Spatial Distribution and Quantification of Forest Treatment Residues for Bioenergy Production

Lucas A. Wells
The University of Montana

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Spatial Distribution and Quantification of Forest Treatment Residues for Bioenergy Production

By

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BSc Forestry, University of Kentucky, Lexington, KY, 2011

Thesis

Presented in partial fulfillment of the requirements for the degree of

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The availability and spatial distribution of forest treatment residues are prerequisites to supply chain development for bioenergy production. To accurately estimate potential residue quantities, data must be provided to simulate stand-level silviculture across the landscape of interest. However, biomass utilization assessments often consider broad regions where adequate data are not supplied. At present, these measures are addressed using strategic level assessments and broad-based management that may not be applicable to all areas of the landscape. This thesis introduces a new methodology for spatially describing stand-level treatment residue quantities based on detailed silvicultural prescriptions and site specific management. Using National Agricultural Imagery Program (NAIP) imagery, the forest is segmented into treatment units based on user defined size constraints. Using a remote sensing model based on NAIP imagery and FIA plot data, these units are attributed with stand-level descriptions of basal area, tree density, above ground biomass, and quadratic mean diameter (qmd). The outputs are used to develop silvicultural prescriptions and estimate available treatment residues under three alternative management scenarios at a range of delivered prices per bone dried ton (bdt) to a nearby bioenergy facility in southwestern Colorado. Using a marginal cost approach where treatment costs were covered by merchantable yields, the breakeven delivered price of treatment residues in this study is $48.94 \text{ bdt}^{-1}$ yielding $167,685 \text{ bdt}$ following a 10 year (yr) management simulation at a 5,000 acre (ac) yr$^{-1}$ annual allowable treatment level.
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CHAPTER 1

General Introduction
1.1 Biomass Utilization

The interior west of the United States, as in many regions around the country, has experienced growing interests in using forest derived biomass as a renewable source of energy. Historically, the utilization of forest biomass has been dominated by the forest products industry for generating heat, steam, and electricity for manufacturing processes (Guo et al., 2007). However, emerging markets for forest biomass as a fuel and feedstock for bioenergy applications outside the forest sector can be found throughout the U.S.. In the western U.S., interest in these potential and emerging markets are closely linked to the increasing risk of significant forest disturbances, such as fire, insects and disease, and the broad agreement that active management by means of forest treatments including thinning and prescribed fire is urgently needed to restore historic stand dynamics and improve forest health (Brown et al., 2004). Broad-scale treatments throughout western forests present opportunities to increase the use of renewable energy sources and stimulate local economic development with new bioenergy and bioproducts enterprises.

In recent years, several federal and state incentives have promoted the use of forest biomass as feedstocks for bioenergy production. On the research side, many grants were awarded through the Biomass Reserach and Development Act of 2000 (Title III of the Agricultural Risk Protection Act) to improve conversion technologies for biobased products. The national USDA-Agriculture and Food Research Initiative’s Coordinated Agricultural Project program has been successful in supporting large integrated research teams like the Northwest Advanced Renewable Alliance (http://www.nararenewables.org) - a program engaged in converting forest biomass to jet fuel. The National Fire Plan
of 2000, motivated by severe wildfires during previous years, developed strategies to promote markets for the use of small-diameter trees produced from hazardous fuels reduction treatments. In addition, a range of state and federal policies have been enacted to directly stimulate the growth of the bioenergy and bioproducts sectors. States such as Minnesota, California, Washington, and Maryland have provided financial assistance for the development and establishment of production facilities to create and expand biomass markets. Federal programs and policies include the Biomass Crop Assistance Program, added to the energy title in the 2008 farm bill to incentivise wood and agricultural residue collection and the Renewable Fuel Standards proposed by the Environmental Protection Agency to ensure that transportation fuel sold in the United States contains a minimum volume of renewable fuel as required by the Energy Independence and Security Act of 2007. Other efforts, such as the Regional Greenhouse Gas Initiative by states and provinces in and around the Northeastern United States, the cap-and-trade program, and other carbon oriented systems provide financial offsets for biomass harvest and utilization.

In the 15 Western States there are at least 28 million acres that could benefit from some type of restorative treatment to refurbish healthy ecosystems, protect water and soil quality, and improve forest and rangeland resilience (Rummer et al., 2005). An estimated biomass availability of 270 million bdt could result from forest treatments on 10.6 million of these acres assuming management only on forests producing at least 300 ft$^3$ of timber per ac, per yr (Western Governors’ Association 2005). The U.S. Department of Energy and USDA Forest Service estimated that an annual supply of one billion bdt of biomass would displace 30% or more of domestic petroleum consumption. Of this amount, the continental U.S. could potentially produce 473 million bdt at $60
bdt$^{-1}$ from forest residue and agricultural waste in 2012. (Perlack and Stokes, 2011).

Although previous strategic level assessments regarding biomass availability suggests a promising future in forest biomass utilization, many questions remain unanswered. The availability of biomass at tactical and operational scales rely on many factors including, but not limited to, current biomass stocks, harvesting systems, terrain, road network, species, forest characteristics, silviculture, ownership, local markets and management objectives. Existing harvest scheduling and transportation models can provide optimized solutions regarding the extraction and delivery of biomass, however there is a need for an integrated system to supply scientifically based biomass inputs with the capacity to accurately simulate forest management at multiple scales and time frames.

1.1.1 Benefits of Treatment Residue Utilization

Recent studies have evaluated the benefits associated with the utilization of treatment residues for bioenergy production. Results from Jones et al. (2010) show that bioenergy, as an alternative to on-site burning, generates fewer carbon dioxide, methane, and particulate matter emissions. Gan and Smith (2007) found that removing logging residues would save $200-250 per hectare in site preparation costs during forest regeneration in East Texas. Loeffler and Anderson (2013) examined emissions from cofiring forest biomass with coal ranging to a 20% substitution by heat content and found at maximum displacement using 120,717 tons of forest biomass per year, total system emissions are projected to decrease by 15% for CO$_2$, 95% for CH$_4$, 18% for NO$_X$, 82% for PM$_{10}$, and 27% for SO$_X$. Furthermore, the commercial use of thinned trees have high potential to offset treatment costs (Brown et al., 2004). Buchholz et al. (2011) found that substantial quantities, 4.2 to 6.3 million tonnes of forest residues could be available over a large region in Northeastern U.S. without competing with the pulp
and paper industry. Although the benefits of bioenergy have been identified and analyzed, there are limitations regarding the sustainability of the resource. Buchholz et al. (2011) highlight biological, physical, social, and economic constraints and mention that bioenergy production could lead to forest degradation and actually release more carbon to the atmosphere than comparable energy production from fossil fuels. However, they conclude that responsible harvesting in regions with large forestland bases and low energy consumption could establish sustainable markets for forest treatment residues.

1.1.2 Conversion Technologies for Woody Biomass

Several conversion technologies have emerged over the past few decades with emphasis on woody biomass. The existing technologies consist of i) thermochemical conversion processes such as combustion, gasification, and pyrolysis, and ii) biochemical conversion using fermentation and digestion (Gallagher, 2006). Combustion is the most well-developed of the current technologies and is widely used in the residential, utility and industrial sectors, especially for heat and power (Bain and Overend, 2002). Combustion technologies can be categorized as co-firing and direct-firing. Co-firing refers to the use of biomass as a supplementary energy source in conventional boiler systems fired primarily by another fuel, most often coal. Conversely, direct-firing describes the combustion of biomass as a primary fuel source, most often to produce heat and sometimes both heat and electricity, which is called co-generation.

The biochemical transformation of biomass by microbes includes both fermentation and digestion, with primary outputs being alcohols and methane respectively. Although these technologies have demonstrated successful yields in the corn-ethanol industry, and are the subject of recent commercial-scale installations (Dattal et al., 2011), biochemical conversions of woody biomass are more difficult due to high levels of lignin in wood and
have not yet proven to be commercially viable over the long term (Guo et al., 2007).

Gasification has received considerable attention for decades in the U.S. and worldwide (Bain and Overend, 2002; Faaij, 2006). A wide range of products can be generated from gasification processes. These products include heat, electricity, methane, ethanol, syngas, and a variety of bio-based chemicals. This is a developing industry and recently has been applied on small scales. Gasification for heat and power is generally considered technically mature, but biomass gasification for liquid fuel production using catalysts is emerging and the subject of intense ongoing research (www.nrel.gov, banr.colostate.edu).

Pyrolysis is a chemical decomposition process that involves exposing small chips of biomass to extreme temperatures for a short period of time in the absence of oxygen (Faaij, 2006). A range of temperatures are used to configure the process for specific applications and products. Generally, pyrolysis systems operating at relatively low temperatures (200 - 300 °C) produce a devolatilized, hydrophobic high-carbon content product called torrefied wood. This product is considered suitable for combustion applications, including cofiring with coal, but can be used as a raw material in some manufacturing processes such as gasification and liquid fuel production (Anderson et al., 2013). Configurations involving higher temperatures (300 to 700 °C) produce recalcitrant charcoal known as biochar along with a volatile gas, a fraction of which can be rapidly cooled and condense to liquid oil called bio-oil. These yields can be used as fuel in heating or electricity generation applications (Faaij, 2006). This technology has been considered as a pretreatment option for transporting biomass over long distances due to its high energy density. Commercial biooil production is currently in experimental phase using small, portable facilities to increase transportation efficiency. Using con-
version, bulky biomass can be transformed into dense liquid and solid products that can be transported longer distances economically. (Bridgewater, 2005).

Of the existing conversion technologies, combustion is the most developed and has been widely used in the forest products and utility sectors. As other technologies mature, the demand for forest residues will likely follow. According to the U.S. Department of Energy (2011), biomass accounted for 48% of all renewable energy production in the U.S. Of this amount, 65% was from woody biomass. The anticipated commercialization of the developing technologies for the conversion of woody biomass to bioenergy products may greatly increase biomass consumption in coming years, including biomass from both agricultural and forest feedstocks.

1.1.3 Availability of Treatment Residues

The availability of forest treatment residues on any given site is limited by several metrics of availability:  

i) When all treatment residues for a given area are considered extractable regardless of ecological, technical and economic factors that may limit availability, the quantity of residue is defined as “unconditionally available”, and defines the baseline stocks on the landscape. It is rarely, if ever the case that total residue amounts are extractable because of small twigs and foliage that are simply lost or destroyed during harvest and transport.  

ii) “Ecologically available” biomass includes residues that can be removed from the site without having long-term negative effects on site productivity or result in other long-term environmental harm. Barrett et al. (2009) found that according to current biomass harvesting standards, long-term site productivity is not impacted if widely accepted best management practices are followed. However, relatively high removal of treatment residues, 20 tons ac$^{-1}$ or more off productive sites, would result in nitrogen deficiencies over the course of the next rotation. This metric
can vary drastically from site to site prohibiting the extraction of residues in certain situations and having no effect in others. iii) Residues that are considered operationally accessible and can be effectively accessed and handled by the equipment used for extraction on a given site are defined as “technically available” residues. This amount can vary according to terrain and other geographical features as well as the capabilities of the equipment used for extraction and the characteristics of the biomass itself. iv) Lastly, and possibly the most influential in terms of biomass supply chains, are “economically available” residues. Simply put, economically available residues are residues for which the delivered price for the material covers the extraction cost. Financial feasibility analyses regarding treatment residue supply are often designed to provide the quantity of residue that can be supplied at a given delivered price and the sensitivity of this amount to a range of delivered prices and an array of other variables, potentially including subsidies and other types of cost offsets like avoided disposal costs.

Although each of the aforementioned metrics of availability have been addressed by researchers in some manner, they are difficult to generalize and operationalize across dissimilar landscapes. Forest and site specific assessments are necessary to estimate how much of the total forest treatment residues are available as feedstocks for bioenergy production.

1.1.4 Supply Chain Development

Unlike some renewable energy technologies such as solar and wind energy, the conversion of biomass to energy does not happen passively once infrastructure is in place. Biomass must be located, collected, processed, and in most cases transported before conversion takes place. Arguably, the most prohibitive component in establishing a biomass supply chain is the development of a mechanism to bring enough low density plant material to
CHAPTER 1. GENERAL INTRODUCTION

a central point for conversion (Tallaksen, 2011).

A forest biomass energy system is unique in contrast to other, more mature energy resource industries that follow highly evolved, efficient strategies for minimizing costs associated with locating and delivering products. With the exception of dedicated biomass harvesting operations most often associated with plantations, forest biomass is generally a byproduct of other activities (such as timber harvest), and must be. In other words, often the location of residues and associated costs must be considered according to treatment distributions and activities related to objectives other than biomass supply. Careful planning and appropriate preparation are key elements when developing efficient forest biomass supply chains.

Abundant available residue is not enough justification for an efficient supply chain. Other considerations such as market demand for available and appropriate conversion technologies, competing resources and uses, public interest and perspectives, social, economic and environmental benefits and constraints all play a role in a well-developed supply chain. Assembling a system often requires collaborative research with emphasis in each component of supply to guide efficient, practical and environmentally sound decisions. Such decisions are made through a hierarchical framework where long-term objectives and the general direction of the supply chain are arranged prior to establishing medium-term assessments of the actual steps toward the strategic objectives. Finally short-term decisions are made day-by-day, second-by-second regarding the scheduling of transport, resource allocation and continuous analyses of supply chain efficiency. These decision scales are termed strategic, tactical and operational respectively.
1.2 The Issue of Forest Health

Aside from the widespread interest of society to increase the use of renewable energy sources and the numerous reported benefits of forest biomass utilization, the maturing markets for treatment residues as feedstocks for bioenergy production can be partially attributed to the simple philosophy of ‘use it or lose it’, in which these materials are often burned for disposal or burned in wildfires rather than used for a productive purpose. The anticipated accrual of biomass residues, and potential availability for bioenergy applications in coming years is essentially an issue of forest managers addressing the general decline of forest health as well as fuel loads accumulated over time as a result of fire suppression. A prime example is this case on the Uncompahgre Plateau National Forest (UPNF).

1.2.1 An Example from the UPNF

In recent years, forests and rangelands of the UPNF in southwestern Colorado have fallen subject to significant land management challenges. Increasing risks of fire, insect, and disease outbreaks have initiated concerns and investigations regarding forest health and long-term management of forest ecosystems. Many of the current forest types on the Plateau are outside of historic patterns of structure and composition which has subsequently increased the potential for high intensity wildfire and insect/disease outbreaks. These alterations are largely attributed to human and natural disturbances including logging, grazing, fire exclusion, insect and disease, wildfire, drought and climate change.

A comprehensive assessment carried out by the USDA Forest Service in 2006 found that i) The lack of fire disturbance due to suppression efforts over the past 100 years
has resulted in 71% of all woodland cover types having dense canopy closures with limited early seral conditions and has interrupted the frequent fire regime, resulting in significant amounts of fuel accretion in under-stories and denser stand conditions. 

ii) The ponderosa pine forest type has been impacted by past timber harvests, grazing and fire suppression increasing the susceptibility to uncharacteristic high intensity stand replacement wildfire, as demonstrated in 2002 when 13,000 acres of this forest type burned. 

iii) Current stand conditions in mixed conifer forests are primarily late-mid seral stages, which generally are prone to fire, insect and pathogen outbreaks. 

iv) Aspen stands throughout the UPNF have experienced significant mortality due to Sudden Aspen Decline (SAD) and there is an urgent need to stimulate new age classes through harvest and/or prescribe burning. 

v) A comparison of conditions between 1937 and 1994 indicates that pinyon-juniper has expanded into areas formerly dominated by shrublands and grasslands, and the density of pinyon-juniper stands has increased.

These changes have decreased the amount of available forage for both wildlife and domestic livestock and have resulted in loss of Gunnison sage-grouse (Centrocercus minimus [Young]) habitat. Historically, pinyon-juniper cover type had a patchy distribution of different aged stands. Currently, most (95%) of pinyon-juniper on the Plateau is in late seral conditions of continuous dense even-aged stands. Pinyon-juniper has also encroached into sagebrush stands due to fire suppression, and some areas of the Plateau have become dense stands of pinyon-juniper where sagebrush stands were historically located. Approximately 70% of the UPNF is in fire regime condition class 2 or 3 (Hardy and other 2001, Schmidt and others 2002). This classification suggests that these areas have potential to experience uncharacteristic high intensity fires. These fire disturbances are likely to alter the current mosaic landscape and produce permanent,
negative effects on soil and water quality and accelerate invasive species encroachment (USDA Forest Service 2006). The UPNF region of Colorado has one of the highest occurrences of wildland fires in the state, with fuel conditions that are conducive to dramatic fire disturbances.

There is broad agreement that active management is needed to restore these ecosystems, increasing their resiliency to future disturbances. This accord has initiated the Uncompahgre Plateau Collaborative Restoration Project (UPCRP). This collaborative project includes representatives from the Bureau of Land Management including the Uncompahgre and Grand Junction Field Offices; Colorado Division of Wildlife; the U.S. Forest Service Grand Mesa, Uncompahgre and Gunnison National Forests; Colorado Forest Restoration Institute; and Colorado State Forest Service. This project is engaged in 10 years of active management spanning 572,000 acres of national forest lands on a 1 million acre landscape. The proposed treatments include: pinyon-juniper mastication on 2,500 acres to create more natural patch mosaics and spatial heterogeneity, commercial and non-commercial mechanical treatments on 22,000 acres of ponderosa pine forests to reduce tree density and fuel load, 15,000 acres of tree density reduction in mixed conifer stand to reduce fuels and favor the perpetuation of aspen, 12,000 acres of harvest in disease damaged aspen stands to regenerate a new age class and 5,000 acres of harvest in spruce-fir stands to increase diversity in age, size and seral conditions and ameliorate wildfire spread and insect/pathogen outbreaks.

The mitigation of these threats coincides with restoration efforts to restore healthy ecosystems, reduce fire and pathogen risk, protect water and soil quality, and improve forest and rangeland resilience. Restoration efforts such as fuel reduction thinning, salvage/sanitation cuts and invasive species removal implemented over vast landscapes
can produce large quantities of woody biomass. This is especially true in areas where management is focused on degraded ecosystems that yield low value products in contrast to stands managed for timber production. Biomass yields can be used to generate heat and electricity to local communities near the UPNF, as well as produce liquid fuels and other chemical products using a wide range of conversion technologies. Also, revenues produced from these sales can help offset some of the treatment costs. Furthermore, substituting woody biomass for fossil fuels in energy production or co-firing the two can reduce greenhouse gas emissions, especially if residues are open burned for disposal (Jones et al., 2010; Loeffler and Anderson, 2013).

Bioenergy production using treatment residues from restoration activities can facilitate active management practices. Quantifying available and recoverable biomass can inform the location and type of operations used to treat forest stands. However, many factors that influence the economic feasibility and efficiency of bioenergy production at these scales are unknown, especially in Western regions with limited history in biomass utilization. Efforts to develop a comprehensive biomass flow model on the UPNF rest upon the ability to determine the availability and distribution of residues following various treatment configurations on a range of cover types throughout the landscape.

1.3 Objectives

The primary goal of this thesis was to develop a methodology using readily available and inexpensive data sources to estimate the quantity and spatial distribution of forest treatment residues available as feedstocks for bioenergy production. This research was designed to be directly coupled with existing harvest scheduling and transportation models to evaluate alternative management objectives and optimize the extraction and
flow of biomass subject to a range of environmental, social, and physical constraints. The first stage in addressing treatment residues involved segmentation of forests into operational and silvicultural scaled management units attributed with detailed stand descriptive characteristics. Based on the size, location, juxtaposition, and forest characteristics of these stands, silvicultural instruction and alternative management can be simulated and feedstock supply chains evaluated. This thesis addresses the following four objectives.

i) Develop an automated image segmentation algorithm that delineates realistic and spatially representative forest stands for landscapes of arbitrary size and accommodates region specific size constraints.

ii) Attribute forest stands with detailed stand-level descriptors using a forest characteristics model and validate the model with independent, ground-based inventory data.

iii) Use the outputs from the first two objectives to develop forest-wide silvicultural prescriptions catering to a range of management objectives.

iv) Simulate 10 years of management and estimate potential treatment residue quantities and spatial distribution following two alternative management scenarios at a range of delivered prices.

1.4 Outline

The following two chapters describe the development of the methodology used to fulfill the objectives of this thesis. Chapter 2 covers the stand delineation algorithm and the implementation and validation of the forest characteristics model. Chapter 3 demon-
strates the utility of the stand delineation and characteristics attribution in stand-level silvicultural modeling, simulating alternative management, and quantifying forest treatment residues at a range of delivered prices. The integration of chapters 2 and 3 presents a flexible and portable framework for estimating forest treatment residues. Chapter 4 provides a summary of the current state of biomass utilization, an overview of the components addressed by this thesis, and suggestions for future research in the field.
CHAPTER 2

Forest Stand Delineation and Inventory for Landscape-scale Treatment Residue Supply Models
CHAPTER 2. LANDSCAPE-SCALE FOREST STAND DELINEATION AND INVENTORY

ABSTRACT

... The forest stand and descriptive attributes are prerequisites to operational planning and the foundation on which silvicultural and operational decisions are made. To date, the most common method for obtaining stand boundaries and stand level attributes is manual interpretation of aerial photography combined with some degree of ground-based inventory. However, these classical methods may not be appropriate for use in treatment scheduling and supply applications employing broad landscapes of varying forest types and structural configurations. The proposed method integrates computer vision and remote sensing technologies to obtain realistic stand boundaries attributed with stand descriptive characteristics across landscapes of arbitrary size and locale using readily available and inexpensive data sources. A sub-space, multiscale image segmentation algorithm was developed to delineate forest stands with configurable minimum and maximum area constraints. These stands were then attributed with stand level descriptors using a forest characteristic model. The resulting stand boundaries were compliant with the minimum and maximum size of 5 and 100 ac respectively. The four primary species across the study area showed no significant differences between predicted and observed values for basal area and above ground biomass. This vector-based approach can be directly coupled with existing treatment scheduling and transportation models and presents the opportunity for detailed supply analysis across landscapes of any size.
2.1 Introduction

Forest inventory plays a major role in natural resource management. Although the scale and design for such inventories may differ, the prevailing motivation of inventory is to make informed decision about forest management (Scott and Gove, 2002). Large-scale inventories, such as nationwide mandated surveys are often used to evaluate trends in broad forested areas, make projections to assess sustainable management practices, and monitor responses to climate change. Conversely, silvicultural and operational decisions are based on stand level surveys bounded by a predefined geographic area. Depending on the size and variation of stands, stand level inventory by means of field survey can be very time consuming, expensive and sometimes infeasible to carry out across large landscapes.

Recently, methods have been developed to sufficiently estimate forest attributes using satellite and aerial imagery (Tuominen and Pekkarinen, 2005; McRoberts et al., 2002; Hall et al., 2006; Kim et al., 2009). Although these techniques demonstrate utility in estimating forest parameters previously obtained only through field measurement, their portability to dissimilar landscapes is limited by the intensity and design of ground-based inventory within the area of interest that is used in model development to predict attributes for all areas of the forest. In cases when the intensity of existing inventory data is not adequate, supplementary field collection is needed, which, as previously mentioned, can be time consuming and expensive. Moreover, the majority of work in the field is strictly pixel-based making it difficult to incorporate into harvesting and transportation scheduling applications without preexisting vector data defining stand or treatment unit boundaries.
In the past decade, the rise of object-based image analysis (OBIA) has provided the potential for remote sensing applications to be directly coupled with harvesting and transportation problems that employ spatially tabulated data sources. Previously, remote sensing outputs were converted to vectors by averaging the cells within homogeneous areas across the forest. However, obtaining the boundaries of these homogeneous areas was often problematic on large landscapes. Furthermore, OBIA has been proven the most appropriate remote sensing technique when employing high resolution imagery due to the increase in spatial resolution and spectral variability, or variation in pixel values, reducing the statistical separability between classes (Yu et al., 2006). OBIA methods have been implemented in many studies improving species classification accuracy over traditional pixel based methods (Hay et al., 2005; Chen et al., 2011; Chubey et al., 2006). However, previous OBIA studies with emphasis in forest management have yet to promote the use of image objects as stand boundaries (treatment units) while considering forest specific management objectives and harvesting regulations.

Harvest scheduling models have been used for over 40 years to help identify optimal or near-optimal solutions for the most profitable management alternative while addressing a variety of sustainability concerns (Toth and McDill, 2008). Stand boundaries and their attributes, such as size, location, volume, age and species are integral components in these models, but are often difficult to accurately estimate without ground-based observations. The objective of this study was to develop a portable methodology using readily available and inexpensive data sources to construct realistic, size restricted candidate treatment unit boundaries attributed with detailed stand characteristics for use in silvicultural and treatment scheduling models across landscapes of arbitrary size and location.
2.1.1 The Forest Stand

The forest stand is a prerequisite to operational planning and is the foundation on which silvicultural and operational decision are made. The most popular method for obtaining these boundaries is manual interpretation of aerial photographs combined with some level of field survey. Although photo interpretation for forestry purposes has been developed into a highly specialized brand of classic photogrammetry, results may vary drastically from one photo interpreter to the next. Discrepancies in the spatial alignment of stand boundaries delineated by different interpreters are intrinsic due to the subjectivity in the definition of a forest stand. According to the Dictionary of Forestry (SAF, 1998), a forest stand is defined as “A contiguous group of trees sufficiently uniform in age-class distribution, composition, structure, and growing on a site of sufficiently uniform quality, to be a distinguishable unit”. Although the phrasing of this definition allows for subjectivity in its interpretation, it provides a certain level of flexibility to account for the varying degree of local heterogeneity within a stand. Figure 2.1 illustrates two examples of forest stand delineation. The left image showing a less desirable approach of delineating a stand into a completely homogeneous unit and the right, a more desirable delineation ignoring subtle structural changes.

To date, manual stand delineation is still appropriate in many forestry applications on a local scale. However, this may not be a practicable approach across broad areas. For example, a 500,000 ac landscape with a desired average unit size of 50 ac would require approximately 10,000 stands boundaries to be manually delineated. Fortunately, advancements in the field of computer vision has resulted in numerous efficient image segmentation algorithms to automatically extract objects from images.
2.1.2 Image Segmentation Software

Over the past 40 years, over one thousand image segmentation techniques have been developed (Zhang, 2006). Demand for these algorithms has resulted in the distribution of many commercial softwares used by researchers and industry. The workhorse for image segmentation in environmental studies dealing with remotely sensed data has been Definiens software package eCognition (Flanders et al., 2003; U.C. Benz et al., 2004). Other popular software developments include Feature Analyst (Opitz and Blundell, 2008), SAGA (Bohner et al., 2006), Erdas Imagine 9.3 and ENVI Feature Extraction (Holbling and Neubert, 2008).

Although a significant number of applications, more than 800 articles (Blaschke, 2010), have employed the Definiens software and others alike, open-source distributions provide opportunities for complete programmable flexibility and parameterization of these algorithms. A plethora of open-source repositories with emphasis in image pro-
cessing and segmentation are readily available through the GNU General Public License allowing users to copy, distribute and/or modify the source code. This is advantageous from both an implementation and economic perspective due to restrictive licensing issues and the sometimes high price of specialized commercial software.

A generalized methodology tailored to forest management applications for obtaining size constrained treatment unit boundaries and stand-level attributes is needed to increase the resolution and confidence of decisions made throughout the logistical spectrum from strategic to operational scales. This work introduces a methodology designed to be flexible and configurable, accommodating forest specific management while providing transferability across landscapes.

2.2 Study Area

The Uncompahgre Plateau National Forest covers approximately 550,000 ac on the west slope of the Colorado Rocky Mountains. Stretching northwest to southeast for 125 miles, the plateau ranges in elevation from 5,800-6,000 feet in canyon bottoms to upland elevations around 8,000-10,000 feet. Across the range of elevation, four primary vegetation strata occupy the plateau. Pinyon-juniper (*Pinus edulis* [Engelm.]; *Juniperus osteosperma* [Torr.; *Juniperus scopulorum* [Sarg.]) cover occurs at the lower elevations ranging from 6,000 to 7,000 feet, Gamble oak and Ponderosa pine (*Quercus gambelii* [Nutt.]; *Pinus ponderosa* [Lawson & C. Lawson]) forests inhabit elevations from 7,200 to 8,800 feet and the upland zone is dominated by aspen (*Populus tremuloides* [Michx.]) and spruce-fir (*Picea engelmannii* [Parry ex Engelm.]; *Abies lasiocarpa* [Nutt.]) forests.

Approximately 70% of the UPNF is in fire regime condition class 2 or 3 (Schmidt et al., 2002; Hardy et al., 2001), suggesting that these areas exhibit fuel conditions
that are conducive to uncharacteristic, high intensity fires. The potential for these disturbance events have initiated active restoration management across the plateau to reduce fuel loading in mixed-conifer and Ponderosa pine, increase diversity in age, size and seral conditions in spruce-fir, regenerate damaged aspen stands from sudden aspen decline and mitigate pinyon-juniper encroachment into native grasslands and sagebrush ecosystems.

Figure 2.2: Study area: The Uncompahgre Plateau National Forest located in southwest Colorado.
2.3 Imagery

National Agricultural Imagery Program (NAIP) imagery was chosen as the remote sensing data source for this study. NAIP, of the United States Department of Agriculture (USDA), acquires aerial digital orthophotos during the agricultural growing seasons and the imagery is available to governmental agencies and the public within a year of acquisition. The imagery has a 1 meter ground sample distance (1 meter resolution) with a horizontal accuracy of within 6 meters at a 95% confidence level (USDA-FSA-APFO, 2011). The default spectral resolution is natural color (RGB) with a "buy-up" option to include the near infrared band. The configuration used in this study was a 3 band composite including near infrared, green and blue bands (Color-infrared).

2.4 Methods

2.4.1 Stand Delineation

An automated segmentation algorithm was developed in this study to delineate forest stands. This is an iterative process where segmentation is performed initially at a relatively coarse resolution and the resulting segments are used to subset the image and further decompose the image at progressively finer scales to meet a given range of typical treatment unit sizes. During each sub-space process, there are two primary steps in segmentation: image filtering and mean shift segmentation. These two processes are described in detail in the following two sections prior to describing their integration in the stand delineation algorithm.
CHAPTER 2. LANDSCAPE-SCALE FOREST STAND DELINEATION AND INVENTORY

Image Filtering

Prior to segmentation, the image is preprocessed by using two filtering routines to reduce the degree of local spectral variation prevalent in high resolution imagery. Preprocessing is a necessary step in the segmentation framework, notably when the objective of segmentation is to yield smooth, compact delineations ignoring local spectral heterogeneity. The image is first passed by a 1-dimensional implementation of the Gaussian filter. The filter takes the form:

\[ G(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2}{2\sigma^2}} \tag{2.1} \]

where \( x \) is the distance from the origin (spatial radius) and \( \sigma \) is the standard deviation of the Gaussian distribution. A spatial radius of one meter was used for this filter to blur canopy shadows and non-distinct edges while preserving abrupt changes in vegetation and edges between forest and field. Figure 2.3 shows the results of the Gaussian filter.

![Figure 2.3: Gaussian filtering: Before (left) and after (right) filtering](image)

Following the Gaussian filter, an anisotropic diffusion filter is used to further blur
the image while preserving prominent edges not weakened by the Gaussian filter.

Anisotropic diffusion, introduced by Perona and Malik (1990), is a non-linear partial differential equation-based diffusion process. Anisotropic diffusion can successfully smooth noise while respecting region boundaries between homogeneous regions within the image (Tsiotsios and Petrou, 2012). The basic equation takes the form:

$$\frac{\partial I(x, y, t)}{\partial t} = \text{div}[g(||\nabla I(x, y, t)||)\nabla I(x, y, t)]$$  \hspace{1cm} (2.2)

where $I(x, y, 0)$ is the image, $\nabla I(\cdot)$ defines the gradient of the version of the image at time $t$, and the conductance function, $g(\cdot)$, which is chosen to satisfy $\lim_{x \to 0} g(x) = 1$, maximizing diffusion within homogeneous regions, and $\lim_{x \to \infty} g(x) = 0$, stopping diffusion across edges in the image.

The process takes two parameters: a time-step involved in solving the partial differential equation and the number of iterations or passes of the filter. Guidelines suggested by Tsiotsios and Petrou (2012) for choosing these parameters were followed and further
investigation was carried out to tailor parameterization for forest stand delineation. Parameters selected were 0.125 for the time-step with 50 iterations. These values had the most satisfactory results in diffusing local spectral differences while preserving obtrusive changes in vegetation. Figure 2.4 shows the results of the anisotropic diffusion filter.

Mean Shift Segmentation

Following the filtering process, the image is segmented by the mean shift algorithm introduced by Fukunaga and Hostetler (1975). Mean shift is a non-parametric feature space analysis, also known as a mode-seeking algorithm (Yizong, 1995). After mapping pixels within the image into feature space, the mean shift procedure begins by defining a window around each data point, $x_i \ldots x_n$, in a given dataset. The radius of the window is denoted by $h$ in equation 2.3. Within the neighborhood of points the probability density $f$ is estimated using a kernel density estimator

$$
\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)
$$

where $nh$ is the number of points within the radius $h$ and $K(\cdot)$ is an Epanechnikov kernel defined as $\frac{3}{4}(1 - u^2)1_{(|u| \leq 1)}$ where $u = (x - x_i)/h$ (Epanechnikov, 1969). Next, the gradient ascent of the estimated probability density is computed by

$$
\nabla \hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K'(\frac{x - x_i}{h})
$$

The gradient ascent calculates the direction of the steepest ascent to the area within the window with the highest density. Setting this to zero, we locate the peak, or maxima, of the estimated density function $f$. Assuming $g(x) = -K'(x)$, the mean shift for each
data point \( x_i \) is defined as

\[
m(x) = \frac{\sum_{i=1}^{n} g(\frac{x-x_i}{h})x_i}{\sum_{i=1}^{n} g(\frac{x-x_i}{h})} - x
\]

(2.5)

where \( m(x) \) is the quantity of the mean shift. This value denotes the next location where the procedure is repeated. In summary, for each data point \( x_i \) the mean shift procedure first estimates the probability density of the data within radius \( h \) of \( x_i \), computes the mean shift vector \( m(x) \), moves the density estimation window by \( m(x) \), and repeats till convergence. Convergence is considered to be where the density estimation window becomes stationary and all points associated with the same stationary location belong to the same mode or cluster.

The mean shift process commonly takes three parameters. A spatial radius, \( h \), defining the radius of the kernel density estimator, a mode convergence threshold to terminate the iterative scheme when the distance between \( x_i \) and \(-K'(x)\) is less than or equal to this value and a maximum number of iterations to terminate the iterative scheme if convergence hasn’t been reached. When employing the mean shift algorithm on color images a forth parameter, spectral radius, is used to merge adjacent modes, or clusters, whose spectral value is within this threshold. The parameters used for this study were: spatial radius = 10, spectral radius = 5, mode convergence threshold = 0.1 and the maximum number of iteration = 100 (parameters are unitless because the procedure takes place in feature space). These parameters were selected according to guidance in Comaniciu and Meer (2002) and further tailored for forest stand segmentation. Figures 2.5 and 2.6 are visual examples of the mean shift procedure. The dataset in the figures represent two local maxima or modes. The blue and red circles denote the spatial radius \( h \) defined around two randomly drawn data points associated
with different modes. The green line illustrates the mean shift vector $m(x)$. The blue and red dots represent the stationary points where the respective data points converge. See **Figure 12** in Appendix for an animated example of the mean shift algorithm.

Figure 2.5: Example of the mean shift algorithm on two data points belonging to different local maxima. The green line denotes the mean shift vector.
Figure 2.6: Result of mean shift segmentation from data in Figure 2.5. The color of the points represent which local maxima they are associated with.

**Stand Delineation Algorithm**

The mean shift algorithm is a non-parametric technique and does not assume an empirical function describing the probability distribution of the underlying data. This characteristic of the algorithm limits processing to datasets that can be reserved in random access memory (RAM). To circumvent RAM saturation, researchers at the French Space Agency (CNES: National Centre for Space Studies) have developed a methodology for segmenting infinitely large images by implementing a tile-based approach. The size of tiles are calculated according to available memory and the image within each tile is independently segmented, storing a vectorized output for each tile in
a global database. However, this tile-based approach inevitably leads to tile boundary artifacts where objects spanning tile borders are processed independently and potentially converge with local maxima of other features.

Another commonly used method is spatial resampling: the cell size is increased, resulting in smaller data that can be stored for processing. Multi-scale segmentation methods use resampling and hierarchy theory to extract varying sized, shaped and spatially distributed objects that appear at different scales (Dinis et al., 2010). However, very large images require significant rescaling and the finest manageable resolution in a multi-scale framework may be too coarse to extract objects defining forest stand delineations and result in under-segmentation.

The algorithm developed in this study takes advantage of the previous approaches without producing tile boundary artifacts or under-segmenting the image. The algorithm is an iterative subspace, multi-scale segmentation process where objects created at large extents are used to subset the data for segmentation at progressively smaller scales (Figures 2.7 and 2.8). To circumvent significant resampling of very large images the algorithm uses USGS hydrologic unit 12 sub-watershed boundaries as initial subspace geometries. New geometries created by the segmentation process within each sub-watershed are stored in a vector database and used to subset the image in the next iteration. As objects become smaller, finer resolutions are used for segmentation, locating features that may not be visible at coarse scales. The algorithm can also be parameterized to comply with minimum and maximum treatment unit area. In this study, the minimum and maximum treatment unit sizes were 5 and 100 ac respectively.

The algorithm begins by querying geometry i from database j. If geometry i is less than the maximum specified treatment unit size and greater than the minimum specified
treatment unit size then the geometry is not segmented further. It is appended to vector
database \( j + 1 \) and the algorithm moves to the next geometry \( i + 1 \). If the geometry
is less than the minimum specified treatment unit size then adjacent geometries are
located and geometry \( i \) is merged with the candidate adjacent geometry most alike in
terms of the average spectral value. If geometry \( i \) is greater than the maximum specified
treatment unit size then the imagery within the geometry is extracted for segmentation.

The next step tests if the extracted image results in memory saturation. If the image
is too large, it is resampled by continuously decreasing the resolution (i.e. 1m, 2m, 4m,
8m, 16m, etc.) until the image can be stored in RAM. Once the image is of sufficient
resolution the image is filtered by one pass of a Gaussian filter with a spatial radius of
1 and 50 iterations of the anisotropic diffusion filter with a time step of 0.125. Next
the mean shift algorithm segments the image, grouping cells to their associated local
maxima and labelling groups sequentially. The resulting labeled raster is vectorized
and appended to database \( j + 1 \).

In some cases the new geometry \( i \) in database \( j + n \) could match geometry \( i \) in
database \( j + (n - 1) \) if the chosen resolution for segmentation is the same resolution at
which geometry \( i \) in database \( j + (n - 1) \) was processed. If this occurs the spectral
radius parameter of the mean shift algorithm is reduced by one until new geometries
are created. Reducing this parameter allows the mean shift segmentation to produce
more geometries with similar spectral values opposed to merging these modes as one
cluster. When new geometries are created, they are appended to vector database \( j + 1 \).

Once all geometries in database \( j \) have been processed the algorithm iterates through
the geometries in database \( j + 1 \). When all the geometries in database \( j + n \) meet the
minimum and maximum unit size criteria the final vector database is rasterized to a 1 meter resolution and the dataset is smoothed by one pass of a majority filter. The majority filter is a moving window analysis where the center cell in the window is replaced by the mode of the values within the window each time the window is shifted. Next the smoothed raster is vectorized and the process is terminated. Figure 2.7 illustrates this process. The hierarchy of spatial vector data is used in the flowchart where 'layer' describes the database where geometries or 'features' are stored. Figure 2.8 shows a visual example of the segmentation process on a sub-set of the study area.
Figure 2.7: Flowchart of the stand delineation algorithm developed in this study.
Figure 2.8: Visual example of the stand delineation algorithm
2.4.2 Qualitative Assessment of Stand Boundaries

The stand boundary outputs were assessed for their quality pertaining to two geometric measures: compactness and smoothness. Compactness is a proportional metric between the area of a feature and the area of a circle having the same perimeter of said feature. Compactness was determined an important measure for forest stands due to operational inefficiencies in elongated (non-compact) areas where the area to perimeter ratio is low. Equation 2.6 was used to calculate the average compactness value for all stand boundary outputs.

\[
\frac{1}{N} \sum_{i=1}^{N} \frac{A_i}{\pi \left(\frac{P_i}{\pi}\right)^2}
\]

Equation 2.6

Where \( N \) is the number of units, \( A_i \) is equal to the area of \( N_i \) and \( P_i \) is the perimeter of \( N_i \).

Figure 2.9 illustrates two examples of stand boundaries with low and high compactness values where the example on the right has a higher compactness value. A shape with a compactness value of 1 would be a perfect circle.
The second measure, smoothness, evaluates how jagged or smooth the boundaries are. This metric, like compactness, is a proportional measure between shared elements of the feature of interest and a perfect circle. The smoothness measure calculates the proportion between the perimeter of a feature and the perimeter of a circle with an area equal to that of the feature (Figure 2.10). Cell tracing boundaries are an artifact of the segmentation algorithm and the smoothing process removes a large amount of jagged edges yielding a more representative, natural boundary for stands. However, the smoothing process is a majority filter and there is a positive relationship between window size and execution time. This metric provided a method in which an optimal smoothing window size could be selected in lieu of choosing an arbitrary window size that may increase processing time and not provide an added benefit of smoothness. Equation 2.7 was used to compute the mean smoothness value for delineated stands.
\[ \frac{1}{N} \sum_{i=1}^{N} \frac{2\pi \left( \sqrt{\frac{A_i}{\pi}} \right)}{P_i} \]  

(2.7)

Where \( N \) is the number of units, \( A_i \) is equal to the area of \( N_i \) and \( P_i \) is the perimeter of \( N_i \).

The smoothing process was performed on several iterations of the stand outputs at progressively increasing window sizes. The average smoothness value was calculated for each window configuration of the smoothing process. The optimal window size was determined by locating where the smoothness values stabilized. (Figure 2.11)

2.4.3 Forest Characteristics

Forest characteristics such as basal area, trees density, and above ground biomass were estimated for each forest stand using the Forest Characteristics Model (FCM) developed by Hogland et al. (2012). The FCM is a two-tiered remote sensing model where the first stage uses a number of image processing techniques, polytomous logistic regression, and
Figure 2.11: Global smoothness values at increasing window sizes. A 25x25 window size was selected for the smoothing process.
first and second order texture measures to calculate the probability that a given pixel in the NAIP imagery represents an identifiable class (e.g., tree canopy, shadow, grass, or water). This creates a set of probabilistic surfaces that are used as inputs in the second stage where forest characteristics by species were estimated using multivariate regression. Response variables in the models include summarized Forest Inventory Analysis (FIA) plot data and independent variables consist of a series of first and second order texture metrics performed on the stage 1 probabilistic outputs and values from a principle components analysis. Outputs from the model were stored as multiband raster datasets.

Output rasters from the FCM were averaged for the spatial domain of each forest stand providing stand level characteristics by species tabulated in a spatially indexed database. Quadratic mean diameter was also attributed to each stand by $\sqrt{\frac{BA}{kn}}$ where $BA$ is basal area, $k$ is tree density, and $n = 0.005454$.

### 2.4.4 Model Validation

The FCM was developed by USDA Forest Service collaborators at the Rocky Mountain Research Station - Human Dimensions Program for use in biomass utilization projects on the UPNF. Although the methodology was designed to be portable and provide utility in dissimilar landscapes it is currently in the final stages of development and has not been thoroughly tested. To evaluate the accuracy of the model, the following validation steps were carried out in the summer of 2012.

#### Sample size and location

A type-III F-test power analysis assuming 7 predictor variables was used to determine the number of samples needed to achieve a $r^2$ ranging from 0.1 to 0.9 at a 0.05 signifi-
cance level (Table 2.1, Copyright © 2012 SAS Institute Inc.). A total of 100 samples was determined to be an appropriate sample size.

<table>
<thead>
<tr>
<th>$r^2$</th>
<th>Actual Power</th>
<th>N Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.901</td>
<td>176</td>
</tr>
<tr>
<td>0.2</td>
<td>0.900</td>
<td>84</td>
</tr>
<tr>
<td>0.3</td>
<td>0.904</td>
<td>54</td>
</tr>
<tr>
<td>0.4</td>
<td>0.909</td>
<td>39</td>
</tr>
<tr>
<td>0.5</td>
<td>0.901</td>
<td>29</td>
</tr>
<tr>
<td>0.6</td>
<td>0.905</td>
<td>23</td>
</tr>
<tr>
<td>0.7</td>
<td>0.920</td>
<td>19</td>
</tr>
<tr>
<td>0.8</td>
<td>0.906</td>
<td>15</td>
</tr>
<tr>
<td>0.9</td>
<td>0.956</td>
<td>13</td>
</tr>
</tbody>
</table>

These samples were equally allocated to 20 strata derived from an iterative self-organizing (ISO) clustering routine performed on the native NAIP-CIR imagery. The ISO clustering routine groups pixels whose spectral signatures are statistically similar providing a spectral stratification of the study area to allocate sample plots. Next, a 50 meter buffer was placed around all roads currently navigable by 4-wheel drive vehicles to restrict plots from being located in areas where roads might have altered forest conditions. Relatively high sample intensity and limited time motivated further sample location restriction to a 500 meter buffer placed around the 50 meter road buffer. Thus, all candidate sample locations were at least 50 meters away from forest roads and no further than 550 meters. This minimized commute between plots and maximized time available for a spatially distributed sample of the area. Finally, the sample selection area was clipped to private parcels insuring all plot locations were selected on publicly accessible lands and a stratified random sample of 100 sample units were selected from the ISO clustering dataset allocating 5 samples to each of the 20 spectral classes (Figure 2.12).
Figure 2.12: Validation plot locations across the study area.
Field Protocol

The field collection methods mimicked the phase 2 FIA protocol (U.S. Department of Agriculture, 2005). Plots were located using a handheld Garmin GPS 60. After navigating to the plot center, the GPS was placed on the ground at plot center to strengthen satellite reception. After the data was collected, the coordinates from the GPS were recorded onto the datasheet for that plot. Each sample location represented the spatial centroid (subplot 1) of the FIA subplot arrangement (Figure 2.13). Subplots 2, 3 and 4 are positioned 120 feet from subplot 1 at 0°, 120° and 240° azimuths, respectively. Within each subplot a 24 foot radius was defined and all trees greater than or equal to 5 inches in dbh or drc (diameter at root collar for woodland species [pinyon-juniper]) were tallied as well as their species and diameter. A site description including slope, aspect, ground cover and a general stand characteristics were recorded for each plot.
Figure 2.13: FIA subplot layout for phase 2 tree data inventory. The blue dashed line shows the radius of the spatial footprint of the plot layout and the red dashed line is equal to the radius of the buffer to account for rectification errors in the imagery and proximity errors in the GPS.

Statistical Analysis

After field data collection, the data was summarized to provide basal area, tree density, and above ground biomass (Jenkins et al., 2003) estimations for each plot by species. A buffer was created around the spatial footprint of the FIA plot to account for rec-
CHAPTER 2. LANDSCAPE-SCALE FOREST STAND DELINEATION AND INVENTORY

tification errors in the imagery and proximity errors in the GPS and the independent
variables for the forest characteristics model were created for the buffered spatial foot-
print of a FIA plot at each sampled location. The regression equations were used to
predict basal area, tree density and above ground biomass. A paired t-test was per-
formed on the predicted and observed data to test for significant differences.

2.5 Results and Discussion

2.5.1 Qualitative Assessment of Stand Boundaries

Stand boundaries were assessed qualitatively by visual evaluation, compliance with the
size restrictions, and the overall compactness value. The visual assessment consisted
of scanning all stand boundaries superimposed on the NAIP imagery and checking for
delineations that did not line up with vegetation changes in the imagery. The place-
ment of the boundaries were satisfying, segregating extreme differences in vegetation
while ignoring subtle textural and spectral variations. Manual alterations to any of the
boundaries were not necessary. Figure 2.14 shows a subset of the study area with the
outputs from the stand delineation algorithm.

Few boundaries separated very homogeneous areas, most likely due to the maximum
stand area restriction and the computers ability to statistically discriminate areas that
are not distinguishable by the human eye. The average size of the delineated stands was
35.99 ac. All stands met the minimum and maximum size restrictions with a minimum
size of 7.29 ac and a maximum of 98.78 ac (Table 2.2). The average shape compactness
value was 0.49 with a maximum value of 0.89 and a minimum of 0.11 (Figure 2.15).
The majority of shape compactness values less than 0.2 were a result of the segmentation
algorithm following roads and streams yielding elongated shapes with poor compactness
values. Buffering roads and streams prior to implementing segmentation would likely resolve this issue and subsequently increase the average compactness value.

Figure 2.14: Subset of the study area. NAIP imagery superimposed with outputs from the stand delineation algorithm.

Table 2.2: Treatment unit size and compactness value distributions

<table>
<thead>
<tr>
<th>Measure</th>
<th>N Units</th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (acres)</td>
<td>25,538</td>
<td>98.78</td>
<td>7.29</td>
<td>35.99</td>
<td>21.767</td>
</tr>
<tr>
<td>Compactness</td>
<td>25,538</td>
<td>0.89</td>
<td>0.11</td>
<td>0.49</td>
<td>0.14</td>
</tr>
</tbody>
</table>
2.5.2 Forest Characteristics

Using the stand level averages from the FCM, stands were characterized into forest types. Pure stands were classified by having a basal area weighted composition of at least 80% in a single species (NCDFR, 2009). Forest types described by two species were classified by having an additive composition of at least 80% in two species with no one species greater than 80%. Mixed-conifer stands were classified by a joint composition of 80% in spruce, fir, and aspen. The ‘other’ category describes scrub-oak, mountain mahogany, and/or stands with minimal contribution of the five primary species. Summarized outputs from the forest characteristics model are shown in Table 2.3.

Figure 2.16 shows the distribution of cover types across the UPNF. Cover types including scrub-oak, mountain mahogany, and other species cover 25.5% of the plateau. Mixed-conifer had the second highest coverage of 22.4%. Pinyon-Juniper occupies 12.8% of the plateau inhabiting the lower elevations on the east and west extents. Pure aspen stands occur on the higher elevations covering approximately 8.5% of the plateau. Ponderosa pine, spruce-fir, and other mixed-species (pine-juniper, aspen-pine) stands cover
the remaining of the forested area and non-forested areas account for approximately 8% of the landscape.

Table 2.3: Summary of forest characteristics by forest type. Values for basal area, density, and above ground biomass represent the mean with standard deviation in parentheses.

<table>
<thead>
<tr>
<th>Forest Type</th>
<th># of stands</th>
<th>Acres</th>
<th>BAA(\text{std}) ft$^2$/ac</th>
<th>TPA(\text{std}) stems ac$^{-1}$</th>
<th>QMD(\text{std}) inches</th>
<th>AGB(\text{std}) tons ac$^{-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspen</td>
<td>2,123</td>
<td>49,090</td>
<td>100(42.8)</td>
<td>180(77.97)</td>
<td>10(0.29)</td>
<td>54(23.33)</td>
</tr>
<tr>
<td>Aspen-Pine</td>
<td>3,015</td>
<td>66,352</td>
<td>73(28.1)</td>
<td>112(50.57)</td>
<td>11(0.69)</td>
<td>39(15.61)</td>
</tr>
<tr>
<td>Pin-Jun</td>
<td>3,266</td>
<td>74,431</td>
<td>64(27.74)</td>
<td>58(27.72)</td>
<td>14(1.36)</td>
<td>17(6.89)</td>
</tr>
<tr>
<td>Juniper-Pine</td>
<td>950</td>
<td>21,667</td>
<td>46(16.49)</td>
<td>45(19.89)</td>
<td>14(1.5)</td>
<td>17(6.16)</td>
</tr>
<tr>
<td>Mixed-Conifer</td>
<td>5,385</td>
<td>130,266</td>
<td>111(46.55)</td>
<td>206(85.03)</td>
<td>10(0.35)</td>
<td>59(24.94)</td>
</tr>
<tr>
<td>Pine</td>
<td>1,033</td>
<td>20,609</td>
<td>41(12.43)</td>
<td>44(18.53)</td>
<td>13(1.55)</td>
<td>21(7.41)</td>
</tr>
<tr>
<td>Spruce-Fir</td>
<td>1,060</td>
<td>22,410</td>
<td>117(53.47)</td>
<td>217(95.01)</td>
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</tr>
<tr>
<td>Other</td>
<td>6,764</td>
<td>148,175</td>
<td>79(38.15)</td>
<td>129(71.55)</td>
<td>11(0.94)</td>
<td>34(20.80)</td>
</tr>
<tr>
<td>Non-Forested</td>
<td>1,943</td>
<td>47,301</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

2.5.3 Model Validation

Field observed values versus predicted values from the FCM are shown in Figure 2.17. Scatter plots represent cross species sums for the three predicted parameters and bar plots show predicted and observed values broken out by species subtotals across all 100 validation plots. Plotting the predicted and observed values for the cross species sums on a 1:1 scale shows a general linear trend. Of the 100 validation plots, eight were in non-forested areas and overestimation occurred in all models where observed values were zero (non-forested). Although these areas are non-forested, there may be a substantial degree of contrast represented in the imagery from low cover vegetation such as sage brush. The texture related variables in the models may recognize non-forested areas as forested and subsequently overestimate the parameters. Overestimation also occurred in all forested plots that had observed values less than 60 ft$^2$/ac. Overestimations in the cross species sums for basal area can largely be credited to overestimations in
Figure 2.16: Mapped forest types across the study area. Zoomed areas show stand boundaries.
Figure 2.17: Predicted vs. Observed: Scatter plots represent summed values across all species for the three predicted and observed parameters at 100 sampled locations. Barplots show per species comparisons for the three parameters.
pinyon and juniper cover types. Conversely, underestimation occurred when observed values were relatively high. This was due to the increasing spectral homogeneity in the imagery when stem density was extremely high: as density increases, especially in aspen stands where tree heights are often very homogeneous, canopies become less differentiable (less shadow). In some cases this is problematic when predicting forest characteristics with texture based analysis.

Paired t-test results between the observed and predicted values (Table 2.4) showed significant differences in three cover types, pinyon, juniper, and scrub-oak for basal area and above ground biomass. Treatments in pinyon-juniper woodland often do not play a role in forest residue utilization since treatments commonly involve mastication and the dispersion of residues. Furthermore, shrub-oak stands are not a primary concern in restoration management on the UPNF and in most case do not coexists with other species where restoration treatments take place. According to the t-test for basal area and above ground biomass in the other four species (aspen, fir, spruce, and pine) there was not enough evidence to discount the possibility that the predicted and observed values coincide. However, due to an insufficient amount of data collected in pine, it is difficult to conclude that there is a high probability of zero difference between predicted and observed even though the test results suggest otherwise. The strongest correspondence in both basal area and above ground biomass occurred in fir and, in part, may be attributable to a large sample and low variability in the cover type. T-test results for tree density showed significant differences between predicted and observed values in all species except for fir and juniper. The largest discrepancies were overestimations in aspen and spruce with difference of 22.76 and 18.1 trees ac\(^{-1}\), respectively. There were numerous observations of recent mortality in aspen and spruce during the valida-
CHAPTER 2. LANDSCAPE-SCALE FOREST STAND DELINEATION AND INVENTORY

tion inventory in the summer of 2012. Since the FCM is based on imagery from 2009, mortality may explain these differences. Overall, the t-test shows satisfying results in basal area and above ground biomass for the primary species across the UPNF. However, results for tree density warrant further investigation in the independent variables selected in the final models for all species.

Table 2.4: Paired t-test between observed and predicted values for each modeled parameter by species; $n = 100$.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>species</th>
<th>t-stat</th>
<th>difference</th>
<th>p-value</th>
<th>sig.(^a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAA</td>
<td>Aspen</td>
<td>1.29</td>
<td>2.69</td>
<td>0.1973</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fir</td>
<td>0.11</td>
<td>0.27</td>
<td>0.9091</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spruce</td>
<td>0.94</td>
<td>3.10</td>
<td>0.3503</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Juniper</td>
<td>2.27</td>
<td>4.42</td>
<td>0.0254</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Pinyon</td>
<td>3.46</td>
<td>5.33</td>
<td>0.0008</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Pine</td>
<td>0.70</td>
<td>-2.27</td>
<td>0.4829</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Scruboak</td>
<td>2.12</td>
<td>2.36</td>
<td>0.03543</td>
<td>*</td>
</tr>
<tr>
<td>TPA</td>
<td>Aspen</td>
<td>3.61</td>
<td>22.76</td>
<td>0.0004</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Fir</td>
<td>0.66</td>
<td>2.55</td>
<td>0.5135</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spruce</td>
<td>4.31</td>
<td>18.1</td>
<td>3.79e-05*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Juniper</td>
<td>0.38</td>
<td>6.59</td>
<td>0.7036</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pinyon</td>
<td>-2.67</td>
<td>-6.62</td>
<td>0.009</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Pine</td>
<td>-2.14</td>
<td>-5.61</td>
<td>0.0348</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Scruboak</td>
<td>3.13</td>
<td>14.3</td>
<td>0.0023</td>
<td>*</td>
</tr>
<tr>
<td>AGB</td>
<td>Aspen</td>
<td>1.29</td>
<td>2.69</td>
<td>0.1973</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fir</td>
<td>-0.02</td>
<td>-0.03</td>
<td>0.9849</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spruce</td>
<td>0.52</td>
<td>0.95</td>
<td>0.6059</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Juniper</td>
<td>2.02</td>
<td>0.79</td>
<td>0.0457</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Pinyon</td>
<td>3.84</td>
<td>1.29</td>
<td>0.0002</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>Pine</td>
<td>-0.17</td>
<td>-0.32</td>
<td>0.8621</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Scruboak</td>
<td>2.29</td>
<td>0.69</td>
<td>0.02419</td>
<td>*</td>
</tr>
</tbody>
</table>

\(^a\)Asterisk denotes significant difference between observed and predicted values at $\alpha = 0.05$
2.6 Conclusion

The present research was designed to provide detailed and accurate inputs for high resolution treatment scheduling and biomass supply modeling over large areas using readily available and inexpensive data sources. The stand delineation algorithm is an efficient and flexible approach to acquire spatially representative, size restricted stand boundaries to accommodate a range of management objectives across landscapes of arbitrary size. In situations where roads, streams, utility corridors, and other man-made features are prevalent in the imagery, preprocessing may be necessary to restrict segmentation from these areas. Although the algorithm outputs were satisfactory for the study area, it has not been tested on other landscapes. Parameterization of the image filtering steps and the mean-shift procedure may be necessary if the algorithm is implemented in other areas dissimilar in vegetation and landform. However, the algorithm is easily configurable and the input data sources can be obtained for any landscape within the continental United States.

Outputs from the FCM provided detailed stand-level descriptions that can be used throughout the hierarchy of forest planning logistics at strategic, tactical, and operational scales. These outputs, integrated with forest specific management objectives can be used to develop silvicultural prescriptions, evaluate alternative management, and/or prioritize extraction efforts of treatment residues for bioenergy production and other bio-based products. The FCM successfully predicts basal area and above ground biomass in all species except for pinyon, juniper, and scrub-oak. Predictions for tree density were not as satisfactory and may require further investigation. As the FCM and SDA methodologies develop and are implemented on other landscapes, further calibra-
tion and validation will be needed. The validation method used in the study was plot based: predictions and observations were linked at very small scales. Other validation methods such as assessments at the stand-level may be more appropriate for capturing spatial inaccuracies in the GPS and rectification errors in the imagery.

The integration of object-based and pixel-based image analysis used in this study provides direct coupling with treatment scheduling and forest management planning models which rely on vector and/or spatially tabulated data sources. One of the advantages of the developed methodology is that inputs (i.e. NAIP imagery and FIA data) can be acquired for any area within the continental U.S.
CHAPTER 3

Landscape-scale Estimation of Forest Treatment Residues
Available for Bioenergy Production
ABSTRACT

Growing interests in the utilization of biomass has initiated interests in expanding the use of forest treatment residues as feedstocks for energy production. The establishment of new biomass supply chains rests upon the availability of the resource and the degree of demand. In areas with limited history of industrial biomass utilization, uncertainties in key components of the biomass supply chain, such as the quantity, distribution, and financial feasibility of the market may prohibit the development of bioenergy production. The methodology presented here integrates remote sensing technologies using inexpensive and readily available data sources to spatially map treatment residue quantities following alternative management scenarios. Using National Agricultural Imagery Program (NAIP) imagery, the forest is segmented into treatment units based on user defined area constraints. Using a remote sensing model based on NAIP imagery and FIA plot data, these units are attributed with stand-level descriptions of basal area, tree density, above ground biomass, and quadratic mean diameter. The outputs were used to developed silvicultural prescriptions and estimate available treatment residues following two alternative management scenarios at a range of delivered prices per bone dried ton (bdt) to a nearby bioenergy facility in southwestern Colorado. The breakeven delivered price of treatment residues in this study was $48.94 bdt\textsuperscript{−1} yielding 167,685 bdt following a 10 year management simulation with a 5,000 ac yr\textsuperscript{−1} annual allowable treatment level. The methodology was designed for adaptability to accommodate a range of management objectives for a diversity of resources.
3.1 Introduction

Many forests in the interior west of the United States are subject to significant disturbances including fire, insects, disease and invasive species encroachment. These events are largely attributed to human and natural disturbances including logging, fire exclusion, grazing, drought and climate change (Skinner and Chang, 1996; Brown et al., 2004). Data provided by the Colorado Forest Restoration Institute (2004) suggests that many of the current forest types are incongruent with historic patterns of structure and composition which subsequently has increased the potential for high intensity wildfire and insect/disease outbreaks.

There is a broad agreement that active management via forest treatments including thinning and prescribed fire are urgently needed to restore historic stand dynamics (Brown et al., 2004). In the 15 Western States there are at least 28 million ac that could benefit from some type of restorative treatment to refurbish healthy ecosystems, protect water and soil quality and improve forest and rangeland resilience (Rummer et al., 2005). Restoration efforts such as fuel reduction thinning, salvage/sanitation cuts and invasive species removal carried out over vast landscapes can produce large quantities of treatment residues (Loeffler et al., 2010); the majority of restoration strategies remove trees too small to have commercial value by conventional standards. Commonly, most of these residues are gathered and disposed on-site by burning.

The anticipated accrual of forest treatment residues has initiated interests in expanding the use of residues as feedstocks for energy production (Rummer et al., 2005; Malmsheimer et al., 2008). Recent studies have evaluated the benefits associated with the utilization of residues for bioenergy production. Results from Jones et al. (2010)
show that bioenergy, as an alternative to on-site burning, generates fewer carbon dioxide, methane, and particulate matter emissions. Gan and Smith (2007) found that removing logging residues would save $200-250 per hectare in site preparation costs during forest regeneration in East Texas. Furthermore, the commercial use of thinned trees have high potential to offset treatment costs (Brown et al., 2004).

Although there are environmental and economic benefits associated with the utilization of treatment residues, many factors influence their availability for bioenergy production. Measures of availability are largely connected to the quantity, spatial distribution, and accessibility of potential residues across a landscape. Furthermore, these measures are difficult to generalize across different regions where management strategies and site specific conditions may vary drastically. In areas where improving forest health is the primary objective, residues may be abundant due to the removal of non-merchantable stock. In other areas where this is not the case, the development of markets for utilization may be infeasible.

Numerous studies have addressed the availability of residues and the feasibility of developing markets for bioenergy production. Perlack et al. (2005) estimated that an annual supply of one billion bone dried tons (bdt) of biomass would displace 30% or more of domestic petroleum consumption and the continental U.S. could potentially produce 368 million bdt per year from forest lands alone. The Coordinated Resource Offering Protocol (CROP; http://www.crop-usa.com) undertook a series of projects to address the growing potential of catastrophic wildfire risk and developed models to increase the certainty of levelized biomass supply offerings from public agencies. The Biomass Site Assessment Tool (BioSAT; http://www.biosat.net) is a model used to locate the top 20 bioenergy production facilities for 13 southern U.S. states. These
studies focus on residue availability and extraction feasibility to make strategic decisions and have limited applicability to tactical and operational planning.

As biomass markets continue to develop in the U.S. there is a growing need for a methodology to facilitate tactical and operational level planning for biomass utilization across landscapes of arbitrary size and locale. Forest planning at the stand level is often prohibitive on large landscapes due to the lack of data to accurately estimate biomass quantities and make informed decisions regarding silviculture and treatment priorities. The objective of this study was to develop a methodology to estimate the amount stand level treatment residues that are economically available while accommodating strategic level management objectives and assist tactical and operational decisions for biomass utilization on the study area. The methodology in the present paper is applied to a region in southwest Colorado and demonstrates its utility in modeling silvicultural prescriptions, simulating alternative management objectives, and estimating available treatment residues following multiple scenarios of feedstock delivered price.

### 3.2 Study Area

The UPNF covers approximately 550,000 ac on the west slope of the Colorado Rocky Mountains (Figure 3.1). Stretching northwest to southeast for 125 miles, the plateau ranges in elevation from 5,800-6,000 feet in canyon bottoms to upland elevations around 8,000-10,000 feet. Across the range of elevation, four primary vegetation strata occupy the plateau. Pinyon-juniper (Pinus edulis [Engelm.]; Juniperus osteosperma [Torr.]; Juniperus scopulorum [Sarg.]) cover occurs at the lower elevations ranging from 6,000 to 7,000 feet, Gamble oak and Ponderosa pine (Quercus gambelii [Nutt.]; Pinus ponderosa [Lawson & C. Lawson]) forests inhabit elevations from 7,200 to 8,800 feet and the
upland zone is dominated by aspen (*Populus tremuloides* [Michx.]) and spruce-fir (*Picea engelmannii*; [Parry ex Engelm.]; *Abies lasiocarpa* [Nutt.]) forests.

Approximately 70% of the UPNF is in fire regime condition class 2 or 3 (Schmidt et al., 2002; Hardy et al., 2001), suggesting that these areas exhibit fuel conditions that are conducive to uncharacteristic, high intensity fires. The potential for these disturbance events have initiated active restoration management across the plateau to reduce fuel loading. Restoration management is also proposed to regenerate declining aspen stands and mitigate pinyon-juniper encroachment.

Figure 3.1: Study area: The Uncompahgre Plateau National Forest located in southwest Colorado. Green areas show national forest.
CHAPTER 3. FOREST TREATMENT RESIDUES FOR BIOENERGY PRODUCTION

3.3 Methods

3.3.1 Treatment Units and Stand Characteristics

Treatment units were created using the stand delineation algorithm (SDA, see chapter 1). A three band, color-infrared composite of National Agricultural Imagery Program (NAIP) imagery was used as the input data source to the SDA. The SDA was parameterized to constrain units to a minimum and maximum area of 5 and 100 ac respectively. The spatial radius of the Gaussian filter was set at one meter. Parameters for the anisotropic diffusion filter were 0.125 for the time-step and 50 for the number of iterations. The mean shift segmenter was parameterized with a spatial radius = 10, spectral radius = 5, mode convergence threshold = 0.1, and maximum number of iterations = 100. The resulting geometries were visually assessed and checked for compliance with minimum and maximum unit sizes of 5 and 100 ac respectively. Segmentation resulted in 25,538 units with an average size of 35.99 ac.

Forest characteristics such as basal area, tree density, and tons of above ground biomass were estimated for each treatment units using the Forest Characteristics Model (FCM) developed by Hogland et al. (2012) using a two-tiered remote sensing approach (Table 3.1). The first stage uses an iterative self-organizing clustering routine, principle components analysis (PCA), polytomous logistic regression, and first and second order texture measures to calculate the probability that a given pixel in the NAIP imagery represents an identifiable class (e.g., tree canopy, shadow, grass, or water). This creates a set of probabilistic surfaces that are used as inputs in the second stage where forest characteristics by species were estimated using multivariate regression. Response variables in the models include summarized Forest Inventory Analysis (FIA) plot data.
and independent variables consist of a series of first and second order texture metrics performed on the stage 1 probabilistic outputs and PCA values. Outputs from the model were stored as multiband raster datasets.

Output rasters from the FCM were average for the spatial domain of each forest stand provided stand level characteristics by species tabulated in a spatially indexed database. Quadratic mean diameter was also attributed to each stand by $\sqrt{\frac{BA}{kn}}$ where \( BA \) is basal area, \( k \) is tree density, and \( n = 0.005454 \).

Table 3.1: Summary of forest characteristics by forest type. Values for basal area, density, and above ground biomass represent the mean with standard deviation in parentheses.

<table>
<thead>
<tr>
<th>Forest Type</th>
<th># of stands</th>
<th>Acres</th>
<th>BAA(\text{std}) ft.(^2)/ac</th>
<th>TPA(\text{std}) stems ac(^{-1})</th>
<th>QMD(\text{std}) inches</th>
<th>AGB(\text{std}) tons ac(^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspen</td>
<td>2,123</td>
<td>49,090</td>
<td>100(42.8)</td>
<td>180(77.97)</td>
<td>10(0.29)</td>
<td>54(23.33)</td>
</tr>
<tr>
<td>Aspen-Pine</td>
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<td>74,431</td>
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<td>58(27.72)</td>
<td>14(1.36)</td>
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</tr>
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<td>17(6.16)</td>
</tr>
<tr>
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</tr>
<tr>
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<td>148,175</td>
<td>79(38.15)</td>
<td>129(71.55)</td>
<td>11(0.94)</td>
<td>34(20.80)</td>
</tr>
<tr>
<td>Non-Forested</td>
<td>1,943</td>
<td>47,301</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

GIS coverage of forest roads on the UPNF was used to select all treatment units whose centroid fell within the maximum skidding distance for whole tree harvesting of a road edge, assumed to be 2,000 feet for this study. This selection resulted in 13,387 candidate treatment units. To accommodate potential changes in the current management plan, predefined management designations were not considered in the candidate unit selection. Congressionally designated areas were handled implicitly by the road-side configuration.
3.3.2 Modeling Silvicultural Treatments

Four quantifiable silvicultural prescriptions were developed to model removal and retention of treatable stands. These prescriptions are generalized adaptations from a management plan assembled by the Uncompahgre Plateau Collaborative Restoration Project (UPCRP) - a project funded by the USDA Collaborative Forest Landscape Restoration Program (2009). The management plan provided detailed information regarding issues with forest health and desired future conditions. Stand-based prescriptions were employed with regards to the documented desired future conditions. Stands were aggregated based on a basal area weighted species composition into four species groups and the following prescriptions were assigned to the groups.

Stocking-based Management

Stocking-based management for fuel reduction was applied to spruce, fir, and mixed-conifer forest types. Stands were selected based on the following criteria using a basal area weighted composition. Pure stands: greater than or equal to 80% composition for a single species; mixed species stands: a composition greater than or equal to 80% comprised of any combination of spruce, fir, pine and aspen with no one species greater than 80%.

Stand density index, introduced by Reineke (1933), was used to develop silvicultural guidelines specific to the study area. The maximum stand density index (SDI) was located by plotting tree density against qmd for all stands selected for stocking-based management on log-log axes (Figure 3.2). A line with a slope of -1.605, suggested by Reineke (1933) as the cross-species slope of the 100% stocking line was hand fitted on the right edge of the data. Trees ac$^{-1}$ was then indexed where the 100% stocking line
and qmd of 10 inches crossed, resulting in a maximum SDI of 290. SDI was calculated for all stands using equation 3.1.

\[
SDI = TPA \left( \frac{QMD}{10} \right)^{1.605}
\] (3.1)

Relative density (RD) was calculated for each stand by dividing SDI by the maximum SDI (290). Stands with a RD >= 60% were considered eligible stands for a treatment throughout the simulation time frame. The target management zone was bounded by a lower zone at 35% of maximum SDI and an upper zone at 60% of maximum SDI. When a given stand was selected for treatment, the stand’s SDI was reduced to 47.5% (half of the distance between the lower and upper management zones) of the maximum SDI with a 10% allowable error in terms of SDI to mimic stochasticity in real-world management. Trees density and basal area for the treated stands were updated using equations 3.2 and 3.3.

\[
TPA_{pt} = \frac{SDI_{max} \times \delta \sim N[.475, 0.3] \times 10^{1.605}}{QMD^{1.605}}
\] (3.2)

\[
BAA_{pt} = TPA_{pt} \times 0.005454 \times QMD^2
\] (3.3)

Where TPA_{pt} is post treatment tree density, SDI_{max} is the maximum SDI, \( \delta \sim N[.475, 0.3] \) is a random number drawn from a normal distribution with a mean of .475 and a standard deviation of 0.03, QMD is the quadratic mean diameter, and BAA_{pt} is post treatment basal area. Figure 3.3 illustrates these guidelines in a stocking chart.
Figure 3.2: Tree density vs. quadratic mean diameter for spruce, fir and pine stands. The line of self thinning was located at a stand density index of 290.
Figure 3.3: Stocking guide developed in this study for stands comprised of spruce, fir and/or pine. Upper and lower management zones (UMZ and LMZ) at 35 and 60% respectively. The red dashed line represents the target relative density and blue lines show upper and lower bounds of the 10% allowable error.
Regeneration Management

Regeneration management was applied to pure aspen stands and aspen stands with a conifer component no greater than 40%. Two cardinal focuses of aspen management across the study area are sudden aspen decline (SAD) and conifer encroachment. The cardinal goal in both situations is to generate a vigorous regenerative age class. Branch dieback in aspen stands was first noted in southwestern Colorado in 2004 (Worral et al., 2008) and soon after dubbed ‘sudden aspen decline’, characterizing the sudden, rapid progression of the disease. To this end, the etiology of SAD has been widely studied and recent assessments suggest that SAD appears to have a strong correlation with climate and SAD-like events commonly occur earlier in regions with higher temperatures and drier climates (Hogg and Hurdle, 1995; Shields and Bockheim, 1981).

Results from Worral et al. (2010) conclude that the areas that experienced the greatest mean moisture deficit during the drought of 2002 showed the highest degree of decline in 2008. This was statistically tested by relating climate moisture index (CMI) values to inventoried aspen stands. Since outputs from the forest characteristics model do not provide information regarding mortality, aspen management was prioritized by calculating CMI for the study area and allocating treatments to stands with the highest susceptibility to decline in the event of extreme heat and moisture deficiency.

CMI is an index of moisture surplus or deficit, simply precipitation minus potential evapotranspiration. CMI was calculated using an approach outlined by Hogg (1997). Monthly PRISM climate data (Daly et al., 2009) for 2002 on a 4-km grid and a digital elevation model with 10-m resolution were obtained covering the extent of the study area. Equation 3.4 was used to calculate the monthly CMI for each 4-km cell. The 2002 annual CMI was determined by summing the monthly CMI values. Climate data
from 2002 was used to locate susceptible areas during extreme conditions similar to the drought of that year.

\[
\text{CMI} = P - (93Dce^{A/9300})
\]  \hspace{1cm} (3.4)

where:

\(P\) is precipitation (mm);

\[
D = 0.5(e_{T_{\text{max}}} + e_{T_{\text{min}}}) - e_{T_{\text{dew}}}
\]

\[
e_{T_{\text{max}}} = 0.61078e^{(17.269T_{\text{max}}/(237.3+T_{\text{max}}))}
\]

\[
e_{T_{\text{mix}}} = 0.61078e^{(17.269T_{\text{mix}}/(237.3+T_{\text{mix}}))}
\]

\[
e_{T_{\text{dew}}} = 0.61078e^{(17.269T_{\text{dew}}/(237.3+T_{\text{dew}}))}
\]

\(T_{\text{max}}\) and \(T_{\text{min}}\) are mean monthly max and min temps (°C)

\(T_{\text{dew}}\) is mean monthly dew point, \(T_{\text{min}} - 2.5\) (°C)

\(c\) is a cold-temperature reduction factor based on \(T_{\text{mean}} = 0.5(T_{\text{max}} + T_{\text{min}})\)

When:

\(T_{\text{mean}} \geq 10\) °C, \(c = 1\);

\(10\) °C > \(T_{\text{mean}} > -5\) °C, \(c\) is reduced linearly from 1 to 0;

\(T_{\text{mean}} \leq -5\) °C, \(c = 0\);

\(e\) is the base of the natural logarithm

\(A\) is elevation in meters
Since multiple stands fall within each CMI grid cell, auxiliary information was needed to further prioritize treatments. To augment CMI, the topographic wetness index (TWI) was calculated for the study area using the 10-meter elevation dataset. Topography affects the spatial distribution of soil moisture and sub-surface flow often follows surface topography (Burt and Butcher, 1986; Seibert et al., 1997; Rodhe and Seibert, 1999; Zinko et al., 2005). Therefore this index has been used to depict spatial soil moisture patterns (Burt and Butcher, 1986; Moore et al., 1991). TWI (Figure 3.4) provided local information regarding potential stress in aspen stands due to moisture deficit within each 4-km cell of the CMI. TWI was computed by \( \ln\left(\frac{a}{\tan\beta}\right) \) where \( a \) is the local upslope area draining through a certain point per unit contour length and \( \tan\beta \) is the local slope (Beven and Kirkby, 1979).

Figure 3.4: Topographic wetness index for a subarea of the study area.
Both CMI and TWI are indicies where the low and high values represent low and high soil moisture respectively. Treatments were prioritized first by locating stands within the CMI cell with the lowest value, then locating stands with the lowest average TWI values. When a given stand encountered a treatment event, a regeneration cut was simulated removing 100% of the estimated growing stock and subtracting merchantable yield.

**Age and Structural Diversification**

According to the UPCR management plan, approximately 95% of pinyon-juniper woodlands on the Plateau are in late seral condition of continuous dense even-aged stands. Historically, pinyon-juniper cover type had a patchy distribution of different age classes. The desired future conditions for pinyon-juniper cover type is to increase age and structural diversity across the study area. Mastication will be used to accomplish this goal by spatially distributing treatments across the extent of pinyon-juniper cover.

Candidate treatments were prioritized by selecting non-adjacent stands with the highest basal area value. Yields from mastication treatments in pinyon-juniper were assumed to be dispersed across the treatment area and did not contribute to available treatment residues. Although the residue from the these treatments were considered unavailable, they were still simulated to show the distribution of high priority stands.

**Restoration in Ponderosa Pine**

The majority of ponderosa pine stands across the plateau no longer retain the structure that was most common in the 19th century (Binkley et al., 2008). Historically these stands had a clumped distribution, interspersed with small (0.1 to 0.5 ac) meadows and basal area ranging from 20 to 90 sq. ft. Many of the stands on the plateau exceed
90 ft$^2$/ac and few well over 150 ft$^2$/ac. Restoration treatments for ponderosa pine in this study aim to reduce basal area to 20-50 sq. ft.$^{-}$ac following recommendations from Binkley et al. (2008). The basal area of each treated stand was reduced to 35 ft$^2$/ac ± 15 ft$^2$/ac. Treatments were prioritized by iteratively selecting the stand with the highest basal area value and thinning to a target basal area of a random number drawn from a normal distribution with a mean of 35 and a standard deviation of 4. Unconditionally available residues were calculated by subtracting retention and merchantable yield from above ground biomass for each treated stand. Figure 3.5 shows the current distribution of basal area and the target management zone for ponderosa pine stands across the study area.

The annual treatment area constraint was set according to the UPCRP management plan. Spruce-fir and mixed-conifer stands were constrained to 2,100 ac yr$^{-1}$, aspen stands constrained to 1,450 ac yr$^{-1}$, pinyon-juniper constrained to 350 ac yr$^{-1}$, and pine stands constrained to 1,100 ac yr$^{-1}$ totaling to 5,000 ac yr$^{-1}$. Figure 3.6 shows the distribution of stands eligible for treatment colored coded by their silvicultural prescriptions.

### 3.3.3 Treatment Residue

When a given stand encountered a treatment event, residue was estimated by first subtracting the harvested biomass from the total above ground biomass then subtracting gross merchantable yield. The amount of removed biomass was determined by the silvicultural prescription and the gross merchantable yield was calculated by using a component ratio estimator for stem wood and stem bark based on qmd from a 12” stump to a 4” top diameter (Jenkins et al., 2003). Unconditionally available residues were reduced by 10% to account for leakage during transport from stump to landing.
Figure 3.5: Current distribution of basal area for ponderosa pine stands across the study area. The blue denotes the target post treatment basal area and the red polygon shows the upper and lower bounds of the management zones.
Figure 3.6: Eligible stands for treatment across the study area. Yellow = stocking-based management, green = regeneration management, red = age and structural diversification management and blue = restoration in ponderosa pine.
and the recovery rate was assumed to be 80% of the residue at the landing (Baral and Guha, 2006; Fight et al., 2010). Equation 3.5 was used to calculate residue \( R \) where \( B_{ag} \) is above ground biomass, \( B_{sr} \) is silviculturally retained biomass, \( B_0 \) and \( B_1 \) are the component ratio coefficients for stem wood and stem bark, \( d \) is the quadratic mean diameter for the stand and \( r \) is the additive value of leakage and recovery rates. Residue extraction was assumed to take place after the removal of the commercial component and residue was allowed time to dry to a moisture content of 30% (Han et al., 2010).

\[
R = \left( B_{ag} - B_{sr} \right) \left( 1 - \left( \exp \left( \beta_0 + \frac{\beta_1}{d} \right) \right) \right) \times r
\]  

(3.5)

3.3.4 Simulating Alternative Management

Management simulations were conducted following three management scenarios for a 10 year time period. The first scenario was an ecological, cost-independent approach where treatment scheduling was prioritized by stand conditions. The second scenario followed a maximized net revenue formulation. Gross revenue was calculated for each eligible treatment unit by multiplying treatment residue by a range of delivered prices. Net revenue was calculated by subtracting transportation costs and operation costs from the gross revenue. Treatments were prioritized by maximizing net revenue subject to the same acreage constraints in the first scenario. The final scenario consisted of net revenue maximization without the acreage constraints.

Cost-independent Scenario

For the cost-independent scenario spruce-fir and mixed-conifer stands were prioritized by ordering SDI values from high to low and selecting the first 2,100 ac in each simulated
year. Aspen stands were prioritized ordering first by CMI then by TWI and selecting the first 1,450 ac in each simulated year. Ponderosa pine and pinyon-juniper stands were prioritized by ordering basal area from high to low and selecting the first 1,100 and 350 ac, respectively, in each simulated year. Treatment residues were calculated as described in the silvicultural prescriptions above while accounting for recovery rates and moisture content. The resulting residue quantity from this scenario was considered to be the highest and used as the baseline maximum 10 year treatment residue yield.

Cost-dependent with Constraints

Treatments in the second scenario were prioritized by maximizing net revenue. In this scenario, the harvesting system was assumed to be whole-tree skidding and the tops and limbs of the removed trees were left at a roadside landing designated for each unit. The extraction operation was assumed to be road-side grinding since all candidate treatment stands were selected within skidding distance of roads. A marginal cost approach was used to calculate forest operations costs (Puttock, 1995). This approach considers biomass to be a byproduct of the production of higher value products like sawlogs, and fully allocates harvest costs of felling, extraction, processing, road construction, and stumpage to these products. Therefore the costs begin to accrue with the collection of residues. Handling, processing and loading costs for residues were calculated following methods from Anderson (2011) by averaging the results from 40 scientific studies examining biomass removal from timber harvest, fuel treatments, and other residue related operations and standardizing to 2013 $\text{bdt}^{-1}$ resulting in $34.33 \text{ bdt}^{-1}$.

Transportation costs were calculated for each candidate treatment unit. Optimized round trip delivery times, denoted by variable $h$ in equation 3.6, from each unit to
a potential bioenergy production facility located in Nucla, CO were calculated using a GIS coverage of all UPNF roads (Figure 3.7). A non-spatial transportation network optimization program was used to determine the least cost route for each unit based on engineered road speed (Chung and Sessions, 2003). Other variables used to calculate transportation costs were load time \( (l) \) and unload time \( (u) \) each assumed to be 0.5 hours, non-fuel trucking (operator) cost \( (n) \) set at $48.03 hr^{-1} \) (ATRI, 2010), a specialized trucking premium \( (p) \) of $12.00 hr^{-1}, $3.94 gal^{-1} \) for diesel fuel price \( (d) \) (EIA, 2013), average fuel economy \( (e) \) of $4.65 mi gal^{-1}, average truck speed \( (v) \) which depends on the engineered road speed of the shortest path distance for each unit, lubrication price \( (a) \) set at 10% of the diesel fuel price assumed to correlate perfectly with diesel fuel price, van capacity \( (m) \) of 30 tons, and biomass moisture content \( (w) \) of 30% (Anderson, 2011).

\[
T = \frac{(h + l + u) \cdot \left( n + p + \left( (d \cdot e^{-1} \cdot v) + a \right) \right)}{m \cdot (1 - w)} \tag{3.6}
\]

Equation 3.7a is the mathematical representation of the maximization problem where net revenue \( (R_{net}) \) is equal to the sum of the gross revenue \( (R_{gross}) \) minus forest operations costs \( O \) minus transportation costs \( T \) for all treated units. The problem is constrained by the 5,000 ac annual allowable harvest minus the 350 ac yr^{-1} allowable harvest in diversification management since these treatments do not yield any available residues. Constraints for the three residue producing treatments were 2,100 ac yr^{-1} allocated to stocking based management \( U_s \) (Equation 3.7b), 1,450 ac yr^{-1} allocated to regeneration management \( U_r \) (Equation 3.7c), and 1,100 ac yr^{-1} allocated to restoration in ponderosa pine \( U_p \) (Equation 3.7d). As, Ar, and Ap denote the acreage constraints for stocking-based, regeneration, and pine restoration management.
Figure 3.7: Travel time in hours for all eligible treatment units.
respectively.

Available treatment residues for the maximized net revenue scenario were evaluated at a sequence of delivered prices from $5 \text{ bdt}^{-1}$ to $100 \text{ bdt}^{-1}$ in intervals of $5 \text{ bdt}^{-1}$. Total available residue quantities and their spatial distributions were reported for the cost-independent scenario and for each simulation at the 20 delivered prices of the maximized net revenue scenario.

Maximize \( R_{\text{net}} = \sum_{i \in U} R_{\text{gross}_i} - O_i - T_i \) \hspace{1cm} (3.7a)

Subject to:

\[ 2,000 \text{ ac} < \sum_{i \in U} A_{s_i} < 2,100 \text{ ac} \quad \forall i \in U_s \] \hspace{1cm} (3.7b)

\[ 1,350 \text{ ac} < \sum_{i \in U} A_{r_i} < 1,450 \text{ ac} \quad \forall i \in U_r \] \hspace{1cm} (3.7c)

\[ 1,000 \text{ ac} < \sum_{i \in U} A_{p_i} < 1,100 \text{ ac} \quad \forall i \in U_p \] \hspace{1cm} (3.7d)

Cost-dependent without Constraints

The final management scenario was simulated prioritizing treatments by maximizing net revenue without considering acreage constraints (Equation 3.7a). As in the previous scenario, the spatial distribution of treated stands with a positive net revenue were evaluated at a sequence of delivered prices ranging from $5 \text{ bdt}^{-1}$ to $100 \text{ bdt}^{-1}$. The acres treated and delivered bdt were reported for each simulation.
3.4 Results and Discussion

3.4.1 Cost-independent Scenario

The 10 year management simulation for the cost-independent scenario resulted in 48,898 ac treated with 20,317 ac in stocking-based management, 14,383 in regeneration management, 3,390 in age and structural diversification, and 10,808 in ponderosa pine restoration. Residue quantities were 60,816 bdt, 75,129 bdt, and 17,406 bdt for stocking-based, regeneration, and restoration respectively after accounting for moisture content and recovery rates. Figure 3.8 shows the spatial distribution of the stands selected for treatments. Yellow stands show stands selected for stocking-based treatments. These areas can be interpreted as the most dense areas of spruce-fir and mixed-conifer. The green areas show stands selected for regeneration treatments. These areas show aspen stands that have the highest likelihood of moisture deficit and SAD induced mortality. Red areas show stands selected for age and structural diversification. These areas are dispersed relative to the other treatments due to the adjacency constraints. Blue stands show the distribution of stands selected for ponderosa pine restoration. With the exception of the stands selected for diversification, most of the stands selected for treatments fall relatively close to the primary forest road spanning the UPNF boundary running southeast to northwest. Conveniently, this would significantly reduce extraction cost since the speed class for this road is 30 mph compared to 15 mph for the majority of the roads covering the study area.

Table 3.2 shows the average total biomass, total removed biomass, merchantable removals and residues for the three silvicultural prescriptions. Stocking-based management had the highest average pre-treatment above ground biomass. However, due
Figure 3.8: Spatial distribution of treated stands for the cost-independent scenario.
to silvicultural retention, these stands had the second lowest average residue following pine restoration stands. Stands selected for regeneration management had the highest residue amounts because all the growing stock was removed.

Table 3.2: Average total biomass, total removed biomass, merchantable removals, and residue for the four silvicultural prescriptions. Biomass in green tons ac\(^{-1}\). Standard deviations in parentheses.

<table>
<thead>
<tr>
<th>Management</th>
<th>Total Biomass tons ac(^{-1})</th>
<th>Total Removed tons ac(^{-1})</th>
<th>Merch. Removed tons ac(^{-1})</th>
<th>Residue tons ac(^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stocking-based</td>
<td>91.03(13.18)</td>
<td>39.73(14.8)</td>
<td>25.50(0.97)</td>
<td>14.25(0.51)</td>
</tr>
<tr>
<td>Regeneration</td>
<td>61.77(21.31)</td>
<td>61.77(21.31)</td>
<td>36.86(12.73)</td>
<td>24.90(8.58)</td>
</tr>
<tr>
<td>Diversification</td>
<td>21.35(4.75)</td>
<td>21.35(4.75)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Restoration</td>
<td>58.38(9.17)</td>
<td>21.59(0.43)</td>
<td>13.92(0.29)</td>
<td>7.67(0.14)</td>
</tr>
</tbody>
</table>

### 3.4.2 Cost-dependent Scenario

Outputs from the cost-dependent scenario show a range of costs over the 20 simulated delivery prices. Values range linearly from a negative net revenue of $-7,598,736 at $5 bdt\(^{-1}\) delivered price to a positive net revenue of $8,854,049 at $100 bdt\(^{-1}\) delivered price. Using the outputs from the simulations, a linear model describing net revenue as a function of delivered price was constructed to predict the breakeven delivered price (Figure 3.9). When net revenue was zero, the delivered price was $48.94 bdt\(^{-1}\).

The first delivered price in the simulation to show any profitable stands was $45 bdt\(^{-1}\). However, this resulted in a negative net revenue of $-594,976 with only 5,120 profitable ac of the 48,898 treated ac. A delivery price of $50 bdt\(^{-1}\) resulted in a positive net revenue of $353,878 with 42,117 profitable ac of the 48,898 treated. Finally, at $55 bdt\(^{-1}\), all treated stands were profitable with a positive net revenue of $1,108,114. The net revenue continued to increase at approximately $1,000,000 over each $5 increment of delivered price. Figure 3.10 illustrates the change in the distribution of treated stands.
Figure 3.9: Costs vs. Delivered Price. The black line shows the fitted linear model of costs as a function of delivered price. Red line denotes the delivered price where costs are equal to zero (blue line).
Figure 3.10: Change in the distribution of profitable (red) and nonprofitable (green) stands over 4 increments of delivered price. No profitable stands at $40 \text{ bdt}^{-1}$. Profitable stands at $45 \text{ bdt}^{-1}$ with a negative net revenue. Positive net revenue at $50 \text{ bdt}^{-1}$. All stands profitable at $55 \text{ bdt}^{-1}$. 
with a negative net revenue (green) and treated stands with a positive net revenue (red) at $40 \text{ bdt}^{-1}$, $45 \text{ bdt}^{-1}$, $50 \text{ bdt}^{-1}$, and $55 \text{ bdt}^{-1}$.

### 3.4.3 Cost-dependent without Constraints

Management for the cost-dependent scenario was simulated without acreage allocation constraints (stocking = 2,100 ac, regeneration = 1,450 ac, and restoration = 1,100 ac) to estimate the maximum residue yields over the range of delivered prices (Table 3.3). A delivered price of $45 \text{ bdt}^{-1}$ resulted in 5,120 profitable ac yielding a total of 14,209 bdt and a net revenue of $16,280. A total of 65,887 profitable ac were treated at $50 \text{ bdt}^{-1}$ yielding 200,402 bdt with a net revenue of $457,650. At $55 \text{ bdt}^{-1}$ 106,945 ac were treated yielding 338,144 bdt and a net revenue of $1,890,460. All eligible stands were treated at $60 \text{ bdt}^{-1}$ yielding 363,406 bdt with a net revenue of $3,677,365. Figure 3.11 displays the spatial distribution of available treatment residue at $45$, $50$, $55$, and $60 \text{ bdt}^{-1}$ delivered price. See Figure 13 in appendix for an animation of spatial distribution of treated stands and used road network of the cost-dependent without constraints scenario.

Approximately 90% of the available treatment residues at $45 \text{ bdt}^{-1}$ are located in aspen and pine stands. Although the largest contributor to the total available residues at $60 \text{ bdt}^{-1}$ is spruce-fir and mixed-conifer stands, they are generally distributed further from the bioenergy facility and are not available at the lowest delivered price with a positive net revenue. These results can be used to prioritize treatments early in the development of a bioenergy supply chain to initiate markets by allocating efforts to residues available at relatively low costs. As markets develop, managers can begin to incorporate the acreage allocation constraints to meet forest-wide desired future conditions.
Figure 3.11: Spatial distribution of the unconstrained available treatment residues over a range of delivered prices.
### 3.5 Conclusion

The integration of the stand delineation algorithm and the forest characteristics model presents the opportunity to carry out detailed spatial analysis for a diverse array of resources on very large landscapes. As demonstrated in this study, the methodology can be employed to assess the feasibility of biomass utilization, assist silvicultural decisions, and facilitate operational planning at strategic, tactical, and operational scales. The ability to not only estimate residue quantities, but also map the spatial distribution of stand-level residues following alternative management regimes is integral in areas with limited history of industrial biomass utilization and uncertainties in biomass markets.

In certain forests, the primary focus is to improve forest health by means of restoration treatments. Commonly, these treatments produce a large amount of low-grade materials that might only have an outlet in the bioenergy industry. In such cases, similar to that of the UPNF where 70% of the forest is in fire regime condition class 2 or 3, a strategic approach to initiate biomass markets may be to prioritize treatments by minimizing the delivery cost to a near-by facility. In other situations, such as forests where broad-scale restoration is not a primary concern different strategies may be more appropriate. Nonetheless, this methodology was designed with adaptability in mind to accommodate a range of management objectives across a diversity of resources.
Research is still needed to fill the knowledge gap regarding residue leakage from stump to landing and recovery rates at the landing. Although this study assumed a 10% reduction rate due to leakage and 80% recovery at the landing, these amounts may be substantially different. Other steps to improving the presented methodology would be to incorporate forest growth. This augmentation would broaden the planning horizon to better understand the sustainability of biomass flows. Future studies could use this methodology to optimally locate bioenergy facilities and determine the scale at which they could operate.
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CHAPTER 4

Conclusion
4.1 Forest Biomass and Bioenergy

For centuries, forest biomass has been among the primary resources for energy to human populations around the globe. As a result to technological developments and increasing intelligence in the mineral extraction industry and other mature markets, forest biomass, as a source of energy, has been out competed. In the midst of climate change, forest biomass utilization is gaining momentum as a renewable resource to mitigate atmospheric concentrations of green house gases, especially carbon dioxide ($\text{CO}_2$), reduce dependency on scarce fossil fuels, and provide a secure energy supply. Research and development in bioenergy conversion technologies has played an important role in the effort to vitalize bioenergy supply. Furthermore, policy makers are becoming increasingly aware of the benefits and potential commercial implications of bioenergy production and, through standards and regulations, have fortified opinions and incentivized interests in the industry.

The future of global dependency on biofuels is unknown, however the foundation for forest biomass utilization and bioenergy production on a local scale is strong and in some areas may provide an opportunity for a sustainable and secure supply of energy. The prohibitive factors in establishing a bioenergy supply chain in forests that are managed for primary products or general forest health is that the quantity and distribution of economically available biomass is driven by management objectives that pay no regards to any component of the bioenergy market. Thus, to quantify and map biomass available as feedstock for bioenergy production, the logistical decision scheme must integrate forest specific management elements such as silviculture, harvesting configurations, harvesting regulations, environmental concerns, road infrastructure, etc.
4.2 Integration of Presented Work

It is important to understand the difference, as well as the connection between biomass stocks and bioenergy feedstock. As demonstrated in Chapter 2, quantifying biomass stocks, or simply above ground biomass, is a prerequisite to predicting feedstock quantity. Bioenergy feedstock will forever be a derivative of biomass stocks, however the proportion that is derived is variable. The estimate of biomass stocks must be supplemented with other forest characteristics to simulate desired silvicultural practices and predict what fraction of the stocks will be removed.

Forest stand boundaries have an integral utility in estimating available treatment residue. Stand delineations allow for silvicultural prescriptions to be assigned at the appropriate extent and mimics real-world management where groups of trees, or units, are managed, not areas represented by pixels in an image. Because silviculture is assigned at the stand-level, outputs from the management simulation can be mapped back to the stand, providing detailed spatial information on available residues and not just a forest-wide estimate. This quality of the methodology presented in Chapter 2 is very important in making tactical level decisions where the quantity, as well as the distribution of the resource influences the viability of supplying feedstock.

Chapter 3 demonstrates how the outputs from the methodology developed the Chapter 2 can be used to address questions regarding the availability of treatment residue across multiple management scenarios. Although the methods from Chapter 2 were designed to be transferable across diverse landscapes with little to no parameterization, the methods presented in Chapter 3 will likely be substantially different for similar analysis in areas dissimilar in vegetation, ownership, history, etc. The work in this
chapter is largely based on quantifying and mapping residue at a range of delivered prices. However, the outputs from the SDA and FCM can be integrated into other configurations and objectives to understand the economic feasibility of treatment residue utilization, assess the sustainability of a supply chain, and evaluate the environmental impacts of intensive biomass utilization.

4.3 Applications

The methods in this thesis are heavily management oriented and, in turn, the results have direct applications to management on the region evaluated in this study. Firstly, since silviculture and treatment prioritization was modeled following a well developed management plan from the study site, the results can be used to supplement management decisions. Managers often have information and maps regarding cover types across their forest, however commonly have limited inventory data, especially in areas far from the existing road infrastructure. Results from Chapter 2 provide managers with representative stand boundaries, stand-level inventory, species composition, and a silvicultural prescriptions according to desired future conditions for the entire extent of the forest.

Chapter 3 provided insight into biomass utilization potential across the study site. Not only did the results from this chapter provide estimates of the quantity and spatial distribution of treatment residue following 10 years of management, it gave insight to where the most cost efficient residues could be located, as well as where the most cost prohibitive areas are. These results can be used to allocate management efforts early in the development of a bioenergy supply chain to areas that both need treatments and are predicted to yield residues at a relatively low cost. As markets develop, managers
can begin to shift treatment efforts to areas that are most beneficial to forest health and were previously, for one reason or another, prohibitive to residue extraction. Lastly, simulating alternative management scenarios gave rise to the influence of acreage constraints on the quantity and distribution of available treatment residue. For example, allowing the annual treatment level to simply be a function of delivered price showed over a two-fold increase in the potential available residue at \$60 \text{ bdt}^{-1}$.

4.4 Future Work

Although the presented work introduces new methods to analyze many key components of feedstock supply, knowledge gaps still exist. Recovery rates for forest treatment residue are often assumed to be constant across treatments regardless of variables that may significantly change the quantity that is actually extracted. Research is needed to provide recovery rates that account for variables such as pretreatment stocking, terrain, operational configuration, harvesting intensity, etc. This is especially true for in-woods transport (stump-to-landing) leakage rates that are not as well understood as recovery rates at the landing. Secondly, incorporating forest growth into this framework would allow managers to increase the planning horizon and perform long-term assessments of biomass flows. Accounting for forest growth can have useful applications to industry that may rely on long-term returns that are used to indemnify the development of new infrastructure for bioenergy production.
Bibliography


BIBLIOGRAPHY


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Appendix
Figure 1: Animation of the mean-shift algorithm: Red points are associated with mode A and green points associated with mode B. Blue line denotes the mean shift vector.
Figure 2: Change in the spatial distribution of treated stands as delivered price increases.