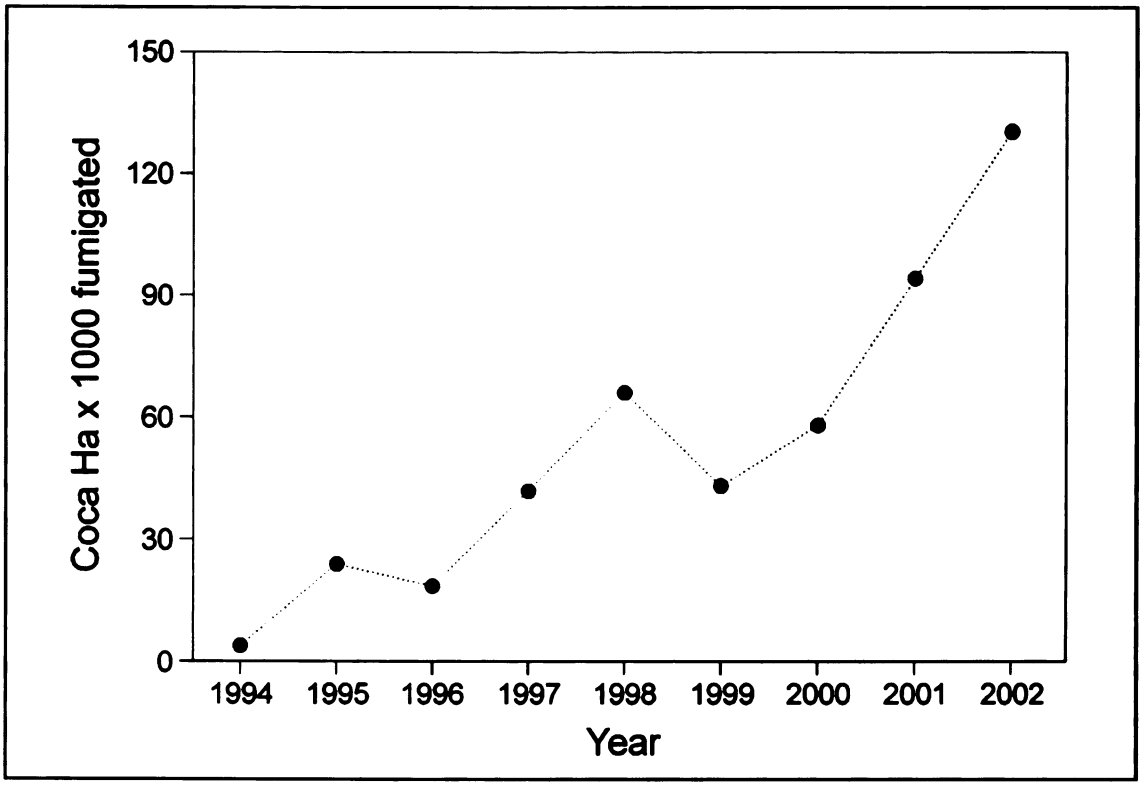


Figure 2.2 UNODC estimates of coca fumigation in Colombia

Often, the farmers grow food crops in fields directly adjacent to their coca crops or intermixed with coca crops and have seen these fields damaged or destroyed by the fumigation efforts (Forero 2002). County officials in the Guamuez Valley have tallied more than 800 cases where there was a claim of legal crops being destroyed by spraying (Hodgson 2001) (see Figure 2.3).

Others argue that fumigation is also harmful to ecosystems and the environment, threatening the biodiversity of the area (Peterson 2002; Vargas 2002), and fosters displacement of farmers, causing deforestation (Dudley 2000; Ecuador 2001; Forero 2002; Vargas 2002; Wilson 2003).

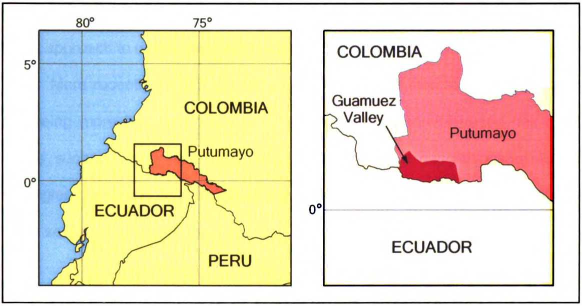


Figure 2.3 Guamez Valley Map

As of 2000, there were already reports of hundreds of Colombian refugees fleeing across the border to Ecuador causing the US to increase related aid to Ecuador (LaFranchi 2000) and during the first 10 months of 2001, an estimated 13,500 people fled Colombia with most of them going to Ecuador (Valenzuela 2002).

There also exists the possibility of moving coca production to bordering countries. Reports have surfaced of Ecuadorian farmers living near the southern Colombian border being offered money by drug traffickers to begin coca production (Cooper 2001). The overseer of the United Nations Drug Control Programs's (UNDCP) office in Colombia, Klaus Nyholm, commented, "Fumigation has an effect, but we would argue it's an effect of displacement" (Forero 2002). Critics of Plan Colombia also point to statistics from the UN and UNDCP (2002a) that showed a rise in the amount of area in coca cultivation despite the eradication efforts. They use this as evidence that eradication is a failed approach to drug control (Moreno-Sanchez et al. 2003).

More recently the US has attempted to distance themselves from further promising more help to Colombia. President Bush's administration has used words such as "endgame" and "exit strategy" in the descriptions of future strategies pertaining to Colombian aid, even as Colombian President Alvaro Uribe seeks more help (Wilson 2003).

MONITORING VEGETATION USING REMOTE SENSING

The data collected by many earth observing satellites throughout the past 30+ years has given birth to a variety of methods for researchers to use in monitoring vegetation change. The development of extensive imagery databases has been the major factor contributing to the growth of remote sensing technologies for studying change detection (Lunetta et al. 2002). Also, as time progressed, visual interpretation of aerial photography and satellite imagery has given way to quantitative and qualitative measures of the information collected by the sensor. These measures attempt to remove the bias that can occur during human interpretation. Included in these measures are numerous vegetation indices that try to model the characteristics and the biophysical attributes of the vegetation present on the ground. These indices are a primary source of information for operational monitoring of vegetation cover (Gilabert et al. 2002). Many of the indices have become very popular such as the Normalized Difference Vegetation Index (**NDVI**) (Rouse et al. 1974), the Soil Adjusted

Vegetation Index (**SAVI**) (Huete 1988), the Modified **SAVI** (**MSAVI**) (Qi et al. 1994), the Leaf Area Index (**LAI**) (Price and Bausch 1995), and Green Fractional Coverage (***fc***) (Qi et al. 2000) and research continues towards efforts to find the most accurate relationships between the calculated biophysical variables and the true state of the vegetation on the ground (Cohen et al. 2003; Xavier and Vettorazzi 2004). Other research has also been conducted that models statistical relationships between each of these indices (Carlson and Ripley 1997; Leprieur et al. 2000; North 2002; Purevdorj et al. 1998; Zha et al. 2003). The most widely used vegetation index is **NDVI** as it is a simple algorithm to compute and most of the satellite imagery in use provide the necessary spectral bands for computation. **NDVI** and the other vegetation indices can be extremely useful in change detection studies using time-series data over the same area. Fung and Siu (2000) used the differences between image **NDVI** values to monitor the environmental changes occurring in Hong Kong from 1987 to 1995 due to such factors as land reclamation (from the sea), new urban development, and forest fires. Weiss et al. (2001) used the Coefficient of Variation observed between **NDVI** values to evaluate the effects of grazing in Saudi Arabia's rangelands. Other studies have used observed changes in **NDVI** to create masks to aid in the search for areas most likely to have undergone a LULC change (Lunetta et al. 2002).

An index that has been derived from **NDVI** in an attempt to model the percent of a pixel covered with green vegetation is ***fc***. Green vegetation cover is an important factor in vegetation status and as an indicator of land degradation

(Purevdorj et al. 1998). Although multiple methods exist that attempt to derive ***fc***, the most popular is a process of linear spectral unmixing of the **NDVI** value. The radiation reflected from heterogeneous materials and recorded in a satellite pixel can be considered a mixture of a number of spectrally pure materials (Van Der Meer 1999). Qi et al. (2000) used this concept assuming that the pixel signal is made up of two components, vegetation and non-vegetation. This study was a preliminary investigation without a proven method of ground truth data collection, however the results were encouraging. Previous studies have also been attempted and showed success using both **NDVI** and **LAI** in the estimation of ***fc*** (Carlson and Ripley 1997; Choudhury et al. 1994; Gillies and Carlson 1995).

Chapter 3 : METHODS

IMAGE PRE-PROCESSING

Three Landsat ETM+ scenes were ordered from the Center for Global Change and Earth Observations at Michigan State University (through www.landsat.org). The three co-located scenes (Path 9, Row 60 of the World Reference System) and were acquired by the satellite on September 9, 2001; September 12, 2002; and October 14, 2002 (see Figure 3.1). These scenes represent the only available images with less than 30% cloud cover that have been acquired by the satellite since the most recent Plan Colombia fumigation commenced. Although these are the only images available, the September and October images were collected during the second of the two major fumigation efforts in Putumayo which (as previously mentioned) lasted from July to October of 2002.

The original images on Compact Discs were imported from the Hierarchical Data Format (HDF) directly into ERDAS Imagine as raw 8-bit data representing Digital Pixel Values or Digital Numbers (DNs). Because the images were going to be compared against each other quantitatively, a series of steps were taken to normalize sensor collection errors and atmospheric effects present in each image.

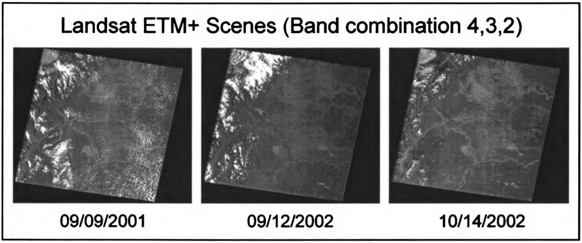


Figure 3.1 Landsat ETM+ Scenes (Path 9, Row 60)

The first step was to perform a Radiometric correction on each of the images. The Radiometric correction involves converting the DNs of the image to Radiance values then converting the Radiance values to Top of Atmosphere (TOA) reflectance values. The equation for the first step, conversion to Radiance (Equation 3.1), is found below (NASA).

$$\mathbf{L}_{\lambda} = \left(\frac{\mathbf{L}_{\max\lambda} - \mathbf{L}_{\min\lambda}}{\mathbf{Qcal}_{\max} - \mathbf{Qcal}_{\min}} \right) * \left(\mathbf{Qcal} - \mathbf{Qcal}_{\min} \right) + \mathbf{L}_{\min\lambda}$$

where:

$\mathbf{L}_{\lambda}$ = Spectral Radiance at the sensor's aperture
$\mathbf{L}_{\max\lambda}$ = Spectral radiance that is scaled to $\mathbf{Qcal}_{\max}$
$\mathbf{L}_{\min\lambda}$ = Spectral radiance that is scaled to $\mathbf{Qcal}_{\min}$
$\mathbf{Qcal}$ = Quantized calibrated pixel value or DN
$\mathbf{Qcal}_{\max}$ = Maximum quantized calibrated pixel value
$\mathbf{Qcal}_{\min}$ = Minimum quantized calibrated pixel value

Equation 3.1 Conversion of DNs to Radiance values

Next, the images were converted to TOA reflectance values using Equation 3.2.

$$\rho_p = \left(\frac{\pi * \mathbf{L}_\lambda * \mathbf{d}^2}{\mathbf{E}_{\mathrm{sun}\lambda} * \cos\Theta_s} \right)$$

where:

ρ_p = Planetary reflectance
$\mathbf{L}_\lambda$ = Spectral Radiance at the sensor's aperture
$\mathbf{d}$ = Earth-Sun distance in astronomical units
$\mathbf{E}_{\mathrm{sun}\lambda}$ = Mean solar exoatmospheric irradiances
$\cos\Theta_s$ = Solar zenith angle

Equation 3.2 Conversion of Radiance to TOA reflectance

After the images were converted to TOA reflectance values, a Simulation of the Satellite Signal in the Solar Spectrum (5S) atmospheric correction (Tanre et al. 1990) was applied to remove the effects of the atmosphere on the signal and to bring the pixel values to surface reflectance values. The code in the 5S correction computes the solar radiation that is backscattered by the surface and atmosphere as observed by the satellite (Mackay et al. 1998). The decision to use an atmospheric correction was driven by studies showing the advantages of correction for change detection studies (Song et al. 2001) and because **NDVI** was going to calculated. Teillet et al. (1997) point out that the best representation of **NDVI** derived from image data is the **NDVI** of the surface reflectance values (ρ) as it is a function of the reflectance values of the vegetation and will be skewed by the effects of the atmosphere found in ρ_p.

Although, there are much more robust methods for this correction, they require detailed information on the local atmospheric conditions on the date of image collection. That information was not available for this area so these methods could not be used. The input parameters used for the 5S correction are found in Table 3.1 and were easily obtainable for the study area except for visibility. I was not able to locate the on-ground visibility data for this region at the specified time period. I chose to use the default value of 17 miles and used this for all the images. The parameters, site elevation, sensor elevation, sensor zenith, sensor azimuth, model type, standard atmospheric model, aerosol model, and visibility did not change between images as all images were collected by the same satellite and the study area is in the same location in all images. The only parameters that were different between images were solar zenith, solar azimuth, and date. I obtained these parameters by viewing the header file of the original image data.

Site Elevation
Sensor Elevation
Solar Zenith
Solar Azimuth
Sensor Zenith
Sensor Azimuth
Model Type
Standard Atmospheric Model
Aerosol Model
Visibility
Date

Table 3.1 5S atmospheric correction input parameters

Other methods of atmospheric correction such as Dark Object Subtraction (DOS) and Psuedo-Invariant Feature (PIF) are easier to use, however they do not perform as well (Song et al. 2001). The output parameters of the 5S correction are a series of values modeling surface reflectance at each band. A model was constructed by using a linear regression through the corresponding ρ and ρ_p values. The 5S atmospheric correction was implemented by using the equations gathered from the 5S code and the linear regression to create the new image in ERDAS Model Maker. The detailed input and output parameters used for the correction of each image and can be found in Appendix A and Appendix B. Equation 3.3 is a simplified representation of the 5S correction of the image.

$$\rho = f(\rho_p, \text{atmospheric conditions})$$

where:

ρ_p = Planetary reflectance
ρ = Surface reflectance

Equation 3.3 5S atmospheric correction

Once the images were converted to surface reflectance, the Normalized Difference Vegetation Index (**NDVI**), a measure of vegetation vigor, was calculated (see Equation 3.4) using Band 4 (NIR) and Band 3 (Red) of each image (Weiss et al. 2001). **NDVI** was calculated as a transition product for ***fc*** calculation. A model was constructed in ERDAS Imagine to create the NDVI layer for each image.

$$\mathbf{NDVI} = \left(\frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \right)$$

where:

ρ_{NIR} = Near Infrared pixel reflectance value (Landsat ETM+ Band 4)
ρ_{Red} = Red pixel reflectance value (Landsat ETM+ Band 3)

Equation 3.4 NDVI calculation

The next step was to calculate the ***fc*** for each pixel. Green fractional coverage (***fc***) is a measure of the areal amount of a pixel that is covered by green vegetation (Qi et al. 2000). This is not biomass or Leaf Area Index (LAI) which attempt to add a 3rd dimension (volume) to the calculation (in the case of LAI, although it's name implies the measurement of area, an attempt is made to model and detect situations where more than one piece of vegetation is directly below another and is more of a density measure). The calculation of ***fc*** is an attempt to construct a 2D model of the amount of area within a pixel that has green vegetation between the sensor and the ground. Typically, the vegetation contained within pixel boundaries is not homogenous therefore ***fc*** is the measure of the combination of all the vegetated areas and bare soil areas contained within a pixel boundary (Equation 3.5).

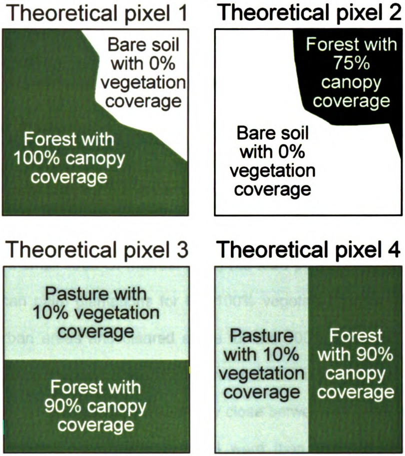
$$fc = \sum_{0}^{n} \text{area}_n * \%\ \text{vegetation cover}_n$$

where:

area_n = Area represented by a homogenous % vegetation cover
% vegatation cover_n = The percent of green vegetation covering the ground

Equation 3.5 ***fc*** definition

Figure 3.2 shows how the ***fc*** of a pixel is determined by the amount of area covered with green vegetation within the pixel boundaries. It also shows some of the infinitely possible scenarios for an ***fc*** pixel value (Scanlon et al. 2002).



$$\boldsymbol{fc}_{\text{pixel 1}} = (75\%)*(100\%) + (25\%)*(0\%) = 75\%$$

$$\boldsymbol{fc}_{\text{pixel 2}} = (75\%)*(0\%) + (25\%)*(75\%) = 18.75\%$$

$$\boldsymbol{fc}_{\text{pixel 3}} = (50\%)*(90\%) + (50\%)*(10\%) = 50\%$$

$$\boldsymbol{fc}_{\text{pixel 4}} = (50\%)*(90\%) + (50\%)*(10\%) = 50\%$$

Figure 3.2 Green Fractional Coverage

The **fc** layers were calculated from the existing **NDVI** layers using Equation 3.6 (Qi et al. 2000).

$$fc = \left(\frac{\mathbf{NDVI} - \mathbf{NDVI}_{\mathrm{soil}}}{\mathbf{NDVI}_{\mathrm{veg}} - \mathbf{NDVI}_{\mathrm{soil}}} \right)$$

where:

NDVI = **NDVI** value of pixel
$\mathbf{NDVI}_{\mathrm{soil}}$ = **NDVI** value of a 100% bare soil pixel
$\mathbf{NDVI}_{\mathrm{veg}}$ = **NDVI** value of a 100% vegetated pixel

Equation 3.6 *fc* calculation

Because the possibility for human error involved in calculating **fc** from **NDVI**, the $\mathbf{NDVI}_{\mathrm{soil}}$ and $\mathbf{NDVI}_{\mathrm{veg}}$ values are very important. These values were selected by first creating a small Area Of Interest (AOI) (25 x 25 pixels) over primary forests and the African palm plantations for the 100% vegetated pixels ($\mathbf{NDVI}_{\mathrm{veg}}$) with downtown urban areas and cleared areas for the 100% bare pixels ($\mathbf{NDVI}_{\mathrm{soil}}$). Because this step involved a visual interpretation of the images, an attempt was made to keep the location of the AOIs very close between all three images. The descriptive statistics from inside the AOI were then used to select the end member values (see Table 3.2).

Landsat Image	$\mathbf{NDVI}_{\mathrm{veg}}$	$\mathbf{NDVI}_{\mathrm{soil}}$
10/14/2002	**0.97**	**0.10**
9/12/2002	**0.95**	**0.10**
9/9/2001	**0.95**	**0.10**

Table 3.2 NDVI values used to calculate *fc* for Landsat images

The maximum **NDVI** value inside the AOIs was assumed to be the best representation of the NDVI value for a 100% vegetated pixel and minimum NDVI value (taken from separate AOIs) for the 100% bare pixel). Although a concerted effort was taken to normalize the images, the variation in the $\mathbf{NDVI_{veg}}$ value from the10/14/2002 image is a result of the small collection differences that occur between every Landsat image and cannot be fully removed.

The decision to use ***fc*** to measure defoliation was based on the theory that ***fc*** actually represents a biophysical measure of the vegetation on the ground. As noted earlier, the defoliation statistics produced by the UNODC and other sources are based on the visual interpretation of satellite imagery. I hypothesize that visual interpretation of the defoliation cannot accurately identify the smaller amounts of defoliation occurring due to drift and/or runoff.

The last step in the image pre-processing step was to geometrically rectify the images and the ***fc*** layers. This correction was completed using an image previously rectified (supplied by the University of North Carolina at Chapel Hill, Carolina Population Center) and finding features identifiable on all images to use as control points. Once the control points were identified, each image was geometrically rectified using a 2nd order polynomial transformation (using the Nearest Neighbor interpolation method) and a model of the rectification parameters for each image was generated. The three images were all corrected to an acceptable level of accuracy (see Table 3.3).

	9/9/2001		9/12/2002		10/14/2002	
	Error (pixels)	Error (meters)	Error (pixels)	Error (meters)	Error (pixels)	Error (meters)
X	**0.0179**	**0.537**	**0.0884**	**2.652**	**0.0234**	**0.702**
Y	**0.0227**	**0.681**	**0.0456**	**1.368**	**0.0262**	**0.786**
Total	**0.0289**	**0.867**	**0.0884**	**2.652**	**0.0351**	**1.053**

Table 3.3 Geometric rectification errors

The ***fc*** layers and the original images were then rectified using the correction models generated in the previous step. This correction was applied to the ***fc*** layer after computation in an effort to reduce the affects that could occur by calculating a biophysical variable (which are very dependent on pixel values) from pixels that had been interpolated during the rectification process.

After the rectification process was completed, a cloud mask was created by heads-up digitizing any and all areas covered by clouds or their shadows in the study area. I attempted to create a classification method that would identify clouds automatically, however I was not able to accurately classify the clouds and shadows. Most of the problem in this was due to the edges of the clouds were signal from the ground reaches the sensor, but is slightly degraded by the cloud. After multiple attempts to solve this problem, I decided that the only method that could produce the level of accuracy for cloud removal was to manually trace the borders of the clouds and shadows, hence the heads-up digitizing. Unless otherwise noted, this cloud mask was used to exclude these areas in all of the following steps in image processing, sample point generation, and change detection.

SAMPLE POINTS

The ***fc*** layers were created for use in preliminary investigations and also as the basis for a stratified random sampling scheme. The stratified random scheme was implemented as an attempt to sample pixels that covered the range (0% - 100%) of ***fc*** values that could be found both on the landscape and in the image. The sample points were based on ***fc*** values from the 09/12/02 image as it contained significantly less cloud cover throughout the study area. Although the 10/14/02 image date is closer to the dates of ground truthing, the clouds sprinkled throughout the study area would have voided too much of the image.

The first step in creating the stratified random sampling scheme was to subset the pixels of the ***fc*** layer of the 09/12/02 image that were within 40 km of Coca, Ecuador and within 250 meters of roads, dirt tracks, and foot paths (see Figure 3.3). The distance of 40 km was chosen using knowledge gained from people who had navigated this region. This distance that would allow the field team adequate time to drive to a point, collect data, and return to the base of operations in one day. The 250 meter buffer of roads, dirt tracks, and foot paths, was based on similar knowledge as mentioned in the previous sentences. The region offers many obstacles that hinder travel away from main roads such as streams, thick forests, varying topography, wild animals, and heavy rainfalls. By only including pixels within 250 meters of roads, this would reduce the time to walk to each sample point. Additional masks were created as AOIs (by heads-up digitizing) to remove unreachable areas (African Palm plantations and river islands). These masks and the aforementioned cloud mask were used to exclude unreachable and unusable pixels from consideration for sample locations. The combination of pixels not masked and within the buffered distance of roads and the city of Coca left an ***fc*** layer that included all of the pixels that were considered acceptable for sampling (see Table 3.4 and Figure 3.3).

A pixel to be considered for sampling must be:
Within 40 km of Coca, Ecuador
Within 250 m of road, dirt track, foot path
Not within a cloud or cloud shadow
Not within an African Palm plantation
Not within an island

Table 3.4 Criteria for a sample pixel

This layer was then separated by ***fc*** value into 10 separate classes (see Table 3.5) so an equal amount of sample points would be generated for each class. Although most of the landscape is composed of pixels of 50% ***fc*** or above, the less than 50% ***fc*** classes were collected as an attempt to observe as wide a range of ***fc*** values as possible for the construction of a statistical model.

Class	*fc* values (%)
1	**0 - 10**
2	**10 - 20**
3	**20 - 30**
4	**30 - 40**
5	**40 - 50**
6	**50 - 60**
7	**60 - 70**
8	**70 - 80**
9	**80 - 90**
10	**90 - 100**

Table 3.5 ***fc*** classes for stratified random points

30 spatially random points were created inside each class giving 300 unique sample locations. Another 300 points were generated as a backup to the original 300 in case of loss of data or inaccessibility of the original locations.

Figure 3.3 Sampling area and sample points

The decision to create 300 points was based on the amount of time that was allotted for fieldwork. When collecting points for an accuracy assessment of a LULC classification, the recommended amount of ground truth points per class is

50 (Congalton and Green 1999). However, the sample point generation was based on collecting data for validating ***fc*** and not LULC. Therefore, the number of ground truth points only had to be enough to build a statistically significant relationship between the image ***fc*** values and the ground truth ***fc*** values.

FIELD EQUIPMENT AND MAPS

Leica LRF 800 Rangefinder – used to measure distances from observer to target

Pentax IQZoom 105 WR 35mm Camera – used for general photos of the sample point

Garmin GPS 12XL Unit – used to navigate to sample points

Nikon Coolpix 4500 Digital Camera – used for general photos and for fisheye canopy photos

Trimble GeoExplorer II Unit – used to collect a GPS position at each sample point

Spherical Densiometer – carried as backup instrument for collecting canopy coverage data

Gateway 3450 Laptop – used for storing data collected each day

Brunton Compass – used for recording bearing data at sample points

A series of maps were constructed for field navigation. These maps were created from the 10/14/02 Landsat ETM+ image that had been sharpened using the 15m resolution panchromatic band. I chose to create the maps with a 7,4,2 band combination, which results in vegetation appearing green on the image. I was attempting to avoid the confusion that often results when showing the maps produced with the popular 4,3,2 combination (resulting in vegetation appearing red) to people not familiar with satellite imagery (especially drivers and property owners who I assumed would be viewing the maps). The maps' scale was 1:60388.57 which maximized the map area on a sheet of 8.5" x 11" paper and each map contained the image as a backdrop with the sample points and the road network overlayed.

FIELD DATA COLLECTION

Field data collection took place in and around Coca, Ecuador from June 4 to June 21 of 2003. Coca is roughly 100 km from the center of the intensive study area. However, as mentioned previously (Chapter 1), the physical (vegetation and soils) and climatic (temperature and precipitation) conditions are the same in both areas. The only differences in the area are due to anthropogenic causes. Considering that both areas fall in the same Landsat scene and are physically similar, data collected in and around Coca will be used to validate ***fc*** over the entire study area.

We navigated by vehicle or on foot to each sample point location using the Garmin GPS unit. When the point fell on land that was not privately owned, we walked to the point and collected our information. If the point fell on private property, such as in a field behind someone's house, we explained our purpose to the owner of the property and asked permission to collect information on their land. In most situations, the owner complied and allowed us to collect our data,

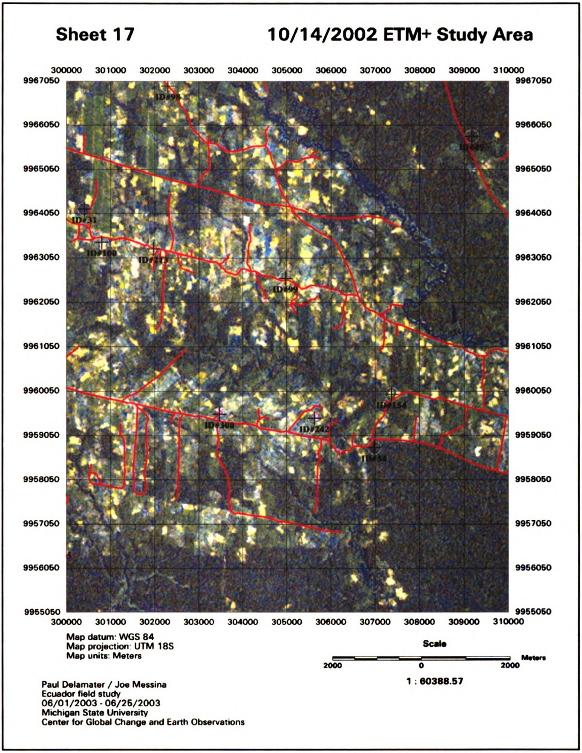


Figure 3.4 Example of a field map sheet

however, in a few cases we were denied permission. Once we reached a point, the Trimble GeoExplorerII GPS unit was used to collect the precise location of the point (minimum of 200 readings with a PDOP blanket of 4). While collecting the location with the Trimble unit, the LULC and ***fc*** attribute information was recorded. In each location, a GPS point was collected. However, in areas of homogenous cover (LULC or ***fc*** cover), polygon information was recorded. This method included using the laser rangefinder to find the distance from the point to a different cover and then using a compass to observe the bearing of which the distance measurement was taken (see Figure 3.5). In most cases, this involved collecting 4 readings to accurately describe the homogenous area of the landscape. As many as 8 readings were collected in other situations where the homogenous area was oddly shaped. Collecting the polygon information allowed for more than one pixel of ground truth data to be collected while only taking the time to collect one GPS point.

Whereas, there does not exist a proven method for collecting ***fc*** ground truth data where a canopy is not present, a method of collection and a set of decision rules were created in an effort to match ground truth data to the theory behind ***fc***. At each sample location, a theoretical "pixel" (matching the 30m x 30m Landsat pixel) was constructed using the rangefinder and compass. In areas where the ground cover is homogenous, I visually interpreted the fraction coverage. This visual interpretation was only completed by one person (Paul

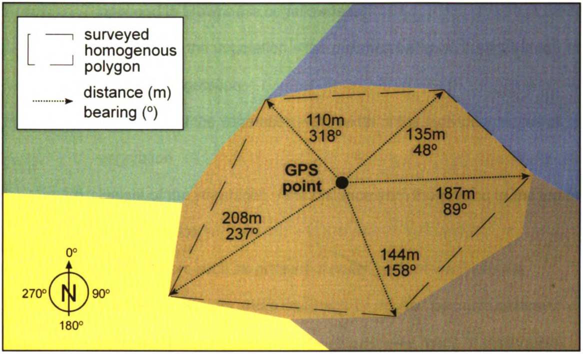


Figure 3.5 Collection of homogenous (LULC or ***fc***) polygon information

Delamater) and, as a quality control, verified by others in the group (Dr. Joe Messina or Francis Baquero).

- The visual estimation of the fractional coverage was based on the vegetation in a polygon area (collected with the rangefinder and compass) or the vegetation within the distance of one pixel (15-20 meters in every direction from the GPS point). The following factors (in order of importance) were used to determine the actual estimate at each collection point.
    1. Amount of vegetation – the amount of individual pieces of vegetation

2. Greenness of the vegetation – the greenness of the vegetation (as opposed to brownness or yellowness)
3. Proximity of the vegetation – the distance between the individual pieces of vegetation
4. Thickness of the vegetation – the width of the individual pieces of vegetation
5. Height of the vegetation – the distance from the ground to the top of the vegetation
6. Other factors such as amount of water present went into the estimation as often areas were slightly flooded because of heavy rains that had just occurred. An attempt was made to distinguish between permanently flooded areas and areas that were only temporarily flooded.

Considering all of these factors, an ***fc*** percentage was estimated from 0% to 100%. The units were estimated in 5% minimum unit increments (e.g. 80 or 85, but not 83). The decision to estimate at this level was based on the confidence of estimation and the lack of another method to gather fractional coverage information of a non-canopy area. In a few cases (urban settings), the fractional coverage was listed at 2% or 3%. This was a result of the amount of vegetation in an area being present but confidence of at least 5% in the pixel area being low. In non-homogenous areas, the ***fc*** estimation was completed by using the previously stated method, then factoring in the amount of bare area and/or the amount of different vegetation percentages in the pixel area (see

Figure 3.6). This was often accomplished easily in the field estimation. Very complex and heterogeneous pixels often required a sketch that was later interpreted manually with a calculator and a transparent grid. This is much like former methods for estimating area from an aerial photo. (Lay the grid on top of the sketch and count boxes at each fractional coverage percent. Take the counts and percents and compute the fractional coverage for the whole area).

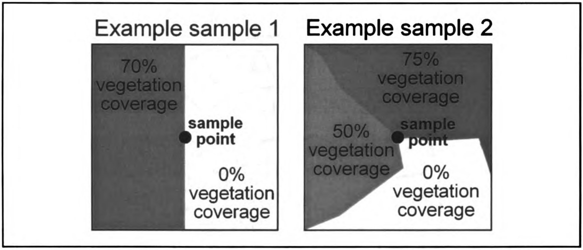


Figure 3.6 Examples of possible non-homogenous vegetation covers at sample point locations

In forested areas we used the 4500 camera with the fisheye lens for our field measurement of ***fc***. To do this, we held the camera above head, and as level as possible (as close to vertical) and shoot the picture of the canopy (See Figure 3.7 for examples of the fisheye canopy photos). This was made quite easy as the the 4500 is designed to photograph vertically (it has a swiveling viewfinder that allows the camera to be held comfortably while the lens is pointing straight up). Then I recorded the ***fc*** information of the understory, which was defined as any

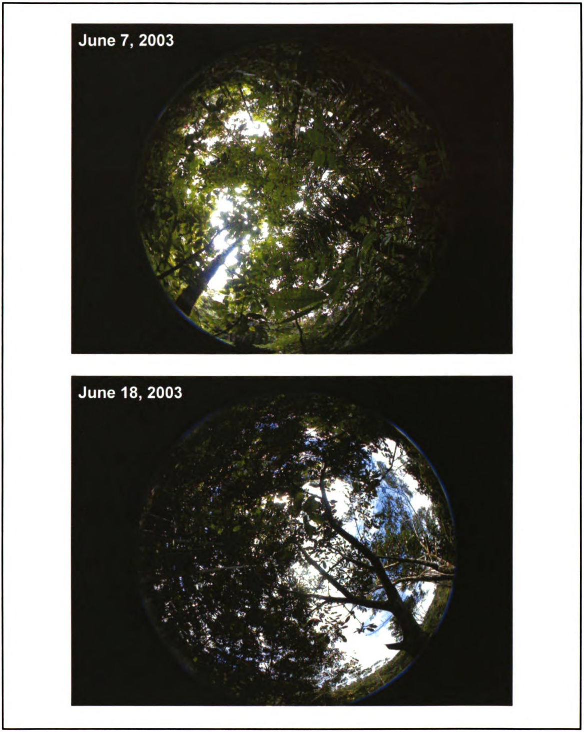


Figure 3.7 Examples of canopy photos taken with the fisheye lens

vegetation lower than the level of the camera at photo collection, using the previously detailed visual collection method.

All information was collected on a field sheet (see Figure 3.8 and Appendix C), which was created, from previous field sheets used in Ecuador by Dr. Joe Messina during similar data collection trips. The field sheet was designed to maximize the amount of area for the primary information to be recorded while also allowing for ease of use in recording. Also considered were areas on the sheet for ancillary information to be collected and an attempt was made to keep the sheet at one half of a page (to fit 4 sample collections on one piece of paper).

The field team was able to collect 211 points in the 18 days in Coca, Ecuador. This number was less than the 300 point goal, however considering the unpredictability of the weather (rain) and the sometimes rigorous challenges associated with collecting points on the Amazonian landscape, we were pleased with the amount of data collected.

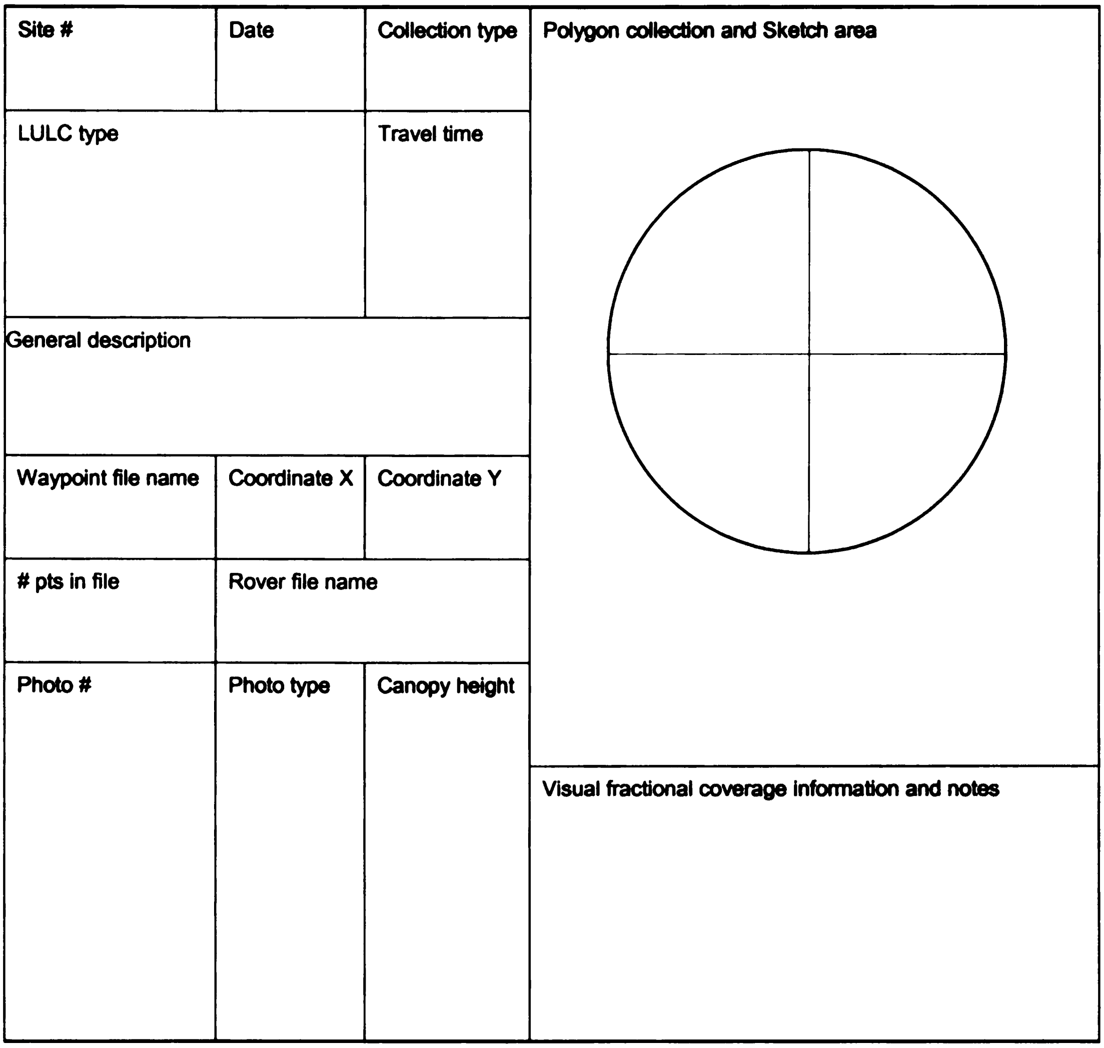


Figure 3.8 Field data collection form

FIELD DATA PROCESSING

Each night during field data collection, the points collected during the day were downloaded from the Trimble GPS units to a laptop computer. The attribute data gathered were entered into a Microsoft Access database that contained a relational field to link the database information to the GPS point location. After field data collection, the GPS points were differentially corrected using base point data collected in Quito, Ecuador. Unfortunately, three days worth of base point data were unavailable from the base station and therefore, the points collected on these days were not useable. Once the GPS data points were differentially corrected, they were converted to an ArcINFO coverage using ArcTools.

The next step was to calculate the ***fc*** of the points taken under a canopy. This was performed using the Gap Light Analyzer™ (GLA) software created by Simon Fraser University and the Institute of Ecosystem Studies. This software was specifically built for use with fisheye lens photography to measure the amount of canopy coverage by converting the photograph to a binary image and comparing pixels of sky to canopy. The inputs for the GLA software included: absolute center of the image, the dimensions of the photo, the distance from the center of the image, and the threshold for sky. The threshold value is where adjustments were made for the varied conditions of the sky in each image. After viewing all of the images, sky conditions were categorized into the following table and a threshold value (between 0-255) was chosen to best represent the difference between sky and canopy for each category (see Table 3.6).

Sky Condition	Threshold level
Sunny	**180**
Cloudy	**140**
Hidden Sunny	**125**
Very Cloudy	**75**

Table 3.6 GLA threshold values for fisheye lens canopy photos

After the threshold value was selected, the image was converted to binary data type as a representation of sky and canopy pixels. The GLA software then constructed a table with the photograph's file name and the canopy coverage attributes. The percentage of canopy coverage at each point (generated by the GLA software) and the understory ***fc*** values (recorded in the field) were then used to construct a model of the true ***fc*** at each point by utilizing a custom neutral model built in the Research Systems Inc. (RSI) Interactive Data Language (IDL™). Neutral models are spatial models often used in landscape ecology studies (Gardner et al. 1987). One specific use is as a means of generating landscapes that share statistical properties with an observed landscape (Keitt 2000). Although the canopy photos are not a traditional landscape generally used in landscape ecology, they are a spatial representation of the vegetation over an area. The ***fc*** value at each point was calculated by modeling the canopy ***fc*** and the understory ***fc*** using neutral models, then overlaying the layers to create a comprehensive model of the vegetation cover. This method implies a random distribution of the vegetation throughout the canopy and understory. Although this may not be the most robust method to model the vegetation, it makes an attempt to include all of the vegetation found at each point. First, a binary neutral model representing the canopy photo, with the exact same dimensions and shape (from the inputs of the GLA software), was randomly generated using the ***fc*** value calculated by the GLA software. Next, another binary neutral model (with the same dimensions as the canopy model) was created using the ***fc*** value of the understory. The two neutral models were combined as any pixel with a value of 1 or 2 representing vegetation cover (see Appendix D for IDL code). The vegetated pixels were then compared to the total number of pixels to create the ***fc*** value at the point location. These values were then entered into the attribute data contained in the Access database.

The final attribute data were imported as a table from the Access database and joined to the point coverage using a table join in ArcMap. The GPS points with polygon information were then subsetted using the "collection type" field. The polygons were constructed according to a set of steps created by the Carolina Population Center. The steps included creating a temporary line coverage that held the distance and bearing information collected at the point. Once the lines representing the distance and bearing information were constructed around each point, a polygon coverage was created by heads up digitizing each feature using the endpoints from the line coverage. This process was greatly aided by the snapping options in ArcMap. The name of the point with the polygon information was then added as a field in the attributes of the coverage. The attribute data were joined to the polygon coverage using the same method discussed earlier.

fc VALIDATION

The first step in validating ***fc*** was to remove the points from the ground truth data where ***fc*** information was not collected (e.g. road control points). Next, to compare the ***fc*** values calculated from the image to the ground truth data, the image ***fc*** layer was converted to a point coverage using ArcToolbox. This conversion creates a point feature at the center of each pixel in the image containing the image value in the attributes of the corresponding point. A spatial join was then performed between the ground truth points and the image points. A point to point spatial join finds the point nearest the point being joined to (ground truth) and assigns the attribute value (image ***fc***) to that point. The resulting point coverage contained the ground truth and image ***fc*** values in its attributes. The attributes were then exported to an Excel spreadsheet and a linear regression was modeled on the data using the image ***fc*** value as the dependent variable and the ground truth ***fc*** as the independent variable (further discussed in Chapter 4). However, after noticing that many of the ground truth points did not fall directly in the center of a pixel, the decision was made to include the image ***fc*** values of neighboring pixels in an attempt to model the image ***fc*** value away from the center of a pixel. Because the ***fc*** value recorded on the ground was a function of the vegetation surrounding the point (in my theoretical pixel), I needed to account for when my theoretical pixel bounds did not match the true pixel bounds in the image. A buffer of 21.5 meters (just over half the distance from the pixel center to the pixel corner, see Figure 3.9) was constructed around each of the ground truth points. This distance was chosen considering that if a ground truth point fell directly in the corner of four pixels, then the ***fc*** value of all four pixels would be represented as the image ***fc*** value at that point. By including the values of the adjacent pixels, I was able to construct an image ***fc*** value that was a better representation of what was on the ground at points away from the center of a pixel.

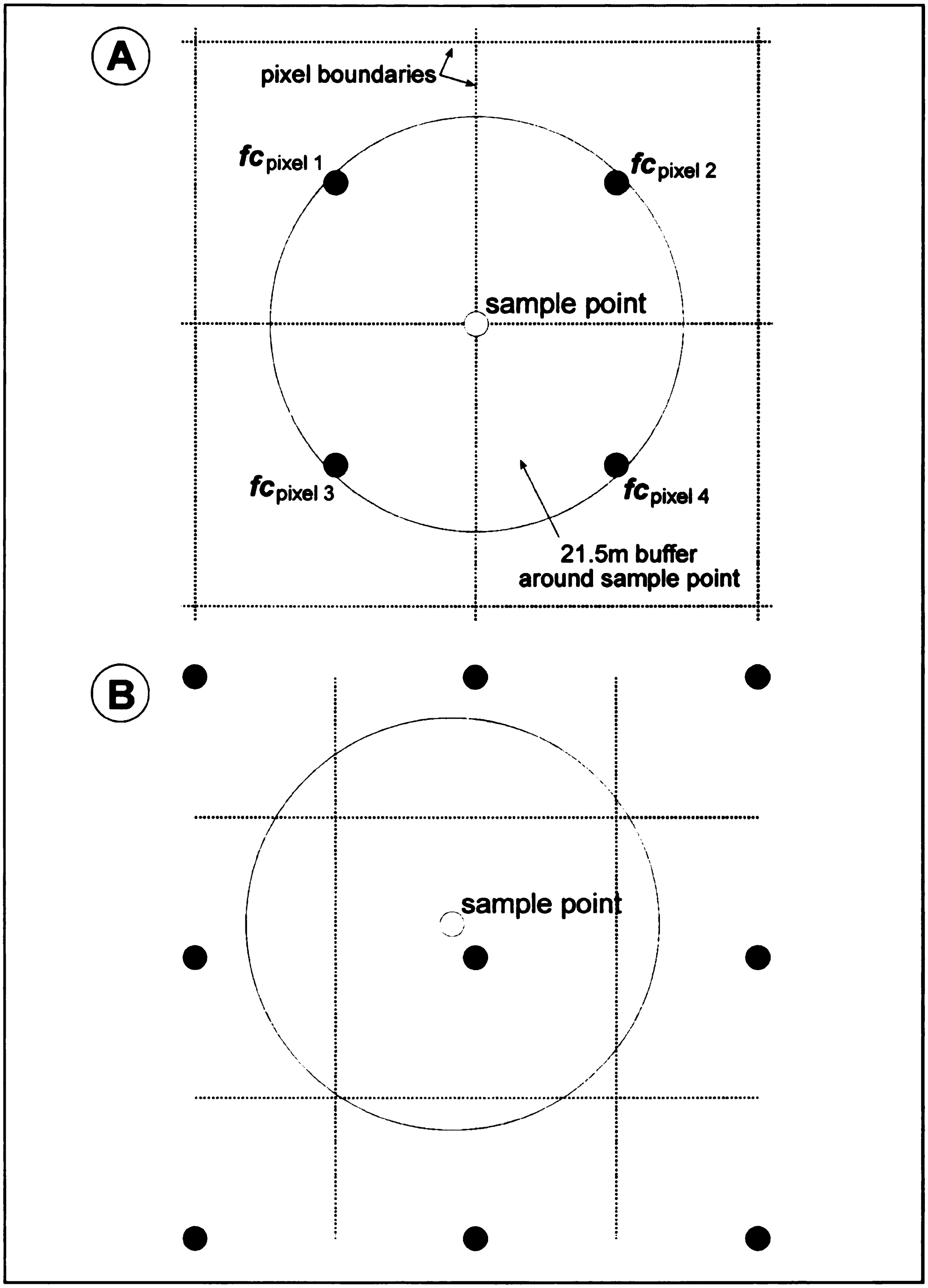


Figure 3.9 Sample point buffer where (A) the sample point falls in the center of four pixels and (B) falls near the center of one pixel

However, if the sample point fell directly on or very near the center of a pixel, no other pixel values would be represented. The points generated from the image ***fc*** values were then spatially joined to the buffer polygon layer. A point to polygon spatial join finds the points that fall within the polygon and assigns the attributes of the points to the polygon. The attributes were then exported to an Excel spreadsheet. For each of the polygons, the mean of the image ***fc*** values contained within the polygon was calculated. A linear regression was modeled using the mean image ***fc*** value as the dependent variable and the ground truth ***fc*** value as the independent variable.

LULC CLASSIFICATION

The LULC classification, performed on the 9/9/2001 image, was a hybrid method, combining an unsupervised classification, evaluation of classes, and a supervised classification. A very similar LULC classification was performed in this region by Messina and Walsh (2001). The image was chosen for classification in an attempt to identify classes previous to the fumigation efforts of 2002. The ISODATA unsupervised classification was initialized from the statistics of the image along the diagonal axis and had 255 potential classes. The significance of 255 classes is to allow the maximum number of classes to be generated while keeping the resulting dataset in an 8-bit data structure (which keeps processing time and file size low). The convergence threshold of the classification was set at 0.98 or 30 iterations before completion. Each image reached the desired threshold level before the maximum number of iterations.

The signatures gathered from this classification were then compared against each other in an effort to isolate the spectrally significant classes. This comparison included the evaluation of the transformed divergence matrix composed of the best average values between classes. The threshold for keeping classes was a transformed divergence value of >1960. This threshold value (1960) was chosen after considering the complexity of the landscape and in an effort to keep the overlap between classes very limited. Each signature was compared against all of the other signatures in the set. This method included evaluating an array that contained the transformed divergence values between signatures and eliminating those with that shared low values with many other signatures. The end product of the evaluation was a set containing 90 spectrally significant signatures. The last step in the classification was a maximum likelihood supervised classification performed using the spectrally significant signatures. This created a classified layer with the value for each pixel representing the signature (of the 90 spectrally significant signatures) that the pixel was assigned to. This classified layer was then attributed to a very simple LULC scheme (see Table 3.7) via a visual interpretation using colors, textures, and location on the image and a knowledge of the research area (gained during field work) (Messina and Walsh 2001). The Coca class was identified using the visual interpretation and also by isolating agricultural areas that only appeared north of the Rio San Miguel (dividing Colombia and Ecuador) and comprised a small percentage of the overall image area.

LULC classes	# of classes	% of image area
Primary forest	**3**	**38**
Secondary forest	**1**	**17**
Pasture with trees or Rastrojo	**2**	**13**
Agriculture or pasture with no trees	**5**	**13**
Possible coca	**5**	**6**
Other (includes urban, water, and other LULCs)	**74**	**13**
totals:	***90***	***100***

Table 3.7 LULC classification scheme

An accuracy assessment was not performed on the classification as 1) I did not have ground truth data for the coca classes (see previously mentioned dangers of conducting research in Colombia or near its border), 2) the confidence of the classification was high considering the simple scheme and prior knowledge of the area, and 3) the desired results did not call for an accuracy assessment (with more emphasis placed on the number of classes affected).

CHANGE DETECTION

For change detection, a subset of the affected area was created via an AOI in Imagine. The AOI was digitized (heads-up) and represents the area of the image north of the Ecuador/Colombia border that appeared to be an agricultural region. The change detection was accomplished by overlaying the ***fc*** layers, subtracting the values of the earlier dated layer from the more recent layer, recoding the data to only show the pixels that had lost 10% or more of their ***fc***, then subsetting the newly created layer using the AOI of the affected area. The changes occurring between 9/9/2001 and 9/12/2002 were labeled as Event 1 and the changes occurring between 9/12/2002 and 10/14/2002 were labeled as Event 2. The LULC classification layer was then overlayed with the results of Event 2 to identify the classes with an ***fc*** loss of more than 10%.

Chapter 4 : RESULTS AND DISCUSSION

fc VALIDATION RESULTS

The image ***fc*** values and the ground-truth ***fc*** values were compared using a linear regression with the ground-truth ***fc*** values as the independent variable and the image ***fc*** values the dependent variable. A linear regression was chosen, as the expected results were to find a 1:1 relationship between the two variables. The results of the original regression are found in Figure 4.1A and Table 4.1. This regression was based on the point to point overlay where the image ***fc*** value was compared only against the ground-truth ***fc*** value of the pixel that it fell in. The results of the regression of the mean of the image ***fc*** values within 21.5 meters (see Figure 3.9) against the ground-truth value are found in Figure 4.1B and Table 4.2. As the results show, these regressions both are statistically significant. The regressions were also performed after taking out the large outliers in the data. Given that the Northern Oriente is a very dynamic landscape and that there was a 9-month lag between the date of image acquisition and field data collection, I observed changes that had occurred throughout the landscape. These changes included agricultural plots cleared for less than 3 months and a farm, for example, where a large portion of secondary forest had been cut down and cleared the day prior to our visit.

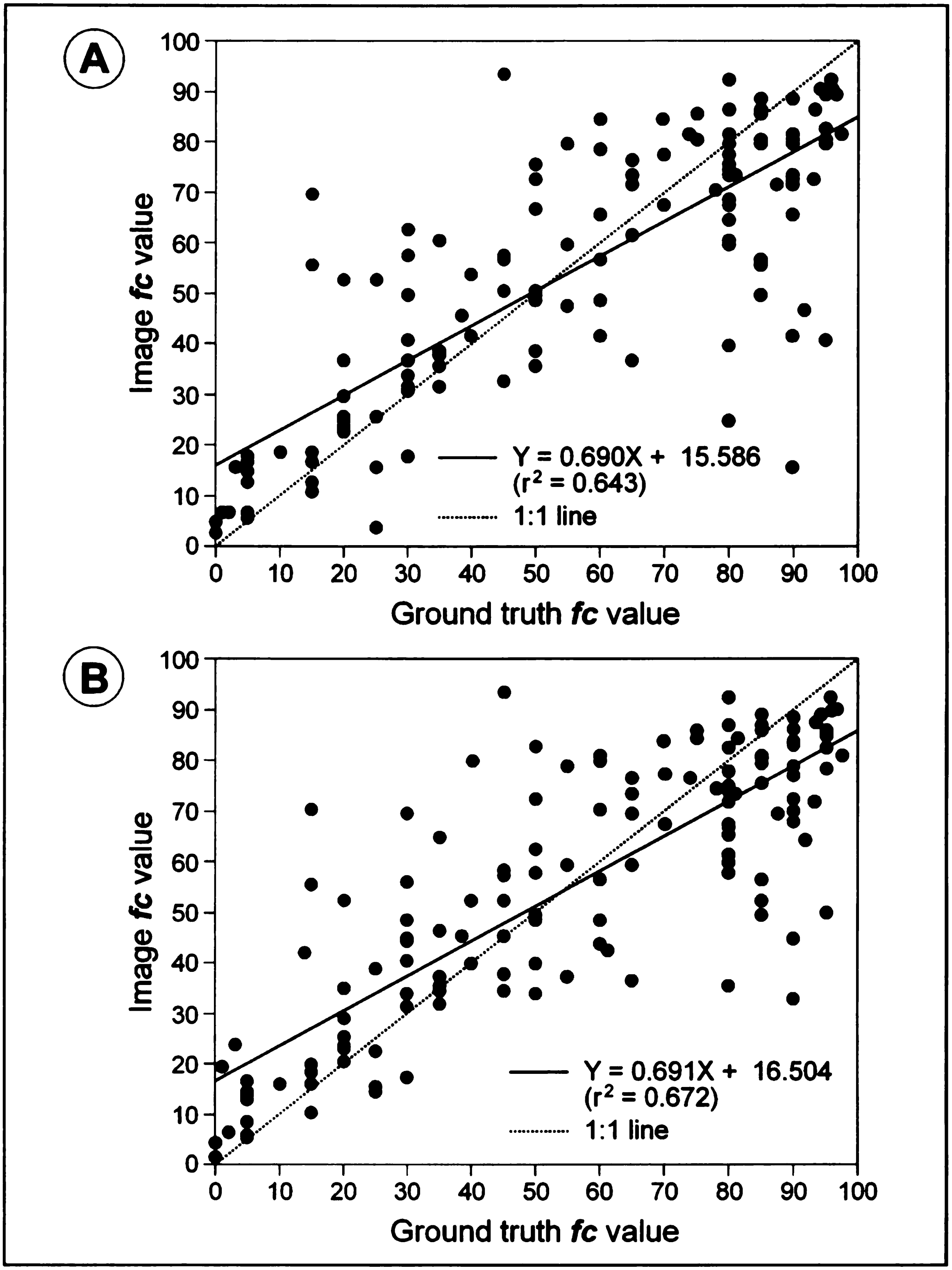


Figure 4.1 Regression results using (A) the point to point overlay and (B) the point to mean of points within 21.5m overlay

Observations	**145**
R Square	**0.64261**
F	**249.936**
Significance F	**7.4E-33**
t Stat (intercept)	**5.62976**
t Stat (slope)	**15.8094**
P-value (intercept)	**9.6E-08**
P-value (slope)	**7.4E-33**

Table 4.1 Regression results for point to point overlay with the full dataset

Observations	**145**
R Square	**0.67173**
F	**292.621**
Significance F	**2.1E-36**
t Stat (intercept)	**6.46025**
t Stat (slope)	**17.1062**
P-value (intercept)	**1.5E-09**
P-value (slope)	**2.1E-36**

Table 4.2 Regression results for point to mean of points overlay with the full dataset

At this point, the image ***fc*** value was 70% and my field estimation, only accounting for the remaining understory vegetation, was 15% (see Table 4.3 for full list). I chose to remove 10% of the data points based on the LULC information from my field forms and the evaluation of the most erroneous outliers in the dataset. A total of 14 points were removed from each dataset and the regressions were completed again. This number of points to remove was chosen in an attempt to keep a high percentage of the data points (>90%), yet also account for the changes that may have occurred to the landscape due to anthropogenic or natural causes. The sample points that were removed were chosen by selecting those with the largest difference between image ***fc*** value and ground truth ***fc*** value and deleting them from the dataset.

	ground fc	image fc	difference
1	**15**	**55**	**40**
2	**15**	**70**	**55**
3	**20**	**52**	**32**
4	**30**	**69**	**39**
5	**40**	**79.5**	**39.5**
6	**45**	**93**	**48**
7	**50**	**82.333**	**32.333**
8	**65**	**36**	**29**
9	**80**	**35**	**45**
10	**85**	**52**	**33**
11	**85**	**49**	**36**
12	**90**	**44.5**	**45.5**
13	**90**	**32.5**	**57.5**
14	**95**	**49.667**	**45.333**

Table 4.3 Removed sample points

The regression results can be found Figures 4.2A and 4.2B and Tables 4.4 and 4.5 and show very improved results. The linear regressions of the image ***fc*** data and the ground truth ***fc*** data show a promising trend. Although none of the relationships proved to be a perfect 1:1, there are factors that may have contributed to this. The first factor may be the method of calculating the ***fc*** value as a linear function of the **NDVI** value of the image. Other vegetation indices such a **SAVI** and **MSAVI** are possibly better models of the biophysical properties of the vegetation as they attempt to eliminate the effects of varying soil conditions, however the elimination of soil effects should be inherent in the calculation of ***fc***.

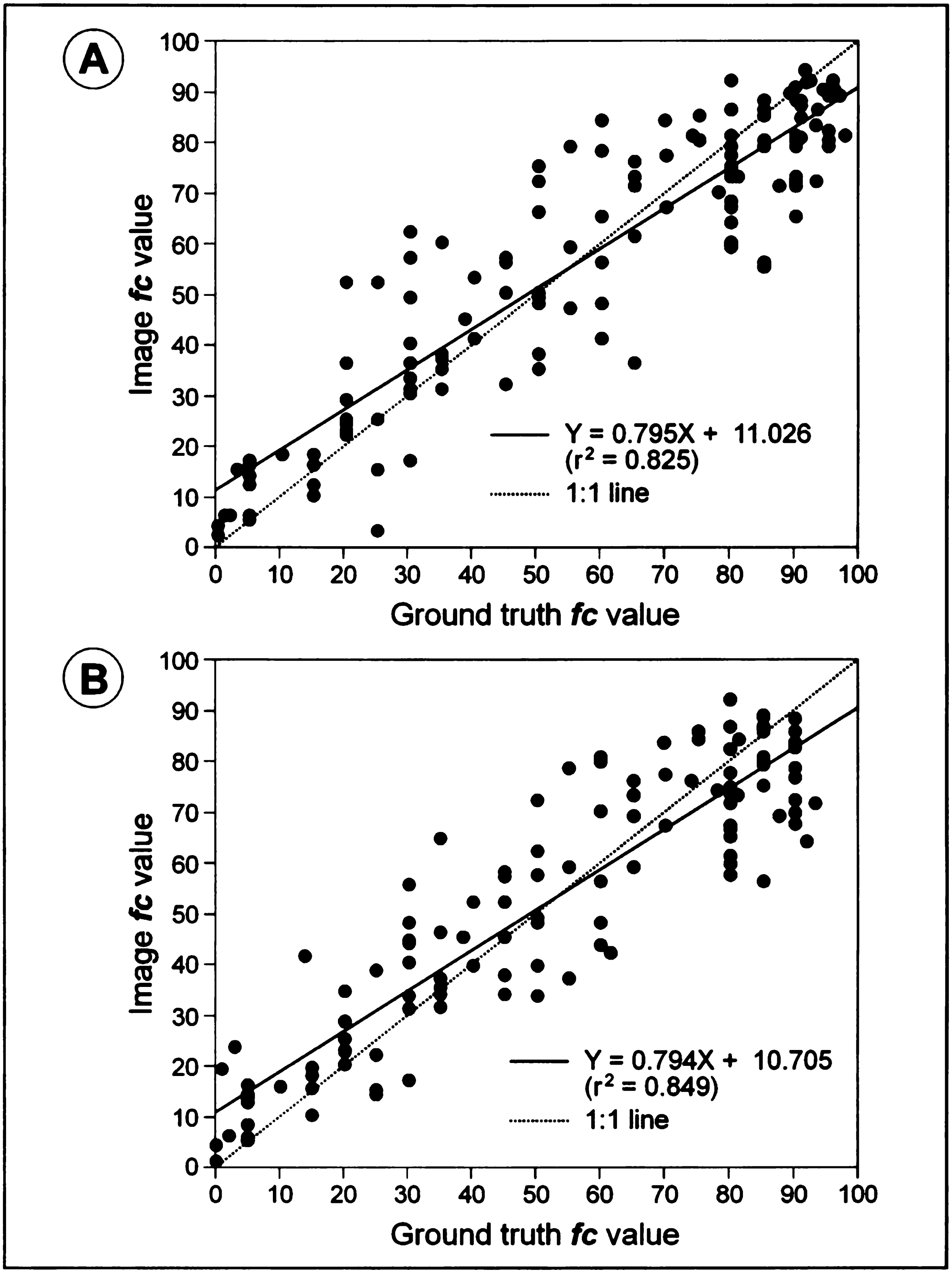


Figure 4.2 Regression results minus outliers in the data using (A) the point to point overlay and (B) the point to mean of points within 21.5m overlay

Observations	**131**
R Square	**0.82472**
F	**606.969**
Significance F	**1.3E-50**
t Stat (intercept)	**5.46723**
t Stat (slope)	**24.6367**
P-value (intercept)	**2.3E-07**
P-value (slope)	**1.3E-50**

Table 4.4 Regression results for point to point overlay without the outliers in the dataset

Observations	**131**
R Square	**0.8489**
F	**724.741**
Significance F	**8.8E-55**
t Stat (intercept)	**5.75114**
t Stat (slope)	**26.921**
P-value (intercept)	**6.1E-08**
P-value (slope)	**8.8E-55**

Table 4.5 Regression results for point to mean of points overlay without the outliers in the dataset

Subtracting the $\mathbf{NDVI_{soil}}$ value in each pixel should eliminate the amount of **NDVI** gained from bare soil in each pixel. Other studies have looked at the possibility of estimating ***fc*** (referred to as VF [vegetation fraction] in the study) from information in narrow visible bands instead of using NDVI values (Gitelson et al. 2002). Although the results were promising, this study was conducted only for wheat and corn over very small areas. Leprieur et al. (2000) and Purevdorj (1998) have suggested that the relationship between **NDVI** and ***fc*** may be non-linear when vegetation cover is sparse.

Another factor causing the non-perfect relationship may be the visual estimation as a method of collection of ground-truth data. As Figures 4.1 and 4.2 show, the regression matches a variable with a continuous scale against a variable that borders between continuous and categorical. Although the ground truth data may appear categorical, it is really a continuous variable with a lesser precision in collection. This problem was considered in the genesis of creating a method for collecting ground-truth ***fc*** data, however no solution was apparent in the literature. Zha et al. (2003) attempted to relate ***fc*** to NDVI in a semi-arid grassland in China, but only collected ground ***fc*** measurements in $1m^2$ areas to compare to the $30m^2$ Landsat pixel. Other studies used color photography taken at each sample site to estimate the ***fc*** of an area (Purevdorj et al. 1998). This "void" of a proven method of collection for ***fc*** data in non-canopied areas cannot be filled without studies such as this, which attempt to discover a new method. However, these results verify my hypothesis that a linear relationship exists between image ***fc*** and ground ***fc*** used in this study.

fc AND LULC CHANGE DETECTION

Considering the nature of the observed relationship between ***fc*** calculated from the image and the ***fc*** observed on the ground and the likelihood for natural changes on the landscape, the change detection was only considered for pixels that lost more than 10% of their fractional coverage between images. 10% change was chosen considering non-perfect (not 1:1) relationship between image ***fc*** and ground ***fc*** values and in an attempt to not include smaller defoliation events that were not due to Plan Colombia fumigation. Zha et al. (2003) showed that ***fc*** was 89% accurate in when comparing ground truth data and image results grouped in 10% increments (the same increments used for the sampling scheme in this study, see Table 3.5).

We found that 56,627 ha of 10 % or greater defoliation occurred during Event 1 (9/9/2001 to 9/12/2002) and 49,551 ha during Event 2 (9/12/2002 to 10/14/2002) of the southwestern Putumayo coca eradication effort. The total area experiencing 10% or greater defoliation during 2002 coca eradication effort in the region was 106,178 ha. The results of the change detection in Events 1 and 2 are found in Figures 4.3 and 4.4. The distinguishing characteristic of the spatial organization of defoliation in both events are the linear patterns that emerge. Patterns such as these are not found in a naturally occurring environment and the linearity of the patterns are believed to be the result of the flight lines taken by the aircraft while spraying. Another observation that shows that the defoliation is due to spraying is the scale at which it is occurring. As discussed earlier, the farmers in this area live on very small plots. To have all of them clear their areas at the same time would require a very large and very unrealistic organized effort. The last distinguishing spatial characteristic is the temporal variability that exists between the events. A very noticeable trend is that the defoliated areas of Event 2 are shifted away from the areas in Event 1. This shift in the defoliated areas of Event 2 is noticeable as the linear patterns of defoliation still generally run north to south, but are moved to the west of the linear patterns of Event 1.

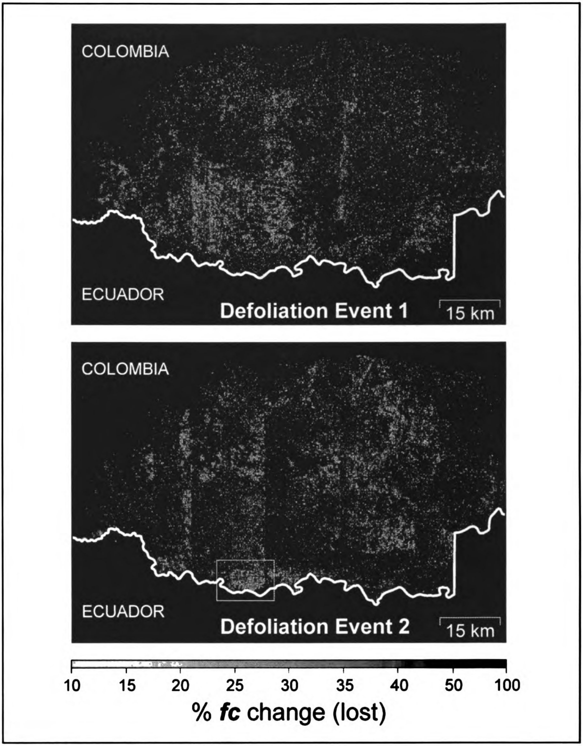


Figure 4.3 Maps for defoliation Event 1 and Event 2 (notice extent box for Figure 4.4)

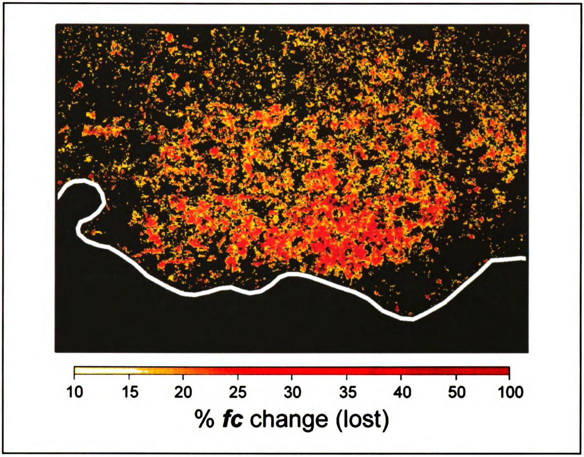


Figure 4.4 Close up of defoliation near the Ecuador-Colombia border in Event 2 (notice where identified in Figure 4.3)

This would signal that the defoliation occurring was planned in advance and the result of fumigation, not due to natural causes or farmers clearing their land.

According to the UNODC report, coca production over all of Putumayo was reduced by 71,891 ha versus our measured defoliation of 106,178 ha (which does not cover all of Putumayo), an unexplained difference of 34,287 ha. I believe that this unexplained difference is due to drift and runoff of the herbicide and also (discussed in the next paragraph), due to non-coca LULCs being excluded from the defoliation figures.

Discriminate spraying of coca would limit the total number of spectral classes heavily impacted by spraying. Further, the areas of greatest magnitude change in fractional cover would theoretically contain significantly fewer spectral classes. The defoliation images for each event were broken into defoliation classes to compare the number of classes represented as the intensity of defoliation became greater. Surprisingly, in each defoliation class, the numbers of classes represented are quite similar (see Table 4.6).

% fc lost	Classes represented (Event 1)	Classes represented (Event 2)
10-14	**49**	**47**
15-19	**47**	**49**
20-24	**47**	**47**
25-29	**45**	**46**
30-39	**45**	**46**
40-49	**43**	**44**
50-100	**38**	**42**

Table 4.6 Defoliation classes and LULC classes represented in each

Also for Events 1 and 2, the three dominant spectral classes represent 24% and 36% of the defoliated landscape, respectively, with the top 10 classes representing 60% and 69%, respectively. Even assuming that the top 10 most impacted classes capture most forms of coca production, this still leaves 40% (Event 1) and 31% (Event 2) of the defoliation occurring in non-coca or coca intercropped lands. For the 50% and above defoliation class, 57% of the total spectral classes in event 1 and 63% in event 2, including crops and other non-coca producing lands captured in both events, were represented (see Appendix E for the expanded results).

While a trend exists with fewer classes being defoliated, it does not represent the expected dramatic reduction one would expect. The complex spatial organization of the Colombian coca producing landscape appears to prevent discriminate spraying of defoliants.

CONCLUSIONS

This study used remote sensing technology and fieldwork to quantitatively and qualitatively measure the defoliation of the vegetation due to the Plan Colombia fumigation in Putumayo, Colombia. The objectives of the study were met by:

1. Identifying ***fc*** as a biophysical variable that would sufficiently characterize the effects of defoliation due to Plan Colombia.
2. Validating the use of ***fc*** in this study by collecting ground truth data and using that data to show the linear relationship that exists between image ***fc*** and ground ***fc***.
3. Quantifying the amount of Plan Colombia defoliation using the field-calibrated ***fc*** data.
4. Identifying the number of LULC classes affected by fumigation and showing that the Plan Colombia spraying during 2002 was not discriminate over the landscape.

I hypothesized that:

1. Green fractional coverage derived from ETM+ data accurately quantifies vegetation cover.
2. Hybrid classification techniques applied to ETM+ data identify LULC classes.
3. Changes in ***fc*** indicate changes due to defoliation.
4. Defoliation in Putumayo, Colombia occurs indiscriminately over the landscape affecting cover types other than coca.
5. Landsat ETM+ data provides the synoptic coverage with adequate resolution characteristics suitable for study.

My hypotheses were verified by 1) validating the linear relationship that exists between image ***fc*** and ground truth ***fc***, 2) performing a LULC classification using the hybrid method resulting in 90 spectrally significant classes, 3) revealing the linear spatial patterns of defoliation using an ***fc*** change detection, 4) using the number of LULC classes represented in each defoliation class to show that a dramatic reduction of classes does not exist and the most conservative estimates place over 30% of defoliation in non-coca LULC classes, and 5) performing the aforementioned analysis using Landsat ETM+ data.

FUTURE RESEARCH

Although this study identified effects of aerial fumigation on the landscape in Putumayo, there exist many possibilities for improvement and also extension of the research. One area that I would like to explore further is the algorithm used to calculate ***fc***. I believe that revisiting the statistical relationship between **NDVI** (or any other of the previously mentioned vegetation indices) and ***fc*** could lead to image ***fc*** values that match ground ***fc*** values with a 1:1 relationship. Another possibility is to refine the method used for ground truth fc calculation. The use of aerial photos and/or high spatial resolution satellite imagery to calculate ***fc*** added to the field estimation improvements could create a high level of confidence in using ***fc*** derived from images of more coarse spatial resolution such as Landsat ETM+.

I would also like to verify the LULC classes that were created using the hybrid method. Although an accuracy assessment was not necessary for the results of this study, the accuracy information would greatly enhance the understanding of the LULC classes being fumigated and possibly help to explain the effects of wind drift and runoff of the herbicide used in the fumigation. Although the chances to find coca in Ecuador are limited, the possibility of verifying the other LULC classes could illuminate, through a process of elimination, the coca classes.

In future research, I would like to explore changes that have occurred on Colombia's landscape after fumigation. As was mentioned previously, many believe that fumigation could lead to deforestation. I would like to conduct a LULC change detection of the area in an attempt to illuminate possible rising deforestation rates in Putumayo.

I also believe that I should extend this research to northern Ecuador. Some of the possibilities are: showing whether Plan Colombia fumigation has affected vegetation in Ecuador (near the border), calculating deforestation rates near the border, locating coca cultivation in Ecuador, illuminating changes of the spatial organization of the landscape in Ecuador due to the influx of Colombians, and modeling the possible effects of Plan Colombia (the migration of Colombians into Ecuador) using spatial simulation models.

LITERATURE CITED

Alvarez, M. D. 2003. Forests in the Time of Violence: Conservation Implications of the Colombian War. *Journal of Sustainable Forestry* 16 (3/4):49-70.

Bagley, B. M. 1988a. The New Hundred Years War? Us National Security and the War on Drugs in Latin America. *Journal of Interamerican Studies and World Affairs* 30 (1):161-182.

Bagley, B. M. 1988b. US Foreign Policy and the War on Drugs: Analysis of a Policy Failure. *Journal of Interamerican Studies and World Affairs* 30 (2/3):189-212.

Berger, R. M. 2001. The time of coca: on the Colombian front of the drug war, it's hard to tell who--or what--is the real enemy. *Sojourners* 30 (3):20-24.

Bibes, P. 2001. Transnational Organized Crime and Terrorism. *Journal of Contemporary Criminal Justice* 17 (3):243-258.

Browitt, J. 2001. Capital punishment: the fragmentation of Colombia and the crisis of the nation-state. *Third World Quarterly* 22 (6):1063-1078.

Brown, J. 2000. Doubt about US antidrug effort in Colombia. *Christian Science Monitor*, July 3 2000, 3.

Carlson, T. N., and D. A. Ripley. 1997. On the Relation between NDVI, Fractional Vegetation Cover, and Leaf Area Index. *Remote Sensing of Environment* 62:241-252.

Choudhury, B. J., N. U. Ahmed, S. B. Idso, R. J. Reginato, and C. S. T. Daughtry. 1994. Relations between evaporation coefficients and vegetation indices studied by model simulations. *Remote Sensing of Environment* 50:1-17.

Clawson, P. L., and R. W. Lee. 1996. *The Andean Cocaine Industry*. New York: St. Martin's.

Cohen, W. B., T. K. Maiersperger, S. T. Gower, and D. P. Turner. 2003. An improved strategy for regression of biophysical variables and Landsat ETM+ data. *Remote Sensing of the Environment* 84:561-571.

Congalton, R. G., and K. Green. 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton: Lewis Publishers.

Cooper, M. 2001. Plan Colombia: wrong issue, wrong enemy, wrong coutry. *The Nation* 272 (11):11-18.

Crandall, R. 2002. *Driven by Drugs: U.S. Policy towards Colombia*. Boulder: Lynne Reinner Publishers.

Dishman, C. 2001. Terrorism, Crime, and Transformation. *Studies in Conflict & Terrorism* (24):43-58.

DNE. 2000. Existencias historicas do los cultivos ilicitos y su erradicacion. Bogota: Departamento Nacioal de Estupefacientes.

Driver, T. F. 2001. Colombia's war: drugs, oil and markets. *The Christian Century*, November 7 2001, 14-19.

Dudley, S. 2000. The Colombia quagmire: the drug war goes south. *American Prospect* 11 (17):32-37.

Ecuador, E. o. 2001. Ecuador in Brief. Washington, DC: Embassy of Ecuador.

Ehrenfeld, R. 1990. *Narco-terrorism*. New York: Basic Books.

Ernst, J. 2002. Plan Colombia. *SAIS Review* 22 (1):97-102.

Farnam, A. 2002. Colombia's civil war drifts south into Ecuador. *Christian Science Monitor*, July 11 2002, 7.

Ford, J. T. 2003. Drug Contol: Coca Cultivation and Eradication Estimates in Colombia, a letter to Charles H. Taylor, House of Representatives. Washington D.C.: U.S. General Accounting Office.

Forero, J. 2002. U.S. is Stepping Up Drive to Destroy Coca in Colombia. *The New York Times*, September 4 2002, A1, A6.

Fratepietro, S. 2001. Plan Colombia: the hidden front in the U.S. drug war. *The Humanist* 61 (4):18-21.

Frechette, M. 2003. In Search of the Endgame: A Long-Term Multilateral Strategy for Colombia. Coral Gables, FL: North-South Center and Strategic Studies Institute (Joint Publication).

Fung, T., and W. Siu. 2000. Environmental quality and its changes, an analysis using NDVI. *International Journal of Remote Sensing* 21 (5):1011-1024.

Gardner, D. 2001. The Failed War on Drugs. *Chicago Sun-Times*, January 21, 42.

Gardner, R. H., B. T. Milne, R. V. O'Neill, and M. G. Turner. 1987. Neutral models for the analysis of broad-scale landscape patterns. *Landscape Ecology* 1:19-28.

Gilabert, M. A., J. Gonzalez-Piqueras, F. J. Garcia-Haro, and J. Melia. 2002. A generalized soil-adjusted vegetation index. *Remote Sensing of Environment* 82:303-310.

Gillies, R. R., and T. N. Carlson. 1995. Thermal remote sensing of surface soil water content with partial vegetation cover for incorporation into climate models. *Journal of Applied Meteorology* 34:745-756.

Gitelson, A. A., Y. J. Kaufman, R. Stark, and D. Rundquist. 2002. Novel algorithms for remote estimation of vegetation fraction. *Remote Sensing of Environment* 80:76-87.

Guzman, G., O. Fals-Borda, and E. Umana-Luna. 1962. *La violencia en Colombia: estudio de un proceso social*. 2nd ed. Bogota, Colombia: Ediciones Tercer Mundo.

Hodgson, M. 2001. Side effects hit Plan Colombia. *Christian Science Monitor*, February 27 2001, 6.

Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* 25:295-309.

Isacson, A., and I. Vaicius. 2001. Plan Colombia's "Ground Zero". Washington DC: Center for International Policy.

Kalmanovitz, S. 1988. *Economia y nacion: una breve historia de Colombia*. Bogota, Colombia: Siglo XXI Editores.

Kay, B. H. 1999. Violent Opportunities: The Rise and Fall of "King Coca" and Shining Path. *Journal of Interamerican Studies and World Affairs* 41 (3):97-127.

Keitt, T. H. 2000. Spectral representation of neutral landscapes. *Landscape Ecology* 15:479-493.

Kratz, V. 2002. Lethal Dose. *Sierra Magazine*, July/August 2002.

LaFranchi, H. 2000. What's at stake? *Christian Science Monitor*, December 12 2000, 10.

LaFranchi, H. 2001. A drug war down on the farm. *Christian Science Monitor*, May 23 2001, 6.

Leprieur, C., Y. H. Kerr, S. Mastorchio, and J. C. Meunier. 2000. Monitoring vegetation cover across semi-arid regions: comparison of remote observations from various scales. *International Journal of Remote Sensing* 21 (2):281-300.

Lunetta, R. S., J. Ediriwickrema, D. M. Johnson, J. G. Lyon, and A. McKerrow. 2002. Impacts of vegetation dynamics on the identification of land-cover change in a biologically complex community in North Carolina, USA. *Remote Sensing of Environment* 82:258-270.

Mabry, D. 1988. The US Military and the War on Drugs in Latin America. *Journal of Interamerican Studies and World Affairs* 30 (2/3):53-76.

Mackay, G., M. D. Steven, and J. A. Clark. 1998. An atmospheric correction procedure for the ATSR-2 visible and near-infrared land surface data. *International Journal of Remote Sensing* 19 (15):2949-2968.

Marcella, G. 2002. The U.S. Engagement with Colombia: Legitimate State Authority and Human Rights. Coral Gables, FL: North-South Center.

Meltzer, J. 2001. The Enduring Colombian Conflict: A Canadian Perspective. Ottawa, Ontario: Canadian Foundation for the Americas.

Messina, J. P., and S. J. Walsh. 2001. 2.5D Morphogenesis: modeling landuse and landcover dynamics in the Ecuadorian Amazon. *Plant Ecology* 156:75-88.

Millett, R. L. 1997. The United States and Latin America's Armed Forces: A Troubled Relationship. *Journal of Interamerican Studies and World Affairs* 39 (1):121-136.

Moreno-Sanchez, R., D. S. Kraybill, and S. R. Thompson. 2003. An Econometric Analysis of Coca Eradication Policy in Colombia. *World Development* 31 (2):375-383.

Nagle, L. E. 2002. Plan Colombia: Reality of the Colombian Crisis and Implication for Hemispheric Security. Carlisle, PA: Strategic Studies Institue.

NASA. Landsat 7 Science Data Users Handbook.

North, P. R. J. 2002. Estimation of fapar, LAI, and vegetation fractional cover from ATSR-2 imagery. *Remote Sensing of the Environment* 80:114-121.

Penhaul, K. 2001. Making a deal with the devil. *U.S. News & World Report*, April 16 2001, 28-29.

Perreault, T. 2003. Making Space: Community Organization, Agrarian Change, and the Politics of Scale in the Ecuadorian Amazon. *Latin American Perspectives* 30 (128):96-121.

Peterson, S. 2002. People and Ecosystems in Colombia: Casualties of the Drug War. *The Independent Review* 6 (3):427-440.

Petras, J. 2001. The geopolitics of Plan Colombia. *Monthly Review* 53 (1):30-48.

Price, J. C., and W. C. Bausch. 1995. Leaf Area Index Estimation from Visible and Near-Infrared Reflectance Data. *Remote Sensing of the Environment* 52:55-65.

Purevdorj, T., R. Tateishi, T. Ishiyama, and Y. Honda. 1998. Relationships between percent vegetation cover and vegetation indices. *International Journal of Remote Sensing* 19 (18):3519-3535.

Qi, J., A. Chehbouni, A. R. Huete, Y. H. Kerr, and S. Sorooshian. 1994. A modified soil adjusted vegetation index (MSAVI). *Remote Sensing of Environment* 48:119-126.

Qi, J., R. C. Marsett, M. S. Moran, D. C. Goodrich, P. Heilman, Y. H. Kerr, G. Dedieu, A. Chehbouni, and X. X. Zhang. 2000. Spatial and temporal dynamics of vegetation in the San Pedro River Basin area. *Agricultural and Forest Meteorology* 105:55-68.

Rojas, I. 2003. The push for zero coca: Democratic transition and counternarcotics policy in Peru. Washington, D.C.: Washington Office on Latin America.

Rouse, J. W., R. H. Haas, J. A. Schell, D. W. Deering, and J. C. Harlan. 1974. Monitoring the vernal advancement of retrogradation of natural vegetation. Greenbelt, MD: NASA/GSFC (Type III, Final Report).

Scanlon, T. M., J. D. Albertson, K. K. Caylor, and C. A. Williams. 2002. Determining land surface fractional cover from NDVI and rainfall time series for a savanna ecosystem. *Remote Sensing of the Environment* 82:376-388.

Sharpe, K. E. 1988. The Drug War: Going After Supply: A Commentary. *Journal of Interamerican Studies and World Affairs* 30 (2/3):77-85.

Song, C., C. E. Woodcock, K. C. Seto, M. P. Lenney, and S. A. Macomber. 2001. Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects? *Remote Sensing of the Environment* 75:230-244.

Stauder, M. 2001. Colombia's cocaine frontier. *Mother Jones* 26 (6):58-63.

Strahler, A. H., and A. N. Strahler. 1992. *Modern Physical Geograpy*. 4th ed. New York: John Wiley & Sons, Inc.

Tanre, D., C. Deroo, P. Duhaut, M. Herman, J. J. Morcrette, J. Perbos, and P. Y. Deschamps. 1990. Description of a computer code to simulate the satellite signal in the solar spectrum: the 5S code. *International Journal of Remote Sensing* 11 (4):659-668.

Teillet, P. M., K. Staenz, and D. J. Williams. 1997. Effects of Spectral, Spatial, and Radiometric Characteristics on Remote Sensing Vegetation Indices of Ferested Regions. *Remote Sensing of the Environment* 61:139-149.

Thoumi, F. E. 1992. Why the Illegal Psychoactive Drugs Industry Grew in Colombia. *Journal of Interamerican Studies and World Affairs* 34 (3):37-63.

Thoumi, F. E. 2002. Illegal Drugs in Colombia: From Illegal Economic Boom to Social Crisis. *Annals of the American Academy of Political and Social Science* 582:102-116.

UNDCP. 2002. Colombia: Annual Coca Cultivation Survey 2001: United Nations Drug Control Program.

UNODC. 2003a. Colombia: Coca Survey for 2002: United Nations Office on Drugs and Crime.

UNODC. 2003b. Colombia: Coca Survey for December 2002 and Semi-Annual Estimate for July 2003: United Nations Office on Drugs and Crime.

Uribe, S. 1997. Evaluacion: Extension, tecnicas y tecnologias para la produccion y rendimientos y magnitud de la industria. In *Drogas ilicitas en Colombia: Su impacto economico, politico y social*, edited by F. E. Thoumi. Bogota, Colombia: Editrial Planeta.

United States Senate. 2003. Caucus on Intenational Narcotics Control. *US Policy Regarding Narcotics Control In Colombia*. 1st. June 3, 2003.

USDS. 2001. International Narcotics Control Strategy Report. Washington D.C.: United States Department of State.

USDS. 2002. Report on Issues Related to the Aerial Eradication of Illicit Coca in Colombia. Washington D.C.: United States Department of State.

USGAO. 2003. Drug Control: Specific Performance Measures and Long-Term Costs for U.S. Programs in Colombia Have Not Been Developed. Washington DC: United States General Accounting Office.

Vaicius, I., and A. Isacson. 2003. The "War on Drugs" meets the "War on Terror". Washington DC: Center for International Policy.

Valenzuela, P. 2002. Conflict Analysis- Colombia, Bolivia and the Andean Region. Stockholm: Swedish International Development Cooperation Agency.

Van Der Meer, F. 1999. Iterative spectral unmixing (ISU). *International Journal of Remote Sensing* 20 (17):3431-3436.

Vargas, R. 2002. The anti-drug policy, aerial spraying of illicit crops and their social, environmental and political impacts in Colombia. *Journal of Drug Issues* 32 (1):11-60.

Vellinga, M. 2000. The War On Drugs and Why It Cannot Be Won. *Journal of Third World Studies* 17 (2):113-128.

Weiss, E., S. E. Marsh, and E. S. Pfirman. 2001. Application of NOAA_AVHRR NDVI time-series data to assess changes in Saudi Arabia's rangelands. *International Journal of Remote Sensing* 22 (6):1005-1027.

Wilson, S. 2003. U.S. Seeks to Avoid Deeper Role in Colombia. *Washington Post Foreign Service*, March 9, 2003, A16.

Xavier, A. C., and C. A. Vettorazzi. 2004. Mapping leaf area index through spectral vegetation indices in a subtropical watershed. *International Journal of Remote Sensing* 25 (9):1661-1672.

Zha, Y., J. Gao, S. Ni, Y. Liu, J. Jiang, and Y. Wei. 2003. A spectral reflectance-based approach to quantification of grassland cover from Landsat TM imagery. *Remote Sensing of the Environment* 87:371-375.

APPENDIX A

5S INPUT PARAMETERS

09/09/2001 Image ETM+

Site Elevation	**500 meters**
Sensor Elevation	**705 kilometers**
Solar Zenith	**29.5321637**
Solar Azimuth	**79.5446957**
Sensor Zenith	**0**
Sensor Azimuth	**0**
Model Type	**Predefined**
Standard Atmos. Model	**Tropical**
Aerosol Model	**Continental**
Visibility	**17 kilometers**
Date	**9/9/2001**

09/12/2002 Image ETM+

Site Elevation	**500 meters**
Sensor Elevation	**705 kilometers**
Solar Zenith	**29.3394215**
Solar Azimuth	**81.645768**
Sensor Zenith	**0**
Sensor Azimuth	**0**
Model Type	**Predefined**
Standard Atmos. Model	**Tropical**
Aerosol Model	**Continental**
Visibility	**17 kilometers**
Date	**9/12/2002**

<u>10/14/2002 Image ETM+</u>

Site Elevation	**500 meters**
Sensor Elevation	**705 kilometers**
Solar Zenith	**27.727403**
Solar Azimuth	**107.930127**
Sensor Zenith	**0**
Sensonr Azimuth	**0**
Model Type	**Predefined**
Standard Atmos. Model	**Tropical**
Aerosol Model	**Continental**
Visibility	**17 kilometers**
Date	**10/14/2002**

APPENDIX B

5S OUTPUT PARAMETERS

9/9/2001 Image

Reflectance	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
0	**0.0719**	**0.0395**	**0.025**	**0.0123**	**0.0026**	**0.0012**
0.1	**0.1492**	**0.1188**	**0.1089**	**0.0968**	**0.0893**	**0.0903**
0.2	**0.2292**	**0.1999**	**0.1944**	**0.1822**	**0.1762**	**0.1796**
0.3	**0.312**	**0.2831**	**0.2813**	**0.2684**	**0.2634**	**0.269**
0.4	**0.3977**	**0.3683**	**0.3697**	**0.3555**	**0.3508**	**0.3585**
0.5	**0.4866**	**0.4556**	**0.4597**	**0.4435**	**0.4384**	**0.4481**

9/12/2002 Image

Reflectance	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
0	**0.0719**	**0.0395**	**0.025**	**0.0123**	**0.0026**	**0.0012**
0.1	**0.1492**	**0.1188**	**0.109**	**0.0968**	**0.0893**	**0.0903**
0.2	**0.2292**	**0.2**	**0.1944**	**0.1822**	**0.1762**	**0.1796**
0.3	**0.312**	**0.2831**	**0.2813**	**0.2684**	**0.2634**	**0.269**
0.4	**0.3978**	**0.3684**	**0.3698**	**0.3556**	**0.3508**	**0.3585**
0.5	**0.4867**	**0.4557**	**0.4598**	**0.4436**	**0.4385**	**0.4481**

10/14/2002 Image

Reflectance	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
0	**0.0717**	**0.0394**	**0.0249**	**0.0123**	**0.0026**	**0.0012**
0.1	**0.1492**	**0.1189**	**0.109**	**0.0969**	**0.0893**	**0.0904**
0.2	**0.2295**	**0.2003**	**0.1947**	**0.1824**	**0.1764**	**0.1797**
0.3	**0.3125**	**0.2836**	**0.2818**	**0.2688**	**0.2636**	**0.2692**
0.4	**0.3985**	**0.3691**	**0.3704**	**0.356**	**0.3511**	**0.3588**
0.5	**0.4877**	**0.4566**	**0.4606**	**0.4442**	**0.4388**	**0.4485**

APPENDIX C

DESCRIPTION OF FIELD DATA COLLECTION FORM

Site #: The site # from the field maps

Date: The date that the information was recorded on

Travel time: The time traveled between the starting point and the current collection point. Starting point should be noted

LULC type: The LULC at the collection point (see LULC sheet for guidelines)

Collection type: This is either a point, line, or polygon (using just GPS, or GPS plus rangefinder)

General description: Any comments on general features at the collection point. This can include vegetation, location, soils, man-made

 # pts in file: The number of points collected by the GPS unit at the collection point

Rover file name: The name given to the rover file location by the GPS unit

Waypoint file name: The name given to each waypoint file by the GPS unit

Coordinate X: The X coordinate recorded by the GPS unit

Coordinate Y: The Y coordinate recorded by the GPS unit

Photo #: The photo number, if needed, at the collection point (may have multiples)

Photo type: The name of camera that was used to take the photo (Pentax 105, Pentax 4500)

Canopy height: The height of the canopy (where applicable) in meters measured with the rangefinder

Polygon collection and Sketch area: The distance and azimuth of polygon collection and sketches of the area

Visual fractional coverage information: The FC collection notes, what kind of collection (photo, visual)

APPENDIX D

IDL CODE TO SIMULATE CANOPY AND UNDERSTORY

```
;IDL program photo_fix.pro
;written by Paul Delamater for AAG ELWL and thesis
;creates neutral models to create one fc value when
;a fc photo and fc ground cover data are present

pro photo_fix

time = systime(1)

;define variables
fcphoto = [.83215, .808, .5681, .5612, .0973, .6587, $ .86415,
.1459, .7082, .7824, .7351, .87835]
fcground = [.75, .35, .3, .85, .71, .80, .40, .28, .80, $ .85,
.85, .80]
fcfinal = fltarr(12)
maxiter = 12

;open mask image
mask = read_tiff('c:\paul\research\thesis\mask.tif')

;get circle area
circlearea = n_elements(where(mask eq 1))

      ;start the loop
      for i=0, maxiter-1 do begin

      ;create neutral model 1
      neutral1 = randomu (seed, 1395, 1395)

      ;create photo model
      photo_fc = neutral1 le fcphoto(i)

      ;create neutral model 2
      neutral2 = randomu (seed, 1395, 1395)

      ;create groung model
      ground_fc = neutral2 le fcground(i)

      ;create combined model
      comb_fc = photo_fc + ground_fc
      greencover = comb_fc gt 0

      ;mask out edges
      greencover = greencover * mask
```

```
      ;calculate fractional coverage
      greenpix = n_elements(where(greencover eq 1))
      fcfinal(i) = (greenpix * 1.0) / (circlearea * 1.0)

      endfor

print, fcfinal


;get the processing time... this code ran very fast
print, 'Total processing time =',(SYSTIME(1) - time)/60, '$
Minutes'

;all good things must come to an
end
```

APPENDIX E

EVENT 1: % OF DEFOLIATED AREA PER LULC CLASS

	% of defoliated area
Class 5	**0.0002**
Class 16	**0.0027**
Class 17	**0.0089**
Class 18	**0.0008**
Class 19	**0.0051**
Class 20	**0.0035**
Class 21	**0.0613**
Class 22	**0.0238**
Class 23	**0.0145**
Class 24	**0.0002**
Class 25	**0.2600**
Class 26	**9.6925**
Class 27	**0.1113**
Class 29	**7.0257**
Class 31	**0.7780**
Class 32	**1.2643**
Class 33	**5.3065**
Class 34	**3.9008**
Class 35	**6.9527**
Class 37	**0.2784**
Class 38	**0.0084**
Class 39	**0.0003**
Class 40	**7.3625**
Class 41	**2.7892**
Class 42	**0.0029**
Class 43	**0.0143**
Class 44	**0.1753**
Class 45	**0.0722**
Class 46	**0.0030**
Class 48	**0.0002**
Class 66	**0.6842**
Class 67	**1.1430**
Class 68	**1.6723**

Primary forest
Secondary forest
Pasture with trees or Rastrojo
Agriculture or pasture with no trees
Coca
Other (includes urban, water, and other LULCs)

note: classes not represented have been removed

Class 69	**4.2085**
Class 70	**5.1627**
Class 71	**5.8334**
Class 72	**3.6934**
Class 73	**2.5256**
Class 74	**4.6641**
Class 75	**2.7261**
Class 76	**0.0010**
Class 77	**0.0882**
Class 78	**0.2502**
Class 79	**1.3042**
Class 80	**1.5804**
Class 81	**2.5547**
Class 82	**2.8871**
Class 83	**3.6285**
Class 84	**3.0705**
Class 85	**1.0358**
Class 86	**2.7090**
Class 87	**0.8970**
Class 88	**1.2721**
Class 89	**0.2886**

EVENT 2: % OF DEFOLIATED AREA PER LULC CLASS

	% of defoliated area
Class 7	**0.0087**
Class 13	**0.0005**
Class 16	**0.0706**
Class 17	**0.0118**
Class 18	**0.0005**
Class 19	**0.0517**
Class 20	**0.0069**
Class 21	**0.3430**
Class 22	**0.0178**
Class 23	**0.2309**
Class 24	**0.0004**
Class 25	**0.6205**

Primary forest
Secondary forest
Pasture with trees or Rastrojo
Agriculture or pasture with no trees
Coca
Other (includes urban, water, and other LULCs)

note: classes not represented have been removed

Class 26	**9.3433**
Class 27	**0.0835**
Class 29	**17.4570**
Class 31	**0.4964**
Class 32	**0.6147**
Class 33	**3.7392**
Class 34	**2.3307**
Class 35	**3.2758**
Class 37	**0.0991**
Class 38	**0.0033**
Class 39	**0.0004**
Class 40	**4.2537**
Class 41	**8.7620**
Class 42	**0.0098**
Class 43	**0.0681**
Class 44	**0.0966**
Class 45	**0.3642**
Class 46	**0.0027**
Class 47	**0.0004**
Class 48	**0.0004**
Class 50	**0.0002**
Class 53	**0.0002**
Class 54	**0.0002**
Class 66	**0.5091**
Class 67	**0.9947**
Class 68	**1.9325**
Class 69	**5.2301**
Class 70	**4.9096**
Class 71	**6.5257**
Class 72	**4.8446**
Class 73	**3.5553**
Class 74	**2.7809**
Class 75	**2.6956**
Class 77	**0.0470**
Class 78	**0.1780**
Class 79	**0.9621**
Class 80	**1.2279**
Class 81	**1.8660**
Class 82	**1.9339**

Class 83	**2.2731**
Class 84	**1.6886**
Class 85	**0.5853**
Class 86	**1.6112**
Class 87	**0.4430**
Class 88	**0.5726**
Class 89	**0.2682**