REFORESTATION OF RED SPRUCE (*PICEA RUBENS*) ON THE CHEAT MOUNTAIN RANGE, WEST VIRGINIA

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Preface

This thesis contains an overall introduction and four chapters. Chapters II, III, and IV are presented in manuscript form; therefore, the study area may be repeated, pronouns reflect manuscript authorship, and tables and figures appear at the end. A single reference section occurs at the end for literature cited throughout the thesis.

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Table of Contents

Preface
Acknowledgements
List of Tables
List of Figures
Chapter 1
Introduction
Chapter 2
Abstract
Introduction
Methods1
Study Area1
Town of Spruce1
Results1
Change Detection1
Discussion1
Chapter 3
Abstract
Abstract a Introduction a Methods a Study Area a Habitat Modeling a Forest Fragmentation Model a Critical Forest Model a Results a Forest Fragmentation Results a
Abstract a Introduction a Methods a Study Area a Habitat Modeling a Forest Fragmentation Model a Critical Forest Model a Forest Fragmentation Results a Critical Forest Model a
Abstract Introduction Int
Abstract Introduction Int
Abstract 3 Introduction 3 Methods 3 Study Area 3 Habitat Modeling 3 Forest Fragmentation Model 4 Critical Forest Model 4 Results 4 Forest Fragmentation Results 4 Critical Forest Model 4 Chapter 4 5 Abstract 5

Methods	58
Maxent Modeling	59
Results	60
Discussion	61
Chapter 5	66
Conclusion	66
Literature Cited	68
Vita	76

List of Tables

Cable 2.1- Diagrams of Union process in ArcGIS 10.01	8
Cable 2.2- Percent of P. rubens change over the past 26 years	9
Cable 2.3- Results of change detection over the past 26 years	20
Cable 2.4- Landsat Imagery used in landscape classification 2	21
Cable 3.1- Index Values for Aspect Analysis4	14
Cable 3.2- Index Values for Slope Analysis4	15
Cable 3.3- Index Analysis for Lithology4	-6
Cable 3.4- Index Values for Fragmentation Results4	1 7
Cable 3.5- Final Index Values of Critical Forest based on (Fragmentation, Aspect, Slope, and .ithology)4	8

List of Figures

Figure 2.1- Study Area located in Pocahontas & Randolph County, West Virginia22
Figure 2.2- Conceptual Diagrams depicting changes on Cheat Mountain over the last 26 years
Figure 2.3- Old town of Spruce had major impacts on the biota of Cheat Mountain during the logging era
Figure 2.4- 24-Mar-86 Classification of <i>P. rubens</i> at study site25
Figure 2.5- 28-Mar-02 Classification of <i>P. rubens</i> at study site
Figure 2.6- 7-Mar-12 Classification of <i>P. rubens</i> at study site27
Figure 2.7- Landsat 5 imagery of study area on 24-Mar-86
Figure 2.8- Landsat 7 imagery of study area on 28-Mar-02
Figure 2.9- Landsat 7 imagery of study area on 7-Mar-12
Figure 2.10- Acres of change among <i>P. rubens</i> between 1986-2002 in the Cheat Mountain range
Figure 2.11- Change between 24-Mar-86 to 28-Mar-02
Figure 2.12- Growth of <i>P. rubens</i> between 2002-2012
Figure 2.13- Change between 1986, 2002, and 2012
Figure 3.1- Aspect map categorized based on habitat preferences of <i>P.nettingi</i>
Figure 3.2- Slope map categorized based on habitat preferences of <i>P.nettingi</i>
Figure 3.3- Lithology map categorized based on habitat preferences of <i>P.nettingi</i> 51
Figure 3.4- Forest Fragmentation model results based on <i>P. rubens</i> classification
Figure 3.5- Critical forest based on habitat preferences of <i>P.nettingi</i>
Figure 3.6- Highly critical forest from critical forest model results
Figure 4.1- Bioclimatic variables with highest contributions
Figure 4.2- Predicted P. rubens distribution from Historical to end of century A2 Scenario65

Chapter 1

Introduction

Interest in restoration of red spruce (*Picea rubens*) forest communities in West Virginia has been driven by three concerns. First, these forests provide habitat for threatened or endangered species such as the Cheat Mountain salamander (*Plethodon nettingi*) and the recently de-listed Virginia northern flying squirrel (*Glaucomys sabrinus fuscus*);(Menzel et al., 2006a; Ford et al., 2010), as well as other globally rare fungal, lichen, plant and animal associates (Selva, 1994; Byers et al., 2010). Second, *P. rubens*, along with eastern hemlock (*Tsuga canadensis*) provides an evergreen canopy critical for maintaining temperatures and water quality of cold water fisheries in high-elevation, headwater streams (Martin and Petty, 2009). Finally, concern about the impacts of climate change on existing and future habitat has provided impetus for forest restoration. Although some vegetation models (e.g., Prasad et al., 2007) suggest that climate change may significantly reduce current *P. rubens* distribution, restoration may also mitigate some of the impacts of climate change by increasing biodiversity, forest connectivity, and ecosystem resilience (SER, 2009).

The possible role of climate change in promoting forest declines has received recent attention due to the unexplained decline and mortality of *P. rubens* in the Appalachian Mountains of eastern North America. Although air pollution is a suspected cause of this decline (Johnson and Siccama, 1983; McLaughlin, 1985), the currently available evidence for pollution effects is largely circumstantial and still unconvincing (Woodman and Cowling, 1987).

Climate change is one of the newest and least understood threats to *P. rubens* communities. West Virginia is predicted to warm approximately 5 degrees Fahrenheit by

midcentury under medium emissions scenarios (Gervitz et al., 2009). Precipitation is predicted to increase from 5% to 8% in the same time period. The increased precipitation will not, however, be enough to offset increased evapotranspiration as habitats warm. Overall, habitats are predicted to experience net drying throughout the state, especially during summer and early fall (Gervitz et al., 2009; Young et al., 2010). Extreme events, including floods, droughts, and severe storms are expected to increase as well (Pachauri and Reisinger, 2007). These coming changes will have significant but as yet poorly understood impacts on species and communities. Some species and communities are likely to be resilient, and some are at risk. *P. rubens* communities occupy the highest and coldest climate niche in the state, and are clearly at risk due to climate change.

Today, roughly 25,000 acres of *P. rubens* dominated forests remain in West Virginia (Griffith and Widmann, 2003). Although much of the historic habitat does contain understory *P. rubens*, it is largely devoid of a significant *P. rubens* overstory component. The Monongahela National Forest (MNF), the largest owner of this forest type in the region, recently revised its Land Management Plan to include active and passive restoration projects on >148,000 acres (USDA, 2006). Statewide, approximately 553,500 acres could support *P. rubens*, singly or in mixed forest conditions (Menzel et al., 2006b).

Appalachian *P. rubens* forest communities are considered one of the most endangered forest systems in the United States (Christensen et al., 1996; Noss et al., 1995). In east-central West Virginia, *P. rubens* forests have a fragmented distribution on high peaks and ridgelines in the Allegheny Mountains. Moreover, in addition to *P. nettingi* and *G. sabrinus fuscus* there are numerous other endemics with northern affinities that are largely restricted to these forests (McDonald, 1993; White et al., 1993). Regional assessments of *P. rubens* growth, health and vigor, ownership patterns, and the maturation of the northern hardwood forests that occupy much

of the historic *P. rubens* habitat suggest that the present period might be an optimal time for *P. rubens* restoration. During the 1980s and 1990s, reductions in health and vigor of high-elevation *P. rubens* were reported throughout its eastern range, including the central (Adams et al., 1985; Eager and Adams, 1992) and southern (Cook, 1988; Bruck et al., 1989) Appalachians. However, studies by Leblanc et al., (1992) and Reams et al., (1993) concluded that this decline was within the historical range of variability for southern *P. rubens* populations. Moreover, there are recent reports of stabilization of annual growth rates (Reams et al., 1993; Hornbeck and Kochenderfer, 1998) and improvements in *P. rubens* crown condition and nutrient status (Audley et al., 1998) in the region. Nevertheless, concerns persist that airborne pollution, acid deposition, ozone, and climatic change are contributing to a regional decline in *P. rubens* radial growth (Webster et al., 2004) and ecosystem function (Boggs et al., 2005; Petty and Thorne, 2005). On private lands, surface mining, recreation, second home, and wind energy development also pose ongoing forest fragmentation and conversion threats to *P. rubens* stands (Schuler et al., 2002).

It was not until the logging boom of 1880-1920 that *P. rubens* communities were completely altered. During this period, more than 99% of the forest was harvested or burned. Many areas were burned repeatedly, consuming the organic substrate and potentially setting back natural succession by centuries. Wind and water erosion on these denuded landscapes was severe. Railroad beds were laid down along almost every high elevation stream in order to take out the timber harvest, resulting in channelization of streambeds and hydrologic alteration of surrounding floodplains (Brooks, 1910; Selders, 1917; Allard and Leonard, 1952; Clarkson, 1964). Where degradation was severe, the landscape did not return to *P. rubens* forest, but instead began the slow process of re-establishment of vegetation and re-building of soils. Some sites burned and eroded to bare rock with little vegetation remaining except for bracken fern.

Others became grass balds or shrub barrens (Brooks, 1910; Robison, 1960). Many areas with moderate degradation regenerated to northern hardwood forests (Schuler et al., 2002; Fortney and Rentch, 2003). *P. rubens* forest regenerated only in a few areas where soils remained relatively intact (Lacey, 1920). Ecosystem recovery in the cool climate of the Allegheny Mountains is very slow, but *P. rubens* is gradually growing back on some of its former range. A period of decline in *P. rubens* growth rates and vigor began in the 1980s and lasted for more than a decade due to acid deposition (Adams et al., 1985; McLaughlin et al., 1987; Adams and Stephenson, 1989; Silver et al., 1991; Eager and Adams, 1992; Schutt, 1993; Battles and Fahey, 2000). More recently, *P. rubens* appears to have stabilized and is actively expanding into portions of its former range (Schuler et al., 2002; Rollins, 2005; Rentch et al., 2007).

The current extent of the *P. rubens* ecosystem has not been accurately measured. The U.S. Forest Service estimates that only around 60,000 acres of *P. rubens* forests remain in West Virginia, representing perhaps a 90% decrease in area compared to the late nineteenth century (USFS 2000). Little published information exists on *P. rubens* and more generally, spruce (*Picea sp.*) and fir (*Abies sp.*)communities of the mid-Appalachians (Stephenson and Clovis, 1983; Stephenson and Adams, 1984; Rheinhardt, 1984) and much of this is found in brief notes (e.g., Chappell, 1972).

To help track forest change over time, technical change detection analyses are used. Change detection is the process of identifying differences in the state of a feature or phenomenon by observing it at different times (Singh, 1989). Change detection is useful in many applications related to land use and land cover (LULC) changes, such as shifting cultivation and landscape changes (Imbernon, 1999; Serra et al., 2008). Satellite remote sensing is the most common data source for detection, quantification, and mapping of LULC patterns and changes because of its

repetitive data acquisition, digital format suitable for computer processing, and accurate georeferencing procedures (Chen et al., 2005; Jensen, 1996; Lu et al., 2004). Change detection and monitoring by remote sensing involves the use of several multi-date images to evaluate the differences occurring in LULC between the acquisition dates of images that are due to various environmental conditions and human actions (Singh, 1989). The successful use of satellite remote sensing for LULC change detection depends upon an adequate understanding of landscape features, imaging systems, and methodology employed in relation to the aim of analysis (Yang and Lo, 2002).

Many change detection techniques have been developed and used for monitoring changes in LULC from remotely sensed data, such as post-classification comparison (PCC), image differencing, principle components analysis, and vegetation index differencing (Lu et al., 2004). The PCC method, which is recognized as the most accurate change detection technique, detects land cover changes by comparing independently produced classifications of images from different dates (Singh, 1989; Yuan et al., 1998). Using the PCC method thus minimizes the problems associated with multi-temporal images recorded under different atmospheric and environmental conditions. Data from different dates are separately classified, and hence, reflectance data from multi-dates do not require adjustment for direct comparability (Coppin et al., 2004; Rivera, 2005; Singh, 1989; Warner and Campagna, 2009; Zhou et al., 2008). The PCC method has the additional advantage of indicating the nature of change (Mas, 1999; Yuan et al., 2005). It not only locates changes but also provides 'from-to' change information (Jensen, 2005; Yuan et al., 2005). There are currently numerous satellite programs in operation. For change detection studies, the Landsat program is unique because it provides an historical and continuous record of imagery. Landsat images can be processed to represent land cover over large areas and

over long time spans, which is unique and absolutely indispensable for monitoring, mapping, and management of LULC (Wulder et al., 2008).

Research Objectives and Thesis Format

In an effort to better understand the existing *P. rubens* resource and to assess its current reforestation potential in the Cheat Mountain range, I examined a portion of *P. rubens* on the Cheat Mountain range and tracked its growth habits for a period of 26 years. I had three objectives: (1) to examine growth patterns of *P. rubens* from 1986 to 2012 from Landsat data using change detection methods. (2) To explore habitat connectivity patterns from patches that are currently in existence and how this information can be used to predict patches that are most critical to *P. nettingi* and (3) to assess the potential impacts climate change might have on the current reforestation potential of *P. rubens* along the Cheat Mountain range.

Chapter II focuses on the regrowth of *P. rubens* shortly after the end of the industrial logging era (1960's) to the present time on Cheat Mountain range in Pocahontas County, West Virginia. The primary question was **how much** *P. rubens* **has grown, been lost, and stayed the same from 1986 to 2012 on the Cheat Mountain range, West Virginia?** I used the consistent, long time series, 30m resolution Landsat imagery that is freely and broadly available. I used unsupervised and supervised classification methods to obtain the results for this section.

Chapter III focuses on critical habitat for *P. nettingi* which is only found on this specific mountain range and is listed as federally endangered under the U.S Endangered Species Act. The question to address was **out of the regrowth of** *P. rubens* **which stands are most critical to** *P. nettingi* **survival?** An index based analysis was used to identify the most critical habitat using a fragmentation model after (Vogt et al., 2007). Methodology is described in detail by (Vogt et al.,

2007). Morphological image processing uses mathematical morphology to analyze shape and form of objects. Forest pixels are classified as isolate, edge, perforated, or core using this model. This method has been shown to provide a more accurate representation of fragmentation at the single pixel or landscape level when compared to image convolution.

Chapter IV focuses on the potential impacts of climate change on the regrowth of *P*. *rubens* on the Cheat Mountain range and in West Virginia as a whole. The primary question is **will climate change affect the regrowth of** *P. rubens* **in West Virginia and on the Cheat Mountain range?** WorldClim data and the Maxent habitat modeling algorithm were used to predict future *P. rubens* distribution in West Virginia based on 19 Bioclimatic variables for A1b and A2 climate change scenarios. I evaluated the results to see if they impacted *P. rubens* regrowth on the Cheat Mountain range in West Virginia.

Chapter V summarized the results, discusses general implications, and suggests future research directions.

Chapter 2

Change detection from 1986 to 2012 of red spruce (*Picea rubens*) on the Cheat Mountain range in West Virginia, USA

Abstract

The Cheat Mountain salamander (*Plethodon nettingi*) is a federally endangered species that relies heavily on red spruce (*Picea rubens*) for habitat. *P. rubens* communities on the Cheat Mountain range in West Virginia have been disturbed by fires and logging, and regeneration of *P. rubens* stands are central to the survival of *P. nettingi*. A supervised and unsupervised landscape classification of three Landsat images over the past 26 years was conducted to analyze change in *P. rubens* communities on the Cheat Mountain range. Change detection results revealed that from 1986-2012 *P. rubens* stands had a growth increase of 52%, 18% loss, and 29% stayed the same over the last 26 years. *P. rubens* stands are vital habitat to the federally endangered *P. nettingi* and regrowth of *P. rubens* is vital in restoring a healthy population of the salamander on the Cheat Mountain range.

Introduction

Landscape classification and vegetation mapping are important technical tasks for managing natural resources because vegetation provides a base for all living beings and plays an essential role in affecting global climate change, such as influencing terrestrial CO₂ (Xiao et al., 2004). Vegetation mapping also provides valuable information for understanding the natural and man-made environments through quantifying vegetation cover from local to global scales at a given time point or over a continuous period. It is critical to obtain current states of vegetation cover in order to initiate vegetation protection and restoration programs (Egbert et al., 2002; Hu et al., 2005).

Traditional methods (e.g. field surveys, literature reviews, map interpretation and collateral and ancillary data analysis), however, may not be effective to acquire vegetation cover because they are time consuming, date lagged and often too expensive. The technology of remote sensing offers a practical and economical means to study vegetation cover changes, especially over large areas (Langley et al., 2001; Nordberg and Evertson, 2003). Because of the potential capacity for systematic observations at various scales, remote sensing technology extends possible data archives from present time to over several decades back. For this advantage, enormous efforts have been made by researchers and application specialists to delineate vegetation cover from local scale to global scale by applying remote sensing imagery.

An increasingly popular application of remotely sensed data is for change detection. Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Four aspects of change detection are important when monitoring natural resources: 1) Detecting that change has occurred, 2) identifying the nature of the change, 3) measuring the areal extent of the change, and 4) assessing the spatial pattern of the change (Brothers and Fish, 1978; Malila, 1980; Singh, 1986).

Remote sensing provides a viable source of data from which updated land-cover information can be extracted efficiently and cheaply in order to inventory and monitor these changes effectively. Thus change detection has become a major application of remotely sensed data because of repetitive coverage at short intervals and consistent image quality. The basic premise in using remote sensing data for change detection is that changes in land cover result in

changes in radiance values and changes in radiance due to land cover change are large with respect to radiance changes caused by others factors such as differences in atmospheric conditions, differences in soil moisture and differences in sun angles (Roy et al., 1991; Sader et al., 1991).The impact of sun angle differences and vegetation phenology differences may be partially reduced by selecting data belonging to the same time of the year (Singh, 1989).

Brooks (1945, 1948) indicated that *P.nettingi* were restricted to pure stands of *P. rubens* or mixed *P. rubens* -Yellow Birch (*Betula alleghaniensis*) forest and that *P.nettingi* were more abundant in newly regenerating *P. rubens* stands, although this observation may be related to the scarcity of mature *P. rubens* forest in the area at the time (Clarkson, 1964). Though, without reference to stand age, Dillard (2007) also found a positive landscape-level association between *P.nettingi* occurrence and presence of *P. rubens* cover.

The objective was to focus on regrowth of *P. rubens* on the Cheat Mountain range after the logging era (1960s) to present day. Our goal was to determine how much *P. rubens* has grown, been lost, and stayed the same from 1986 to 2012 on Cheat Mountain using remotely sensed imagery and landscape change detection techniques. This classification of *P. rubens* was used as the basis for determining effects of *P.nettingi*

Methods

Study Area

The Cheat Mountain range is part of the Allegheny Mountains located in eastern West Virginia. The entire range is roughly 50 miles long (north to south) and about 5 mile wide at its widest. Cheat Mountain traverses the entire length of central Randolph County, West Virginia, from a point just west of Parsons, WV to a point, about 5.5 miles south of the

Randolph/Pocahontas County line, near the community of Stony Bottom, where it impinges upon Back Allegheny Mountain (Figure 2-1). All but the northern most 4 miles and the southernmost 5.5 miles are within Randolph County. The western flank of Cheat Mountain is skirted by U.S. Route 219 which connects a string of communities in the Tygart River Valley (notably, from north to south, Montrose, Kerens, Elkins, Beverly, Huttonsville and Valley Head). The eastern flank, overlooking the valley of Shavers Fork, is more remote. However, all but the northern most 15 miles or so of it is skirted by the Western Maryland Railroad, connecting (from north to south) the communities of Bowden, Bemis and Cheat Bridge. Cheat Mountain is crossed (east/west) by two federal highways: U.S. Route 33 in its northern third and U.S. Route 250 in its southern third. The Cheat River, a tributary of the Monongahela, is formed at Parsons, just east of the northern tip of Cheat Mountain, by the confluence of Shavers Fork and Black Fork. This research will be conducted on a portion of Cheat Mountain located in both Pocahontas County and Randolph County. (Figure 2-1) The area of study is around 55,000 acres and includes Snowshoe Ski Resort as well as the old town of Spruce. Cheat Mountain was strategically important during the early operations in Western Virginia campaign of the American Civil War. One engagement — the Battle of Cheat Mountain — took place here September 12–15, 1861. The West Virginia timber industry grew rapidly towards the turn of the 20th Century. In the early 1900s, Cheat Mountain was extensively timbered by the West Virginia Pulp and Paper Company and their Cass operation, West Virginia Spruce Lumber Company. By 1905, the summit had been reached by loggers and by 1960 the mountain was virtually barren. (Figure 2-2)

Town of Spruce

Spruce is an unincorporated community in Pocahontas County, West Virginia. Spruce is 9.5 miles southwest of Durbin, and was settled in 1902 along Shavers Fork of Cheat River. (Figure 2-3) The principal industry in the area was logging, and later coal mining. In 1904 the West Virginia Pulp and Paper Company (later known as Westvaco) built a pulp mill nearby. The new community adjacent to the mill was also named Spruce, and the original settlement was renamed "Old Spruce." The Greenbrier and Elk Railroad served the town. The pulp mill in Spruce closed in 1925, and the equipment was moved to the company's paper mill in Luke, Maryland. Subsequently the town declined and it eventually was abandoned. This town was the main reason why the Cheat Mountain range was almost wiped clean of all of its *P. rubens*, since *P. rubens* is used for paper pulp.

Scan Line Correction in ERDAS[©] Imagine Using Focal Analysis

Scan lines occur in all Landsat imagery collected after 31-May-03. This is a result of the Scan Line Corrector failure. The images are collected in a zigzag fashion and therefore approximately 22% of the data in Landsat 7 scenes is missing. This method computes the values of neighboring pixels and fills in the gaps based on those calculations for a single Landsat 7 scene. Process one consisted of creating a layer stack of Bands 1,2,3,4,5 from the Landsat 7 SCL-off imagery for 7-Mar-12. This process was completed by using the Layer stack toolset in ERDAS[©] Imagine. Process two consists of initiating a filling method, which utilizes the focal analysis tool. This tool evaluates the region surrounding the pixel of interest (pixels with values of 0). The operations that can be performed on the pixel of interest include a variety of functions but for the purpose of this research the mean function was used, which was best suited for

correcting scan lines. The focal analysis tool was used a total of six times, each time using the output from the previous process, which produced a more accurate interpolation of the 0 values.

Supervised and unsupervised classification system using ERDAS[©] Imagine

Multispectral classification is an information extraction process that analyzes the spectral signatures and then assigns pixels to classes based on similar signatures (Sabins, 283). In ERDAS unsupervised classification is performed using an algorithm called the Iterative Self-Organizing Data Analysis Technique (ISODATA). Using this algorithm, the analyst inputs the number of classes desired and a confidence threshold. The software will then build clusters iteratively, meaning that with each new iteration, the clusters become more and more refined. The iterations stop when the confidence level (or a maximum number of iterations specified by the user) is reached (Jensen, 1996). Both unsupervised and supervised classification system was used to derive *P. rubens* layer from the Landsat 7 imagery. (Figure 2.4-6) Once a desired amount of *P. rubens* was classified, supervised classification was used to increase the confidence level of the classes using training sets of known *P. rubens*.

Post Classification Comparison

After each image was classified individually they were added to ESRI ArcGIS 10.0 to execute the change analysis. Each classified image was clipped to the site extents before this process was started. Each year was converted to a polygon using the raster to polygon tool in the conversion toolbox. This converted all of the classified layers to polygons. Change detection was completed on all three years (1986, 2002, and 2012) (Table 2-1) (Figure 2.7-9) by using the union geoprocessing tool. Union essentially creates a new coverage by overlaying two polygon

layers. The output from this operation contains both polygons and the attributes of both (Table 2-2). Arcs of the input coverage polygon are split at their intersection with polygons of the union coverage. The resulting arcs are used to build polygons using a process similar to the build tool with poly option. The feature attribute table for the output coverage contains items from both the input and union coverage attribute tables. Items are merged into the output polygon feature class using the old internal number of each polygon.

The union results were then classified based on all possible options between the three years.

- 1986,2002,2012- No change in *P. rubens* during all three years analyzed
- 1986- P. rubens found just during this year and not in any other year
- 2002- *P. rubens* growth after 1986 but lost from 2002-2012
- 2012- *P. rubens* growth after 2002
- 1986 and 2002- *P. rubens* lost after 2002
- 1986 and 2012- *P. rubens* loss sometime after 1986 and not found again until after 2002 (possible Type 1 error)
- 2002 and 2012- New growth from 2002 to present

These seven classifications were then extracted as individual shapefiles. A field was added in the attribute table to calculate the surface area of each of the above scenarios

Results

Change Detection

Change detection analysis revealed that from 1986-2012 16,195 acres (52%) growth of P. rubens stands, 5,677 acres (18%) loss, and 9,020 acres (29%) stayed the same over the last 26 years. From 24-Mar-86 to 7-Mar-12 approximately 29% (about 9,020 acres) of P. rubens forest communities have remained unaltered. During 28-Mar-02 to 7-Mar-2012 showed a large growth of P. rubens communities with around 7,280 acres (24% of area). Stands found only on 24-Mar-86 and 7-Mar-2012 could result from a number of instances. One, stands were present on 24-Mar-86 but died off due to wind, drought, snow, ice, etc. on 28-Mar-02, (Figure 2-10) then they regrew and were found again on 7-Mar-2012. Two, an error occurred during 28-Mar-02 either from higher/lower cloud cover than the other two years, different time of day which would produce more or less shadows and pixel values, or drought/high precipitation around that time which can all effect DN values and in turn affect the classification of the Landsat Image. This classification accounted for 8% of the area found and approximately 2,402 acres. 6,513 acres (21%) where present on 7-Mar-2012 which means this growth has occurred since 2002. (Figure 2-11)(Table 2-3) Overall there has been minimal loss across the Cheat Mountain range. From 24-Mar-86 to 28-Mar-02 (Figure 2-12) P. rubens communities were found on in these years with no presence in 7-Mar-2012 which accounts for a loss of 476 acres (2%). The greatest loss was before 28-Mar-02 with 4,590 acres (15%) found but not found on 7-Mar-2012. This could be a factor of the same two scenarios present in 24-Mar-86 and 7-Mar-2012 such as an error or a series of loss and growth events. After 24-Mar-86 there is a small loss of 611 acres (2%) this highlights the loss over the entire span of the analysis. Overall, there has been significant growth of *P. rubens* stands over the past 26 years on the Cheat Mountain range. (Table 2-3)

Discussion

After numerous years of logging, fires and near extinction on Cheat Mountain, *P. rubens* has begun regeneration. Even though there has been forest loss over the 26 year time span, the regrowth outweighs the loss, and stands that were present in 1986 are still found in 2012 and continue to grow which is critical for *P.nettingi* and other species that call this unique ecosystem their home. (Figure 2-13) *P. rubens* stands are vital habitat to the endangered *P.nettingi*. Regrowth of *P. rubens* is vital in restoring the population of the salamander on the Cheat Mountain. The regrowth of *P. rubens* on the Cheat Mountain range could mean a thriving *P. rubens* community that was once almost extinct is being restored.

The major limitation to this study is the relatively course spatial resolutions of the Landsat imagery. 30m resolution imagery is available for 1986 and present imagery with higher resolution is very expensive. If higher resolution imagery was used more accurate percentages of *P. rubens* regrowth would result. Errors could result from atmospheric differences between years during classification. This error was reduced by using imagery from the same time period to limit sun angle differences and seasonal changes. Possible Type 1 errors were found in the study but without ground truthing in the past and present it is impossible to know.

Ground truthing is now needed, in addition to long-term plot research to better understand the regrowth patterns of *P. rubens* on Cheat Mountain. Additional research on *P.nettingi* is also needed to determine whether the regrowth of *P. rubens* is having significant impacts on *P. nettingi* habitat. Additional ground truthing would be needed to further verify monotypical classification vs. mixed/transitional classification between each study year. This would verify if the training data has changed from monotypical *P. rubens* to a more mixed forest

type between 1986 to 2012. These areas of regrowth provide locations for future studies as well as large scale conversation efforts for the Cheat Mountain range and *P.nettingi*. The regrowth of *P. rubens* will have positive impacts on habitat for endangered species and other biotic components of these high elevation communities.

INPU	T COVERAGE	UNION	COVERAGE
#	ATTRIBUTE	#	ATTRIBUTE
1		1	
2	A	2	102
3	В	3	103
4	С		
5	D		

OUTPUT COVERAGE	INPUT	COVERAGE	UNIO	N COVERAGE
#	#	ATTRIBUTE	#	ATTRIBUTE
1	1		1	
2	1		2	102
3	2	A	1	
4	2	A	2	102
5	3	В	2	102
6	3	В	1	
7	2	A	3	103
8	3	в	3	103
9	4	С	3	103
10	5	D	3	103
11	4	С	1	
12	4	С	2	102
13	5	D	2	102
14	5	D	1	
15	1		2	102

INPUT

OUTPUT



Table 2-1. Diagrams of Union process in ArcGIS 10.0

Category	Acres	Percent
1986,2002,2012	9019.997	29.19807
2002,2012	7280.122	23.56603
1986,2012	2402.083	7.775632
1986,2002	476.064	1.541037
2012	6512.945	21.08265
2002	4590.184	14.8586
1986	611.052	1.977998

Total Acres

30892.447

* Blue= Stayed the same, Green= Growth, Red= Loss

Table 2-2. Percent of *P. rubens* change over the past 26 years*.

Acres	Min	Max	Range	Mean	STD
9019.997	3070.87	4888.45	1817.59	4276.16	287.47
7280.122	2969.16	4865.49	1896.33	4260.65	293.12
2402.083	3074.15	4842.52	1768.37	4202.53	261.26
476.064	3569.55	4862.2	1292.65	4260.65	334.48
6512.945	2969.16	4865.49	1896.33	4260.65	293.11
4590 184	2988.85	4862.2	1873.36	4097.68	283.96
611.052	3395.67	4862.2	1466.54	4208.58	286.26
	Acres 9019.997 7280.122 2402.083 476.064 6512.945 4590.184 611.052	Acres Min 9019.997 3070.87 7280.122 2969.16 2402.083 3074.15 476.064 3569.55 6512.945 2969.16 4590.184 2988.85 611.052 3395.67	Acres Min Max 9019.997 3070.87 4888.45 7280.122 2969.16 4865.49 2402.083 3074.15 4842.52 476.064 3569.55 4865.49 6512.945 2969.16 4865.49 4590.184 2988.85 4862.2 611.052 3395.67 4862.2	Acres Min Max Range 9019.997 3070.87 4888.45 1817.59 7280.122 2969.16 4865.49 1896.33 2402.083 3074.15 4842.52 1768.37 476.064 3569.55 4862.2 1292.65 6512.945 2969.16 4865.49 1896.33 4590.184 2988.85 4862.2 1873.36 611.052 3395.67 4862.2 1466.54	Acres Min Max Range Mean 9019.997 3070.87 4888.45 1817.59 4276.16 7280.122 2969.16 4865.49 1896.33 4260.65 2402.083 3074.15 4842.52 1768.37 4202.53 476.064 3569.55 4862.2 1292.65 4260.65 6512.945 2969.16 4865.49 1896.33 4260.65 4590.184 2988.85 4862.2 1873.36 4097.68 611.052 3395.67 4862.2 1466.54 4208.58

* Blue= Stayed the same, Green= Growth, Red= Loss

Table 2-3. Results of change detection over the past 26 years*.

	March 24 th , 1986	March 28 th , 2002	March 7 th , 2012
Landsat	Landsat 5	Landsat 7	Landsat 7
Bands	1-7 Bands	1-8 Bands	7 Bands
Bit	8-Bit Dataset	8-Bit Dataset	8-Bit Dataset
Resolution	30 Meter Resolution	30 Meter Resolution	30 Meter Resolution
Sensor	TM Sensor Terrain Process Level	ETM+ Sensor Terrain Process Level	ETM Sensor Terrain Process Level
Cloud cover	0% Cloud Cover	0% Cloud Cover	22% Cloud Cover

Table 2-4. Landsat Imagery used in landscape classification.



Figure 2.1- Study area located in Pocahontas & Randolph County, West Virginia



Most surrounding towns around the Cheat Mountain Range consist of cattle and corn farms. The valley is considered to be very low development.

The West Virginia timber industry grew rapidly towards the turn of the 20th Century. In the early 1900s, Cheat was extensively timbered by the West Virginia Pulp and Paper Company and their Cass operation, West Virginia Spruce Lumber Company. By 1905, the summit had been reached by loggers and by 1960 the mountain was virtually barren.

Spruce was settled in 1902 along Shavers Fork of Cheat River. The principal industry in the area was logging, and later coal mining. In 1904 the West Virginia Pulp and Paper Company (later known as Westvaco) built a pulp mill nearby. The new community adjacent to the mill was also named Spruce, and the original settlement was renamed



Range consist of cattle and corn farms. The valley is considered to be very low development. Small towns are more developed but still considered light development

Forest and is protected.

Logging continuted till about the 1960's. There are a few small cabins around the area but most of it has grown up into forest.





Figure 2.3- Old town of Spruce had major impacts on the biota of Cheat Mountain during the logging era.



Figure 2.4- 24-Mar-86 classification of *P. rubens* at study area.



Figure 2.5- 28-Mar-02 Classification of *P. rubens* at study area



Figure 2.6- 7-Mar-12 classification of *P. rubens* at study area.



Figure 2.7- Landsat 5 imagery of study area on 24-Mar-86

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Figure 2.8- Landsat 7 imagery of study area on 28-Mar-02



Figure 2.9- Landsat 7 imagery of study area on 7-Mar-12



Figure 2.10- Acres of change among *P. rubens* from 1986-2002 in the Cheat Mountain range.



Figure 2.11- Change from 24-Mar-86 to 28-Mar-02



Figure 2.12- Growth of *P. rubens* from 2002-2012



Figure 2.13- Change between 1986, 2002, and 2012

Chapter 3

Modeling critical forest habitat for the Cheat Mountain salamander (*Plethodon nettingi*) on the Cheat Mountain range in West Virginia, USA

Abstract

The regrowth of red spruce (*Picea rubens*) on the Cheat Mountain range is critical to the survival of the Cheat Mountain salamander (*Plethodon nettingi*). Identifying critical forest as it relates to salamander habitat is essential for conservation efforts. Since not all *P. rubens* stands are of equal significance to *P.nettingi*, it is important to identify and map those that adhere to their stringent habitat needs as defined by forest fragmentation, aspect, slope, and lithology. I used spatial analysis and remote sensing techniques to define critical forest characteristics by applying a forest fragmentation model utilizing morphological image analysis, northeast and southwest aspects, moderate slopes, and limestone lithology. Patches were ranked based on this quantitative model and key *P. rubens* stands identified using spatial statistics. The results could aid in prioritizing research areas as well as conservation planning in regards to *P. rubens* and *P.nettingi*.

Introduction

Forests provide many benefits to society and the natural environment that include wildlife habitat (Chiras, 2002), maintaining biodiversity (Lovejoy, 1986), regulating climate change via carbon storage (Nemani, 1995; Houghton, 1999), nitrogen cycling (Vitousek, 1997; Carpenter, 1998), and altering and moderating hydrologic functions, through evapotranspiration rate and surface runoff volume (Dickenson, 1991). Human land use needs and resource extraction often result in the loss of forested land cover, leading to an impact on biodiversity from habitat conversion (Kopp, 2003; Dobson, 1997; Westman, 1990; Poiani, 2000).

Habitat modeling can be an effective approach to assess habitat distribution and suitability (Mladenoff et al., 1995; Smith et al., 1997; Wiser et al., 1998). Remote sensing and GIS technologies and spatial analysis and modeling approaches can help to scale local-scale information, based on field investigations, to landscape- and regional-scales for development of habitat models for effective conservation and development planning (Sperduto and Congalton, 1996; Ortigosa et al., 2000).

Despite their often high densities, many woodland salamander species have small ranges and patchy distributions generally attributable to physiological restrictions to a relatively narrow range of past and present environmental conditions (Petranka, 1998). Because plethodontids are lung-less and rely entirely on cutaneous respiration, their skin must remain moist to permit efficient gas exchange (Feder, 1983). Accordingly, the moist and permeable skin of woodland salamanders makes them vulnerable to desiccation and limits surface activity to periods when humidity and soil moisture are high (Spotila, 1972). Even when environmental conditions are favorable, terrestrial salamanders risk desiccation during periods of surface activity and must periodically retreat to moist microhabitats for rehydration (Feder, 1983).

P.nettingi is a small terrestrial plethodontid endemic to high-elevation forests of the Allegheny Mountains in Tucker, Randolph, Pocahontas, Grant, and Pendleton counties of eastern West Virginia (Green, 1938; Green and Pauley, 1987). *P.nettingi* was listed as a threatened species in 1989 by the US Fish and Wildlife Service (US Fish and Wildlife Service, 1991). Historically, the range of *P.nettingi* was possibly more extensive than the current restricted distribution (US Fish and Wildlife Service, 1991). However, exploitative logging and large

wildfires in the region eliminated 93% of *P. rubens* forests by 1920 (Clarkson, 1964; Clovis, 1979; Mielke et al., 1986). Accordingly, many *P.nettingi* populations were thought to have been extirpated by this date. Although no published studies have directly assessed effects of forest disturbance on *P.nettingi*, presumably this species responds in a manner similar to other woodland salamanders to the microclimatic, vegetational, and structural changes that occur after timber harvest (Maynadier and Hunter, 1995; Russell et al., 2004a).

In addition to forest stand composition, surface microhabitats that retain moisture also may be important site-level habitat elements for *P.nettingi*. Brooks (1948) described typical *P.nettingi* habitat as a forest floor with decaying *P. rubens* logs covered with mosses and lichens or moss-covered emergent rock. Surface-active *P.nettingi* have been observed under emergent rocks, within and under decaying logs, on the trunks and lower limbs of trees (≤ 2 m high), on sandstone cliff faces, and along road banks (Brooks, 1945 and 1948; Green and Pauley, 1987; Pauley, 1998). Brooks (1948) found *P.nettingi* on both gentle and steep slopes, and did not observe any discernible association between *P.nettingi* presence and riparian habitats.

I examined previous work on modeling critical forest habitat and expanded on the methodology to index critical forest stands on a pixel-by-pixel basis relative to fragmentation patterns, aspect, slope, and lithology as it pertains to *P.nettingi*. Therefore, the objective was to develop a site-level habitat model of critical forest for *P.nettingi* on Cheat Mountain, West Virginia. More specifically, I want to use *P. rubens* stands that were remotely sensed in Chapter 2 as well as a fragmentation model utilizing morphological image analysis to obtain forest fragmentation patterns. I wanted to index aspect, slope, and lithology based on importance to *P.nettingi* (Dillard, 2008). Lastly, I want to identify patterns of critical forest as it pertains to *P.nettingi*.

Methods

Study Area

The Cheat Mountain range is part of the Allegheny Mountains located in eastern West Virginia. The entire range is roughly 50 miles long (north to south) and about 5 mile wide at its widest. Cheat Mountain traverses the entire length of central Randolph County, West Virginia, from a point just west of Parsons, WV to a point, about 5.5 miles south of the Randolph/Pocahontas County line, near the community of Stony Bottom, where it impinges upon Back Allegheny Mountain. All but the northern most 4 miles and the southernmost 5.5 miles are within Randolph County. The western flank of Cheat Mountain is skirted by U.S. Route 219 which connects a string of communities in the Tygart River Valley (notably, from north to south, Montrose, Kerens, Elkins, Beverly, Huttonsville and Valley Head). The eastern flank, overlooking the valley of Shavers Fork, is more remote. However, all but the northern most 15 miles or so of it is skirted by the Western Maryland Railroad, connecting (from north to south) the communities of Bowden, Bemis and Cheat Bridge. Cheat Mountain is crossed (east/west) by two federal highways: U.S. Route 33 in its northern third and U.S. Route 250 in its southern third. The Cheat River, a tributary of the Monongahela, is formed at Parsons, just east of the northern tip of Cheat Mountain, by the confluence of Shavers Fork and Black Fork. This research will be conducted on a portion of Cheat Mountain located in both Pocahontas County and Randolph County. The area of study is around 25,000 acres and includes Snowshoe Ski Resort as well as the old town of Spruce. Cheat Mountain was strategically important during the early operations in Western Virginia campaign of the American Civil War. One engagement —

the Battle of Cheat Mountain — took place here September 12–15, 1861. The West Virginia timber industry grew rapidly towards the turn of the 20th Century. In the early 1900s, Cheat was extensively timbered by the West Virginia Pulp and Paper Company and their Cass operation, West Virginia Spruce Lumber Company. By 1905, the summit had been reached by loggers and by 1960 the mountain was virtually barren.

Habitat Modeling

Recent landscape-level modeling indicated a strong positive association between *P.nettingi* distribution and increasing elevation, sandstone surficial geology, and northeasterly aspects, and a negative association with other geological types and steep slopes (Dillard, 2007). I used this information as the basis for my habitat model.

Computing critical forest habitat for *P.nettingi* range involved remote sensing image classifications and spatial analysis processes. First, 2012 Landsat 7 TM imagery was used to derive *P. rubens* land cover using supervised and unsupervised classification methods (Chapter 2). The classified *P. rubens* pixels were then converted to vector format to fit the proper input standards for the fragmentation model.

Predictor variables in the habitat model included measures of aspect, slope, and lithology. Aspect and slope were derived from a 30-m resolution digital elevation model obtained from the United States Geological Survey (USGS) National Elevation Database (NED). Aspect was categorized with northeasterly facing slopes (22.5-67.5 degrees) having highest values (5) and southwesterly aspects having lowest values (1) (Table 3-1)(Figure 3-1). Slope was categorized in the same fashion with moderate slopes (27-45%) having highest values and slopes farthest from

moderate having lowest values (Table 3-2)(Figure 3-2). Lastly, I used lithology from a 1968 georeferenced and digitized West Virginia Geological and Economic Survey (WVGES) obtained from the Natural Resource Analysis Center (NRCA) at West Virginia University to show favorable spots for *P.nettingi*. The lithology from the NRCA was comprised of four categories instead of five. Unlike aspect and slope lithology had to be categorized 2-5 instead of 1-5 (Table 3-3)(Figure 3-3). This was done because sandstone is an important part of *P.nettingi* habitat and giving the sandstone a 4 instead of 5 would give it less significance in the final model (Dillard, 2008).

Forest Fragmentation Model

P.nettingi has also been shown to be highly sensitive to forest fragmentation (Highton, 1972; Pauley, 1980 and 1998). Morphological image processing was applied to extract forest fragmentation data using Guidos 3.x (Vogt et al., 2007). Morphological image processing uses mathematical morphology to analyze shape and form of objects. Forest pixels are classified as isolate, edge, perforated, or core using this model. This method has been shown to provide a more accurate representation of fragmentation at the single pixel or landscape level when compared to image convolution (Maxwell et al., 2012). For the purposes of this analysis, I used P. *rubens* landcover from the 2012 classification (Chapter 2) as the input. The output from the fragmentation model was reclassified on a scale of 1-5 with 5 being largest core stands and 1 being isolates (Table 3-4)(Figure 3-4).

Critical Forest Model

The critical forest model was created by combining the output from the fragmentation model, aspect, lithology, and slope. These layers were combined as binary raster layers to produce an index grid. Possible values ranged from 5 (not critical) to 19 (most critical) (Maxwell et al., 2012). The final results were an index grid that describes critical forest of *P.nettingi* on a 30m pixel scale.

Results

Forest Fragmentation Results

Of *P. rubens* growth on Cheat Mountain the forest fragmentation model showed that 47% is edge forest using the morphological model, 19% was categorized as core forest, 17% as isolate, and 17% as perforated. A majority of the core forest was predicted as being <250 acres with 1% being >250 acres (Table 3-4)(Figure 3-4).

Critical Forest Model

Individual results for the fragmentation model, aspect, slope, and lithology are summarized in the following tables and figures (Table 3.1-5)(Figure 3.1-4) The output from the binary index analysis concluded that most of *P. rubens* (69.5%) was predicted as being moderately critical; 23.2% was predicted as highly critical and 7.3% less critical (Table 3-6). This analysis highlights the most critical forest for *P.nettingi*. Although there is a small amount of highly critical forest, a large majority of *P. rubens* is highly suitable for *P.nettingi*. Clusters of critical forest stands represent areas that should be managed or protected in order to preserve biodiversity through the landscape and region (Maxwell et al., 2012). This data suggest that finding stands that meet all the requirements of *P.nettingi* is very difficult and that even the slightest disturbances can alter their habitat and greatly increase mortality among the species.

Discussion

The majority of *P. rubens* on the Cheat Mountain range is moderate to highly critical habitat for *P.nettingi*. The regrowth of *P. rubens* on the Cheat Mountain range is vital for the survival of *P.nettingi* and the results of the binary index analysis alludes to of the importance of this regrowth. Although all of *P. rubens* stands are important for Cheat Mountains ecosystem there are vital areas that encompass a majority of the salamanders habitat needs and would be considered high priority when thinking about preservation. These highly critical areas are ideal habitat for the salamander and are areas that should be researched and protected. However, not all forest plots classified as 'critical' will have *P. nettingi* within them.

These areas should be ground truthed to identify if there are *P. nettingi* present, and to evaluate their potential suitability for species migration. One limitation of this study is the resolution of the spatial data. Having spatial data with finer resolution would strengthen the analysis and better predict critical forest habitat for *P.nettingi*. Further sampling would need to be done to determine the accuracy of this critical forest model. However, this type of analysis can assist large scale conservation and preservation efforts that will better protect *P. rubens* and *P.nettingi* in the future.

P. rubens is vital to the existence of *P.nettingi* and lack of preservation of these areas could mean extinction. Identifying critical forest plots for the salamander can aid in designations of research plots and areas of concern. If history repeats itself and *P. rubens* is exposed to

another major disturbance, it would most likely devastate the fragile ecosystem that his critical to *P.nettingi*.

Aspect Results	Value	Count	Square Meters	Acres
Southwest	1	33067	29760300	7353.919
South, West, Southeast	2	63732	57358800	14173.65
Northwest	3	69531	62577900	15463.31
North, East	4	63436	57092400	14107.82
Northeast	5	28682	25813800	6378.719

Table 3-1. Index Values for Aspect Analysis

Slope Results (%)	Value	Count	Square Meters	Acres
0-13, 57-78	1	29823	26840700	6632.471
13-20, 51-57	2	52054	46848600	11576.52
20-27, 45-51	3	64188	57769200	14275.06
27-34,40-45	4	75493	67943700	16789.23
34-40	5	36890	33201000	8204.133

Table 3-2. Index Values for Slope Analysis

Lithology Results	Value	Count	Square Meters	Acres
Limestone	2	597	537300	132.7695
Shale	3	16333	14699700	3632.369
Shale/Sandstone	4	12311	11079900	2737.899
Sandstone	5	22617	20355300	5029.896

Table 3-3. Index Analysis for Lithology

Fragmentation Results	Value	Count	Square Meters	Acres
Isolate	1	3481	3132900	774.1553
Edge	2	9765	8788500	2171.682
Perforated	3	3531	3177900	785.275
Core (<250 Acres)	4	3860	3474000	858.4428
Core (>250)	5	249	224100	55.37623

Table 3-4. Index Values for Fragmentation Results

Final Results	Value	Count	Square Meters	Acres
Less Critical	5	2	1800	0.444789
	6	27	24300	6.004652
	7	119	107100	26.46495
	8	352	316800	78.28286
	9	888	799200	197.4863
	10	1562	1405800	347.3802
	11	2415	2173500	537.0827
Moderately Critical	12	3054	2748600	679.1928
	13	3242	2917800	721.003
	14	2939	2645100	653.6174
	15	2220	1998000	493.7158
	16	1319	1187100	293.3383
	17	617	555300	137.2174
	18	196	176400	43.58932
Highly Critical	19	50	45000	11.11973

Table 3-5. Final Index Values of Critical Forest based on (Fragmentation, Aspect, Slope, and Lithology)



Figure 3-1. Aspect map categorized based on habitat preferences of *P.nettingi*.



Figure 3-2 Slope map categorized based on habitat preferences of *P.nettingi*.



Figure 3-3 Lithology map categorized based on habitat preferences of *P.nettingi*.



52

Figure 3-4 Forest Fragmentation model results based on *P. rubens* classification.



Figure 3-5 Critical forest based on habitat preferences of *P.nettingi*.



Figure 3-6 Highly critical forest from critical forest model results.

Chapter 4

Climate change analysis on red spruce (*Picea rubens*) in the Cheat Mountain range, West Virginia USA

Abstract

The Cheat Mountain range in West Virginia is home to red spruce (Picea rubens) which grows in a high-elevation ecosystem in the Appalachian mountain range. It is essential habitat for the Cheat Mountain salamander (*Plethodon nettingi*), a federally endangered species which may be highly vulnerable to climate change. In this study, the MaxEnt modeling framework was used to predict habitat suitability for *P. rubens* under current conditions and under two future climate change scenarios. P. rubens distribution data was acquired from the U.S Geological Survey. Both the IPCC A1b and A2 emission scenarios of the HadCM3 global circulation model were projected to years 2040-2069 and 2070-2099. Results showed that a substantial decline in the suitability of future *P. rubens* habitat on the Cheat Mountain is likely under both climate change scenarios, particularly at lower elevations. By the end of the century, *P. rubens* is likely to be extirpated from the Cheat Mountain range. By the end of century, the A1b and A2 scenarios predict the average habitat suitability for *P. rubens* on Cheat Mountain will be 0.0002 and 0.00004 respectively. Conservation as well as species migration efforts for *P. rubens* should be focused on areas such as Cheat Mountain to preserve this vital habitat. However, conservation for P. rubens needs to focus on more than species protection and protected area management, which have been the primary focus of past management efforts. Long term conservation efforts must be considered along with ecosystem process and overall land-use patterns. Currently,

climate change is seen as a future problem and is considered insignificant in comparison to current disturbances. Conservation efforts such as corridors between reserves needs to take into consideration directional impacts of climate change from current climate models.

Introduction

There is now ample evidence that modern climate change is reshuffling the geographic distributions of plant and animal species world-wide (Parmesan and Yohe, 2003). And because climate change is primarily a latitudinal event (i.e., moving northward), the dynamics of populations at the latitudinal margins of their native range are likely to be critically important in determining species responses to expected climate change (e.g. Thomas et al., 2001; Iverson et al., 2004; Travis and Dytham, 2004).

Ongoing climate change is expected to have major impacts on wildlife and wildlife habitats in West Virginia, including range shifts, population declines or expansions, and extinctions. While some of the more high-profile impacts of climate change (such as sea level rise, ocean acidification, and melting glaciers) are not of immediate concern for wildlife managers in West Virginia, climate change is nevertheless likely to stress native wildlife via increasing temperatures, decline in precipitation, and increase in the frequency and intensity of extreme events such as drought, decreases in seasonal and perennial snow and ice events, and changes in atmospheric composition such as increases in greenhouse gases and aerosol content. (IPPC, 2007; TWS, 2008; BPC, 2009; Young et al., 2010). Some of the most sensitive taxonomic groups, such as amphibians, are already being negatively impacted by climate change (Pauley, 2006). *P. nettingi* is a small terrestrial plethodontid endemic to high-elevation; *P. rubens*

dominated forests of the Allegheny Mountains in Tucker, Randolph, Pocahontas, Grant, and Pendleton counties of eastern West Virginia (Green, 1938; Green and Pauley, 1987). The species is restricted to approximately 70 isolated sites distributed across an area of approximately 1800 km² (Pauley and Pauley, 1997; Petranka, 1998). Furthermore, 75% of all known *P. nettingi* populations are thought to consist of 10 or fewer individuals and 80% of all known populations occur in the Monongahela National Forest (MNF; USDI Fish and Wildlife Service, 1991). Here, I argue that species like *P.nettingi* that reside in the latitudinal margins of distribution for *P. rubens*, are disproportionately vulnerable to climate change. Yet protecting these kinds of species will be essential for the long-term conservation of genetic diversity, phylogenetic history and evolutionary potential of species. Accordingly, their investigation and conservation deserve high priority. My objective is to show how *P.nettingi's* primary habitat, *P. rubens* forest on the Cheat Mountain range, is likely to be affected by climate change.

The main objective of this study is to use the Maximum Entropy Species Distribution Modeling (MaxENT) framework to forecast the likely effects of climate change on *P. rubens* distribution across the Cheat Mountain range in West Virginia. This study aims to model the current and future distribution of *P. rubens* based on environmental factors from projected climate models. Specifically, I seek to determine whether climate change is likely to eradicate *P. rubens* from the Cheat Mountain range. Distribution changes on the Cheat Mountain range as well as direction distribution changes throughout the state of West Virginia are examined as well. Implications of shifting *P. rubens* stands in regards to rare, threatened, and endangered species are also taken into consideration.

Methods

To model the contemporary distribution of *P. rubens*, I first downloaded the historic climate data from the WorldClim Global Climate Data website, (WorldClim, 2005). This historic dataset has been downscaled to a resolution of approximately 1 km². Rather than using raw air temperature and precipitation values, I used the 19 Bioclimatic variables in our habitat models. These variables are derived from the monthly temperature and rainfall values in order to generate more biologically meaningful variables. These variables represent annual trends (e.g., mean annual temperature, annual precipitation), seasonality (e.g., annual range in temperature and precipitation), and extreme or limiting environmental factors (e.g., temperature of the coldest and warmest month, and precipitation of the wet and dry quarters), and they are often used in ecological niche models.

Future climate data were acquired from the www.worldclim.org. Projected data were available from 2040-2099 and were partitioned into two time periods: 2040-2069 and 2070-2099. For each of these time periods, the same 19 bioclimatic variables used above were obtained (1 km² resolution). The Hadley Centre Coupled Model version 3 (HadCM3) global circulation model was selected for this study. HadCM3 is one of the most thoroughly documented circulation models (e.g., Stott et al., 2000; Reichler and Kim, 2008) and it was used in the IPCC Third and Fourth Assessments.

Two of the IPCC scenarios were included in our simulations: A1b and A2. The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing population. Economic development is primarily

regionally oriented and per capita economic growth and technological change more fragmented and slower than other storylines. The A1 storyline and scenario family describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. A1b is where balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end-use technologies (IPCC, 2007).

Maxent Modeling

P. rubens distribution models were built using the MaxEnt framework (Maxent; Phillips et al., 2006; Phillips and Dudik, 2008), which utilized two groups of data inputs in order to project *P. rubens* habitat suitability in 2012, and 2040-2099. Current *P. rubens* distribution was inferred from a distribution map compiled by the U.S Geologic Survey (USGS, 1999; Little, 1971). The original distribution shapefile was converted from polygon to point data using the Create Random Points function in ArcGIS 10.1. To randomly place the specified number of points in each polygon, the polygons are partitioned by varying-sized triangles using a standard polygon partitioning algorithm in ArcGIS. Points were created in a random spatial patter at intervals of 10 meters within the bounds of the former polygon. This reflects an average spacing of mature *P. rubens* trees. These random points do not accurately reflect the true (but unknown) density of *P. rubens* on Cheat Mountain. However, the purpose is to distinguish regions of *P. rubens* presence and absence to identify the ecological niche (Stanton, 2009). Response curves

and the jackknife method were used to assess variable importance. I chose 15 as the value for replicates, and model prediction accuracy was assessed by randomly assigning 25% if the input data to an independent validation dataset. Maximum iterations were changed to 5000 instead of the default 500; this allowed the model to have adequate time for convergence. If the model doesn't have enough time to converge, the model may over-predict or under-predict the relationships. (Philips et al., 2006) Subsample was used as the sampling technique for this study. Maxent was run using the 1 km² resolution data for the entire state of West Virginia. Results were then clipped to the Cheat Mountain site using the Extract by Mask tool in ArcGIS. The cell values above the mean value show regions with highest chance of habitat suitability.

Results

The bioclimatic variables with the highest contributions to determine *P. rubens* distribution for the West Virginia were coldest month (BIO06) with an average contribution of 45%. The second highest contributing variable was mean temperature of the warmest quarter (BIO10) with an average contribution of 19%. The third highest contributing variable was annual mean temperature (BIO 01) with and average contribution of 11%.(Figure 4-1) The bioclimatic variables that yielded the lowest contributions was precipitation of coldest quarter (BIO19), mean temperature of driest quarter (BIO09), precipitation of wettest quarter (BIO16), precipitation of driest quarter (BIO17), and precipitation seasonality (BIO15). These bioclimatic variables all had contributions of less than 1% to the models. Reviewing the jackknife output for each scenario and time period it appears that no variable contains a substantial amount of useful information that is not already captured in the other variables. This shows that no one variable

had a large contribution to the models and that all variables, while some had higher contributions than others are all highly correlated.

Both A1b and A2 scenarios with a test of 25% of data yielded an AUC=0.82 which indicated a good predictive performance. The contemporary distribution results indicate high suitability over the historical Cheat Mountain range, with a median predicted habitat suitability of 0.57 (95% CI: 0.5066, 0.6191).

The predicted future suitability of *P. rubens* habitat on the Cheat Mountain range was significantly lower under the A1b climate scenario. Average predicted suitability was 0.01, (95% CI:-.0052, 0.0253) by 2040-2069, and 0.0002, (95% CI:-0.0001, 0.0005) by 2070-2099. Statewide, *P. rubens* distribution was predicted to be limited to a relatively small number of discontinuous, high elevation stands.

Under the A2 scenario, *P. rubens* habitat suitability was predicted to decrease even more. Mean suitability on the Cheat Mountain range was 0.007, (95% CI:-0.0056, 0.0199) by 2040-2069, and 0.00004, (95% CI:-0.000004, 0.000076) by 2070-2099. Thus, *P. rubens* is likely to be entirely extirpated from the Cheat Mountain range by the end of the century, under the A2 emissions scenario. (Figure 4-2)

Discussion

Based on the chosen scenarios and outputs from the Maxent model, it is clear that *P*. *rubens* habitat will be significantly threatened by climate change in the future. These changes are likely to stem from temperature changes in the coldest months and annual temperature values which greatly alter suitable habitat in which *P. rubens* are known to exist. Appalachian *P. rubens* is considered one of the most endangered forest systems in the United States (Christensen et al.,

1966; Noss et al., 1995). Effects of climate change on this already fragile forest system could have severe impacts on its survival. This population of *P. rubens* occurs near the southern margin of the continental *P. rubens* distribution and is disproportionately important for this distinct ecosystems survival, as well as endangered species such as *P.nettingi* that depend on these southern margin *P. rubens*.

Mid-century predictions show *P. rubens* being confined to high elevation ridge tops along Randolph, Pendleton, and Pocahontas County. Areas most at risk in West Virginia appear to be mountain ranges such as Cheat Mountain and Spruce Knob, located in the northeastern part of the state. Directed conservations efforts in these counties may therefore prove critical to the preservation of *P. rubens* stands. Vegetation models (Iverson and Prasad, 1998) suggest that projected climate change may alter *P. rubens* distribution, particularly on marginal habitat and in areas near the southern limit of its range. They suggest that restoration efforts should initially be concentrated in higher elevations where *P. rubens* is most viable, even with potential climate change, and that these patches should be linked to subsequent efforts at lower elevations (Rentch et al., 1997) Long term monitoring should be conducted in various *P. rubens* stands throughout the Cheat Mountain range to better track climate change effects on *P. rubens* communities. This would help future efforts in protecting *P. rubens* as well as habitat for *P.nettingi*.

Perhaps the most important limitation of this study is the uncertainty in actual *P. rubens* distribution change. The randomization procedure that was used to convert distribution polygons to discrete occurrences (i.e., points) may have distorted the true distribution of *P. rubens*. True point data (*P. rubens* occurrences) could potentially strengthen the model. But the clear take home message that was reached in this study is not likely to change: *P. rubens* will become

increasingly imperiled with climate change, as will species that depend on *P. rubens* stands, such as *P.nettingi*.



Bio 1: Annual Mean Temperature

Figure 4-1 Bioclimatic variables with highest contributions


Figure 4-2 Predicted P. rubens distribution from Historical to end of century A2 Scenario

Chapter 5

Conclusion

Three primary questions were addressed in the research above. 1) How much *P. rubens* has grown, been lost, and stayed the same from 1986-2012 on the Cheat Mountain range, West Virginia? 2) Out of this regrowth which stands are most critical to *P.nettingi's* survival? 3) Will climate change affect the regrowth of *P. rubens* in West Virginia and on the Cheat Mountain range?

How much *P.rubens* has grown, been lost, and stayed the same from 1986-2012 on the Cheat Mountain range? After numerous years of logging, fires and near extinction on Cheat Mountain, *P. rubens* has begun regeneration. Even though there has been forest loss over the 26 year time span, the regrowth outweighs the loss, and stands that were present in 1986 are still found in 2012 and continue to grow which is critical for *P.nettingi* and other species that call this unique ecosystem their home.

largest majority of *P. rubens* that have begun to regrow from 1986-2012 on the Cheat Mountain range is moderate to highly critical habitat for *P. nettingi*. The regrowth of *P. rubens* on the Cheat Mountain range is vital for the survival of *P. nettingi* and the results of the binary index analysis prove the importance of this regrowth. Although all of *P. rubens* stands are important for Cheat Mountains ecosystem there are vital areas that encompass a majority of the salamanders habitat needs and would be considered high priority when thinking about preservation.

Out of this regrowth which stands are most critical to *P.nettingi's* survival? The

Will climate change affect the regrowth of *P. rubens* in West Virginia and on the **Cheat Mountain range?** Based on the chosen scenarios and outputs from the Maxent model, it

is clear that *P. rubens* habitat will be significantly threatened by climate change in the future. These changes are likely to stem from temperature changes in the coldest months and annual temperature values which greatly alter suitable habitat in which *P. rubens* are known to exist. Appalachian *P. rubens* is considered one of the most endangered forest systems in the United States (Christensen et al., 1966; Noss et al., 1995). Effects of climate change on this already fragile forest system could have severe impacts on its survival.

In addition the near future threat of climate change, it is important to also remember other serious on-going threats to upland *P. ruben* communities. Despite protection in many areas, *P. rubens* still face significant habitat loss through second home development, industrial wind corridors, fragmentation and loss of buffer from road construction and logging, and invasive species and pathogens. On a positive note, upland *P. ruben* communities have a few key characteristics that make them somewhat resilient to stress. They occur on large tracts of relatively well-connected landscapes in the largest high-elevation area in the northeastern US. *P. rubens* ecosystem as a whole contain high levels of biodiversity, which means that even with some extinction, there may be enough connected threads of the ecosystem left to function (Byers, 2010)

This study could be incorporated into a diverse restoration strategy that includes planting *P.rubens* on historic habitat where it is now absent, carefully managing second-growth stands for older age characteristics and structure, and protecting older stands with legacy elements as remnants of the original forest that was not affected during the logging era (Rentch, 1997). One of the main justifications for restoration of *P.rubens* is *P.nettingi*. Future restoration plans should target critical forests and maximize overall patch size and habitat connectivity (Franklin et al., 2002; Menzel et al., 2006)

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Vita

Justin Michael Madron was born on June 10, 1988, in Richmond, Virginia. He grew up in Pocahontas County, West Virginia and attended Pocahontas County High school until he graduated in June of 2006. He attended West Virginia University from 2006 to 2011 and graduate with a B.S in Landscape Architecture in May 2011. In the fall of 2011, Justin enrolled in the Masters of Environmental Studies program at VCU. Since that time, Justin has worked for the Center for Environmental Studies under the direction of Will Shuart and Dr. Greg Garman. Justin also works at the University of Richmond as a Graduate Assistant in the Department of Geography and the Environment. Justin will be married to Tiffany Marie Alt on June 22nd of this year. Justin and Tiffany both live in Chesterfield County, Virginia. In his spare time, Justin likes to hunt, fish, and mountain bike in West Virginia, and enjoys the outdoors.