Landscape Level Evaluation of Northern Bobwhite Habitats

in Eastern Virginia Using Landsat TM Imagery

by

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(ABSTRACT)

Northern bobwhite (*Colinus virginianus*) are important game birds associated with early successional habitats across the southeastern United States. In the past 30+ years there has been an almost universal decline in bobwhite population numbers despite a long history of management. The Virginia Bobwhite Quail Management Plan was implemented in 1996 to slow and stop the current population declines in Virginia. Virginia Department of Game and Inland Fisheries (VDGIF) personnel identified a lack of knowledge about the broad-scale, landscape level habitats in eastern Virginia. A large scale land cover map along with a detailed understanding of the spatial arrangements of bobwhite habitats will not only aid Virginia's management plan, but also allow focused efforts by our wildlife managers. I explored the possibilities of using remote sensing to map various habitats important to bobwhite. I compared several classification algorithms applied to Landsat TM imagery prior to selecting the classification method that best delineated early successional habitats. After method selection, a classified land cover map for the Coastal Plain and Piedmont of Virginia was generated.

Using the classified images available from the first part of the study and 4 years of bobwhite call count data, I studied the landscape level habitat associations of bobwhite. A number of landscape metrics were calculated for the landscapes surrounding bobwhite call count routes and were used in two modeling exercises to differentiate between high and low bobwhite populations. Both pattern recognition (PATREC) and logistic regression models predicted levels of bobwhite abundance satisfactorily for the modeled (84.0% and 96.0% respectively) and independent (64.3% and 57.1%, respectively) data sets. The models were applied to remotely-sensed habitat maps to develop prediction maps expressing the quality of a landscape for supporting a high population of bobwhite based on existing land cover.

Finally, I explored the possibility of eliminating the time consuming and very costly step of classifying a remotely-sensed image prior to examining its quality for a particular species. Using raw Landsat TM imagery and bobwhite call count data, I developed predictive logistic regression models expressing the quality of a landscape surrounding a pixel. The first model predicted the probability of the landscape supporting a high bobwhite population. Due to a number of stops with an average of zero, I was also able to generate a model that expressed the probability of the landscape supporting any number of bobwhite. This method also satisfactorily predicted high/low population and presence/absence for the modeled data (65.7% and 83.1%, respectively) and independent data (65.3% and 83.7%, respectively). The method described will allow for rapid assessment of our wildlife resources without having to classify remotely-sensed images into habitat classes prior to analyses.

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CHAPTER 1- BOBWHITE NATURAL HISTORY

Habitat

Northern bobwhite (bobwhite) are habitat generalists that are typically found in patchy environments where several cover types come together (Cline 1988, Tonkovich 1995). Bobwhite habitat requirements vary by season, but the birds are typically found across a broad range of climatic and habitat types, providing that they contain certain attributes like herbaceous cover, agricultural areas or other source of food, and woody cover (Rosene 1969, Johnsgard 1988). All of these life requisites need to be proximate due to the birds' low mobility (Roseberry and Klimstra 1984, Johnsgard 1988). The greatest densities of bobwhite are found where the highest diversity of plants occurs (Rosene 1969). The various successional stages of the agricultural/fallow/idle old-field-continuum provide excellent habitat for bobwhite (Stoddard 1931**,** Lehmann 1937**,** Rosene 1969, Exum et al. 1982, Roseberry and Klimstra 1984, McInteer 1986). The juxtaposition of certain early successional habitat types is important for bobwhite. Most of the open-land association is due to the bobwhite's need for open-ground surfaces where they can move, detect predators, and feed (Rosene 1969). Brushy drainage drainages, ditches, windrows, and fence rows are other by-products of human development that are beneficial as bobwhite habitat.

Many early succession habitats are dependent on succession-reverting mechanisms such as fire, mechanical processes, and other disturbances to retain their value for bobwhite (Rosene 1969, Roseberry and Klimstra 1984, Burger et al. 1990, Hays and Farmer 1990). Often these mechanisms are the principal components of bobwhite management plans.

Declines

Despite nearly 2,800 articles and publications concerning bobwhite populations and their management (Scott 1985), little is known about the cause of the current widespread declines that bobwhite are exhibiting across much of their range in the past 3 decades (Brennan 1993). Brennan (1991) examined Breeding Bird Survey (BBS) and Christmas Bird Count (CBC) data (Droege and Sauer 1990) and found that bobwhite trends were consistently negative with 77% of the states exhibiting a downward trend in population numbers. Brennan (1991) noted these alarming declines were greatest in the southern portions of the bobwhite's range, and he thought that if the declines were allowed to continue, bobwhite would likely disappear by the year 2005. More recently, Church et al. (1993) summarized similar data, finding a persistent decline since at least 1966, again with increasing rates during the last decade. They reported an annual decline of 3.5% in the last decade, with elevated rates for Virginia and the Northern Piedmont physiographic region (6.6% and 11.9% declines in the last decade, respectively). During this same time, numerous grassland/shrub land bird species have also exhibited declines when sympatric with bobwhite (Church et al. 1993). Bobwhite have experienced similar declines (Figure 1-1) in Virginia (Sauer et al. 1997).

There are numerous hypotheses about the cause of the bobwhite decline, including clean farming and silvicultural systems (Vance 1976, Roseberry and Klimstra 1984, Brennan 1991, Brennan 1994), increases in predator populations (Brennan 1994, Langner and Flather 1994), the invasion of the imported red fire ant (Church et al. 1993, Brennan 1994), increases in human

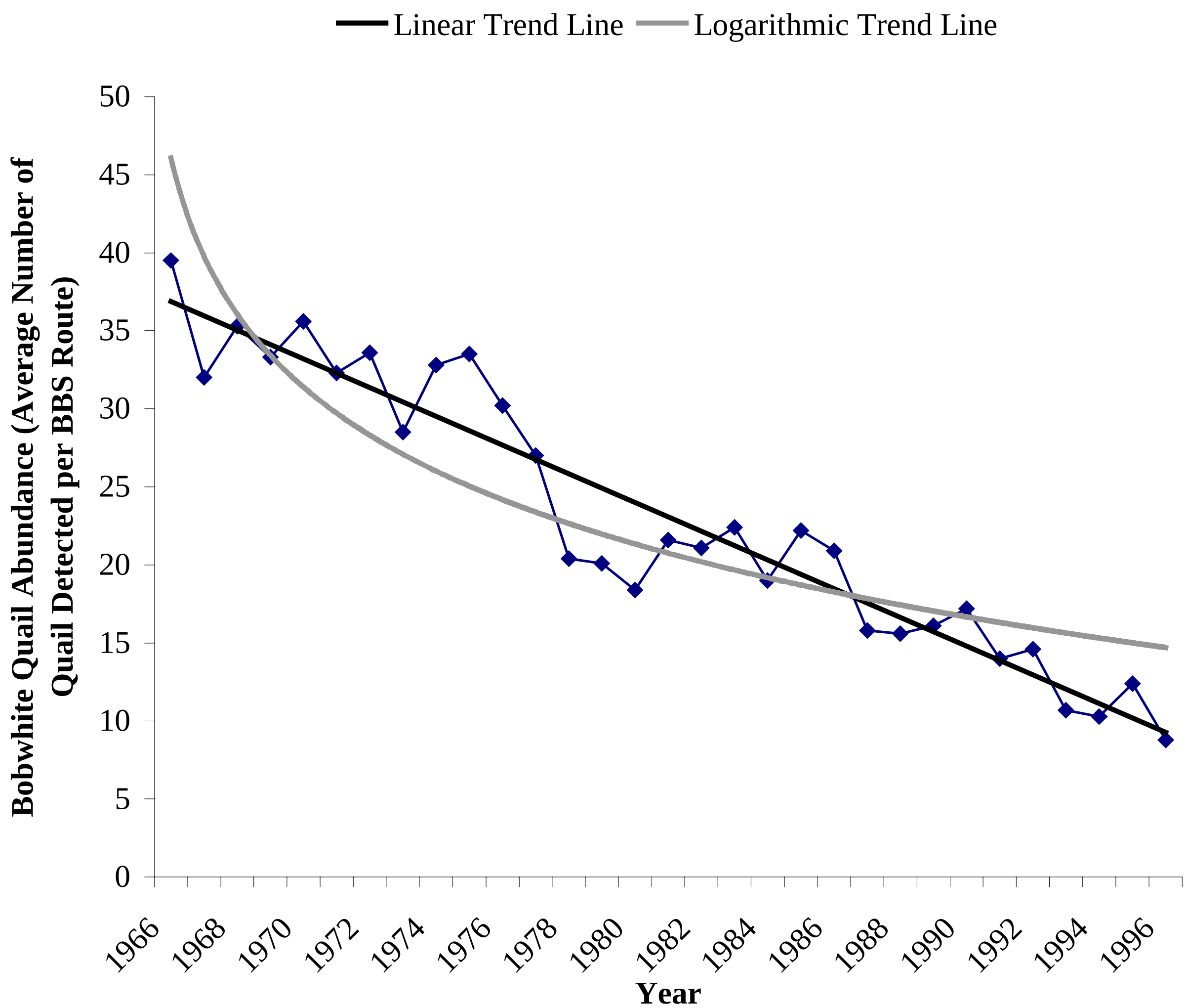


Figure 1- 1. Population trends for bobwhite in Virginia from Breeding Bird Survey data since 1966 (adopted from Sauer et al 1997).

populations (Roseberry and Klimstra 1984), increased restrictions on prescribed fire (Flather and Hoekstra 1989), conversion of fields to fescue (Roseberry and Klimstra 1984, McInteer 1986, Sole 1995), the range expansions of wild turkey and white-tailed deer (Tall Timbers Annual Report 1995), and even global warming (Tall Timbers Annual Report 1995). One major idea consistently reappearing related to the farming system changes noted has been the loss of bobwhite habitat caused by changes in land use practices (Vance 1976, Roseberry and Klimstra 1984, McInteer 1986, Flather and Hoekstra 1989, Brennan 1991, Meseke 1992, Langner and Flather 1994). Agriculture and forestry are the single largest modifiers of lands and waters that provide habitat for wildlife and fish (Natural Resources Council 1982). Much of the upland habitat in the US has been dissected or eliminated by current land use practices, leaving patchy, isolated habitats separated by tracts of inhospitable land (Roseberry 1993). A localized approach to examining the issue of land use change and habitat loss is not sufficient, rather a broad, landscape perspective is needed to examine these changes (Brennan 1993, Kuvlesky et al. 1993, Roseberry 1993).

Association with Agriculture

Most changes in agricultural land uses and agricultural practices are out of the control of game managers but the changes have profound effects on bobwhite, because bobwhite are tightly associated with these habitats (Natural Resources Council 1982, Capel et al. 1993). Early land clearing and low intensity agriculture, that created small fields of diverse plantings and a network of hedgerows and brushy fence rows, created abundant bobwhite habitat (Stoddard 1931, Roseberry and Klimstra 1984, Roseberry 1993). Conversely, advances in agricultural methods and technology that once caused bobwhite numbers to expand are now having largely negative influences on bobwhite populations. Modern agriculture is typified by mechanization, larger field sizes, larger farms, increased use of pesticides and herbicides, and cleaner, more efficient, and more intensive agricultural methods than in the past (Edwards 1972, Vance 1976, Heitmeyer 1980, Exum et al. 1982, Natural Resources Council 1982, Roseberry and Klimstra 1984, Brennan 1991, Stanton 1993, Wallace 1994). These collective practices have eliminated vast areas of habitats of high quality to bobwhite and can be correlated, if not directly linked, to the declines exhibited by bobwhite populations. Clean farming is not new either. In 1931, Stoddard noted that agricultural practices were moving towards cleaner methods that would be unfavorable for bobwhite, and he predicted that bobwhite could be lost due to these changes. Because clean farming is more economical than traditional practices, the agricultural sector has been pushed in the direction of these clean-farm methods that are not conducive to maintaining high quality habitat (Natural Resources Council 1982). Important habitat in brushy fence rows and hedgerows has been lost as methods have become cleaner than past methods and field sizes increased to accommodate larger, efficient machinery.

Status of Agriculture

Average farm size in the United States increased rapidly between 1935 and 1974 (Edwards et al. 1985), but remained very constant from 1974 to 1987 (Stanton 1993). In Virginia (Figure. 1-2a) the average farm size has declined slightly between 1978 and 1992 (US Department of Commerce 1978-1992). Meanwhile the number of farms dropped from 6.81 million in 1935 to 2.24 million in 1982 (Edwards et al. 1985), to 2.09 million farms in 1987 (Stanton 1993), and only 1.93 million farms in 1992 (Gale 1995). In Virginia, the number of farms (Figure 1-2b) has also been declining (US Department of Commerce 1978-1992). Changes in farm numbers and farm sizes offset each other during this redistribution of farm lands, with a mere 8% decline in total acres of land in farms between 1940 and 1982 (Edwards et al. 1985). Similarly there was only a slight decline in total acres farmed between 1987 and 1992, nationally and in Virginia (Figure 1-2c). The loss was most likely caused by urban encroachment (Gale 1995). Since the peak in total acres farmed in the 1950's, agricultural land has slowly been converted to forest, recreational use areas, and urban/suburban developments (Stanton 1993). Between 1939 and 1974, Vance (1976) noted that the average size of farms more than doubled in Illinois, resulting in an 84% reduction in fence rows. Similarly, in Virginia average farm size increased 94.5% between 1925 and 1987, while the state lost nearly 76% of all its farms (Fies et al. 1992). The average farm size almost doubled in the state during that period (Fies et al. 1992). As agriculture intensifies, fewer acres are being farmed and more inter-tilling, or cultivation between the rows, is being employed (Roseberry and Klimstra 1984). Bobwhite are negatively associated with increases in plantings to row crops (Natural Resources Council 1982, Brady 1988). In Illinois, declines in pheasant harvests were also related to increases in row crops (Brady 1988).

Besides the more intensive and efficient use of croplands, other changes in land use are also apparent, including the conversions of lands in pasture, range, and forest to cropland, and the loss of prime farm land to non-agricultural uses like urban development (Natural Resources Council 1982). Using marginal areas for agricultural purposes drives crop production costs up, making cleaner and more effective methods of greater necessity than in the past (Natural Resources Council 1982).

Fescue

The increase in the use of fescue within this changing landscape also appears to be affecting bobwhite populations. Tall fescue (*Festuca arundinacea*) is the predominant cool-season, perennial grass in the United States (Stelly 1979) and is a valuable grass of temperate agriculture (Buckner and Bush 1979). Currently it is one of the most widely grown cool-season grasses in the United States on an estimated 35 million acres (Buckner and Bush 1979). It is grown for livestock feed, turf, and conservation purposes (Burns and Chamblee 1979). Tall fescue has been described as having excellent agronomic properties as a pasture grass (Barnes et al. 1995) and as being highly invasive and competitive, resulting in thick growth and a reduced plant species diversity (Sole 1995). Fields dominated by fescue are marginal habitats for bobwhite (Barnes et al. 1995). Tall fescue fails to provide the food or cover that native species provide (McInteer 1986). Tall fescue seeds nearly meet daily energy requirements of bobwhite, but they are produced during the summer when bobwhite are feeding predominantly upon invertebrates (Barnes et al. 1995). Therefore fescue seeds are used only slightly (Barnes et al. 1995). The arthropod diversity, abundance, and biomass in fescue fields is adequate to support bobwhite and are similar to values reported for legume fields, but the poor vegetative structure of fescue may hinder access to this food source (Barnes et al. 1995). Fescue fields contained abundant dead grass stems used in nesting (Barnes et al. 1995). Sole (1995) found that if a fescue-dominated field was converted to an orchard grass/legume mixture there would be an increase in plant diversity while the overall vegetative quality for bobwhite would increase. Local populations of bobwhite increased following this conversion. There was more bare ground the year following the conversion to the mixture than in the original fescue field, but in both of the next 2 years the area converted to the mixture had a denser ground layer than the original

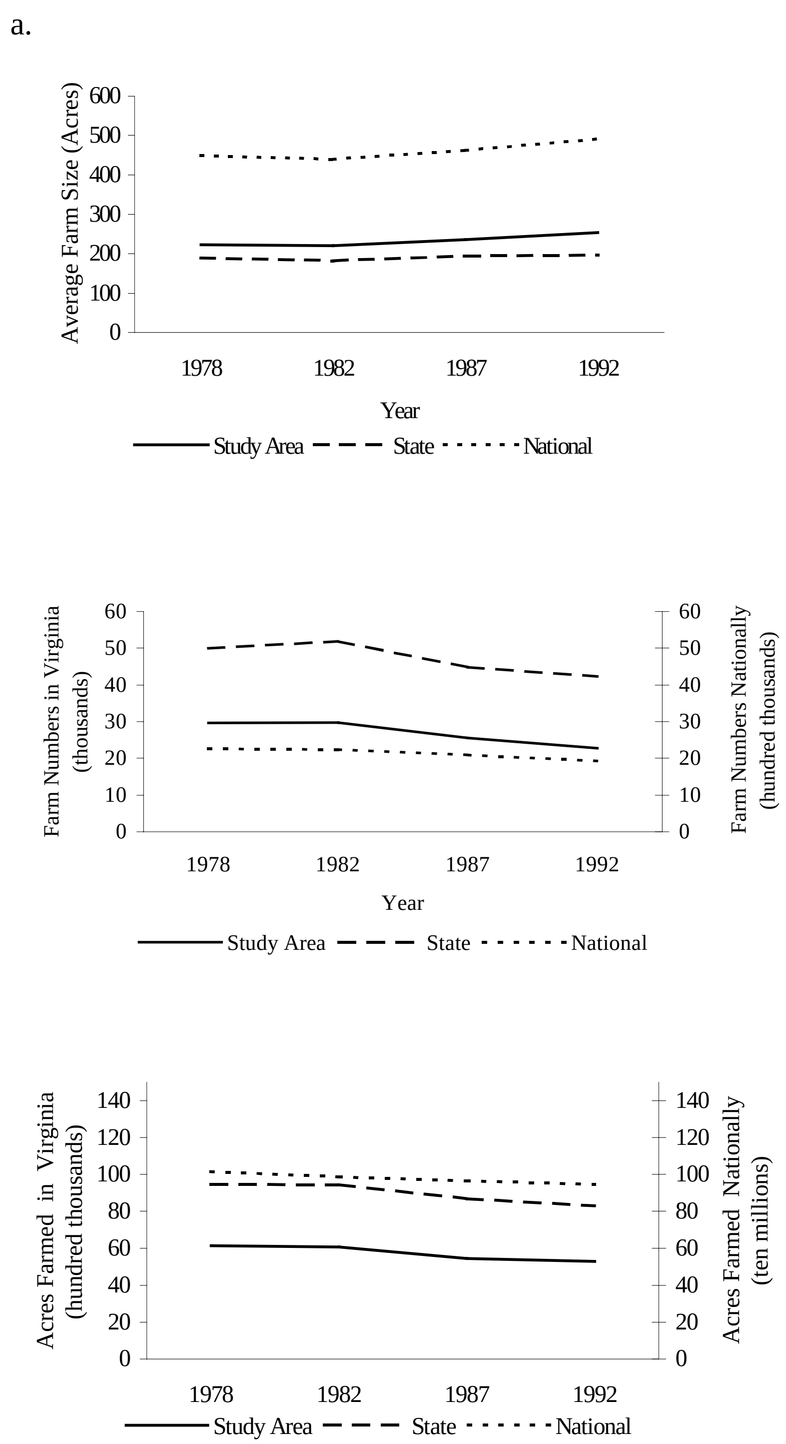


Figure 1- 2. Changes in average farm size (a), the number of farms (b), and the declines in total numbers of acres farmed (c) for the study area, Virginia, and nationally for the period 1978-1992 (US Department of Commerce 1978, 1982, 1987, 1992).

fescue field. By the third year, the vegetation may have become too thick for bobwhite, suggesting the necessity of periodic disturbances to maintain the quality of this habitat. The converted fields in the study also had increased diversity and abundance of legumes that were used as food. Barnes et al. (1995) found that fescue fields during the winter contained no preferred food materials.

The increased use of fescue has been partially attributed to its properties as a pasture grass (Barnes et al. 1995) and livestock feed (Burns and Chamblee 1979). Besides the problems associated with the poor vegetative structure of fescue (Sole 1995), grazing has also been shown to impact populations of all species of quail in North America (Brown et al. 1993). Not all grazing is detrimental to bobwhite populations, however. Short duration grazing (SDG) systems appear to alter the dense vegetative structure of fields, making them more favorable for bobwhite than other grazing systems (Cantu and Everett 1982, Schulz and Guthery 1988, Whiting and Sloan 1993). Areas under SDG systems have a lower standing crop biomass, more soil disturbance, and an increased trail network than areas continuously grazed (Schulz and Guthery 1988). Areas with dense standing vegetation and high litter accumulation are less favorable for bobwhite than open areas because they impede movement and feeding. Areas under SDG systems reduced some of problems associated with idle pastures or continuously grazed pastures (Schulz and Guthery 1988). Also, fields under SDG regimes have been shown to have higher numbers of birds nesting (Cantu and Everett 1982, Schulz and Guthery 1993) and better chick survival than overgrazed pastures or pastures in poorer range condition (Cantu and Everett 1982).

The use of fescue has also increased due to conservation measures (Burns and Chamblee 1979). The Conservation Reserve Program (CRP), Title XII of the Federal Food Security Act of 1985 (Public Law 99-198) encourages farmers to stop growing crops on highly erodible cropland and to plant various permanent cover types (Conservation Practices or CP) for a contract period of at least 10 years. This program was anticipated to have widespread positive effects on wildlife, but these benefits are dependent on the vegetation planted during this program and the spatial relationships of CRP fields with other habitat components (Burger et al. 1990, Stauffer et al. 1990, Roseberry et al. 1994, Roseberry and David 1994). In the Southeast, these plantings have been predominantly CP1 (permanent introduced grasses and legumes-primarily tall fescue and orchard grass mixed with either clover or lespedeza) and CP3 (tree planting-primarily loblolly pine). Stauffer et al. (1990) simulated changes in land cover during this program and how they would influence bobwhite in Virginia. They predicted that the conversions of croplands to CP1 fields would have a positive effect on the quality of bobwhite habitat if enough land was converted. However, to maintain this value, the grass-forb mixture needs to be maintained. If grasses like tall fescue dominate and form dense sod, the effects will rapidly be lost. Capel et al. (1993) warned that programs like the CRP include practices such as promoting exotic cool season grasses (e.g., tall fescue), emphasizing establishment of tree monocultures, failing to manage and maintain old fields (e.g., strip disking), and summer mowing, all practices which reduce the potential benefits of these programs for bobwhite.

Pine Plantations

Much land in the southeastern United States is also being converted to pine plantations, especially loblolly pine (*Pinus taeda*) (Jackson 1990). As indicated previously, many acres are being converted under the Conservation Reserve Program planting CP3. When Stauffer et al. (1990) simulated the effects of this conversion, they determined that the habitat would rapidly decline in value to bobwhite, but would provide beneficial early successional stages for 5-7 years. The initial period after conversion is good for bobwhite populations for it would be in an early successional stage, but after 2 years the stand tends to lose its value to bobwhite as the canopy closes (Jackson 1990, Robinson and Barkalow 1979). Similar to the fescue study (Sole 1995), Jackson (1990) suggested using succession-reverting techniques around and within stands to increase their value to bobwhite. It only takes a short period before succession in any habitat renders the area of little value for bobwhite (Roseberry et al. 1979).

Wildlife habitat loss and degradation also comes as a result of expanding human populations (Roseberry 1993). As the human population has expanded, much land has been converted from agricultural practices, reducing bobwhite habitat (Natural Resources Council 1982).

Objectives

The overall goals of this research were to determine the best means of mapping bobwhite habitat using Landsat Thematic Mapper (TM) imagery and to develop spatially explicit landscape-scale models of northern bobwhite presence and abundance. Specifically the objectives were as follows:

1. To evaluate numerous remote sensing algorithms and band combinations to determine which performed best in the heterogeneous matrix of Virginia.

2. To create a classified habitat map for the coastal plain and piedmont physiographic regions of Virginia.

3. To describe the spatial arrangements of bobwhite habitats.

4. To develop predictive models expressing the probability of bobwhite presence based upon landscape characteristics surrounding a location.

5. To explore the possibilities of creating a probability distribution map of bobwhite presence and abundance based on raw Landsat TM imagery.

I will address Objectives 1 and 2 in Chapter 2, Objectives 3 and 4 in Chapter 3, and Objective 5 in Chapter 4.

CHAPTER 2- REMOTE SENSING

INTRODUCTION

Northern bobwhite populations have been declining across their range for many years (Flather and Hoekstra 1989, Droege and Sauer 1990, Brennan 1991, Church et al. 1993). The factor(s) causing these declines are also not clearly understood. Numerous hypotheses exist, but one seems to re-occur and dominate: changes in land use and losses of superior habitat. A landscape level analysis of the spatial relationships of bobwhite habitat may allow managers to evaluate programs, guide management plans, and develop protocols to hopefully halt the declines in bobwhite populations. New remote sensing methods may enable new analyses that may potentially answer past, unanswerable questions.

Objectives

There were two objectives for this phase of the study: (1) to investigate a number of classification algorithms and band combinations for applicability in eastern Virginia, and (2) to apply the algorithm and band combination with the highest accuracy to the 8 TM scenes covering the Coastal Plain and Piedmont physiographic provinces of Virginia.

LITERATURE REVIEW

Remote Sensing

Remote sensing is the art and science of obtaining information about an object through the use of a device that is not in contact with the object being studied (Lillesand and Kiefer 1994). Many fields utilize remote sensing techniques to evaluate the Earth's surface, including forestry, biology, urban planning, geology, geography, and the military. The level of detail desired, money available, and security clearance dictate what sensor may be used for remote sensing applications.

Spaceborne sensors measure a portion of the electromagnetic spectrum in one or more wavelength bands (Lillesand and Kiefer 1994). The sensors on each platform measure the energy received in a particular band of the spectrum (Lillesand and Kiefer 1994). This measure, usually linearly related to reflectance, is often termed the digital number or brightness value for that band.

One of the most widely used sensors is the Landsat Thematic Mapper (TM) onboard the Landsat-4 and Landsat-5 satellites. Images from this sensor are used by the Gap Analysis Program (GAP), a USGS Biological Resources Division program to map the land cover of each state and combine it with biological presence data to focus conservation efforts (Loveland and Shaw 1996). These sensors measure 7 spectral bands with a surface resolution of 30 meters (Table 2-1), except the thermal band (band 6) which has a resolution of 120 meters (Lillesand and Kiefer 1994). The six non-thermal bands on the Thematic Mapper satellites offer significant data for land cover/land use thematic mapping (Lillesand and Kiefer 1994).

Table 2-1. Spectral ranges of the 7 Landsat Thematic Mapper bands (adapted from Lillesand and Kieffer 1994).

Band	Spectral Range	Nominal Spectral Location
1	0.45 - 0.52 μm	blue-green
2	0.52 - 0.60 μm	green
3	0.63 - 0.69 μm	red
4	0.76 - 0.90 μm	near infrared
5	1.55 - 1.75 μm	mid infrared
6	10.40 -12.50 μm	thermal infrared
7	2.08 - 2.35 μm	mid infrared

Classification Techniques

There are 3 major types of remote sensing classifiers to apply to the bands of spectral reflectance to generate land use/land cover maps. Each relies upon detecting the differences in spectral values between information classes (Lillesand and Kiefer 1994). Supervised classifiers, such as the maximum likelihood decision rule, rely on identifying a number of areas with known ground cover. These training areas and the statistics derived therefrom are used to generate signatures for these land cover classes (Lillesand and Kiefer 1994).
Signatures should be normally distributed, have minimal amounts of overlap, and cover much of the feature space. Signatures can also be combined or deleted to meet these criteria. All the pixels are then classified by comparing each pixel to the means and standard deviations of each signature. The closest land cover class is then coded into the pixel.

Unsupervised classifiers use no initial data and cluster the raw imagery into discrete classes based on the reflectance values in each of the bands (Lillesand and Kiefer 1994). The interpreter then uses large quantities of reference data to identify and label the discrete classes generated by the computer.

Guided clustering is a hybrid technique that attempts to maximize the advantages of supervised and unsupervised algorithms (Bauer et al. 1994). This hybrid method requires training area delineation on areas with complete knowledge of land cover/land use. An unsupervised classification algorithm is then applied within the training areas to distinguish within-class variation. These signatures from the are then applied to the entire area to generate the land cover/land use maps. This method worked well in the forests of Minnesota, but was less reliable in the agricultural areas (Bauer et al. 1994).

METHODS

Remote sensing of natural resources and using geographic information systems (GIS) with remotely-sensed data are increasing in use and applicability in the natural resource management realm. In wildlife research, remote-sensing techniques are commonly employed to quantify and evaluate habitat (i.e., Herr and Queen 1993, Homer et al. 1993).

Differences in the spectral reflectance of objects allow remotely-sensed images to be classified into numerous information classes. The Virginia Gap Analysis Project (GAP) has already prepared a recent land cover map of the state of Virginia (Morton 1998) that is divided into 8 land cover categories adapted from a modified Anderson classification scheme (Anderson et al. 1976). This map was produced from LANDSAT Thematic Mapper data from 1991-1993 and had an overall accuracy of 57.1%.

For this feasibility study, I hoped to increase the categorical specificity and accuracy of the existing land cover map. I sought to delineate early successional habitats because these habitats are important to bobwhite. I tested various classification algorithms and methods for achieving this goal, selecting the method yielding the highest overall and individual class accuracy. Many of these methods or permutations of methods had proven suitable in other studies, so I examined their potential in the heterogeneous landscape of eastern Virginia.

Landsat TM Imagery

The Landsat–4 and –5 satellites carry similar sensors. The images used to map the land cover were collected by Thematic Mapper (TM) sensors onboard these satellites. The imagery was purchased by the Multi-Resolution Land Characteristics consortium (Loveland and Shaw 1996). The majority of the scenes had 2 different dates available. In theory a leaf-off and a leaf-on scene were available. However, true cloud-free leaf-off and leaf-on scenes were available rarely for one year. Therefore, the images used were acquired from 1991-1993 (Figure 2-1). Eight different scenes were required to cover the piedmont and coastal plain of Virginia. These included rows 14, 15, and 16 and paths 33, 34, and 35 of the Worldwide Reference System. Three were full scenes, covering approximately 49,253 km^2 each, while the remaining 5 scenes were half scenes (Figure 2-1).

Prior to use, numerous preprocessing steps were performed on the imagery. Some of this was completed at the EROS Data Center (EDC) of the USGS while the latter parts were performed by Morton (1998). EDC used a debanding algorithm to remove striping and a line averaging process to correct for dropped lines. Scenes were geometrically corrected by EDC using control points from 1:100,000 scale DLGs. Images were resampled using the cubic convolution to get the data in the Universal Transverse Mercator (UTM) projection, NAD83 datum, and 30 m x 30 m pixels. The images had a plus-or-minus 30 m (or 1 pixel) root mean square error (RSME) positional accuracy.

Morton (1998) imported the images from 8 mm tapes using a SUN UNIX workstation. Images were then geometrically corrected using the coordinates provided in the header file for each image. An evaluation of the spatial accuracy of the images using other geographical information (such as 1:100,000 DLG roads and rivers, and county boundaries) revealed that the images were not geometrically accurate and needed to be re-corrected.

Morton (1998) reported using the GCPworks module within PCI EASI/PASE (Ver 5.3, PCI Inc. 50 West Wilmot Street, Richmond Hill, Ontario, Canada, L4B1M5) image processing software to geometrically correct the images to SPOT satellite imagery (10 m resolution, reported positional RMSE of plus or minus 15m). Resampling using a 1st order transformation and a nearest-neighbor algorithm was completed after 20-50 ground control points were collected per scene. The results were images in Universal Transverse Mercator (UTM) projection using NAD27 datum, which matched ancillary data. Three images were in UTM zone 17 while the other 5 were in UTM zone 18.

A portion of scene 15/34 was used to test methodology and evaluate the results. This portion of the scene contained the counties of Sussex, Surry, and Southampton (Figure 2-1). Virginia Department of Game and Inland Fisheries personnel are currently focusing their bobwhite research in 9 counties, including these three.

Training Data

Remote sensing projects require numerous evenly distributed and high quality reference data. Color infrared aerial photographs were the initial reference data. These images were part of the National Aerial Photography Program (NAPP) and cover an area of about 13 km^2 at a scale of 1:40,000. There were 18 of these photos available for these 8 scenes making up the entire study area.

Path	Row	Image Dates	
16	33	March 1, 1992	May 20, 1992
15	33	March 18, 1989	September 16, 1991
16	34	May 10, 1992	September 8, 1993
15	34	April 16, 1992	October 18, 1992
14	34	May 4, 1991	August 10, 1992
16	35	March 1, 1992	September 28, 1993
15	35	October 10, 1992	May 16, 1993
14	35	June 23, 1992	October 13, 1992

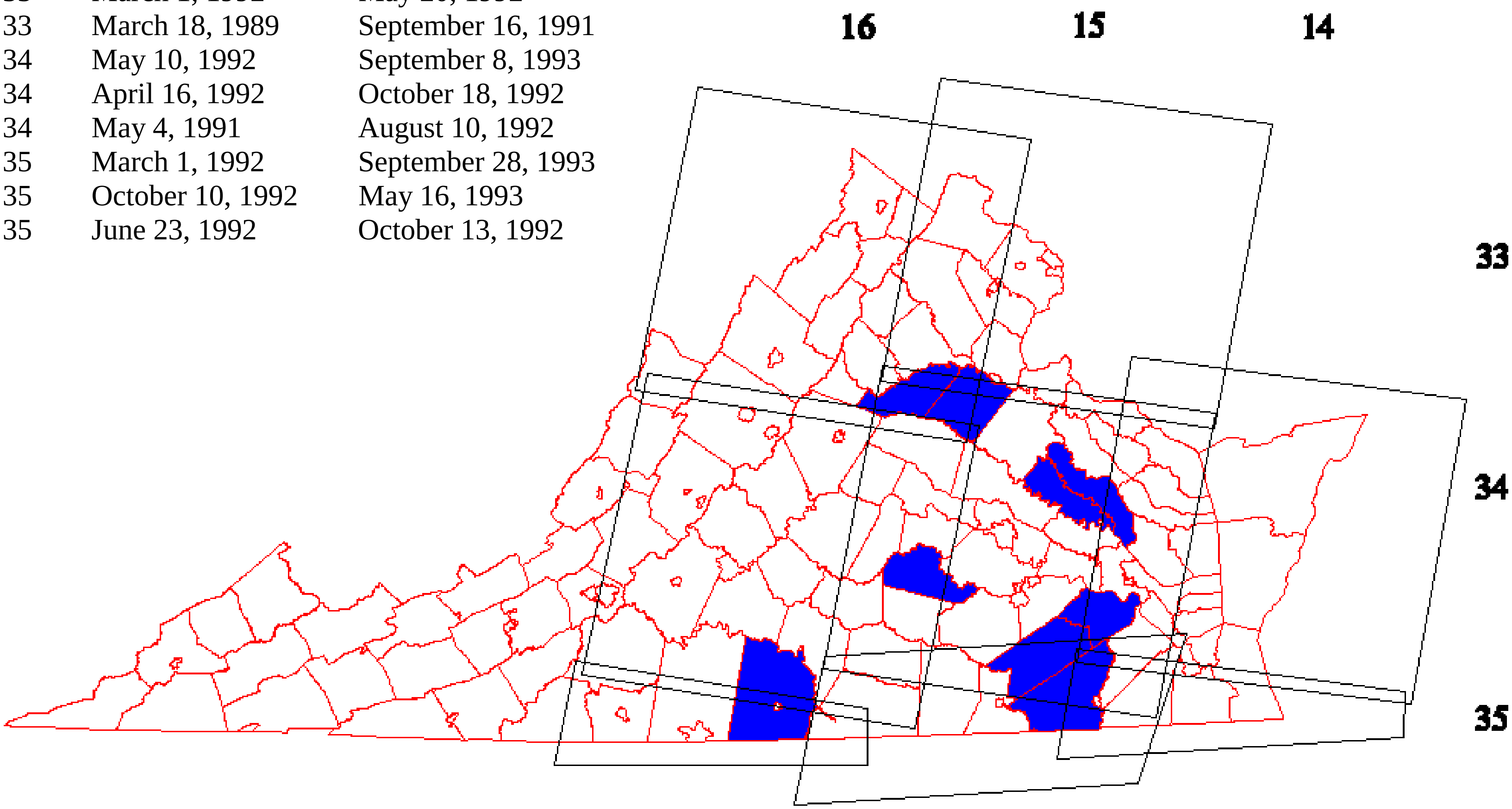


Figure 2-1. State outline showing the 8 Landsat TM scene boundaries that are included in the larger study. The counties colored in blue were the focus counties for data collection.

Windshield Surveys and Data Collection

Aerial photographs were supplemented with ground reference data from "windshield surveys." Known ground cover points were collected while driving along roads in the focus counties. These points were located using differentially-corrected global positioning systems (GPS) coordinates. Later, the raw Landsat TM imagery was directly examined on a laptop while following the 1:100,000 USGS road Digital Line Graph (DLG) coverage (United States Geological Survey, 1996) and points were added directly into an ArcView 3.0a GIS shapefile. This method was extremely time-efficient and it resolved the problem of estimating the effective size of a patch. Using only a GPS unit requires the operator to guess if a particular patch will show up on the raw TM imagery. This led to selecting only very large, homogeneous patches that were much larger than needed. Selecting large patches makes data collecting difficult in the diverse heterogeneous land cover matrix typical in eastern Virginia. By having a laptop in the car with the raw imagery loaded, I was able to add directly collected points into the database. This method eliminated the need for differential-correction or data entry. During data collection, open water points were not collected because water bodies could be readily identified from existing coverages, maps, and visual examination of the imagery.

Agricultural Data

I obtained data from 1992 for agricultural lands in the study counties (Figure 2-1) from Farm Service Agency Offices. This information was added to ArcView 3.0a shapefiles, where the points were manipulated and added to the ground collected points. Once all points were in shapefiles, UTM coordinates could be added using an ArcView script. The points were randomly split into 2 use groups: 40%-50% that would be used for classification, and another 50%-60% that would be used for error assessment.

Classification

Classification Scheme

A classification scheme must be chosen prior to mapping land cover. For this study, I used a modified Anderson Level I classification, with 7 information classes. These classes were chosen because some are important bobwhite habitats and others are dominant land cover types in the study area. Generally, these classes were thought to be spectrally distinct enough to differentiate between them on the image while being able to collect sufficient reference data in the field. At two points in the evaluation phase, it was determined that our classification scheme was more specific than was feasible given limited reference data and sensor resolution (spatial and spectral). The classification scheme underwent two reductions in categorical specificity. The following classes represent the final classification scheme:

Row Crop

The row crop category includes all agricultural crops grown in traditional rows. Within the bounds of the study area, this class includes corn, soybeans, peanuts, and some cotton and tobacco. Separation of individual crops was initially designed, but insufficient data precluded this level of categorical specificity.

Pasture/ Hay/ Grass

The pasture/hay/grass includes all the named components and any fields that were growing cover crops, including clover and alfalfa. This may have presented a temporal problem since these cover or fallow phases are typical in the region on 3 or 4 year cycles. Fields are set aside or left fallow for 1 year in each cycle, potentially causing a problem if the fallow phase falls at the date of image acquisition or data collection. This class would also include any managed grass, including golf courses, lawns, utility rights of way, parks, and even some road medians.

Early Succession

Early succession habitats included a broad array of habitat types. Principally this class included recently clear cut forests, other forest openings, and young pine plantations. Recent clear cuts were generally up to 5 years old, while young pine plantations included any young pine stand up to 8-10 years in age at the date of image acquisition. These classes are spectrally separable, however they could not be split into separate information classes because of insufficient ground reference data. Other seral stages classes fall in this category as well, including older fallow fields, set asides, drainage ditches, hedgerows, and some utility rights of way. Initially I hoped to separate recent clear cuts and young pine plantations, but insufficient reference data precluded this separation. Virginia Department of Forestry personnel were contacted to determine if they could provide accurate reference data in the 1991-1993 temporal window. The amount of data they could provide and the level of work needed to use the data dictated that classifying to this level of categorical specificity was not economically feasible. However, from their demonstration, it is apparent that different aged young stands of forest can be visibly delineated using SPOT (Systeme Pour l'Observation de la Terre) panchromatic data.

Coniferous Forest

Coniferous forest was defined as any forested type older than the early successional category (greater than 11 years old) that was dominated by coniferous species. In the study area, pine plantations dominated this class, typically in Loblolly (*Pinus taeda*) or Virginia (*Pinus virginiana*).

Deciduous Forest

This class was any forest older than the early successional category, Typically this had to be in the pole age or older (11 years or greater), and dominated by deciduous species.

Open Water

Open water was a category that made up some of the study area, and was relatively easy to classify.

Additional classes of information were available from previous efforts for inclusion with the final product, including urban and wetlands layers (Morton, 1998).

Classification Procedure

If the two dates of imagery were not aligned properly, they were co-registered using PCI EASI/PACE software (Version 6.0.1, PCI Inc. 50 West Wilmot Street, Richmond Hill, Ontario, Canada, L4B1M5). To re-register one date of imagery to the other, a minimum of 10 control points were used in second order transformation followed by a nearest neighbor re-sampling algorithm. Both dates of imagery were combined into one file for processing. The process was deemed complete if the root mean square error (RMSE) was below one pixel (or less than 30 m). The images were overlaid and visually inspected to ensure the process was completed satisfactorily.

I evaluated numerous methods and band combinations through an iterative process to determine which would perform best in eastern Virginia. A focus area within the scene was used for algorithm development. The optimal band combination and technique would have the highest overall accuracy and relatively good individual class accuracy.

Four different band combinations were used with the various classification algorithms. The first combination used was the original raw 6 reflectance bands of imagery from 2 dates and a soil brightness layer and a vegetation-greenness layer (making a 14-band image). Soil brightness and vegetation greenness layers were developed using the tasseled cap transformation (Kauth and Thomas 1976, Crist and Cicone 1984, Crist and Kauth 1986). The original 6 raw reflectance bands from 2 dates were also used without the 2 tasseled cap transformations. A study in Illinois (Roseberry and Woolf 1995) provided another band combination. They used bands 4, 5 and 6, the first principal component of bands 1, 2, and 3, and the Normalized Difference Vegetation Index (NDVI). I opted for a leaf-off scene for this band combination because I felt it may be useful in discerning between some of the bobwhite habitat types. The last set of bands used for classification was similar to that used by the Upper Midwest Gap Analysis Program (UMGAP). They used the first three principal components of each of two dates. I used the first three principal components from all 12 bands combined. The difference was a miscommunication from the UMGAP program.

Threshold Method

A modified Anderson Level I land cover map was available from the Virginia Gap Analysis Program (GAP). The first classification iteration examined the possibility of further separating existing classes into more classes. I used a threshold so only areas classified as agriculture and shrub were retained. Upon examination of the results, I noted that the initial classification appeared to have been performed on the leaf-off scene. The inclusion of large areas of agricultural areas in the urban class was indicative of this problem. I added a threshold to include the urban categories to resolve this problem. The resultant bitmap, expressing only the agriculture, shrub/scrub, and urban classes, was applied as a mask over the 12 original bands and the two transformations to generate a new image that only contained spectral data for the areas under this mask. This file then was classified using a supervised classification using aerial photographs for training data.

Unsupervised Classification Method

Next, I looked at using an unsupervised classification approach using the 12 raw bands of Landsat TM imagery. I also examined the possibility of using an unsupervised classification on the first 3 principal components of two dates of imagery. When classified with an unsupervised algorithm, this band combination worked better than the guided clustering approach for agricultural areas in the upper mid-west (Lillesand et al. 1998). The band combination used by the Illinois study (PC1 of bands 1-3, bands 4, 5, 7, and NDVI; Roseberry and Woolf 1995) was also classified using an unsupervised classification algorithm.

Guided Clustering Technique

The guided clustering approach described by Bauer et al. (1994) was also tried with the three band combinations. This method is a combination of both the supervised and unsupervised techniques, and proved superior to either technique in Minnesota. This technique calls for training area delineation as in a supervised classification with the constraint that all training areas must have been reliably ascribed to an information class using reference data. An unsupervised classification algorithm is applied to the training areas to identify spectral classes present within each information class. I evaluated this technique using the original raw imagery. I also evaluated this technique on the Illinois study bands and the first three principal components of the two dates

Guided Spectral Class Rejection Method

I also developed a new hybrid method. For this method, I classified an area using an ISODATA unsupervised clustering technique (Duda and Hart 1973). I reviewed the resultant 125 ISODATA classes using 284 reference points (49.1% of all points available). The signatures for the classes containing less than 75% of one land cover class were considered confused and discarded. The remaining signatures for the unsupervised classes were then classified using the maximum-likelihood decision rule. The outcome from this procedure was then labeled by first identifying those previously known classes from the unsupervised step, then labeling the remaining unknown classes by visually identifying neighboring pixels and holes in apparent homogeneous patches. Once all the spectral classes were labeled, they were aggregated into the desired information classes. Both the Illinois study band combination and the first three principal components of 2 dates were classified using this technique.

Image Postprocessing

After the classification was completed, the imagery was examined to ensure that most if not all of the image was classified. A 3 x 3 scan majority filter was applied to the image to reduce any speckling or "salt and pepper" on the image. This filter removes periodic noise recorded by remote sensors (Jensen 1996). The resultant image is more homogeneous and smooth than the original image.

Accuracy Assessment

Congalton and Green (1999) identified 4 reasons for assessing map accuracy, including: simple curiosity, increasing quality by eliminating errors, comparison of techniques or algorithms, and measuring quality for usage by others. An error matrix can be generated expressing the number of samples assigned a particular class in one classification relative to the number assigned in another classification (Congalton and Green 1999). The classified map is compared to the ground reference points to produce an error matrix identifying the differences between the map and ground based data. Congalton and Green (1999) described 4 measures of map quality that are derived from this matrix. First, the overall accuracy represents the percentage of correctly classified reference points out of all reference points. The second is the producer's accuracy, which is the ratio of the number of correctly classified pixels for a particular class over the total number of reference pixels in that class. This measure represents how well reference pixels of a given are classified. The third measure is the user's accuracy, which is the ratio of the total number of pixels correctly classified over the total number of reference points mapped to that category. This measure represents the probability of a classified pixel being correct on the ground. Finally, an estimate of Kappa is used to express the percent improvement of the classification over a random classification. This statistic determines if one matrix is significantly different from another matrix. Combining the Kappa and Kappa variance from two matrices using a Z score allows a comparison of error matrices to determine if one technique or algorithm performs better than the other does.

The second group of windshield survey points was reserved for the error assessment phase of this study. A software program (ACC4WIND) written by Jonathan Chipman of the University of Wisconsin-Madison was used that calculated these four statistics along with the error matrix. Pair-wise Z-scores between error matrices were also computed, showing if one classification method and band combination was better than another (Congalton and Green 1999). A Bonferroni experiment-wise adjusted alpha level was held constant at 0.05 to reduce the probability of Type I errors (Zar 1994).

RESULTS

Study Area

As indicated, it took numerous iterations to classify the study area. This section will discuss the general results of the various iterations. The overall accuracies for the classification improved with many of the iterations. I sought a method that classified the area completely with an overall accuracy greater than 75%.

The threshold method performed poorly using available aerial videography reference points for assessment (Table 2-2). Similarly, the unsupervised, supervised, and guided clustering approaches using all 12 bands of raw imagery and available videography reference data performed poorly (Table 2-2).

Guided Clustering Approaches

When the guided clustering approach was applied to the band combinations provided by UMGAP and the Illinois study, improved accuracies were realized again (Table 2-2). However, the accuracy of this method with either of the band combinations was below 75%.

Unsupervised Classification Approaches

The unsupervised classification algorithm applied to these two band combinations also showed improvement in accuracy, yet the accuracy was unacceptable. Even with the modified classification scheme, the overall accuracy was not above 75% (Table 2-2).

Table 2-2. Comparison of band combinations and classification algorithms used on the study area showing overall accuracy and kappa statistic for each method tested.

	Classification Algorithm							
	Supervised		Unsupervised		Guided Clustering		GSCR[a]	
	Overall Accuracy	Kappa	Overall Accuracy	Kappa	Overall Accuracy	Kappa	Overall Accuracy	Kappa
Raw + [b]	27.94	15.67	NA		NA		NA	
Raw [c]	NA		22.43	12.22	30.77	17.32	NA	
Bands 4,5,7, NDVI, and PC1 bands 1,2,3 [d, e]								
Individual Crops	NA		58.61	48.19	44.13	37.11	NA	
Row crop class [f]	NA		65.38	56.32	55.06	46.70	64.75	56.72
Early succession class [g] + Row crop class [f]	NA		NA		NA		73.56	67.54
PC 1,2,3 for 2 dates [h]								
Individual Crops	NA		54.17	47.95	48.18	41.29	NA	
Row crop class [f]	NA		65.62	58.39	55.87	46.73	72.54	65.90
Early succession class [g] and Row crop class f	NA		NA		NA		79.32	73.66

[a] Guided Spectral Class Rejection
[b] Raw + is the 12 bands of raw imagery plus the brightness and greenness bands from the tasseled cap transformation
[c] Raw is the 12 bands of raw imagery
[d] After the Illinois study by Roseberry and Woolf (1995)
[e] Using a leaf-off date
[f] Using one row crop class
[g] Using an early successional class made up of recently cut forests and young pine plantations
[h] After Upper Midwest Gap Analysis Program by Lillesand et al. (1998)

Table 2-3. The error matrix for the study area using the hybrid classification algorithm, the Illinois band combination, and the final classification scheme (overall accuracy 73.56%).

Classification Data	Reference Data: Row Crop	Early Succession	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	5	4	5	4	0	0	18
Row Crop	**49**	9	21	0	0	0	79
Early Succession	2	**47**	7	3	3	0	62
Pasture/Hay/Grass	2	2	**39**	0	0	0	43
Coniferous Forest	0	4	0	**70**	4	0	78
Deciduous Forest	0	1	0	2	**2**	0	5
Open Water	0	0	0	0	0	**10**	10
Total	58	67	72	79	9	10	**295**

Table 2-4. The error matrix for the study area using the hybrid classification algorithm on the first three principal components of 2 dates, prior to the final classification scheme condensing (overall accuracy 72.54%).

Classification Data	Reference Data: Row Crop	Recent Forest Cuts	Pasture/Hay/Grass	Coniferous Forest	Young Pine Plantations	Deciduous Forest	Open Water	Total
Unclassified	0	0	2	0	1	0	0	3
Row Crop	**46**	2	11	0	1	0	0	60
Recent Forest Cuts	3	**3**	0	1	12	0	0	19
Pasture/Hay/Grass	7	0	**55**	0	1	0	0	63
Coniferous Forest	0	0	0	**64**	1	3	0	68
Young Pine Plantatio	2	8	4	4	**35**	4	0	57
Deciduous Forest	0	0	0	9	3	**1**	0	13
Open Water	0	0	0	1	0	1	**10**	12
Total	58	13	72	79	54	9	10	**295**

Table 2-5. The error matrix for the study area using the final classification method on the first 3 principal components of the 2 date set of imagery.

	Reference Data						
Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	0	1	2	0	0	0	3
Row Crops	**46**	3	11	0	0	0	60
Early Succession	5	**58**	4	5	4	0	76
Pasture/Hay/Grass	7	1	**55**	0	0	0	63
Coniferous Forest	0	1	0	**64**	3	0	68
Deciduous Forest	0	3	0	9	**1**	0	13
Open Water	0	0	0	1	1	**10**	12
Total	58	67	72	79	9	10	**295**

Guided Spectral Class Rejection (GSCR) Method

The hybrid technique that I developed also performed better than earlier attempts. The overall accuracy of this technique applied to the Illinois band combination was 73.6% with the modified classification scheme (Table 2-2). Table 2-3 shows the error matrix for this classification attempt. When this technique was applied to the three principal components prior to the second classification scheme modification (i.e., with a group crop class but not an early succession class), the accuracy was similar to the Guided Spectral Class Rejection method using the Illinois band combination and the final classification scheme (Table 2-2), with only 3 fewer reference points correctly classified (Table 2-4). With the second modification to the classification scheme, the overall accuracy improved to 79.3% (Table 2-2), classifying 234 of 295 reference points (Table 2-5). This method was the only one determined to be acceptable because it had an overall accuracy > 75%.

Individual class user's accuracy for this method ranged between 7.7% and 94.1% while the producer's accuracy ranged between 11.1% and 100.0% (Table 2-6). The final product (Figure 2-2) with suitable accuracy indicated this technique and band combination was adequate and was chosen for subsequent classification efforts.

When the Z statistics for each classification Kappa were compared to determine if the classification was better than a random result, all methods were significantly better than random at the experiment-wise alpha level 0.05 (Table 2-7). When the Kappa statistics were compared in pairs, it is noticeable that the accuracy of later methods improved drastically over earlier methods (Table 2-8). The final method used (Guided Spectral Class Rejection method, UMGAP band combination and final classification scheme) was significantly better than all previous methods (Table 2-8) except the Guided Spectral Class Rejection method (using the Illinois band combination and final classification scheme) and the Guided Spectral Class Rejection method (using the Upper Midwest Gap Analysis Program band combination and a combined crop class). The latter of the two is the same classification with the exception of a modified classification scheme, so less significance is expected. This case exposes one potential error in interpreting this table. The differences in Z-scores (Table 2-8) represent changes in the classification scheme and changes to the bands and algorithms selected for classification. Consequently, the improvements noted may be combinations of these 2 factors.

Scene 15/34

The scene that contained the study area also contained a number of other counties where I collected data. This resulted in more data being available, so when I classified the entire scene I had 604 ground reference points to identify the ISODATA classes. This split was closer to 40% of all the points, saving more points to better assess the accuracy of the final product. Figure 2-3 shows the final classification of this scene. When the classification procedure was complete, I used the remaining 920 points (Table 2-9) to assess the accuracy of this product. The overall accuracy of the scene dropped slightly to 72.8% when this method was applied across the entire scene using additional reference points. The user's accuracy of individual classes did improve, with a range of 39.5% to 100.0%, while the producer's accuracy of classes also improved from 48.9% to 100.0% (Table 2-10).

Table 2-6. User's and producer's accuracy for each land cover class in the study area including overall accuracy and Kappa statistic for the final classification technique.

Class	User's	Producer's
Row Crops	0.767	0.793
Early Successional	0.763	0.866
Pasture/Hay/Grass	0.873	0.764
Coniferous Forest	0.941	0.810
Deciduous Forest	0.077	0.111
Open Water	0.833	1.000
Overall Accuracy	0.7932	
Kappa	0.7366	
Kappa Variance	0.0009	
Z Statistic	24.988 (P<0.0001)	

Table 2-7. Kappa statistic, Kappa variance, and Z statistic for all 15 methods and band combinations explored. All Z statistics are greater than controlled experiment-wise error rate, indicating a better classification than a random event.

Method	Kappa	Variance	Z statistic [k]
Threshold [a]	0.157	0.0006	6.233
Unsup_raw [b,c]	0.122	0.0006	5.230
Guided_raw [d]	0.173	0.0008	6.312
Unsup_Ill_ic [e,f]	0.482	0.0007	18.902
Guided_Ill_ic	0.371	0.0005	16.120
Unsup_Ill_gc [g]	0.563	0.0007	21.317
Guided_Ill_gc	0.467	0.0006	19.226
GSCR_ILL_gc [h]	0.567	0.0010	17.716
GSCR_ILL_es [i]	0.675	0.0010	21.959
Unsup_Gap_ic [j]	0.480	0.0006	20.102
Guided_Gap_ic	0.413	0.0006	17.527
Unsup_Gap_gc	0.584	0.0008	20.947
Guided_Gap_gc	0.467	0.0006	19.046
GSCR_Gap_gc	0.659	0.0010	21.148
GSCR_Gap_es	0.737	0.0009	24.987

[a] Threshold method, 12 bands of raw imagery plus the first two bands from the tasseled cap transformation

[b] Unsupervised classification algorithm

[c] Using the 12 bands of raw imagery

[d] Guided clustering algorithm

[e] After the Illinois study by Roseberry and Woolf (1995)

[f] Using a classification scheme with individual crops classified

[g] Using a condensed classification scheme with one grouped crop class

[h] Using the Guided Spectral Class Rejection (GSRC) classification technique

[i] Using a condensed classification scheme with grouped crop and grouped early succession (recently cut forests and young pine plantations) classes

[j] After Upper Midwest Gap Analysis Program by Lillesand et al. (1998)

[k] Individual Z statistic for the Kappa statistic; if > 3.14 (experiment-wise ∝ level) then the classification is significantly better than a random classification

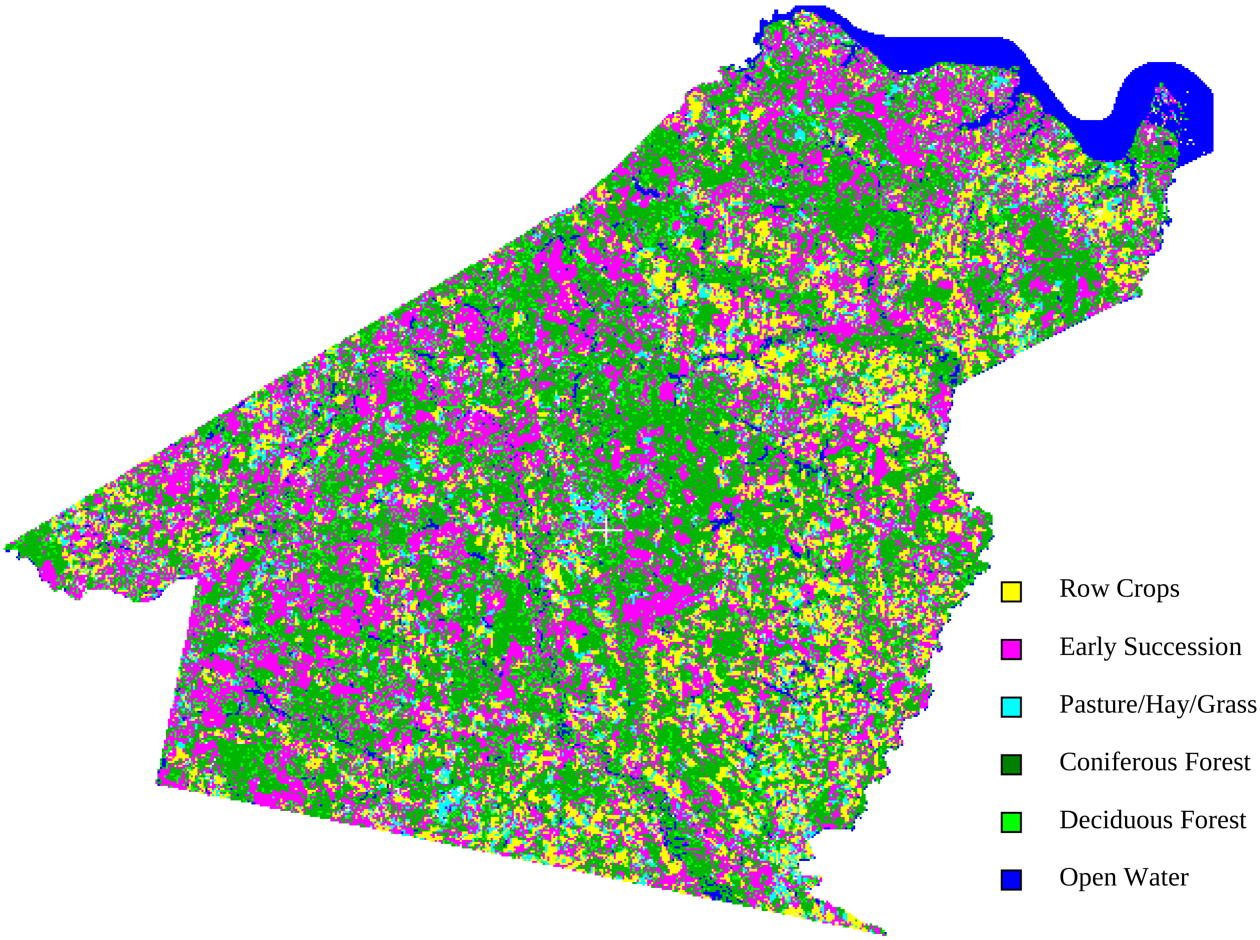


Figure 2-2. Classified image of the study area (Sussex, Surry, and part of Southampton, VA) showing the six information classes. The classified image was developed from Landsat TM imagery for 2 dates in 1992.

Table 2-8. Pair-wise comparisons of Z scores calculated from pairs of error matrices resulting from the classification attempts (significantly different classifications using a Bonferroni adjusted alpha level have a value greater than 3.14 and are shown in bold).

	Classification Techniques and Band Combinations								
	Unsup_raw [b,c]	Guided_raw [d]	Unsup_Ill_ic [e,f]	Guided_Ill_ic	Unsup_Ill_gc [g]	Guided_Ill_gc	GSCR_ILL_gc [h]	GSCR_ILL_es [i]	Unsup_Gap_ic [j]
Threshold [a]	1.005	0.443	**9.083**	**6.29**	**11.146**	**8.877**	**10.084**	**13.058**	**9.315**
Unsup_raw [b,c]		1.415	**10.401**	**7.588**	**12.503**	**10.23**	**11.227**	**14.322**	**10.7**
Guided_raw [d]			**8.242**	**5.525**	**10.238**	**8.017**	**9.344**	**12.184**	**8.424**
Unsup_Ill_ic [e,f]				**3.226**	2.214	0.423	2.084	**4.844**	0.069
Guided_Ill_ic					**5.482**	2.866	**4.973**	**7.921**	**3.27**
Unsup_Ill_gc [g]						2.681	0.096	2.767	2.351
Guided_Ill_gc							2.493	**5.317**	0.367
GSCR_ILL_gc [h]								2.437	2.197
GSCR_ILL_es [i]									**5.033**
Unsup_Gap_ic [j]									
Guided_Gap_ic									
Unsup_Gap_gc									
Guided_Gap_gc									
GSCR_Gap_gc									
GSCR_Gap_es									

[a] Threshold method, 12 bands of raw imagery plus the first two bands from the tasseled cap transformation
[b] Unsupervised classification algorithm
[c] Using the 12 bands of raw imagery
[d] Guided clustering algorithm
[e] After the Illinois study by Roseberry and Woolf (1995)
[f] Using a classification scheme with individual crops classified
[g] Using a condensed classification scheme with one grouped crop class
[h] Using the Guided Spectral Class Rejection (GSRC) classification technique
[i] Using a condensed classification scheme with grouped crop and grouped early succession (recently cut forests and young pine plantations) classes
[j] After Upper Midwest Gap Analysis Program by Lillesand et al. (1998)

Table 2-8 (cont). Pair-wise comparisons of Z scores calculated from pairs of error matrices resulting from the classification attempts (significantly different classifications using a Bonferroni adjusted alpha level have a value greater than 3.14 and are shown in bold).

	Classification Techniques and Band Combinations				
	Guided_Gap_ic	Unsup_Gap_gc	Guided_Gap_gc	GSCR_Gap_gc	GSCR_Gap_es
Threshold [a]	**7.436**	**11.381**	**8.842**	**12.546**	**14.968**
Unsup_raw [b,c]	**8.761**	**12.693**	**10.185**	**13.782**	**16.333**
Guided_raw [d]	**6.628**	**10.5**	**7.99**	**11.7**	**13.989**
Unsup_Ill_ic [e,f]	1.988	2.7	0.413	**4.399**	**6.535**
Guided_Ill_ic	1.269	**5.886**	2.859	**7.431**	**9.772**
Unsup_Ill_gc [g]	**4.246**	0.539	2.66	2.345	**4.38**
Guided_Ill_gc	1.599	**3.162**	0.009	**4.86**	**7.058**
GSCR_ILL_gc [h]	**3.882**	0.393	2.477	2.055	**3.892**
GSCR_ILL_es [i]	**6.775**	2.204	**5.289**	0.375	1.437
Unsup_Gap_ic [j]	1.987	2.846	0.357	**4.574**	**6.78**
Guided_Gap_ic	0	**4.685**	1.599	**6.3**	**8.578**
Unsup_Gap_gc		0	**3.14**	1.796	**3.764**
Guided_Gap_gc			0	**4.833**	**7.022**
GSCR_Gap_gc				0	1.809
GSCR_Gap_es					0

[a] Threshold method, 12 bands of raw imagery plus the first two bands from the tasseled cap transformation
[b] Unsupervised classification algorithm
[c] Using the 12 bands of raw imagery
[d] Guided clustering algorithm
[e] After the Illinois study by Roseberry and Woolf (1995)
[f] Using a classification scheme with individual crops classified
[g] Using a condensed classification scheme with one grouped crop class
[h] Using the Guided Spectral Class Rejection (GSRC) classification technique
[i] Using a condensed classification scheme with grouped crop and grouped early succession (recently cut forests and young pine plantations) classes
[j] After Upper Midwest Gap Analysis Program by Lillesand et al. (1998)

Table 2-9. The error matrix for scene 15/34 using the final classification method.

Classification Data	Reference Data: Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	0	0	0	1	0	0	1
Row Crops	**241**	18	33	3	5	0	300
Early Succession	1	**65**	3	16	28	0	113
Pasture/Hay/Grass	58	3	**174**	0	1	0	236
Coniferous Forest	0	6	0	**135**	8	0	149
Deciduous Forest	10	41	3	12	**43**	0	109
Open Water	0	0	0	0	0	**12**	12
Total	310	133	213	167	85	12	**920**

Table 2-10. User's and producer's accuracy for each land cover class in scene 15/34 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.803	0.777
Early Succession	0.575	0.489
Pasture/Hay/Grass	0.737	0.817
Coniferous Forest	0.906	0.808
Deciduous Forest	0.394	0.506
Open Water	1.000	1.000
Overall Accuracy	0.7283	
Kappa	0.6482	
Kappa Variance	0.0003	
Z Statistic	34.699 (P<0.0001)	

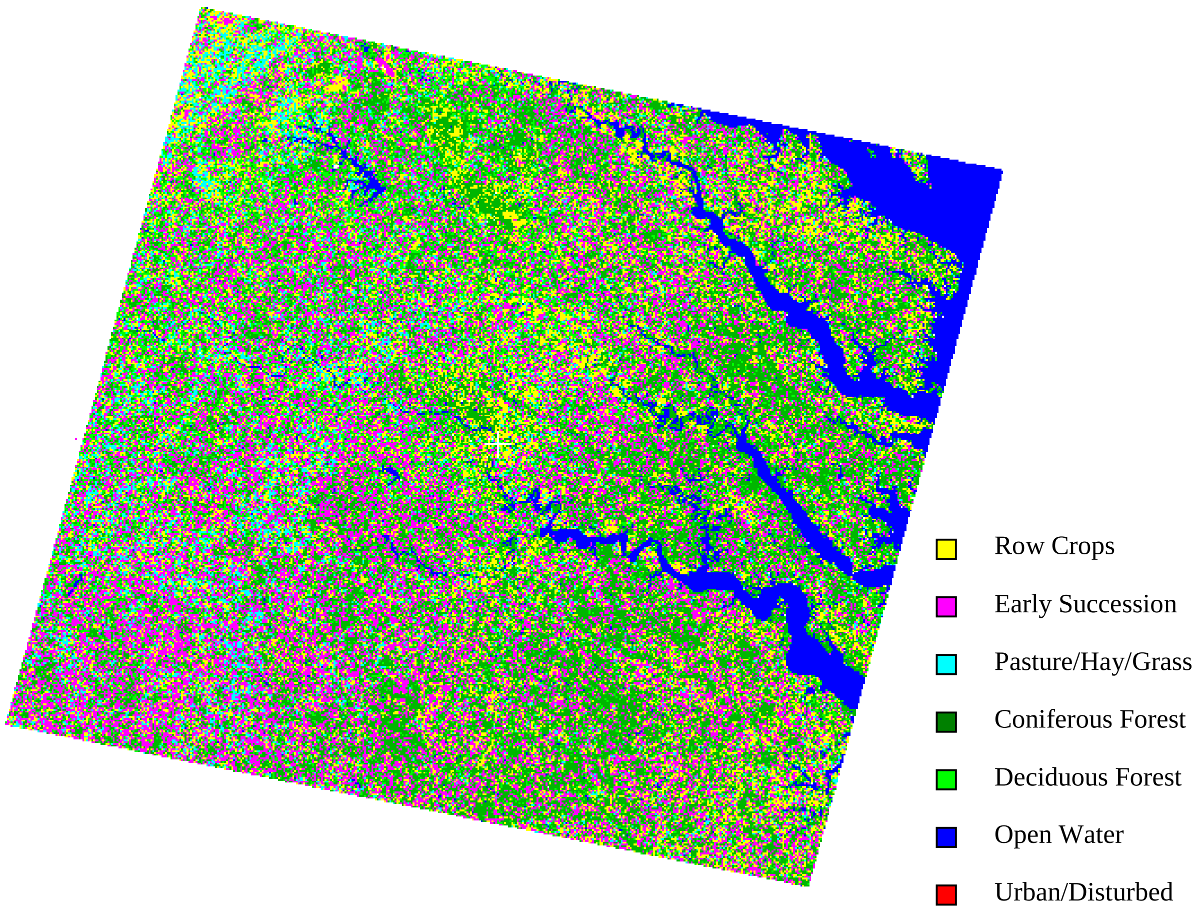


Figure 2-3. Final classification of the entire scene 15/34, including the study area.

Table 2-11. Classification results for scene 15/34, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	4,654,737	418,926.3	13.43
Early Succession	7,372,061	663,485.5	21.27
Pasture/Hay/Grass	3,289,188	296,026.9	9.49
Coniferous Forest	7,909,012	711,811.1	22.82
Deciduous Forest	8,629,815	776,683.4	24.90
Water	2,804,934	252,444.1	8.09
Totals	34,659,747	3,119,377.2	100.00

Deciduous forest was the most common land cover type occupying 24.9% (Table 2-11). However, I express caution due to the low accuracy of deciduous forest classification in this region and the sparse representation in the reference data. Coniferous forest and the early successional categories were close behind deciduous forest with 22.8% and 21.3%, respectively. The estimates of percentage cover in each cover type are comparable to those generated by Morton (1998) in a similar land cover mapping exercise. The one notable exception was an underestimation of the coniferous component in our scene, compared to the earlier work (Morton 1998). The additional early succession class might explain this discrepancy. By definition, this class included recently-cut-over forested areas and young pine plantations. Certainly some of the area in this class could be described as coniferous forest, while some other amount could fall into the shrub category in the previous classification.

Scene 15/35

This scene is a half scene directly south of scene 15/34 (Figure 2-1). One hundred twenty three ground reference points were used to classify this scene, leaving 160 points (56.5%) for accuracy assessment (Table 2-12). The overall accuracy of this scene was comparable at 78.1%. The class user's accuracy ranged between 36.4% and 100.0% while the class producer's accuracy ranged between 47.1% and 100.0% (Table 2-13). The Kappa statistic for this scene was 0.6783. The majority of the landmass in the scene was in 2 classes: early succession and coniferous forest classes (Table 2-14). This classified scene contains more coniferous forest and early succession and less deciduous forest than found by Morton (1998). Figure 2-4 shows the final classification of this scene.

Scene 15/33

This scene is a quarter scene centered on Washington, D.C. (Figure 2-1). Fifty-seven ground reference points were used to classify this scene, leaving 93 points (62.0%) for accuracy assessment (Table 2-15). The overall accuracy of this scene was comparable to scene 15/34 at 74.2%. The class user's accuracy ranged between 33.3% and 100.0% while the class producer's accuracy ranged between 20.0% and 100.0% (Table 2-16). The Kappa statistic for this scene was 0.6653. The majority of the landmass in this scene was in coniferous forest and pasture/hay/grass (Table 2-17). Compared to earlier classification attempts by Morton (1998) this classified scene contains less coniferous forest and similar amounts of open land pixels than he reported. Figure 2-5 shows the final classification of this scene.

Scene 14/34

This is the full scene to the east of scene 15/34 and contains the eastern most portion of Virginia (Figure 2-1). Ninety-five ground reference points were used to classify this scene, leaving 143 points (60.0%) for accuracy assessment (Table 2-18). The overall accuracy of this scene was a little lower than the others scenes, at 67.1%. The user's accuracy ranges from 0.0% to 100.0% while the producer's accuracy ranges from 0.0% to 90.0% (Table 2-19). The Kappa statistic for this scene was 0.4915. The majority of the classified image was in open water (70.9%) then small amounts of the remaining classes (Table 2-20). This includes more water than Morton (1998) does, that may be explained by an inclusion of the whole scene in this study prior to clipping it to the state boundary. Figure 2-6 shows the final classification of this scene.

Scene 14/35

This is the half scene in the southeastern-most corner of Virginia and is south of scene 14/34 (Figure 2-1). Fifty-six ground reference points were used to classify this scene, leaving 95 points (62.9%) for accuracy assessment (Table 2-21). The overall accuracy of this scene was comparable to scene 14/34 at 61.1%. The user's accuracy ranges from 35.7% to 100.0% while the producer's accuracy ranges from 43.8% to 100.0% (Table 2-22). The Kappa statistic for this scene was 0.5369. The major land cover classes in this scene were coniferous forests and deciduous forests (Table 2-23). This classification had relatively similar amounts of deciduous forest, and slightly higher amounts of coniferous forest and the open land categories. Figure 2-7 shows the final classification of this scene.

Scene 16/33

This is the half scene to the east of scene 15/33 (Figure 2-1). One hundred seventy ground reference points were used to classify this scene, leaving 252 points (59.7%) for accuracy assessment (Table 2-24). The overall accuracy of this scene was the best of all scenes at 85.7%. The user's accuracy ranges from 80.43% to 100.00% while the producer's accuracy ranges from 10.00% to 97.50% (Table 2-25). The Kappa statistic for this scene was 0.7839. This scene was mostly pasture/hay/grass, including more open land pixels and less deciduous forest than Morton's (1998) classification (Table 2-26). Figure 2-8 shows the final classification of this scene.

Scene 16/34

This is the full scene to the west of Richmond, including Roanoke, VA (Figure 2-1). A total of 82 ground reference points were used to classify this scene, leaving 130 points (61.3%) for accuracy assessment (Table 2-27). The overall accuracy of this scene was low at 58.5% despite numerous classification attempts. Even using an additional 1,982 points from aerial videography and the USDA Forest Service Forest Inventory and Analysis (FIA) data set (Hansen et al. 1992) I was unable to improve accuracy above the documented level. The user's accuracy ranges from 0.0% to 100.0% while the producer's accuracy ranges from 42.9% to 83.3% (Table 2-28). The Kappa statistic for this scene was 0.4821. Deciduous forest and early succession classes made up the largest portions of this scene (Table 2-29). Most of the early succession component was included in the mountains in the western part of the scene. The topographic variation within the scene, the size of the scene, and insufficient data all contributed to the poorer accuracy. Compared to the work of Morton (1998), this classification contains similar amounts of deciduous forest. Figure 2-9 shows the final classification of this scene.

Scene 16/35

This scene is a half scene to the west of scene 15/35 (Figure 2-1). One hundred ninety five points were used to classify this scene, leaving 294 points (60.1%) for accuracy assessment (Table 2-30). The overall accuracy of this scene was poorer than most of the other scenes at 61.2%. The user's accuracy ranges from 30.6% to 100.0% while the producer's accuracy ranges from 20.6% to 100.0% (Table 2-31). The Kappa statistic for this scene was 0.4850. The scene includes three major land covers in relatively equal amounts: (1) coniferous forest, (2) deciduous forest, and (3) pasture/hay/grass (Table 2-32). Compared to the work of Morton (1998), this classification includes more coniferous forest pixels, and fewer deciduous forest and open land pixels than he found. Figure 2-10 shows the final classification of this scene.

Entire Coastal Plain and Piedmont Provinces

A mosaic image was formed of all 8 classified scenes making up the coastal plain and piedmont physiographic provinces. The order of images (i.e., which scene was on top of another) was determined by placing the scene with the highest accuracy on top of scenes with low overall accuracy. This resulted in one image for the state (Figure 2-11) with an accuracy of 69.3% (Table 2-33). Class user's accuracy ranged between 0.0% and 95.24%, while class producer's accuracy ranged between 0.0% and 77.47% (Table 2-34). Within this region, similar amounts of coniferous forest, deciduous forest, and pasture/hay/grass were classified (Table 2-35).

DISCUSSION

The primary objective of this study was to determine the classification technique best suited for accurate and precise mapping of the land cover classes useful for assessing bobwhite habitat. Once the final method (Guided Spectral Class Rejection method with the UMGAP band combinations and the final classification scheme) was selected, applying it to the 8 scenes in the study area was the next step. The result of this particular study is a land cover map for a portion of the state. Though exhibiting limitations, this final method proved to be the most useful in eastern Virginia. It yielded the highest overall and individual class accuracy using the modified classification scheme. Typically, a classification scheme is determined prior to performing a classification. However, for this study, it became apparent midway through the iterations that separating certain classes would not be feasible, resulting in the collapsed scheme previously described. This reduction in categorical specificity may appear arbitrary in terms of the final product of a land cover map of potential bobwhite habitats, but its discussion is warranted. The reduction in categorical specificity should improve overall accuracy due to fewer classes that could cause confusion. This reduction in categorical specificity was deemed appropriate due to the difficulty in obtaining suitable reference data in the individual row crops, recently-cut forests, and young pine plantations. Some of these relic classes, such as 6-year old clear cuts, were relatively rare on the landscape, making sufficient data collection within them difficult. Still others were temporally dynamic and may have changed numerous times since the date of image acquisition. As indicated, our image was acquired in 1992, and most of our field data collection occurred in January and February 1998. During these 6 years many changes

Table 2-12. The error matrix for scene 15/35 using the Guided Spectral Class Rejection classification method.

Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	0	0	1	0	0	0	1
Row Crops	**74**	5	4	1	0	0	84
Early Succession	1	**8**	3	2	8	0	22
Pasture/Hay/Grass	3	2	**9**	1	0	0	15
Coniferous Forest	0	2	0	**27**	2	0	31
Deciduous Forest	0	0	0	0	**0**	0	0
Open Water	0	0	0	0	0	**7**	7
Total	78	17	17	31	10	7	160

Table 2-13. User's and producer's accuracy for each land cover class in scene 15/35 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.8809	0.9487
Early Succession	0.3636	0.4706
Pasture/Hay/Grass	0.6000	0.5294
Coniferous Forest	0.8709	0.8709
Deciduous Forest	0.0000	0.0000
Open Water	1.0000	1.0000
Overall Accuracy	0.7813	
Kappa	0.6783	
Kappa Variance	0.001968	
Z Statistic	15.2901 (P<0.0001)	

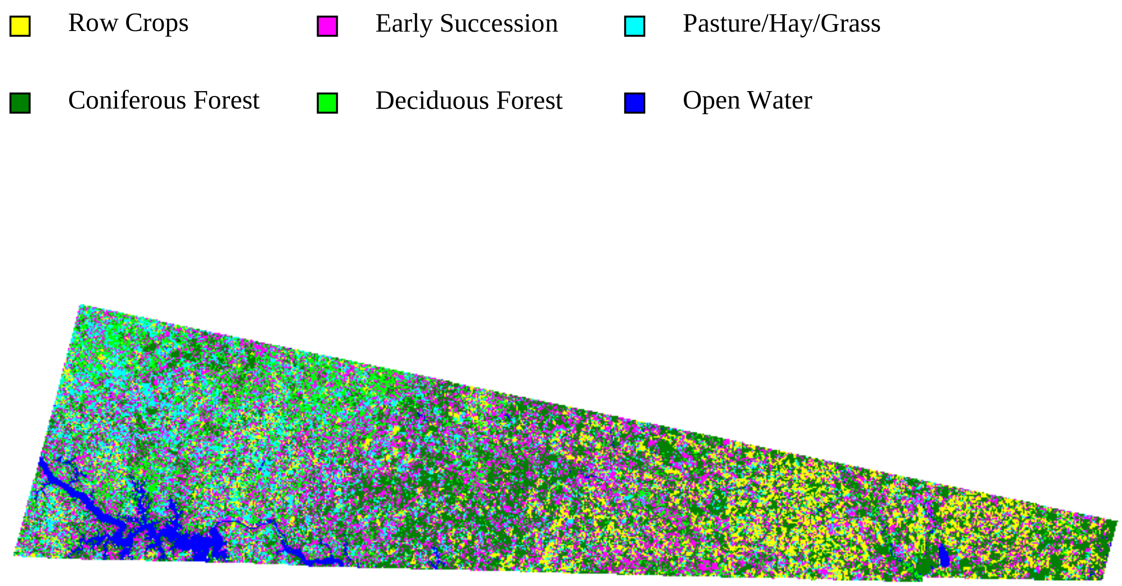


Figure 2-4. Final classification of the scene 15/35.

Table 2-14. Classification results for scene 15/35, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	815,969	73,437.2	13.87
Early Succession	1,572,733	141,546.0	26.74
Pasture/Hay/Grass	879,186	79,126.7	14.95
Coniferous Forest	1,636,085	147,247.7	27.82
Deciduous Forest	788,742	70,986.8	13.41
Water	189,103	17,019.3	3.22
Totals	5,881,818	529,363.6	100.00

Table 2-15. The error matrix for scene 15/33 using the Guided Spectral Class Rejection classification method.

	Reference Data						
Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Urban/ Disturbed
Row Crops	**3**	0	6	0	0	0	0
Early Succession	0	**3**	1	0	1	0	0
Pasture/Hay/Grass	12	0	**27**	0	0	0	0
Coniferous Forest	0	0	1	**11**	2	0	0
Deciduous Forest	0	0	0	1	**13**	0	0
Open Water	0	0	0	0	0	**5**	0
Urban/Disturbed	0	0	0	0	0	0	**7**
Total	15	3	35	12	16	5	7

Table 2-16. User's and producer's accuracy for each land cover class in scene 15/33 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.3333	0.2000
Early Succession	0.6000	1.0000
Pasture/Hay/Grass	0.6923	0.7714
Coniferous Forest	0.7857	0.9167
Deciduous Forest	0.9286	0.8125
Open Water	1.0000	1.0000
Urban/Disturbed	1.0000	1.0000
Overall Accuracy	0.7419	
Kappa	0.6653	
Kappa Variance	0.0036	
Z Statistic	11.0592 (P<0.0001)	

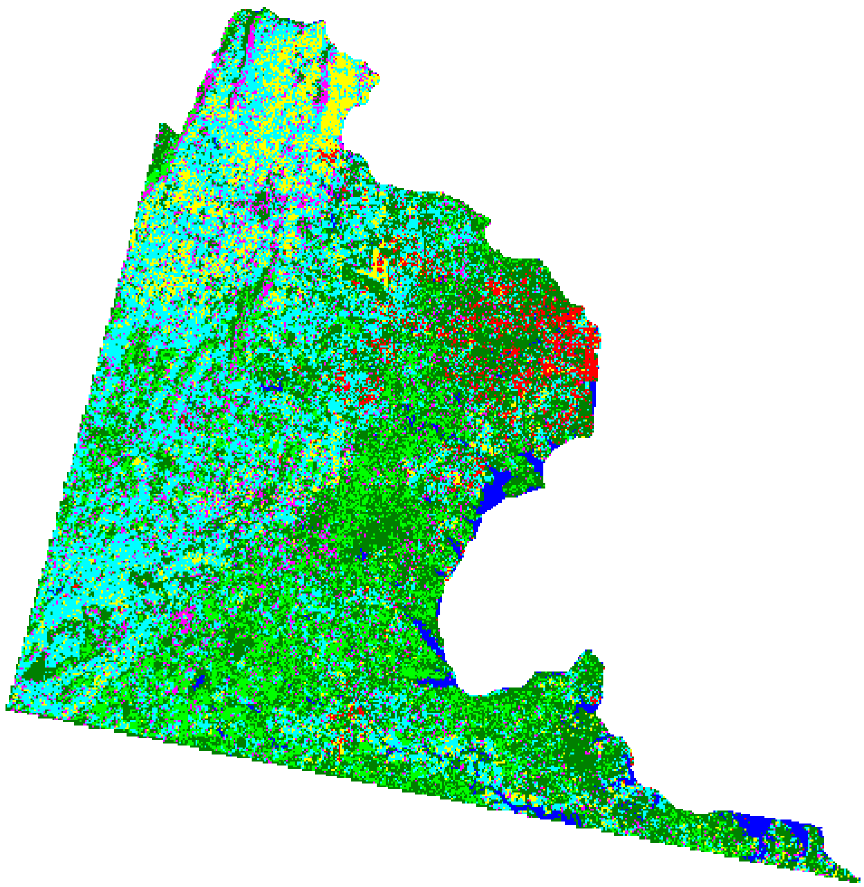


Figure 2-5. Final classification of the scene 15/33.

Table 2-17. Classification results for scene 15/33, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	706,036	63,543.2	8.04
Early Succession	681,758	61,358.2	7.76
Pasture/Hay/Grass	2,715,288	244,375.9	30.91
Coniferous Forest	3,025,572	272,301.5	34.44
Deciduous Forest	1,464,599	131,813.9	16.67
Water	191,213	17,209.2	2.18
Totals	8,784,466	790,601.9	100.00

Table 2-18. The error matrix for scene 14/34 using the Guided Spectral Class Rejection classification method.

Classification Data	Reference Data Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	0	1	1	1	0	0	3
Row Crops	**61**	3	10	9	0	0	83
Early Succession	0	**0**	1	0	0	0	1
Pasture/Hay/Grass	7	1	**14**	3	0	0	25
Coniferous Forest	1	0	0	**12**	0	1	14
Deciduous Forest	4	0	2	2	**0**	0	8
Open Water	0	0	0	0	0	**9**	9
Total	73	5	28	27	0	10	143

Table 2-19. User's and producer's accuracy for each land cover class in scene 14/34 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.7349	0.8356
Early Succession	0.0000	0.0000
Pasture/Hay/Grass	0.5600	0.5000
Coniferous Forest	0.8571	0.4444
Deciduous Forest	0.0000	0.0000
Open Water	1.0000	0.9000
Overall Accuracy	0.6713	
Kappa	0.4915	
Kappa Variance	0.0033	
Z Statistic	8.582 (P<0.0001)	

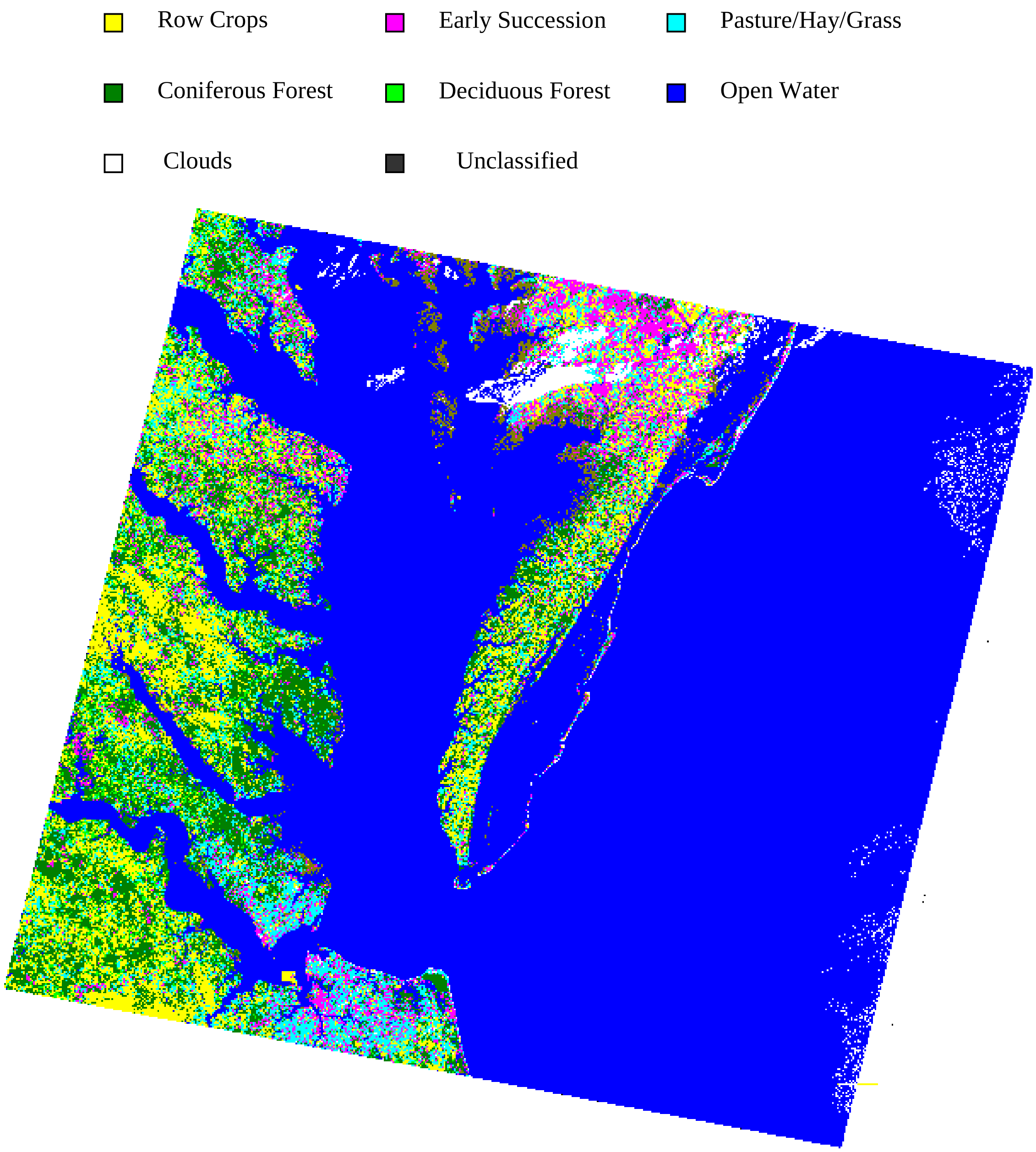


Figure 2-6. Final classification of scene 14/34.

Table 2-20. Classification results for scene 14/34, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	2,774,127	249,671.4	8.36
Early Succession	1,380,051	124,204.6	4.16
Pasture/Hay/Grass	1,987,910	178,911.9	5.99
Coniferous Forest	2,982,060	268,385.4	8.98
Deciduous Forest	545,063	49,055.7	1.64
Water	23,525,609	2,117,304.8	70.87
Totals	33,194,820	2,987,533.8	100.00

Table 2-21. The error matrix for scene 14/35 using the Guided Spectral Class Rejection classification method.

	Reference Data						
Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	0	0	0	0	0	0	0
Row Crops	**14**	5	6	1	0	0	26
Early Succession	0	**13**	2	1	2	0	18
Pasture/Hay/Grass	3	5	**7**	0	0	0	15
Coniferous Forest	1	1	1	**9**	0	0	12
Deciduous Forest	0	3	0	6	**5**	0	14
Open Water	0	0	0	0	0	**10**	10
Total	18	27	16	17	7	10	95

Table 2-22. User's and producer's accuracy for each land cover class in scene 14/35 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.5385	0.7778
Early Succession	0.7222	0.4815
Pasture/Hay/Grass	0.4666	0.4375
Coniferous Forest	0.7500	0.5294
Deciduous Forest	0.3571	0.7143
Open Water	1.0000	1.0000
Overall Accuracy	0.6105	
Kappa	0.4269	
Kappa Variance	0.0037	
Z Statistic	7.047 (P<0.0001)	

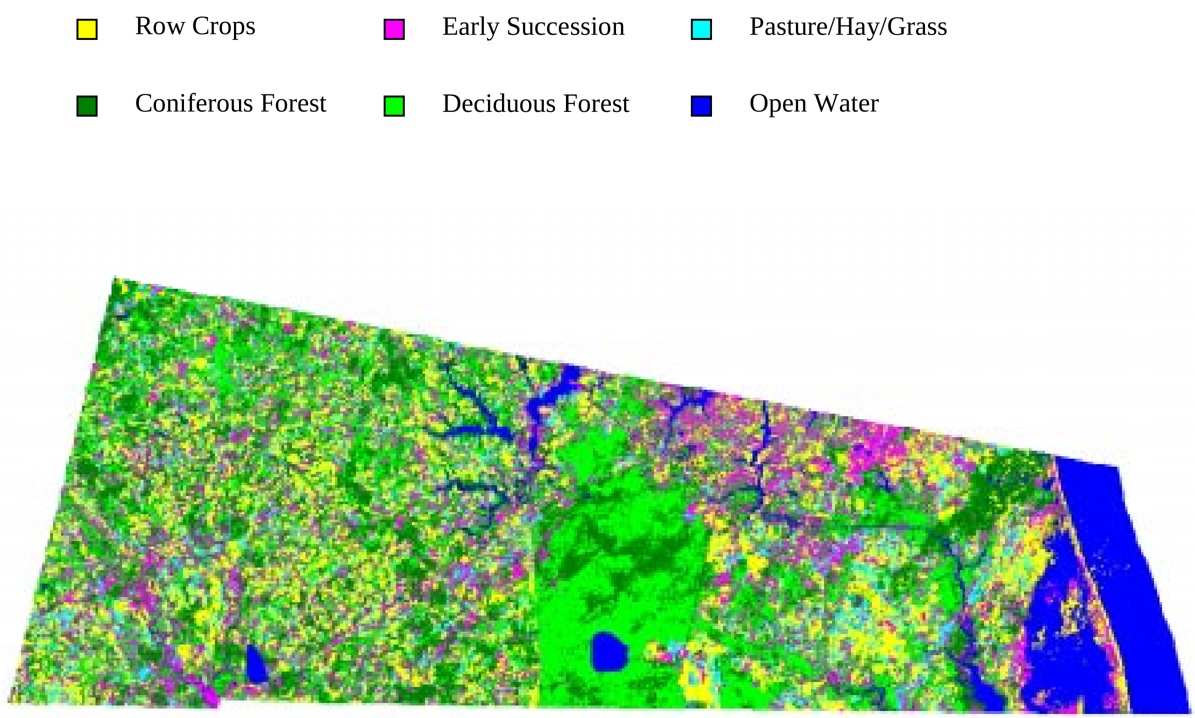


Figure 2-7. Final classification of scene 14/35.

Table 2-23. Classification results for scene 14/35, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	855,975	77,037.8	19.60
Early Succession	754,341	67,890.7	17.27
Pasture/Hay/Grass	385,495	34,694.6	8.82
Coniferous Forest	893,499	80,414.9	20.45
Deciduous Forest	1,072,845	96,556.1	24.56
Water	406,079	36,547.1	9.30
Totals	4,368,234	393,141.1	100.00

Table 2-24. The error matrix for scene 16/33 using the Guided Spectral Class Rejection classification method.

Classification Data	Reference Data: Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Total
Unclassified	0	0	0	0	0	0
Row Crops	**37**	1	8	0	0	46
Early Succession	0	**1**	0	0	0	1
Pasture/Hay/Grass	12	4	**115**	3	1	135
Coniferous Forest	0	2	0	**24**	0	26
Deciduous Forest	0	2	1	2	**39**	44
Total	49	10	124	29	40	252

Table 2-25. User's and producer's accuracy for each land cover class in scene 16/33 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.8043	0.7551
Early Succession	1.0000	0.1000
Pasture/Hay/Grass	0.8518	0.9274
Coniferous Forest	0.9231	0.8275
Deciduous Forest	0.8864	0.9750
Overall Accuracy	0.8571	
Kappa	0.7839	
Kappa Variance	0.0011	
Z Statistic	23.657 (P<0.0001)	

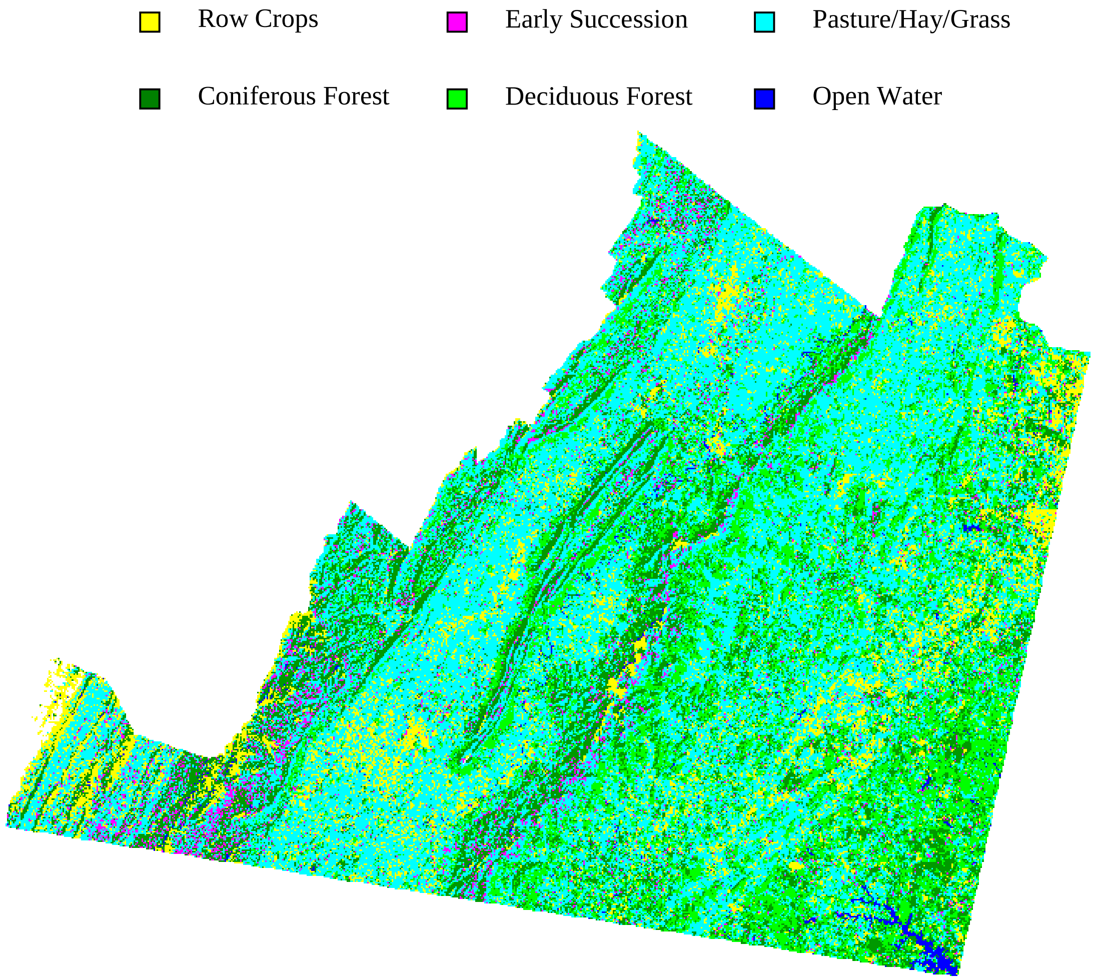


Figure 2-8. Final classification of scene 16/33.

Table 2-26. Classification results for scene 16/33, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	2,131,179	191,806.1	11.23
Early Succession	707,349	63,661.4	3.73
Pasture/Hay/Grass	9,259,491	833,354.2	48.80
Coniferous Forest	3,053,907	274,851.6	16.09
Deciduous Forest	3,684,137	331,572.3	19.41
Water	139,999	12,599.9	0.74
Totals	18,976,062	1,707,845.6	100.00

Table 2-27. The error matrix for scene 16/34 using the Guided Spectral Class Rejection classification method.

	Reference Data						
Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassified	0	0	0	0	0	1	1
Row Crops	**17**	8	6	0	0	0	31
Early Succession	4	**12**	4	6	3	0	29
Pasture/Hay/Grass	5	0	**25**	0	1	0	31
Coniferous Forest	0	3	1	**9**	0	0	13
Deciduous Forest	1	5	2	4	**8**	0	20
Open Water	0	0	0	0	0	**5**	5
Total	27	28	38	19	12	6	130

Table 2-28. User's and producer's accuracy for each land cover class in scene 16/34 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.5484	0.6296
Early Succession	0.4138	0.4286
Pasture/Hay/Grass	0.8065	0.6579
Coniferous Forest	0.6923	0.4737
Deciduous Forest	0.4000	0.6666
Open Water	1.0000	0.8333
Overall Accuracy	0.5846	
Kappa	0.4821	
Kappa Variance	0.0029	
Z Statistic	8.969 (P<0.0001)	

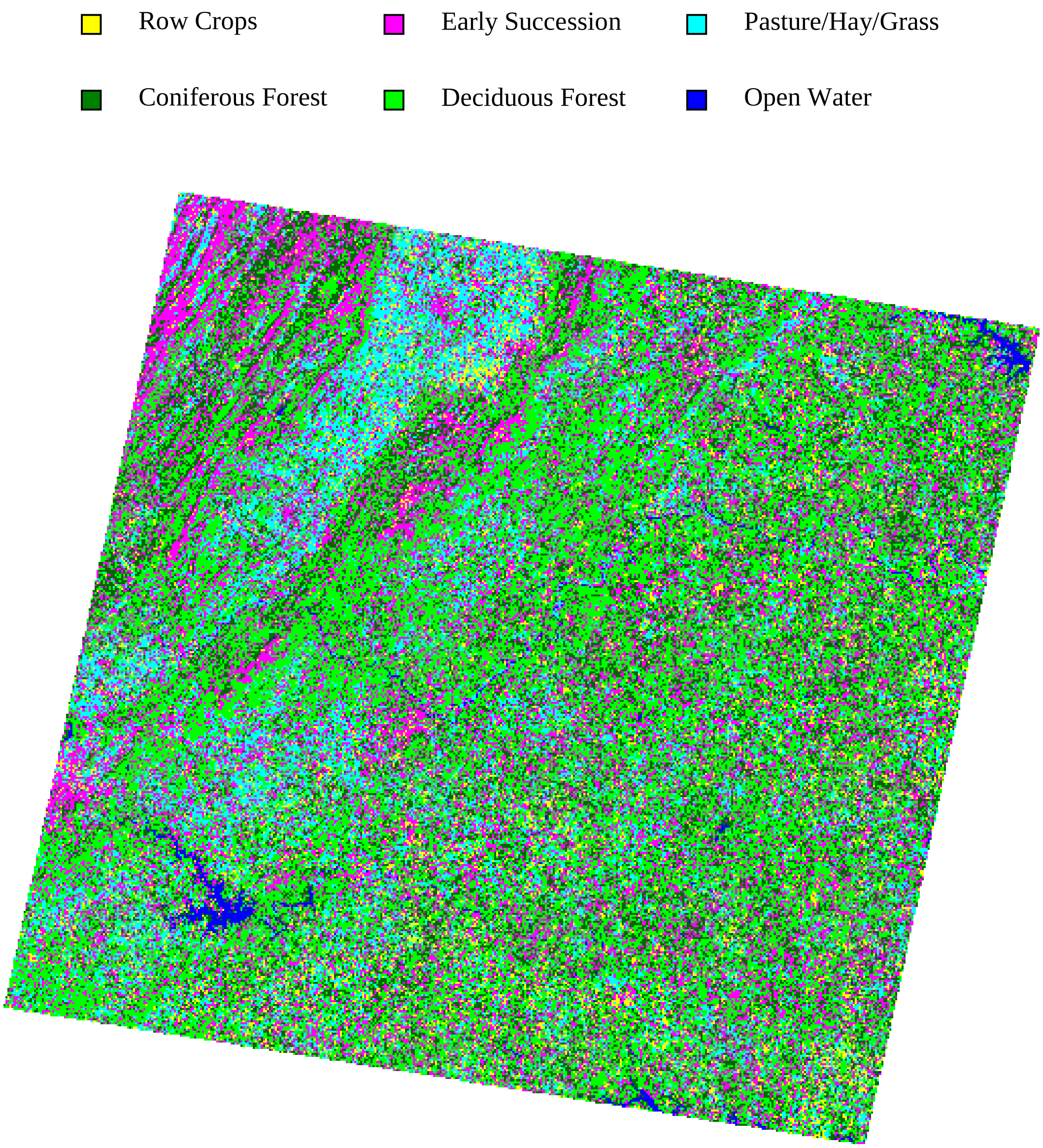


Figure 2-9. Final classification of scene 16/34.

Table 2-29. Classification results for scene 16/34, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	1,935,738	174,216.4	5.76
Early Succession	8,321,164	748,904.8	24.76
Pasture/Hay/Grass	4,660,665	419,459.9	13.87
Coniferous Forest	5,789,499	521,054.9	17.23
Deciduous Forest	12,594,117	1,133,470.5	37.48
Water	301,450	27,130.5	0.90
Totals	33,602,633	3,024,237.0	100.00

Table 2-30. The error matrix for scene 16/35 using the Guided Spectral Class Rejection classification method.

	Reference Data						
Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Total
Unclassifid	0	0	0	0	0	0	0
Row Crops	**15**	2	30	1	1	0	49
Early Succession	2	**7**	1	5	5	0	20
Pasture/Hay/Grass	20	11	**79**	3	6	0	119
Coniferous Forest	1	8	1	**46**	7	0	63
Deciduous Forest	0	6	0	4	**29**	0	39
Open Water	0	0	0	0	0	**4**	4
Total	38	34	111	59	48	4	294

Table 2-31. User's and producer's accuracy for each land cover class in scene 16/35 including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.3061	0.3947
Early Succession	0.3500	0.2059
Pasture/Hay/Grass	0.6639	0.7117
Coniferous Forest	0.7302	0.7797
Deciduous Forest	0.7436	0.6042
Open Water	1.0000	1.0000
Overall Accuracy	0.6122	
Kappa	0.4850	
Kappa Variance	0.0014	
Z Statistic	13.170 (P<0.0001)	

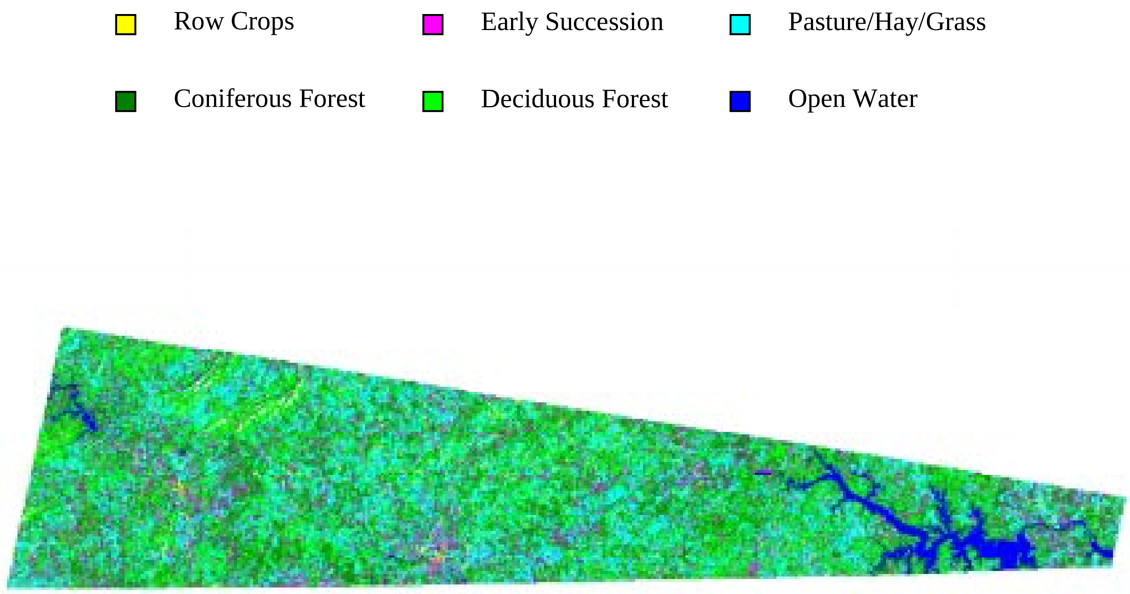


Figure 2-10. Final classification of scene 16/35.

Table 2-32. Classification results for scene 16/35, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	153,591	13,823.2	2.66
Early Succession	770,775	69,369.8	13.33
Pasture/Hay/Grass	1,576,346	141,871.1	27.26
Coniferous Forest	1,449,275	130,434.8	25.07
Deciduous Forest	1,604,289	144,386.0	27.75
Water	227,306	20,457.5	3.93
Totals	5,781,582	520,342.4	100.00

Table 2-33. The error matrix for the mosaic of all 8 images using the Guided Spectral Class Rejection classification method. Reference data are shown as column headings, while classification data represent row headers.

	Reference Data							
Classification Data	Row Crops	Early Successional	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Urban/Disturbed	Total
Unclassified	0	0	0	0	0	13	7	20
Row Crops	**448**	45	88	6	12	0	0	599
Early Succession	12	**115**	14	33	49	0	0	223
Pasture/Hay/Grass	106	12	**384**	5	1	0	0	508
Coniferous Forest	2	21	1	**251**	22	3	0	300
Deciduous Forest	16	56	13	25	**101**	0	0	211
Open Water	0	0	0	2	0	**40**	0	42
Urban/Disturbed	13	2	9	2	4	0	**0**	30
Total	597	251	509	324	189	56	7	1933

Table 2-34. User's and producer's accuracy for each land cover class for the coastal plain and piedmont physiographic provinces including overall accuracy and Kappa statistic.

Class	User's	Producer's
Row Crops	0.7479	0.7504
Early Succession	0.5157	0.4582
Pasture/Hay/Grass	0.7560	0.0154
Coniferous Forest	0.8367	0.7747
Deciduous Forest	0.4787	0.5344
Open Water	0.9524	0.7143
Urban/Disturbed	0.0000	0.0000
Overall Accuracy	0.6927	
Kappa	0.6074	
Kappa Variance	0.0002	
Z Statistic	46.180 (P<0.0001)	

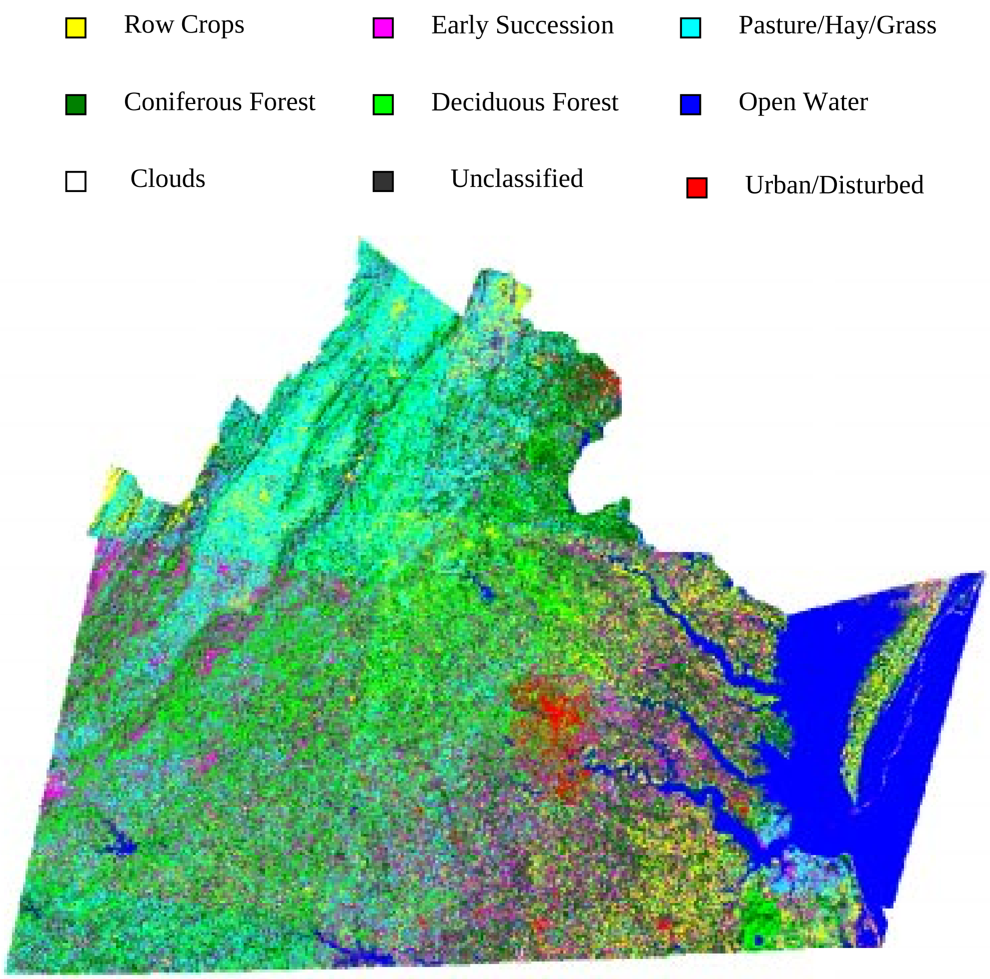


Figure 2-11. Final classification of entire coastal plain and piedmont physiographic provinces of Virginia.

Table 2-35. Classification results for entire coastal plain and physiographic provinces in Virginia, including number of pixels within each class, number of hectares, and percentage of the scene.

Class	Number of Pixels	Hectares	Percentage of Total Area
Row Crops	8,965,683	806,911.5	9.14
Early Succession	16,412,446	1,477,120.1	16.74
Pasture/Hay/Grass	18,155,862	1,634,027.6	18.51
Coniferous Forest	19,531,906	1,757,871.5	19.92
Deciduous Forest	22,083,498	1,987,514.8	22.52
Water	11,356,181	1,022,056.3	11.58
Urban/Disturbed	1,561,697	140,552.7	1.59
Totals	98,067,273	8,826,054.6	100.00

within the agricultural crop matrix may have occurred. Certainly some of these changes could be predicted using a general crop calendar for this area, but the economic influence on these crops precludes back calculation without more specific data. Acquiring data from the county Farm Service Agency (FSA) offices remedied part of this problem. Despite these data, temporal issues have been a problem during the classification work. The error matrix shows this as a large amount of confusion between the row crop and pasture/hay/grass classes. Spectrally these are more similar than some classes, however one would expect better separation between these classes using two dates of imagery. Where this temporal influence may cause confusion is during the data collection phase. Because FSA offices only have records of cash crops and Conservation Reserve Program (CRP) lands, those falling in the pasture/hay/grass class were poorly represented in 1992 specific data. Consequently, many of these pasture/hay/grass points were collected in the field, and though some had the same land cover as they did 6 years ago, I imagine some had changed between the dates. This problem probably is not universal; some fields may look like a full cover crop because of the particular crop or resource grown in a particular year, while looking completely different at another date of data collection. The problem of changing land use patterns only confounds this problem as lands can drastically change in use between image acquisition and data collection phases.

Thus far I have only mentioned the temporal problems within the agricultural row crop and pasture/hay/grass classes. The other form of change I encountered included broad changes in land cover resulting from timber harvesting activities. Much of the forested land in eastern Virginia is intensively managed loblolly and Virginia pine plantations. Loblolly pine is characterized as a medium lived tree with rapid juvenile growth (Baker and Langdon 1990). Conversely, Virginia pine is a small to medium sized tree that commonly inhabits old fields, and is a source of pulpwood and lumber in the southeast (Carter and Snow 1990). Virginia pine are also grown commercially as Christmas trees, with rotations between 5 and 10 years (Carter and Snow 1990). The rotation on these lands is rather short, resulting in rapid turnover and a high degree of change, especially when there is a 6-year window between data sources. A comparison of aerial videography flown in 1995 and 1996 and the imagery used in this study has shown that roughly 16% of the videography points have changed over a 5-year period (VAGAP unpub. data). Using expert knowledge of the Landsat TM imagery, I concluded that roughly half the changed videography points were falling in what was deciduous forest, while the other half fell in coniferous forest on the Landsat TM imagery. On top of that, nearly 65% of the changed deciduous forest points on the Landsat TM scene were being converted to coniferous plantations. It is evident that this landscape is dynamic and disturbance is common in this region making historical land use classification efforts difficult.

This whole discussion leads one to question the timeliness of the product. A number of researchers have touched upon the timeliness or currentness of maps and map production (Williamson 1981, Morton 1998). The scenes used in this study were primarily collected between in 1991 and 1993. I have already discussed the temporal problem with a 6-year difference between image acquisition and reference data collection. The seeming lack of timeliness can be attributed to the cost of the images. As indicated, these images were acquired by the MRLC Consortium for the Virginia GAP program at a reduced price due to the size of the order. Scenes that are more recent than those used can be acquired, however the cost was prohibitive. A geo-corrected July 1998 scene costs $5,500 (Space Imaging website). The second question of timeliness arises with the presentation of the final product, which is a land cover map of 1992. From the research side, this temporal problem caused numerous problems.

The images, however, have been useful in testing land cover mapping methods in Virginia. From the operational side and from the perspective of managers trying to use these products, some utility may have been lost as a number of the dynamic bobwhite habitats delineated may have changed significantly over 7 years, rendering portions of the product useless for present day management.

Accuracy

The methods outlined herein underwent a series of iterations in an attempt to generate the most spatially and temporally accurate map. So far I have discussed the problems associated with temporal differences between image acquisition and data collection. Next, I shall discuss the accuracy of the final product. The overall accuracy and individual class producer's and user's accuracies were presented. Certainly some of the errors are attributable to the temporal issues previously discussed. Knowing I was faced with a temporal problem when collecting field data, I sought to eliminate many or all of the spatial problems others have faced (Morton 1998). I feel that the data collection methods, including the "windshield surveys", were spatially correct. This isolates our confusion problems to indistinguishable spectral classes or error by the classifier during one of the many steps. Varying degrees of human subjectivity during classification probably occurred when performing these classifications. Even the passage of a few hours or a day between classifications could change how the visual cues on the landscape were interpreted or to which class I added a marginal signature. Additionally, depending on the pattern or sequence of this activity, I may be influencing the final map by filling in certain map patches or areas prior to others. Based on the nature of an unsupervised classification, pixels of any class can occur anywhere in the image. By visually identifying holes in apparent homogeneous patches and labeling the holes the same as the surrounding pixels, a number of errors could be occurring. First, that pixel might actually be an island of another cover type within that larger patch of another type. When I performed this step, I avoided calling these central pixels in classes typically lacking solid patterns as the surrounding class. However, central pixels in vast stands of deciduous or coniferous forests or even large early successional areas were hard to not classify as the surrounding class. These central, previously unidentified pixels may actually be similar to the homogeneous patches in which they are found, but dissimilar enough that they appear similar to another spectral class causing inclusion elsewhere. Depending upon the sequence, classifying one central pixel may create another patch, as it may be the major component in that other patch, so the order of classification matters.

Based upon my knowledge of the process, I feel that a spatial problem may also be present. A shift in location between dates by a pixel or two may be potentially causing some problems between classes and magnifying the mixed pixel effect typical in remote sensing studies (Dai and Khorram 1998).

The actual process may also have proven problematic. I used a maximum-likelihood classification algorithm after excluding confused ISODATA classes. Occasionally some points of known cover ended up falling in other land cover types when overlaid on the final map. The potential reasons for this are numerous; these points may be some of the confused points. The points may also be spectrally close to other classes and may be included in the wrong class due to spectral similarity. This methodology was used to combine optimal parts of both the supervised and unsupervised classifications, however error may have been introduced by the interpreter. Finally, some ISODATA classes may include a number of mixed pixels on the edge of multiple cover types, potentially confusing them with other classes. In the traditional supervised classification approach, edge pixels can be avoided during training set selection. By using this technique, these classes may be kept and included in the maximum-likelihood classifier, continuing the confused class signature through into the final map.

Without dwelling upon the problematic data too much, I should also point out that some of the problems seen in this classification might be explained by the insufficient sample sizes of reference data in certain classes. For instance, deciduous forest is relatively sparse in this part of the state, and consequently is poorly represented in the reference data. For the study area, I only had 34 reference points in this class, and after the split between classification and accuracy assessment there were only 9 available for accuracy assessment. That means that for each one incorrectly classified, the producer's accuracy would decrease by 11%. This effect is seen in our accuracies, with those for the deciduous class being very low. In classifying the entire scene containing the study area, there were more deciduous reference points available for both classification and error assessment than when I was examining just the study area. Eighty-five points were available for error assessment alone, which made each single error weigh much less than when only classifying the study area. The result was an increase in the producer's accuracies from 11% to 51%. Similarly, the user's accuracy suffered due to low sample sizes. Again, the need for quality and quantity reference data is noticed when classifying remotely-sensed imagery.

The overall accuracy and individual class accuracies presented in the results section can be modified to represent some of the temporal changes discussed. In a strict error assessment, any confusion is considered wrong. By using a fuzzy logic error assessment method, analysts can express errors caused by changed land covers between data acquisition dates. By considering certain errors with less weight than others, one can partially accommodate these potential changes. I explored this possibility based on the temporal difference that likely had an influence on the product. I reduced the number of errors between the pasture/hay/grass class and the agricultural row crop class by a half. The logic behind this was that these classes could easily be interchanged on a yearly basis. Besides, to bobwhite, both habitats are of high quality compared to the other available habitats. Additionally, I reduced the weight on the error between the coniferous forest class and the early successional class. The latter class included young pine plantations that may have been spectrally similar to the pine plantations. By reducing the relative weights of the incorrectly classified points, I added to the magnitude of influence of correctly classified points, improving our overall accuracy. For the study area, this fuzzy approach improved the overall accuracy from 79.3% to 83.4%, while the overall accuracy for the entire scene 15/34 increased from 72.8% to 79.0%. Other researchers have moved away from traditional, hard classifiers towards fuzzy accuracy assessment and realized much better results (i.e., Gopal and Woodcock 1994, Mickelson et al. 1998). These estimates of accuracy are not final and reportable as the results, but potentially alleviate some of the biases incorporated due to the temporal differences between data sets. The reality of the situation might be an inappropriate inflation of the correctly classified numbers, increasing the accuracy beyond what they truly are. Conversely, this product may even be better than I perceive it to be.

Recommendations and Conclusions

This study has shown the utility in trying tested and untested methods prior to selecting one in particular. In general, the final results are far superior to any of the earlier attempts. At the project start, I was fairly certain I knew what path I would take for the image classification phase of the study, but quickly became aware that the initial choices were not adequate. Our flexibility and research oriented approach allowed us to devise better methods for classifying the eastern portion of Virginia given the imagery and data I had at the time of the study.

This again brings up the question of timely data. I feel the “windshield survey” data collection methods allowed for rather rapid data collection for this study. Ideally, more widespread data would have been better, but the limitations of the method precluded the collection of much more data than I collected. Other methods of data collection can cover greater areas, each with their own limitations. Aerial videography has been useful in some areas, but as Morton (1998) described it has limitations in Virginia.

Tied to this issue is the need for abundant, precise data. As with any project using remotely-sensed data, I too could have used more known reference points. The importance of this information can not be overstated. For this study I may have avoided many difficulties had I had more data at the start of the classification than was available. Many of the problems I encountered were either a result of the lack of data or were constrained by the quality of our data. I feel that additional data early in the process would have saved considerable time and effort.

The timeliness of the product can also be improved, while also eliminating some of the temporal problems with acquiring more recent imagery. As noted, this vastly increases the cost of the project, but may make some of the process easier and more accurate. As new remote sensing platforms with improved resolution become available (Wynne and Carter 1997) I feel the protocols developed herein will allow the classification of numerous early successional classes previously lumped together into one class. Even at the scale of Landsat TM sensors, an accurate map can be completed at a relatively fine level of detail using personal computers. Certainly in the near future, this ability to generate a current map from remotely-sensed data will be available to biologists at their desks. In the past, the ability to perform a study such as this was limited by hardware. Now I have shown that this can be done on most computers with a processor speed greater than 200 MHz. With the ability and knowledge produced by this study, biologists should be able to begin to apply this classification method for a number of wildlife species.

CHAPTER 3- SPATIAL HABITAT ANALYSIS

INTRODUCTION

Despite the long history of management and research on bobwhite, insufficient knowledge about the spatial arrangements of habitats at a level of detail greater than a covey home range is available. In 1996, Virginia implemented the Bobwhite Quail Management Plan to identify and resolve a number of areas with incomplete knowledge that may be causing the current population declines. One research topic identified in this plan was the need for detailed information about habitat availability at the landscape scale and a good description of the spatial arrangements of these different habitats. Broader scale approaches have been advocated for bobwhite quail. The need to study bobwhite populations within landscapes was expressed during a special workshop at the 3rd National Quail Symposium in 1992 where biologists met to develop a "National Strategic Plan for Quail" (Brennan 1993, Kuvlesky et al. 1993, Roseberry 1993).

This phase of the study was designed to understand better the large-scale patterns affecting bobwhite populations in Virginia. Specifically, I describe the spatial arrangements of these habitats and predict areas likely to support bobwhite populations using modeling techniques. Pattern Recognition (PATREC) and stepwise logistic regression models are developed to express the probability that a given landscape surrounding a point would support a high bobwhite population.

Objectives

The objective of this phase of the study was to investigate the spatial arrangements of bobwhite habitat as described by a remotely-sensed land cover map. After the spatial patterns were identified, I attempted to develop a model to predict bobwhite population abundance levels across the landscape.

LITERATURE REVIEW

Bobwhite and Landscape Ecology

Chapter 1 includes a comprehensive review of the status of bobwhite quail, so little detail will be covered here. General land use patterns are discernible from United States Census of Agriculture data (United States Department of Commerce 1978-1992). Census data have been used to describe county-level bobwhite habitat availability (Fies et al. 1992). However, these data failed to provide sub-county information and lack information about the spatial arrangements of the various habitat components.

Recently, the spatial arrangements of bobwhite habitats have been described in detail for Illinois and to a lesser degree for Georgia. In Georgia, Michener et al. (1998) described the optimal spatial arrangements of habitats on hunt courses indicating where the most coveys would be found. They found that the bobwhite densities were positively associated with 3 factors: percentage of the landscape in agriculture and food plots, mean patch size of agricultural fields and food plots, and mean shape index of agricultural fields and food plots. In Illinois, Roseberry and Sudkamp (1998) found similar landscape metrics were important to bobwhite populations.

Based on a Pattern Recognition (PATREC) modeling exercise, higher populations of bobwhite would be most likely found in areas with moderate amounts of row crops and grasslands, have a higher percentage contagion, and have edges with woods (Roseberry and Sudkamp 1998). Their work described typical bobwhite habitat, with a structurally diverse, brushy areas interspersed with row crops and grasslands, while containing abundant edges. Spatial arrangements have been described for a number of other species as well, including prairie dogs (Reading and Matchett 1997), black-tailed jack rabbits (Knick and Dyer 1997), neotropical migratory songbirds (Keller and Anderson 1992), black-tailed deer (Boroski et al. 1996), and spotted owls (Hunter et al. 1995).

Guthery (1997) explored the published research to develop a philosophy about habitat management. He theorized that if a population is persisting, there is some constancy in habitat quality through temporal space. As climates, predators and landscapes change around a population, Guthery (1997) saw comparable demographics, supporting his thought that habitat of high quality needs to be continually available for bobwhite to persist. Food abundance and habitat type interspersion failed to be general predictors of population abundance beyond the minimum threshold that is required for a population to exist. He felt that management needs to make this continuum of habitat space through time (space-time saturation) available to bobwhite populations.

Habitat Modeling

Habitat modeling is an exercise that attempts to simplify the relationships between an animal population and its habitat. Wildlife researchers commonly use models to predict population numbers and population responses to habitat quality and quantity (Thomas 1980, Gaudette 1986). Berry (1986) noted that responses to quality and quantity of habitat have been the basis for a number of different models, including Habitat Suitability Index (HSI) models, Pattern Recognition Models (PATREC), and Habitat Capability (HC) models.

PATREC Modeling

Pattern recognition models were first used in the medical field to express the uncertainty and risk associated with diagnosing medical conditions (Williams et al. 1978). They were designed to include three phases of the thought process: (1) the perception of a set of conditions, (2) interpretation of these conditions, and (3) decision-making based upon interpretation (Williams et al. 1978). Within the wildlife profession, PATREC models have been adapted to improve managers' likelihood of making a decision that favorably impacts a species. PATREC models can be species-specific models that rely on Bayesian statistics to measure the quality of a habitat for a species (Williams et al. 1978). These models recognize the differences in habitat characteristics between areas with high and low populations of a species. By examining these patterns, the models assess the potential of a site to support a high population. The ability to assign a classification to a set of conditions, based on recognition of patterns, allows the inclusion of probabilities within the decision-making framework (Williams et al. 1978). PATREC modeling on conditional probabilities of an area supporting high or low populations based upon existing habitat conditions. Once the conditional probabilities are established, a posterior probability is calculated using the conditional probabilities for selected habitat variables and the prior probabilities. Williams et al. (1978) provided the framework for

PATREC modeling, while the works of Kling (1980), Kurzejeski and Lewis (1985), Gaudette (1986), and Grubb (1988) provided much needed case studies.

The guidelines for producing a PATREC model are based on Williams et al. (1978) work. First, the species, geographic boundaries, and seasonal application are defined. Mutually exclusive classes of habitat quality (i.e., high/low) need to be defined (Figure 3-1) that express the partitioning of the densities that the modeler hopes to separate. Next, prior probabilities are calculated that estimate the occurrence of each condition. These can be decided upon *a priori* or by examining data for a natural break. Prior probabilities should sum to 1.0, and when adequate information is unavailable, prior probabilities can be set to 0.5 for each of the two classes. Next, pertinent habitat information is collected that allows the modeler to discern between the classes to be separated. Habitat characteristics should be limited to those (1) to which a species responds, (2) are measurable or can be estimated, and (3) can be influenced by planning and management decisions (Schamberger and O'Neal 1984). Each habitat variable is split into two or more mutually exclusive classes that reflect the differences between the population levels. Next, conditional probabilities are derived expressing the probability of that habitat variable's level with a given population abundance. This conditional probability is the portion of each quality class that falls in the various habitat variable ranges. Finally to apply the model, habitat conditions on an area with unknown population abundance are collected. Using the prior and conditional probabilities, posterior probabilities expressing the probability of supporting a high population are calculated using Bayesian statistical inference:

$$P(S|E) = \frac{P(S)P(E|S)}{P(S)P(E|S) + P(U)P(E|U)}$$

where

- $P(S)$ equals the prior probability of suitable habitat,
- $P(U)$ equals the prior probability of unsuitable habitat,
- $P(E|S)$ equals the likelihood of sample result E given suitable habitat,
- $P(E|U)$ equals the likelihood of sample result E given unsuitable habitat, and
- $P(S|E)$ equals the revised or posterior probability of suitable habitat given sample result E.

PATREC models have been successfully developed for bobwhite in Illinois (Roseberry and Sudkamp 1998), wild turkey in Missouri (Kurzejeski and Lewis 1985), bald eagles in Arizona (Grubb 1988), and white-tailed deer in Virginia (Gaudette 1986). The bobwhite study in Illinois (Roseberry and Sudkamp 1998) used many of the same variables and techniques I used, and supported the final PATREC model developed in Virginia.

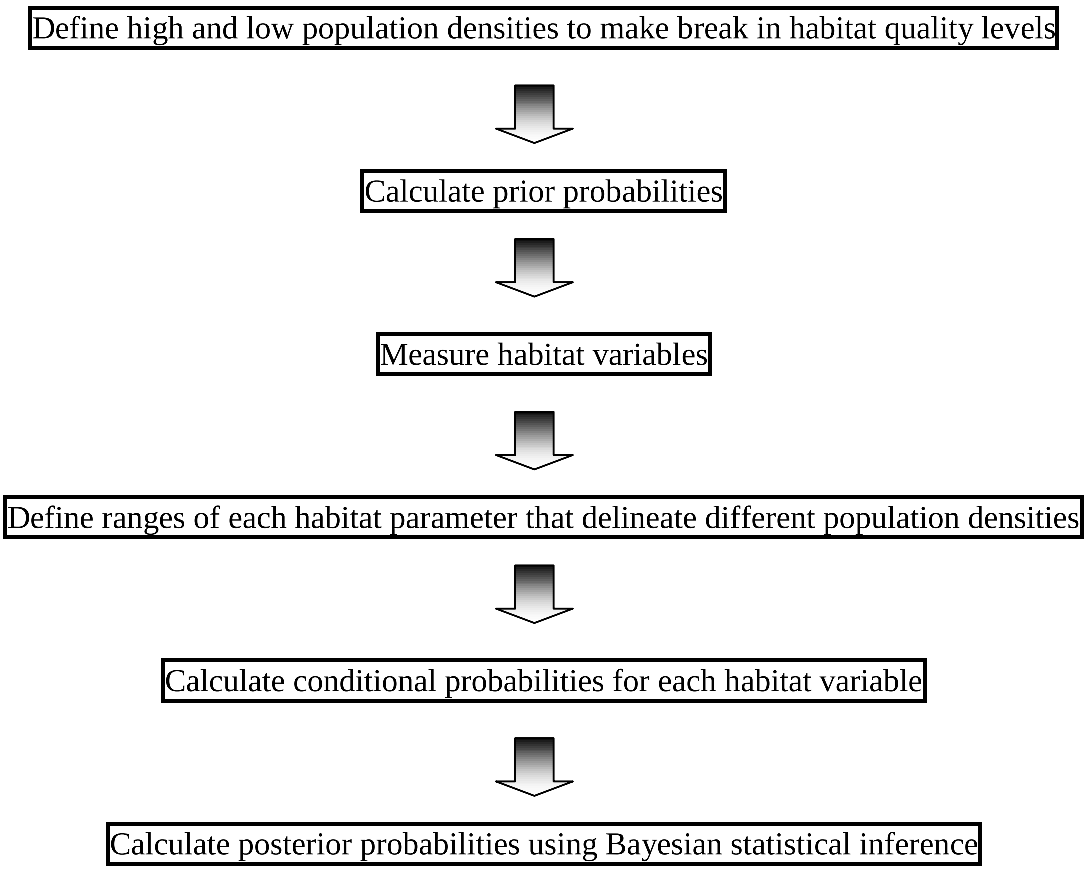


Figure 3-1. Steps taken to develop a PATREC model (after Williams et al. 1978).

Logistic Modeling

Logistic regression is designed to have a number of independent variables (which can be nominal, ordinal, or categorical), and one dichotomous (such as high/low, yes/no, present/absent) dependent variable (Zar 1984). The logistic model predicts the probability of an event occurrence using the equation:

$$\theta = \frac{1}{\left\{1 + e^{-\left(\beta_o + \sum_{j=1}^{k} \beta_j X_j\right)}\right\}}$$

where θ is the final probability, β_0 is the value of the intercept, β_j is the Beta value for the j^{th} dependent variable, and x_j is the value for each of the k landscape metrics.

Logistic models are often used in wildlife management. Robbins et al. (1989) used logistic models to predict the probability of detecting neotropical migrant bird species in forest stands of different sizes. Montopoli and Anderson (1991) used logistic regression to test the cumulative effects of human disturbance on bald eagle foraging and perching. Sherburne and Bissonette (1994) used logistic models to explain the differential use of subnivean access holes used by American marten.

METHODS

A geographic information system was used to combine and manipulate bobwhite call count data and land cover data. I investigated two modeling techniques to generate useful descriptions of bobwhite habitats and likely areas of high quality. A PATREC model was developed to express the probability of an area supporting a high bobwhite population. A logistic regression model was also developed to express the probability that an area supported a high bobwhite population.

Data Acquisition

Land Cover Data

Remotely-sensed digital land cover maps were available from earlier efforts (Chapter 2), and bobwhite call count survey data were available from Virginia Department of Game and Inland Fisheries (VDGIF) staff (Fies unpub. data).

Call Counts

Call count data are collected in Virginia each July along a set of permanent routes, starting at the local sunrise. Bobwhite calls are recorded during 2 minutes at each stop along a 9-mile route. The stops are 1 mile apart resulting in 10 stops per route. VDGIF personnel provided call count data and stop-level route locations.

There has always been concern over road-based bird surveys, but it appears that they are a good indicator of bobwhite abundance in Virginia. Hanowski and Niemi (1995) found road-based routes to detect more species of birds than off-road point counts, many of which were species like bobwhite that are associated with the openings or shrubs associated with edges. Other road-based indices have been used for bobwhite, including Breeding Bird Survey Routes (e.g., Droege and Sauer 1990, Roseberry and Sudkamp 1998), Rural Mail Carrier Surveys (e.g., Wells and Sexson 1982), Christmas Bird Counts (e.g., Brennan 1994), and call counts (e.g., Roseberry and David 1994).

Route maps were acquired from VDGIF personnel and converted to digital format using 1:100,000 USGS Digital Line Graph (DLG) road coverages (United States Geological Survey, 1996). The roads included on each route were identified using ArcView GIS Version 3.01 and ARC/INFO Version 7.1 (Environmental Systems Research Institute, Inc., 380 New York Street, Redlands CA, 92373-8100), selected, and affixed with another attribute indicating the route number. Only road segments with a route number were included in a new call count data layer.

Stop-level call counts were obtained and entered into a database for each of four years. Data from 1990-1993 were used as they corresponded to the years of the imagery and the years leading up to the date of image acquisition. The imagery for the land cover mapping exercise was from a number of dates, but most of the images used were from 1992 (Figure 2- 1). A mean number of bobwhite along each of 39 routes was calculated for the 4-year period and used in the analysis. This eliminated potential spurious years of either good or poor counts along any particular route. Repeated counts can reduce the effect of weather or outside disturbances that may reduce bobwhite detection along these road-based routes. Thirty-nine routes were included in the two Landsat TM scenes encompassing the majority of the Coastal Plain and Piedmont physiographic provinces of Virginia. This subset of the state was selected because it had a suitable land cover mapping accuracy, the image edges matched well, and it contained many bobwhite call count routes.

Routes were buffered a distance of 400 meters to create a zone of detectability. Other studies have determined that most bird songs are not heard beyond this distance (Peterjohn et al. 1996), and in Virginia, it is estimated that bobwhite are not heard beyond this distance (Fies, pers. comm.). The land cover within each of these polygons was extracted from the classified scenes. An index to bobwhite abundance was calculated by dividing the average bobwhite count by the area sampled. I defined the area sampled as 503 hectares per route. This was calculated by taking 10 stops and multiplying them by the area of each circle, which I determined to be 50.3 ha based upon a 400-meter radius circle.

FRAGSTATS

Landscape patterns are increasingly important in land management planning and conservation (Davidson 1998). Understanding these gross scale habitat patterns will enable better bobwhite management. The field of landscape ecology is expanding, and numerous landscape metrics have been developed to express the various measures of landscape structure and function.

To start understanding these habitat arrangements, I explored the possibilities of using FRAGSTATS**,** a US Department of Agriculture Forest Service program for analyzing spatial patterns (McGarigal and Marks 1995). Later, I opted to use the commercial package FRAGSTATS*ARC Version 2.0 (Innovative GIS Solutions Inc., Suite 300, 2000 S. College Avenue, Fort Collins, Colorado 80525) to calculate patch, class, and landscape-level metrics for each route. I used the route level metrics and published studies as tools to decide which metrics appeared to be indicative of bobwhite usage. I hoped to find a few metrics from this phase that could be programmed in TNT Map and Image Processing System (MIPS Version 5.9, MicroImages, Inc., 201 North 8^{th} Street, Suite 15, Lincoln, Nebraska 68508-1347) and then run them on an area the size of the two Landsat scenes.

FRAGSTATS generates patch, class, and landscape level statistics. Patch level statistics (e.g. area and shape index) describe the characteristics of each particular patch. Class level statistics (e.g. mean patch size and percentage of the landscape in each land cover class) describe the nature of all the patches of a particular land cover type. Landscape level statistics (e.g. contagion and interspersion) describe the spatial arrangements of the entire landscape.

I primarily examined the class level statistics. The patch level statistics were not meaningful because they described individual patches and were not at the scale of our bobwhite data. Only a few landscape level statistics were calculated on these small areas. In SAS, these metrics were examined using stepwise multiple regression techniques to determine which ones appeared to be influential factors influencing bobwhite usage. I exercised caution through this phase to avoid the "shotgun" approach to landscape modeling. I did not want to include all 41 metrics (many of which were performed for each land cover class on the map) that FRAGSTATS*ARC generated in a regression with an R^2 approaching 1.0. Certainly some of the metrics calculated are not explainable biologically, while others co-vary. The regression included several metrics that were expected to influence bobwhite abundance. If the metric looked sound, was biologically explainable, and was similar to one that another study used it was included.

An area measure (total area or percent of the landscape) appeared in most of the regressions designed to guide metric selection, indicating the potential usefulness of this metric in explaining bobwhite abundance. The mean patch size and mean edge contrast index were also significant for some of the regressions. Finally, I wanted to include a measure of landscape configuration. Frohn (1998) identified potential problems with the traditional contagion measure in raster based systems, and showed that patch per unit (PPU) is a more appropriate measure of landscape fragmentation in raster-based systems than the traditional contagion measure. The PPU measure is "less sensitive to spatial resolution and problematic geometric characteristics of raster based data" than earlier methods (Frohn 1998). Based on the information from the preliminary regression and the feasibility of programming these variables, I selected the following 19 metrics (Table
3-1) to study:

percentage of the landscape in a class—a class level measure expressing the proportion of the landscape in each land cover class. Roseberry and Sudkamp (1998) and Michener et al. (1998) found the percentage of the landscape as an important predictor of bobwhite abundance.

mean patch size for each class—a class level measure expressing the average size of all patches for a given land cover class. Both Roseberry and Sudkamp (1998) and Michener et al. (1998) found mean patch size as an important predictor of bobwhite abundance.

mean edge contrast index for each class— a class level measure expressing a combination of the weighted edges for each land cover class. This measure uses the *a priori* defined contrast weights for all combinations of edges (Table 3-2). This combination tries to express the beneficial function of all types of habitat edges for a particular wildlife species, in this case bobwhite. Generally, edges between early succession, row crops, and pastures classes were rated highly, whereas forests beside any of the agricultural field types or the early succession class were not rated as highly. Edges with disturbed or open water were not considered because bobwhite do not commonly use these habitats. I chose the mean edge contrast index to express the presence of edges and the perceived quality of these edges for bobwhite.

patch per unit --Frohn (1998) offered a landscape level metric that was equivalent to the contagion measure. Contagion measures dispersion and interspersion, and is an index to the degree to which classes are aggregated or lumped (McGarigal and Marks 1995). The patch per unit measure is "less sensitive to spatial resolution and problematic geometric characteristics of raster based data" than the earlier measures (Frohn 1998). Hence, the patch per unit measure is a more appropriate approximation of the contagion measure in raster-based systems. Frohn (1998) defined patch per unit as:

$$PPU = m/(n * \lambda)$$

where m is the total number of patches,
n is the total number of pixels in the study area, and
λ is the scaling constant, equal to the area of a pixel.

As the landscape becomes more fragmented, this measure increases.

These 19 variables (3 metrics x 6 land cover classes + PPU) were hypothesized to include the majority of the variation in the FRAGSTATS metrics, were programmable in the TNT Spatial Manipulation Language (SML), and were thought to explain some of the variation in bobwhite numbers between routes. SML programs were generated to calculate the selected metrics. Original metrics were approximated under the constraints of a raster-based system. The differences between our raster system and the vector systems used in ARC/INFO made the programming of certain measures difficult,

Table 3- 1. Listing of the 19 landscape metrics calculated and entered into northern bobwhite spatial habitat modeling phase.

Percent of the Landscape in Row Crops
Percent of the Landscape in Early Succession
Percent of the Landscape in Pasture/Hay/Grass
Percent of the Landscape in Coniferous Forest
Percent of the Landscape in Deciduous Forest
Percent of the Landscape in Open Water
Mean Patch Size of Row Crops
Mean Patch Size of Early Succession
Mean Patch Size of Pasture/Hay/Grass
Mean Patch Size of Coniferous Forest
Mean Patch Size of Deciduous Forest
Mean Patch Size of Open Water
Mean Edge Contrast Index for Row Crops
Mean Edge Contrast Index for Early Succession
Mean Edge Contrast Index for Pasture/Hay/Grass
Mean Edge Contrast Index for Coniferous Forest
Mean Edge Contrast Index for Deciduous Forest
Mean Edge Contrast Index for Open Water
Patch Per Unit

Table 3- 2. Weighting coefficients used in mean edge contrast index for bobwhite in Virginia using a Landsat TM derived land cover map. Weights of 1.00 represent a high quality edge, whereas weights of 0.00 represent no quality of the edge to bobwhite.

	Row Crops	Early Succession	Pasture/Hay/Grass	Coniferous Forest	Deciduous Forest	Open Water	Urban/Disturbed
Row Crops	-	1.00	1.00	0.50	0.50	0.00	0.00
Early Succession		-	1.00	0.75	0.75	0.00	0.00
Pasture/Hay/Grass			-	0.50	0.50	0.00	0.00
Coniferous Forest				-	0.20	0.00	0.00
Deciduous Forest					-	0.00	0.00
Open Water						-	0.00
Urban/Disturbed							-

including many area measures. The newly programmed metric approximations were applied to the routes again. When all of the programmed metrics produced results similar to the FRAGSTATS output, I proceeded to build the models.

The routes were split into two groups; one for model building and one for assessing the accuracy of the model. I used 25 routes to build the model and reserved 14 routes to assess the accuracy of the model. The average number of bobwhite heard by route was split into two groups, representing high and low population levels.   The split was at 0.02 bobwhite heard per hectare, which was one of the natural breaks in the data (Figure 3-2). This threshold was validated by an examination of the probabilities, leaving a majority in the low population class, which was deemed conservative and seemingly correct for the existing population indices.

Model Building

PATREC Modeling

Habitat quality can be defined as a measurable characteristic indicating how much of a wildlife species that a particular area can support (Kling 1980). More recently, Hall et al. (1997) defined habitat quality as "the ability of the environment to provide conditions appropriate for individual and population persistence." During this work, when I use the term habitat quality, I am implying its ability to provide the requisites for bobwhite.

Modeling populations based upon habitat conditions has its drawbacks. Typically, models operate on the premise that high population numbers are positively associated with habitats of high quality. Numerous population models depend upon this association, and caution should be used when applying these models because these are habitat predictors of population numbers. Model applications based solely on this premise fail to consider other factors besides habitat condition as a regulating agent. Predation, inter- and intra-specific competition, mortality, natality, and weather are a few factors that may severely influence populations that the habitat variables in a model would not reflect.

One advantage of PATREC modeling over other modeling techniques is the less strict set of assumptions regarding the functional relationships between habitat components and species' life requisites (Roseberry and Woolf 1995). In addition, because PATREC models are more general, they are more applicable to coarse scale, remotely-sensed images such as the land cover map used in this exercise.

The selected metrics were used to build a PATREC model to predict habitat quality for bobwhite in the piedmont and coastal plain areas of Virginia. The class level metrics and the one landscape level metric that I calculated from MIPS were used in model development.

Relationships between variables were tested using Pearson product-moment correlation coefficients (Zar 1984, PROC CORR: SAS Institute 1990). For any pair of variables with a correlation greater than 0.5, the variables were examined to see if one

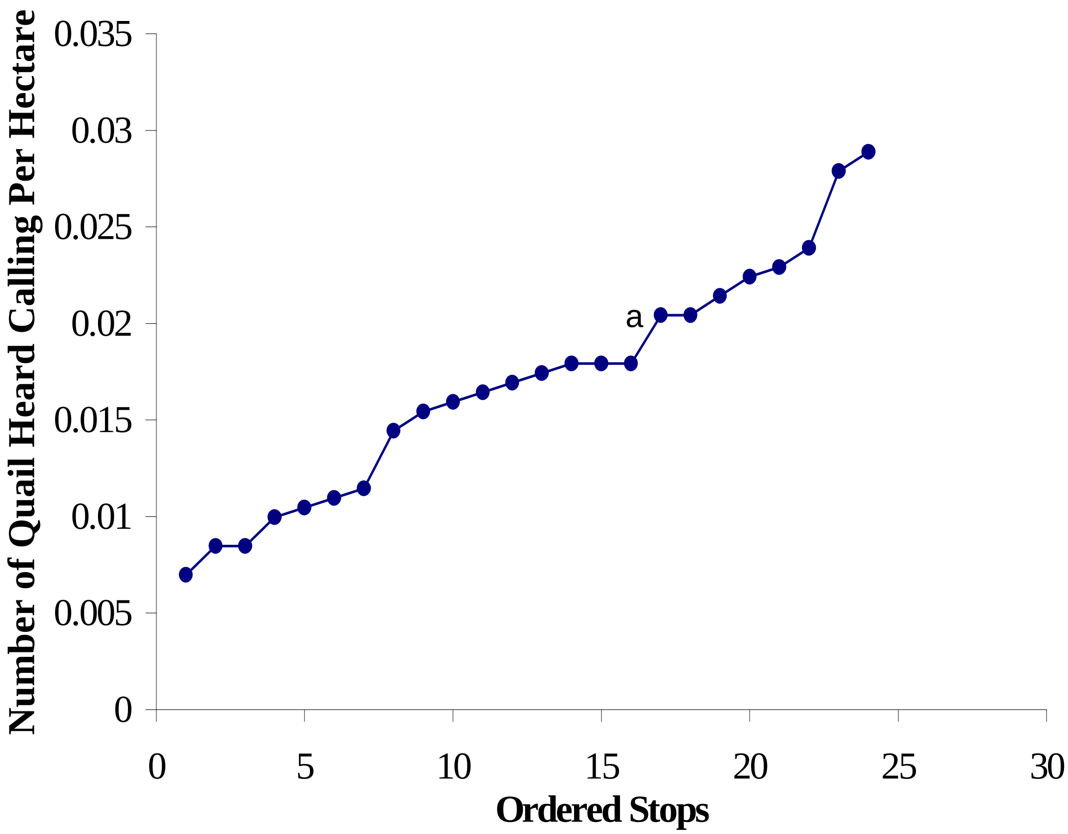


Figure 3-2. Graph showing breaks in data. The split selected occurs at 0.02 bobwhite heard per hectare (Point A).

could be dropped from the model. Other researchers have used a threshold of 0.5 for appropriate separation between variables, while others have used a threshold of 0.7 (Dubuc et al. 1990) or 0.8 (Morrison et al. 1987) for exclusion of one variable. Wilcoxon Rank Sum Tests tested for statistical differences between the high and low population levels for each metric (Zar 1984). Each metric was plotted against the bobwhite call count (Figure 3-3); scatter plots examined for breaks that may explain the differences between the high and low population levels. Next, Bayesian conditional probabilities were calculated for each level of the population (Williams et al. 1978). Bayesian conditional probabilities are defined as the probability of a given condition existing, given it is found in habitat of high quality:

$$\text{The conditional probability } P(E|S) = \frac{N(E,S)}{N(S)}$$

where N(E,S) is the number of suitable areas exhibiting property E, while N(S) is the number of suitable areas.

Bayesian conditional probabilities for suitability and unsuitability were combined with the prior probabilities using the defined formula. The result of this final formula is the probability that the area would support a high population given the landscape metrics. The model was then applied to the independent route data to determine the accuracy of the model. If the model predicted a $\geq$ 50% probability of supporting the high population and the population level of that route was in the high range, then the model was deemed correct for that route. The converse is also true with those routes having $\leq$ 50% probability and a low population level. Those routes that had mixed results, i.e., both a high probability and a low population level or a low probability and a high population level, were deemed incorrectly classified. I assessed the model using both the independent data set and the data set used to build the model. I felt that the model needed not only to classify correctly the independent data, but also should continue to classify correctly the modeled data or else it was not a good model.

Logistic Regression

I developed a logistic regression model for predicting the probability of a high population existing on a particular landscape in eastern Virginia. For this model, I maintained the same split between high and low populations as in the PATREC model. This analysis was accomplished using stepwise logistic regression procedures available in PROC LOGISTIC in SAS (SAS Institute 1990).

The independent set of routes was tested using output from the logistic model. Significant parameter estimates were entered into the logistic equation and applied to the test routes. If the predicted probability was greater than 0.5 then it was thought the route should support a high population. The model was evaluated based on its performance first using the independent data and then the modeled data. Again, if the model had a probability greater than 0.5 and a high population or if the route had a low population and the probability was less than 0.5 then the model was judged to be correct, otherwise it

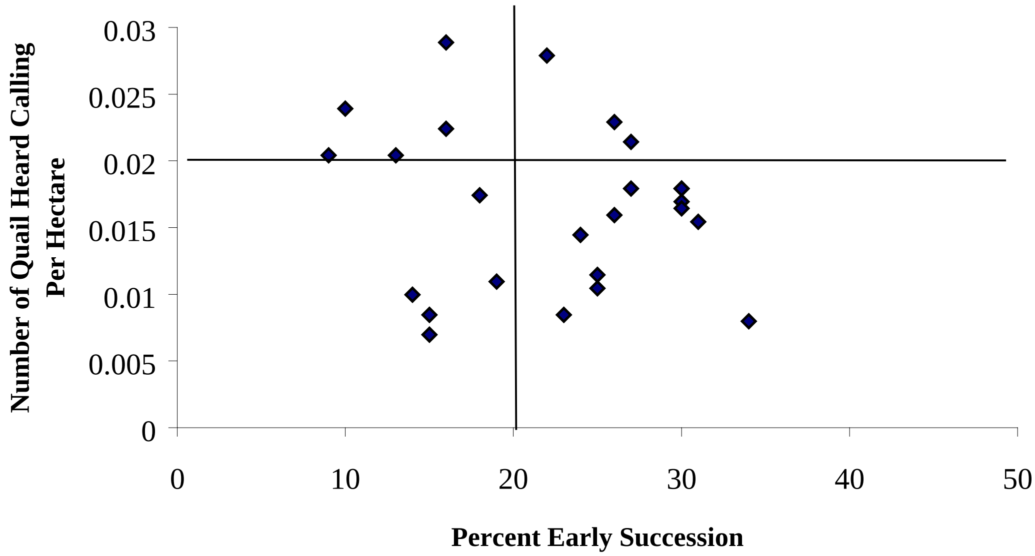


Figure 3-3. Example of the scatter plot of a landscape variable plotted against the area corrected bobwhite call count data. The horizontal line was determined from by examining the data for natural breaks. The vertical line is added to split the range of habitat values between high and low populations. The resultant quadrants represent conditional probabilities of a particular population level given the measured habitat condition.

was judged to be wrong. I assessed the accuracy of the model using the modeled data as well to ensure that the model was still performing well. Finally, Pearson product- moment correlation coefficients were calculated between the final logistic probability for a route and its bobwhite call count to analyze how the model followed the actual data. High correlation coefficients for the independent data set indicate a stronger relationship between the actual counts and the predicted probability.

Model Comparison

The final posterior probabilities from the PATREC model were compared to the logistic model output to evaluate the fit of both models. Pearson product-moment correlation coefficients were calculated between the final PATREC posterior probability and the logistic regression model using PROC CORR in SAS (SAS Institute 1990).

Model Application

The results from the PATREC and logistic regression models were then applied on a pair of Landsat TM scenes (Figure 3-4). These classified Landsat scenes were the base land cover maps from which the individual route land cover maps were extracted. To calculate the metrics across the landscape, slight modifications to the TNT Spatial Manipulation Language (SML) programs were needed so that they would run on a larger area. For this phase of the study, I defined our landscape as the area bounded by a 115 x 115 pixel rectangle, or approximately 1190 hectares. This number was roughly equivalent to the area sampled by a route. Although the shape of this sample is not the same and may cover drastically different features than linear samples, a square was needed for efficient manipulation in a raster system. The values for some of these metrics changed little, if any, from pixel to pixel, so I calculated the value for every 10^{th} row and every 10^{th} column and interpolated between the points. I staggered column starts so that I obtained the optimum sampling scheme for interpolation (Figure 3-5). Inverse distance interpolation techniques were used to complete the remaining portions of the map. Mean edge contrast index values were calculated using the same edge contrast weights (Table 3-2). Finally, the mean patch size calculations were calculated similarly to the original metric calculation. This metric also changed little from pixel to pixel, indicating that I could calculate the metric using the same sampling scheme (Figure 3-5) and interpolate between the points. Again, I used an inverse distance interpolation technique to fill in the rest of the image.

The computations proceeded as follows. The first calculation was the percent of the landscape land cover type and took 70 hours on a computer with a 400 MHz Pentium II CPU and 256 MB RAM to compute. This was only about $1/50^{th}$ of the image and the rest was interpolated (interpolation took over 5 hours for each cover type). Next, the mean edge contrast index values took 20 hours to calculate on the same machine. The mean patch size calculations took a total of 165 hours for both layers, and another 12 hours to interpolate. The patch-per-unit measure required more than 320 hours to compute. Finally, the PATREC model took 6 hours to combine the data layers and the logistic regression model required 9 hours to complete. Roseberry and Sudkamp (1998)

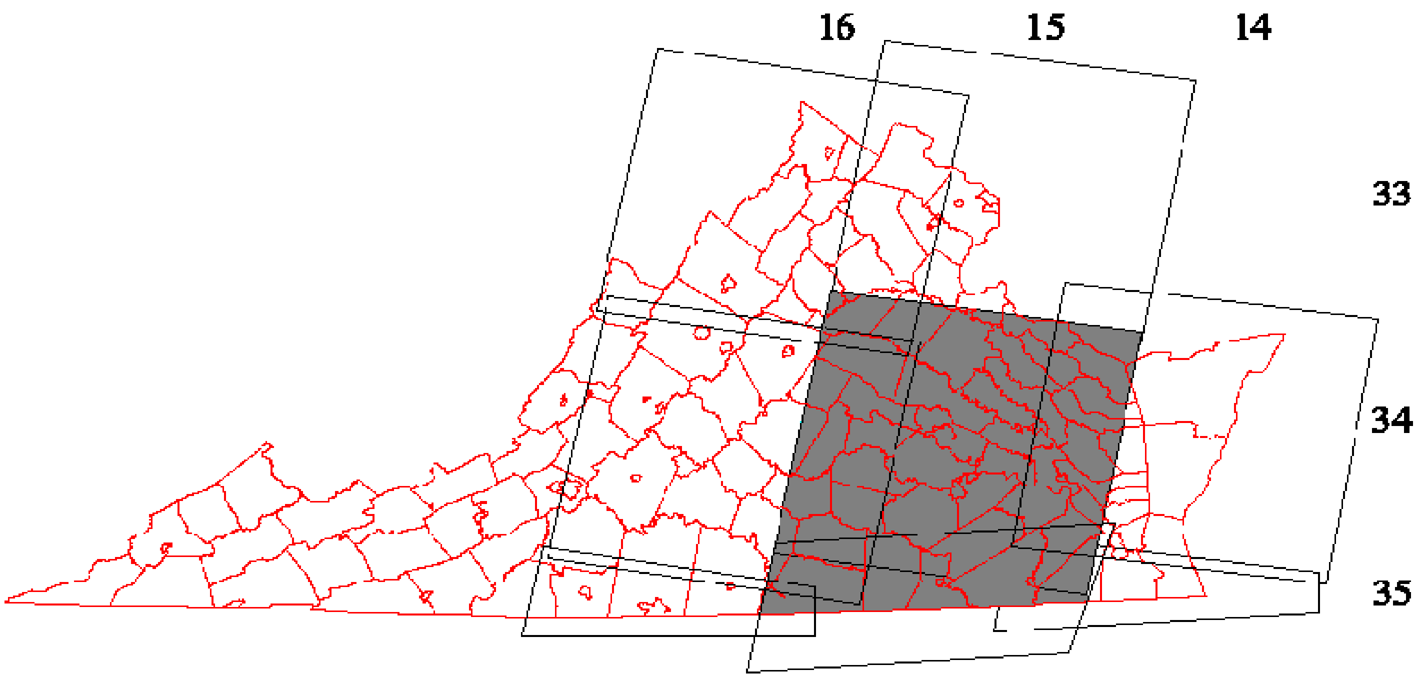


Figure 3-4. Outline of Landsat TM scene boundaries in Virginia, showing the 2 scenes (15/34 and 15/35) used for the spatial habitat modeling phase of the study.

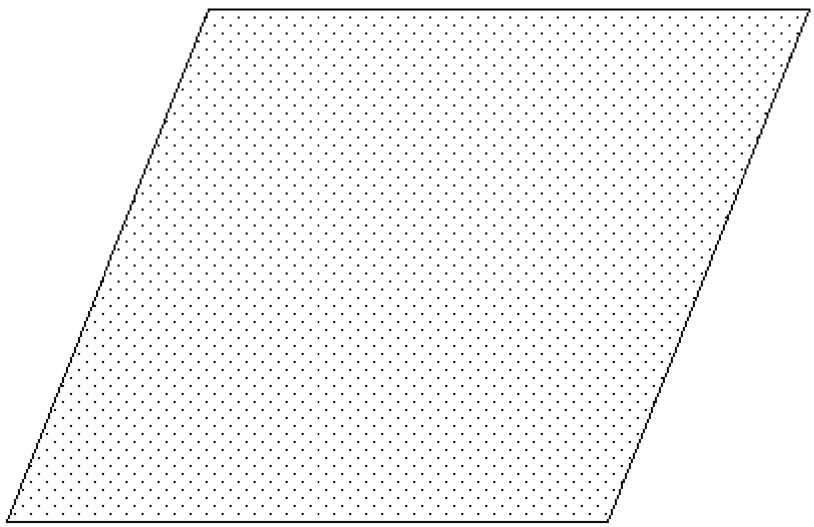


Figure 3-5. Example of optimal sampling scheme for later interpolation of data layers.

faced similar limitations; their solution to this problem was to calculate PATREC probabilities on every third row and column and apply the value to the 8 cells surrounding the focal pixel.

RESULTS

PATREC Model

Model Building

I analyzed the importance of 19 landscape metrics for estimating bobwhite population abundance levels in Virginia. I used a split of 0.02 bobwhite heard per hectare, which equates to an average of 10 birds per route. Our threshold is higher than the threshold of approximately 0.008 bobwhite heard per hectare used in Illinois (Roseberry and Sudkamp 1998). Of the 25 routes used to build the model, 8 had a count above 0.02 bobwhite heard/ha, and the remaining 14 had a count below 0.02 bobwhite heard/ha. I wanted to make a conservative estimate of areas supporting probable high bobwhite numbers. The resultant prior probabilities were 0.32 and 0.68 for high and low populations, respectively.

Eight metrics were statistically significant between the habitat quality levels at an alpha = 0.20. An alpha of 0.20 is appropriate for modeling and planning (R. H. Giles pers. comm).

Correlation coefficients were calculated for the pairs of metrics (Table 3-3), discarding one variable that repeatedly had a correlation > 0.5 with other variables. High bobwhite populations were found in areas with a greater percentage of the landscape in row crops (Wilcoxon Rank Sum test: $S = 135$, $n_1 = 17$, $n_2 = 8$, $\underline{P} = 0.0754$, Table 3-4), a lower percentage in early successional habitats (Wilcoxon rank sum test: $S = 67$, $n_1 = 17$, $n_2 = 8$, $\underline{P} = 0.0330$), a higher percentage in pasture (Wilcoxon rank sum test: $S = 132$, $n_1 = 17$, $n_2 = 8$, $\underline{P} = 0.1081$), a higher mean patch size for row crops (Wilcoxon rank sum test: $S = 129$, $n_1 = 17$, $n_2 = 8$, $\underline{P} = 0.1535$), a lower mean patch size of early successional habitats (Wilcoxon rank sum test: $S = 67$, $n_1 = 17$, $n_2 = 8$, $\underline{P}=0.0335$), and a lower patch per unit (Wilcoxon rank sum test: $S = 77$, $n_1 = 17$, $n_2 = 8$, $\underline{P} = 0.1226$) than areas with a low populations. These 6 variables were split into 2 or 3 classes that attempt to explain the differences between high and low bobwhite call counts. Conditional probabilities were calculated for each habitat variable conditional on being in either population level (Table 3-5). An example calculation of how the posterior probability is calculated expressing the probability of that a particular area belongs in the high habitat quality class is shown in Table 3-6 and an example of the final product is shown in Figure 3- 6.

Table 3-3. Pearson product-moment correlation coefficients for the final 6 variables in the PATREC model for bobwhite, Virginia, 1990-1993. Based upon these results, the mean edge contrast index for coniferous forest and the percent of the landscape in deciduous forest were both eliminated from subsequent modeling exercises.

	Percent Early Succession	Percent Pasture	Mean Patch Size Row Crops	Mean Patch Size Early Succession	Patch Per Unit
Percent Row Crops	-0.23496	-0.08736	0.90282	-0.12076	-0.30767
Percent Early Succession		-0.39370	-0.13078	0.94270	0.19486
Percent Pasture			-0.21568	-0.34653	0.16896
Mean Patch Size-Row Crops				0.05216	-0.40569
Mean Patch Size-Early Succession					0.08087

Table 3-4. Summary statistics for Wilcoxon Sign Rank tests for the six variables in the PATREC model, eastern Virginia, 1990-1993. Low population is defined as having a count below 0.02 bobwhite heard/ha (n=17) and high populations are defined as having a population above 0.02 bobwhite heard/ha (n=8).

Parameter	Mean	S	P
Percent Row Crops			
Low	11.176		
High	16.875	135	0.0754
Percent Early Succession			
Low	15.176		
High	8.375	67	0.0330
Percent Pasture/Grass/Hay			
Low	11.353		
High	16.500	132	0.1081
Mean Patch Size-Row Crops			
Low	11.529		
High	16.125	129	0.1535
Mean Patch Size-Early Succession			
Low	15.176		
High	8.375	67	0.0335
Patch Per Unit			
Low	14.588		
High	9.625	77	0.1226

Table 3- 5. Conditional probabilities for bobwhite PATREC model in eastern Virginia, 1990-1993.

Geographic Area: Eastern piedmont and coastal plain regions of Virginia.
Species and Season of Applicability: Summer bobwhite habitat
Prior Probabilities: High Population = 0.32
Low Population = 0.68

	Habitat Quality Classes	
Feature	**High Population Conditional Probabilities**	**Low Population Conditional Probabilities**
1. Percent of the landscape in row crops		
a. < 20.0%	0.25	0.82
b. ≥ 20.0%	0.75	0.18
2. Percent of the landscape in early succession		
a. < 20.0%	0.63	0.29
b. ≥ 20.0%	0.37	0.71
3. Percent of the landscape in pasture/grass/hay		
a. ≤ 12.0%	0.25	0.72
b. > 12.0%	0.75	0.28
4. Mean patch size of row crops		
a. < 2.0 ha	0.25	0.59
b. 2.0 – 6.0 ha	0.50	0.23
c. > 6.0 ha	0.25	0.18
5. Mean patch size of early succession		
a. < 2.0 ha	0.75	0.29
b. ≥ 2.0 ha	0.25	0.71
6. Patch per unit		
a. < 1.4	0.87	0.47
b. ≥ 1.4	0.13	0.53

Table 3- 6. Sample PATREC model calculations using one bobwhite call count route, showing the steps taken to calculate the posterior probabilities of that route supporting a high bobwhite population based on the habitat characteristics of the sampled route.

Variable	CP(high)	CP(low)
Percent in row crops = 42	0.75	0.18
Percent in Early Succession = 9	0.63	0.29
Percent in Pasture = 20	0.75	0.28
Mean patch size row crops = 7.46	0.25	0.18
Mean patch size early succession = 0.75	0.75	0.29
Patch Per Unit = 1.08	0.87	0.47

Posterior probabilities are calculated to express the probability of a particular route supporting a high bobwhite population given the existing habitat features. Based on Bayes' theorem, the formula used is:

$$P(S|E) = \frac{P(S)P(E|S)}{P(S)P(E|S) + P(U)P(E|U)}$$

where

- P(S) equals the prior probability of suitable habitat,
- P(U) equals the prior probability of unsuitable habitat,
- P(E|S) equals the likelihood of sample result E given suitable habitat,
- P(E|U) equals the likelihood of sample result E given unsuitable habitat, and
- P(S|E) equals the revised or posterior probability of suitable habitat given sample result E.

So: for this route:

$P(S) = 0.32$;
$P(U) = 0.68$;
$P(E|S) = ((0.75)(0.63)(0.75)(0.25)(0.75)(0.87)) = 0.0578075$
$P(E|U) = ((0.18)(0.29)(0.28)(0.18)(0.29)(0.47)) = 0.0003378$

$$P(S|E) = \frac{(0.32)(0.0578075)}{(0.32)(0.0578075) + (0.68)(0.0003378)} = 0.9877$$

or ≈ 99% chance of supporting a high bobwhite population

Model Verification

The conditional probabilities for the 6 metrics then were applied to the remaining independent data to calculate final posterior probabilities for each route. Of these remaining 14 routes, 9 routes were correctly classified (Table 3-7). When the model was applied to the modeled data, it also performed well, yielding an accuracy of 84.0%. For this set of independent data, the correlation coefficient between the call count data and the final PATREC posterior probability was 0.1382. When all 39 routes are examined (Figure 3-6), this same correlation coefficient improved to 0.3479, indicating a slightly better fit.

Logistic Regression Model

Model Building

I analyzed the importance of a number of landscape metrics to estimate the probability of a site supporting a high bobwhite population. Nineteen variables (Table 3-1) were entered into the stepwise logistic equation model. Three (percent of the landscape in row crops, percent of the landscape in coniferous forest, and mean edge contrast index for coniferous forest) were significant factors in describing the differences between bobwhite population abundance levels (Table 3-8). This model had a concordance of 94.9% and accurately predicted bobwhite populations on 24 of the 25 routes (96%) used to build the model, representing a good fit to the modeled data. The correlation coefficient between the actual count on the route and the logistic regression probability for the 14 independent routes was 0.0387. When all 39 routes are examined, this correlation improves to 0.3458. Figure 3-7 shows an example of an area classified using this model and Figure 3-8 shows the entire study area classified using this model.

Model Verification

The resultant logistic equation was applied to the 14 verification routes to determine how well the model performed. Of the 14 routes, the logistic model accurately predicted 8 routes (57.1%) as having the correct bobwhite population level (Table 3-9). The model appears to predict on the conservative side, with many of the apparent errors being caused by a high population estimate and the model classifying the route as having a low population. For the independent data set, the correlation coefficient between the call count data and the final posterior probability was 0.0387. When all 39 routes were examined, this same correlation coefficient improved to 0.3458.

Model Comparison

Pearson product-moment correlation coefficients were calculated between the output of the logistic model and the posterior probabilities from the PATREC model.

Table 3-7. PATREC model classification table for bobwhite population abundance for the modeled bobwhite call count routes and the independent set of routes, eastern Virginia, 1990-1993.

	Predicted Population Abundance					
	Modeled Data (n=25)			Independent Data (n=14)		
Observed Population Abundance	High	Low	Percent Correct	High	Low	Percent Correct
High	5	3	62.5%	2	4	33.3%
Low	1	16	94.1%	1	7	87.5%
Percent Correct	83.3%	84.2%	84.0%	66.6%	63.6%	64.3%

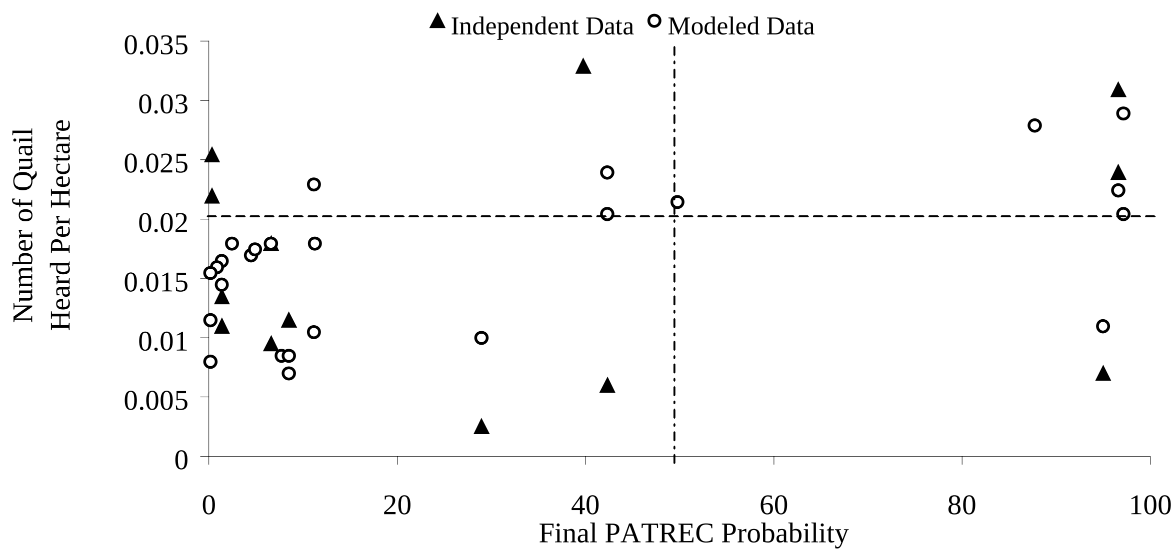


Figure 3-6. Scatterplot of the final PATREC probability for each route and the number of bobwhite heard per hectare for that route. The dashed horizontal line represents the split between high and low populations, while the vertical dashed line represents the split between final classification of high or low quality.

Table 3-8. Logistic regression parameter estimation for 3-variable model predicting high/low bobwhite populations in eastern Virginia, 1990-1993.

Variable	Parameter Estimates	SE	χ^2	P
Intercept	33.0762	17.6789	3.5004	0.0614
Percent in Row Crops	0.2066	0.1367	2.2843	0.1307
Percent in Coniferous Forest	-0.5357	0.2993	3.2033	0.0735
Mean Edge Contrast Index -Coniferous Forest	-2.8633	1.4725	3.7808	0.0518

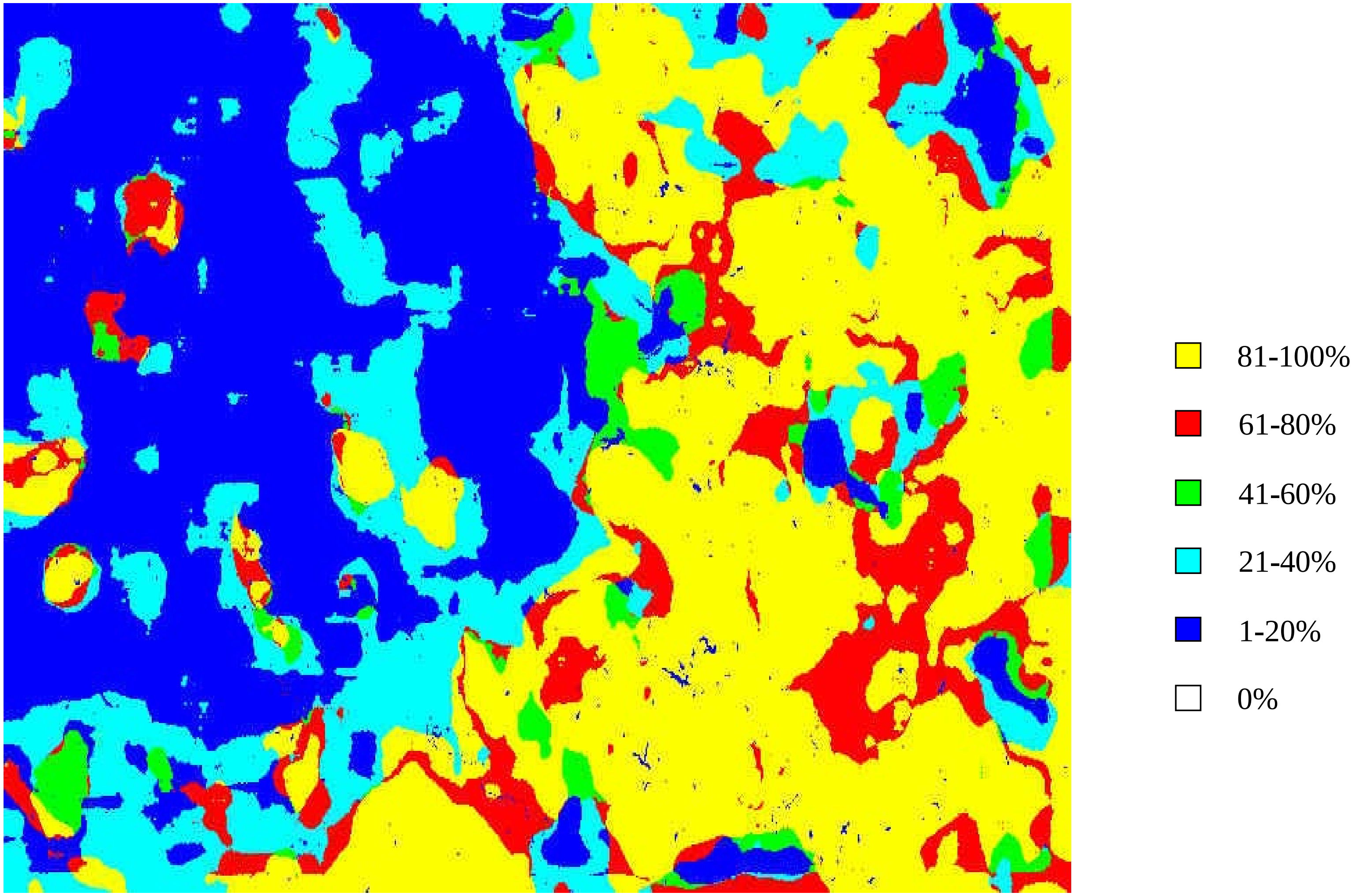


Figure 3-7. Example of the final PATREC probabilities for an area southeast of Richmond, Virginia. Areas in yellow have the highest probability of supporting a high bobwhite population.

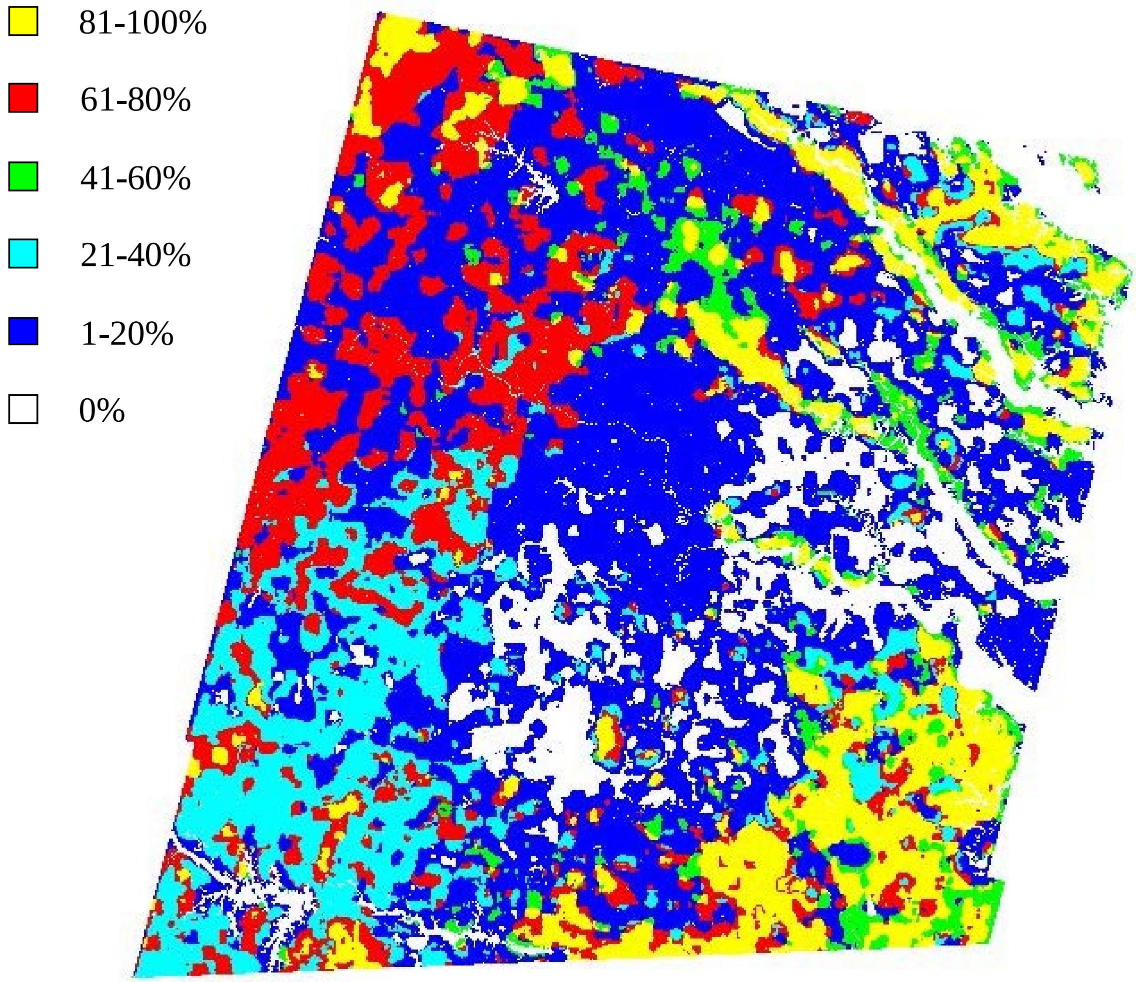


Figure 3-8. The modeled results for the 2 full scenes showing final PATREC probabilities. Areas in yellow have the highest probability of supporting a high bobwhite population.

Table 3-9. Logistic regression classification table for bobwhite population abundance for the modeled bobwhite call count routes and the independent set of routes, eastern Virginia, 1990-1993.

	Predicted Population Abundance					
	Modeled Data (n=25)			Independent Data (n=14)		
Observed Population Abundance	High	Low	Percent Correct	High	Low	Percent Correct
High	7	1	87.5%	3	3	50.0%
Low	0	17	100.0%	3	5	62.5%
Percent Correct	100.0%	94.4%	96.0%	50.0%	62.5%	57.1%

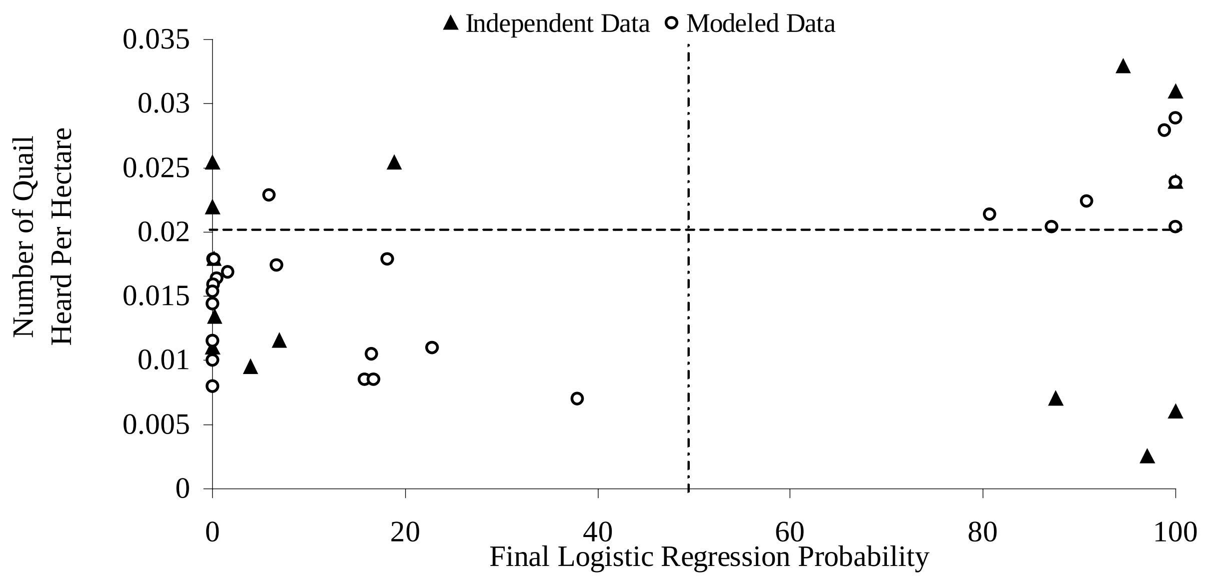


Figure 3-9. Scatterplot of the final PATREC probability for each route and the number of bobwhite heard per hectare for that route. The dashed horizontal line represents the split between high and low populations, while the vertical dashed line represents the split between final classification of high or low quality.

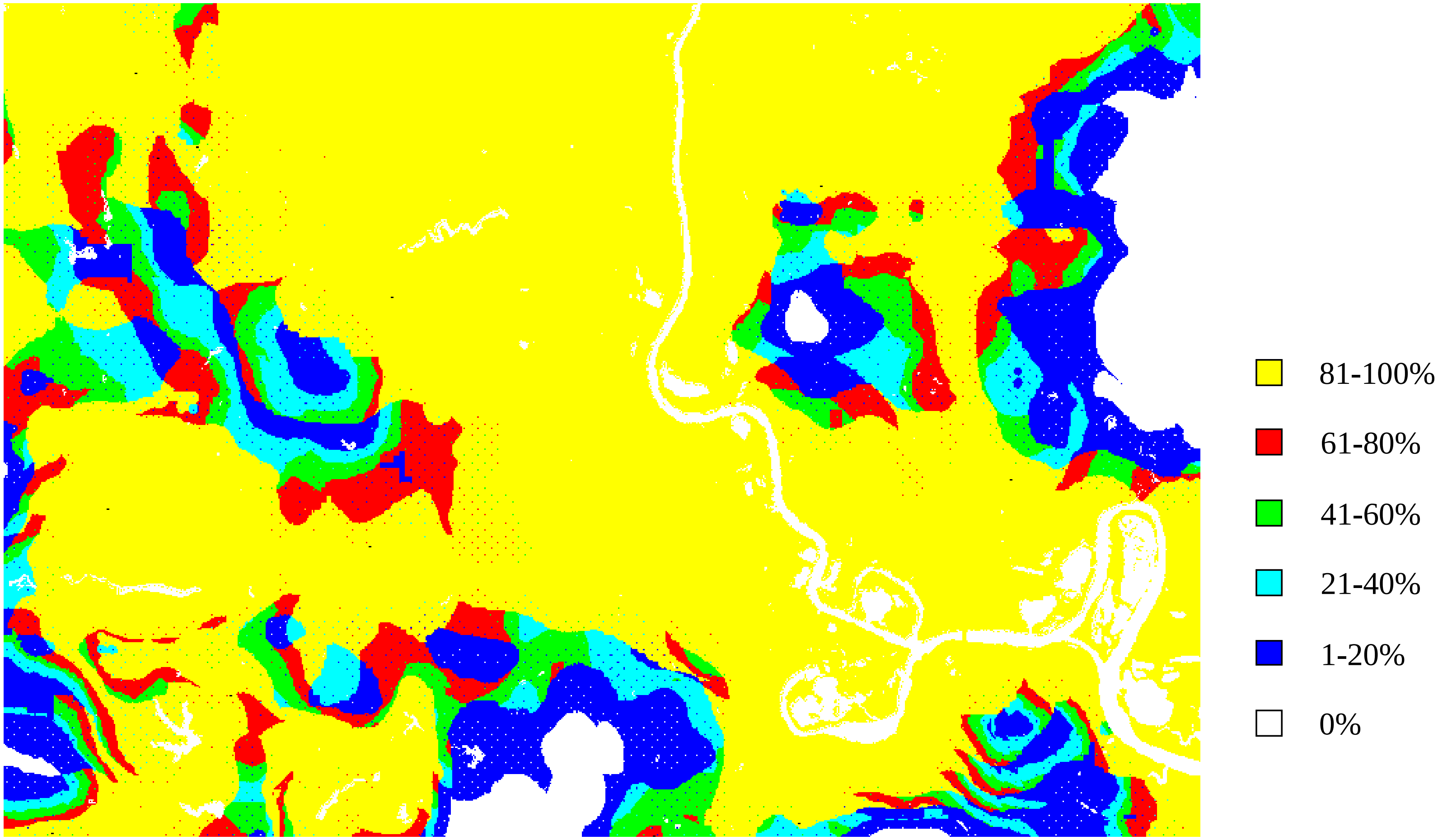


Figure 3-10. Example of the final logistic regression probabilities for an area east of Richmond, Virginia.

The results of the 2 models were highly correlated (Pearson correlation coefficient: r = 0.815164, n = 39, $\underline{P}$ = 0.0001). Pairs of PATREC posterior probabilities and logistic regression probabilities were similar (Wilcoxon Signed Rank Test: S = 51, n = 39, $\underline{P}$ = 0.4838), indicating similar results between modeling exercises.

Model Application

The models were applied to the Landsat TM scenes making up the majority of the coastal plain and piedmont areas of Virginia. The PATREC model predicted the highest amounts of 2-scene area in the 1-20% category (Table 3-10). The logistic regression model predicted a large amount of the landscape as areas having a high probability of supporting high bobwhite populations (Figure 3-9). This model predicts highest percentages in the 0% and 81-100% categories (Table 3-10).

DISCUSSION

FRAGSTATS*ARC generated a number of landscape metrics, some of which appeared to be significant contributors to the patterns in bobwhite densities. I selected only those I felt that were biologically explainable and were programmable in TNT MIPS. The result was 6 metrics that I thought would cover a majority of the landscape features potentially influencing bobwhite densities. O'Neill et al. (1988) found that a small set of landscape indices captured the important aspects of the landscape pattern. They outlined 4 desirable characteristics of a metric: (1) the measured values need to be distributed across the range of possible values, (2) the metric performs well in discriminating the geographic distribution of the landscape pattern, (3) they are independent, and (4) they discriminate between landscape types (O'Neill et al. 1988). The metrics I selected met these characteristics and have been used elsewhere in similar studies.

Modeling

PATREC Model

Some feel PATREC models are more useful when only landscape level, coarse-scale habitat data are available, such as from remotely-sensed images (Roseberry and Sudkamp 1998). The final PATREC model developed appears to fit the data reasonably well and is consistent with other similar studies.
Each of the selected metrics provides different requisites for bobwhite. Row crops provide a food source for periods of the year. Early successional habitats provide protective cover and food resources. The pasture/grass/hay class provides some food resources as well as much needed cover components. Small patches of both row crops and early succession mean more edge and less interior of each. There is some concern that large expanses of row crops are not beneficial to bobwhite, with more interspersion apparently being better for bobwhite. Guthery (1997) believed that food and

Table 3-10. Percentages of the 2-scene area classified by each of the two models.

	Model	
Category	PATREC	Logistic Regression
0%	14.65	32.37
1-20%	41.96	15.45
21-40%	11.91	4.62
41-60%	5.04	3.91
61-80%	15.48	4.58
81-100%	10.97	39.07

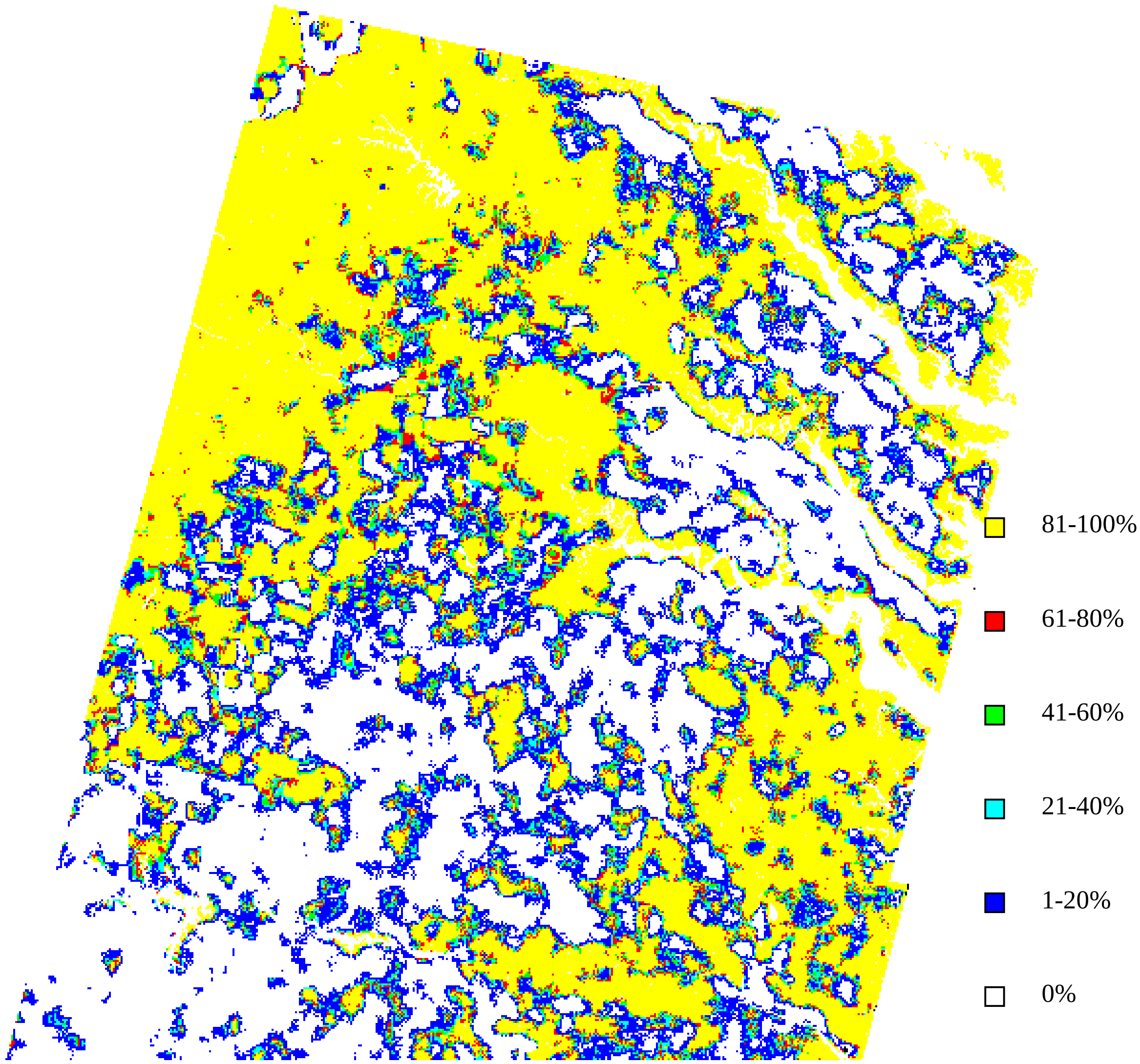


Figure 3-11. The modeled results for the 2 full scenes showing final logistic regression probabilities.

interspersion beyond a minimum threshold have, at best, a neutral effect on bobwhite. If this is the case, then our models are well suited since they incorporate variables that measure habitat availability through time. The habitat map includes the dynamic row crop, pasture/hay/grass, and early successional classes. If these classes are present, they will be available to bobwhite, and if they are absent, the models will reflect the deficit by having a rating of low quality.

By exploring the ranges of each of the variables (Appendix A), I determined that landscapes in Virginia with 40-60% of the landscape in open land types appear to be of high quality to bobwhite. In Missouri, Dailey (1989) found landscapes with 75-90% in open cover types to be optimal for bobwhite, and in Illinois, similar percentages to the Missouri study were found (Roseberry and Sudkamp 1998). On the classified images (Chapter 2), there are 3 classes in the open cover type: row crops, early succession, and pasture/hay/grass (which did not appear in the final model).

The model predicted high bobwhite populations on landscapes with a smaller portion in row crops than landscapes with low populations. The optimum percent in row crops was > 20% of the landscape on Virginia's bobwhite routes. Roseberry and Sudkamp (1998) found an optimum of 30-70% of the landscape in row crops in Illinois. Michener et al. (1998) found the optimum proportion of row crops to be 30-35% in Georgia. In Missouri, Dailey (1989) found that the highest bobwhite populations were found in areas with 50-60% of the landscape in cropland.

The second significant land-cover class of the open land type was the percent of the landscape in the early succession class. The model predicts high populations of bobwhite in landscapes that contained a low percent in early succession habitats. This seems counterintuitive for an early succession/agricultural matrix species, such as bobwhite. Dailey (1989) found the optimal proportion of old fields was 10-20%. This class is similar to our early succession class and our proportion in early succession (10-25%) was similar to their findings in Missouri.

The third important land cover class in this open land category, as described by Roseberry and Sudkamp (1998), is the pasture/grass/hay class. The model predicts high bobwhite numbers on landscapes with > 12% of the landscape in pasture/hay/grass. Roseberry and Sudkamp (1998) reported an optimum of 12-30% for grasslands within their landscapes. In Missouri, the optimal landscape contained 20-30% grassland (Dailey 1989). These results also agreed with our results in Virginia.

The mean patch size of row crops was also a significant variable in our model. It has been hypothesized that increasing field or patch sizes has a negative effect on bobwhite populations due to the loss of edges and larger core field area (Roseberry and Klimstra 1984, Brennan 1991). The model predicts high populations of bobwhite in landscapes with a large mean patch size of row crops. The optimum mean patch size in Virginia was < 2 hectares. This optimum was similar to the 2 to 3 hectares described by Michener (1998) in Georgia.

Landscapes with a low mean patch size of early successional appeared to have a high bobwhite populations. This apparent need for small patches of early successional habitats interspersed across the landscape supports the natural history for bobwhite. They have often been described as a game bird associated with edges and transition areas. Small early successional patches at this scale may be comparable to edges and transition areas, which provide escape cover for bobwhite. Instead, well-interspersed small patches are most suited for bobwhite. Roseberry and Sudkamp (1998) found the length of forest edges to be a significant factor in Illinois, with an optimum > 30 meters per hectare. However, I was unable to delineate edges and transition areas because of the difficulty of identifying such features on satellite images and because these typically change naturally to other types within a few years. The best approximation to these dynamic areas may be these small discrete patches of early successional habitats identified on the land cover map (Figure 2-11).

The final significant variable in the PATREC model was the patch per unit measure for the landscape. Our high bobwhite populations were associated with landscapes with a low patch per unit, meaning the landscapes are "less fragmented". Our split between population levels was at 1.4 patches per hectare, which is a small number. This value indicates that there are 1.4 patches of any land cover class per hectare, making each patch roughly 8 pixels or an average patch size of 0.71 hectares. The landscape in Virginia appears highly fragmented and bobwhite might be avoiding the extremely small patches that may be acting as ecological sinks. There may be a fragmentation threshold for bobwhite; Guthery (1997) felt that a threshold exists and beyond the minimum threshold further interspersion and fragmentation has minimal to no effect on population density. Keyser et al. (1998) found that more fragmentation causes an increase in predation and other forest edge effects in nesting neotropical migrants. Roseberry and Sudkamp (1998) had conflicting results to ours, finding high populations in areas that were patchy. One potential explanation for the discrepancy could be the way the data were collected. The buffers around the routes in Illinois were wider than the polygons I used in Virginia, potentially including more area and reducing the number of spurious partial patches included in the patch per unit estimates. Roseberry and Sudkamp (1998) also used a more detailed land cover map with more land cover classes than we used (12 vs. 7 in Virginia), causing more patches to exist on the landscape and inflating the contagion value. The contagion may be high in Illinois, but the diverse landscape in Virginia may have an even higher contagion value than in Illinois, causing an apparent selection by bobwhite of these diverse, patchy areas. The landscape of the Illinois study appears to be made up of larger patches, so those areas with a high contagion or small farm size better represent the landscape found in eastern Virginia than most of the Illinois landscape. The average farm size in Illinois is 140.9 hectares, and 114.6 hectares in Missouri, whereas in Virginia average farm size is only 78.2 hectares (United States Department of Commerce 1978-1992). Therefore Virginia's farms are smaller than those in other study areas, so smaller patches will be seen in Virginia than in Illinois or Missouri. The characteristics of the landscape and patterns of land use are different enough that the patch per unit measure of fragmentation may be different between the two studies, leading to different conclusions despite similar selection by bobwhite.

Logistic Regression Model

The logistic regression model contained three significant variables. Of these three, two were significant in the PATREC model. The percentage of the landscape in row crops was positively associated with a high bobwhite population index. The importance of crops and early succession habitats has been well documented (Roseberry and Klimstra 1984, Michener et al. 1998, Roseberry and Sudkamp 1998).

The percentage of the landscape in coniferous forest was also significant, being negatively related to bobwhite populations. This variable in our model appears to express this declining value of coniferous forests as they reach a more complete canopy closure than younger stands. Unless older coniferous stands are managed for an open understory that receives sunlight, they tend to be of poor quality to bobwhite (Felix et al. 1986, Brennan 1991).

The mean edge contrast index for coniferous forest was significant in this model as well as in the PATREC model. Unlike the PATREC model, this model retained the mean edge contrast index despite the slight correlation with the percentage in coniferous forest. I used the same reasoning to keep variables in this model as I did with the PATREC model; highly correlated variables were retained if they were different measures on the same land cover class. This index uses the *a priori* assigned edge contrasts between two adjacent habitat types as an indicator of the quality of the edge. I felt the main edge contrast index would express some of the edge effect to which bobwhite appear to be attracted on the landscape, while giving a qualitative value to the length of each edge as it may look to bobwhite.

Model Comparison

The comparison of the models showed similar results between the PATREC and logistic regression modeling efforts. The two models represent the available data reasonably well, and the outputs are similar. They were both structured to predict the probability of supporting a high bobwhite population, using the same population levels of 0.02 bobwhite heard calling per hectare. The accuracy of the two models was similar for the independent, modeled, and the combined data sets (Tables 3-6 and 3-8). They classified approximately the same number of routes as having a high probability of high bobwhite numbers. The correlation coefficients between model outputs showed comparable results between models.

The PATREC model was more difficult and time consuming to generate, but produced slightly better results than the logistic regression model. Conversely, the logistic model was easier to create, will be easier to explain to non-modelers, required little modeling or statistics background to apply, and included fewer variables than the PATREC model. One limitation to the logistic regression modeling procedure was the slightly poorer fit to the independent data used to validate the models. However, the logistic regression model did have a slightly higher overall accuracy among all 39 routes than did the PATREC model.

It seems important to consider the limitations of modeling based upon habitat conditions. The models being discussed both rely exclusively on the existing conditions for an area, and do not include the other biotic or abiotic factors potentially influencing bobwhite populations. A few of the routes may be experiencing these other influences, causing our models to err when predicting populations. Of the 14 independent verification routes, 6 were incorrectly classified by at least one model. Both models incorrectly classified 4 of these 6 routes. Additionally there was one route in the modeled data that was incorrectly classified by both models. The similar results between modeling exercises may indicate that either the models have missed some important habitat component on the landscape or there are some other, non-habitat limitations acting on the populations on these routes.

The PATREC model is conservative. When it incorrectly classified a route, 75% of the time it predicted a low population when the route had a high population (Table 3-7). In modeling, conservatism such as this is often preferred in order to protect decisions made from the model. In Virginia, with a declining bobwhite population, a conservative model is reliable for managers with a population below historic levels. Conversely, when the logistic model incorrectly classified a route, 43% of the errors classified the route with a high population when it was low (Table 3-9). The other 57% of the incorrectly classified routes in the logistic regression model were instances where the model classified the route as having a low population when it was high (Table 3-9).

The small number of routes reserved for model verification (n=14) was notable in the accuracy of the model. I reserved 14 routes for an independent validation of our models. Each verification route, therefore, represents approximately 7% of the overall model accuracy. A change of only one route represents a large shift in the model's accuracy. During the model revision phase, there were instances where moving a threshold slightly could change the resultant model fit.

Model Application

The logistic regression and PATREC model show areas that have the potential to support high bobwhite populations based on existing habitat conditions. The logistic regression model generally predicted two classes (0% and 21-100%). On the full scene (Figure 3-10) it is noticeable that there is a wide strip of low probabilities going across the image, bisecting two areas of high quality. This is an artifact of the classification and the omission of the early succession class in this model. This strip has a large component of early succession in it, reducing the availability of row crops in the area. This omission may be causing the slightly poorer fit for the model than the PATREC model, and suggests that this model may not be expressing the habitat requirements of bobwhite in southeastern Virginia as well as it could.

The products of the models can be used for several of the aspects of the Virginia Bobwhite Quail Management Plan. The models can identify whether the conditions on the various treatment sites are comparable, or if one of the areas is drastically different. If different, then conclusions based upon perceived similarities may need to be re-evaluated. It can also identify areas that should support high populations, those that may be useful for determining the controlling factors acting on the population. Areas with high probabilities of supporting high bobwhite populations are potential relocation and/or release sites for other parts the Virginia Bobwhite Quail Management Plan. Finally, a map showing habitat quality can be used to focus future work on any portion of the bobwhite management plan or any other bobwhite work in the state and neighboring states.

Conclusions

Bobwhite on the coastal plain and piedmont of eastern Virginia were predicted to occur in high numbers in areas with certain landscape characteristics. Depending on the model used, these will vary slightly, however the importance of dynamic habitats, especially row crops, is well documented. I feel I have two reliable models that will predict high and low quality for bobwhite populations. The PATREC model is more time consuming, and difficult to create, however it accurately predicted the population abundance class on more of the independent routes than the logistic model. The logistic model is easier to explain and contained fewer variables than the PATREC model. With the independent data, the logistic regression model had a slightly lower accuracy rate than the PATREC model. However, decreased accuracy may not be enough to preclude the use of this model. The predictive capability of these models will allow wildlife managers to concentrate their work in areas likely to support high bobwhite populations. To improve conditions for bobwhite in Virginia, managers may want to explore the possibilities of improving the deficient metrics on any particular landscape. The score for a landscape can be improved by exploring the metrics going into the model (i.e., percent crop, percent conifer, and mean edge contrast index for the logistic model) that maybe limiting the bobwhite potential for that landscape. Conversely, if the negative influences are removed, an increase in habitat quality may be predicted. By enacting a management plan to manipulate the landscape, altering the metric, managers may be able to see increases in bobwhite numbers on that landscape.

CHAPTER 4- Raw Landsat TM Imagery Modeling

INTRODUCTION

The first requirement in managing habitats for sustainable populations of a wildlife species is a detailed understanding of the habitats used by that species. Evaluating populations in relation to mapped land cover is often performed (Cox 1994). Typically, wildlife researchers use a classified image for modeling purposes. These classified images usually identify a number of land cover types or habitats. Rarely do researchers use raw remotely-sensed imagery to predict population abundance. Creating a detailed land-cover/land-use map from remotely-sensed data adds steps to the modeling procedure. Remote land cover mapping is time intensive, and very costly and, by eliminating this step inherent errors in classification are removed and error propagation into future layers is reduced (Hepinstall and Sader 1997).

This phase of the study was designed to test whether I could eliminate habitat mapping and use raw, remotely-sensed imagery to produce maps of bobwhite presence and abundance. A number of spatial texture measures and combinations of imagery bands were added to the raw imagery prior to model development. Stepwise logistic regression techniques were employed to develop predictive models of bobwhite presence/absence and high/low abundance.

Objectives

The objective for this phase of the study was to explore the possibilities of creating a probability distribution map of bobwhite presence and abundance based on raw Landsat TM imagery.

LITERATURE REVIEW

Landsat TM Sensors

Lillesand and Kiefer (1994) provide the following description of the portions of the spectrum measured by the Thematic Mapper TM sensors on the Landsat satellites. Band 1 measures blue reflectance (Table 2-1) and is useful in water body delineation and delineating the difference between soil and vegetation. Band 2 measures green reflectance, being suitable for some vegetation discrimination. Band 3 measures blue reflectance, often useful in plant species differentiation. Band 4 measures the near-infrared portion of the visible light spectrum and is useful in vegetation delineation and soil moisture indices. Band 5 measures mid-infrared reflectance and is useful in vegetation delineation and soil moisture content analyses. Band 6 is a thermal infrared band useful in thermal mapping. Band 7 measures the mid-infrared spectrum, and is useful for mineral and rock delineation and measuring vegetation moisture. In addition to using the individual bands, bands can be combined to measure additional information. The Normalized Difference Vegetation Index (NDVI) is a normalized ratio of bands 4 and 3 (Rouse et al. 1974, Tucker 1979). This index has been used extensively to monitor the amount of vegetation of the Earth's surface (Jensen 1996). Another index that has been widely used in agricultural research is the tasseled cap transformation (Kauth and Thomas 1976, Crist and Cicone 1984, Crist and Kauth 1986). The tasseled cap transformations calculate four new indices from the original six bands of imagery. The first transformation accounts for most of variation in the bare soil spectrum, while the second index is an orthogonal deviation from the soil brightness index and is a good indication of vegetation greenness (Kauth and Thomas 1976). These two indices account for most of the scene information (95-98%), while the remaining portions included in the yellow stuff and non-such indices (Kauth and Thomas 1976, Jensen 1996).

Call Counts

Road-based point counts are commonly used to monitor populations of many bird species. One major road-based point count system is the Breeding Bird Survey (BBS), a survey performed yearly on a set of permanent routes (Droege and Sauer 1990). Cox (1994) used BBS data in Florida to examine the relationships between mapped land cover and bird abundance. Roseberry and Sudkamp (1998) also used Breeding Bird Survey data to analyze landscape quality for bobwhite. Some studies have used other, species-specific call counts for their analyses (McGowan and Otis 1998, Chapter 3).

Cox (1994) described typical gross scale bird habitat research when they investigated the relationships between land cover and Breeding Bird Survey data. However, few researchers have explored the possibilities of examining bird or mammal populations as a function of the raw, remotely-sensed imagery. Aspinall and Veitch (1993) explored the possibilities of mapping bird habitats from raw Landsat TM imagery and Digital Elevation Models (DEM). Using Bayesian modeling procedures, they were able to create a probability map of curlew (*Numenius arquata)* occurrence using classes of raw digital reflectance values. They used wildlife survey data to guide the classification, effectively eliminating the need for classifying the image into habitat types. Hepinstall and Sader (1997) also explored the possibilities of using raw Landsat TM imagery and BBS data to predict the probability of species occurrence in Maine. They performed their analysis on a number of breeding birds rather than one species. They included a spatial texture measure to determine whether some species are associated with heterogeneous landscapes. Instead of classifying the output into classes of probabilities, Hepinstall and Sader (1997) were able to classify the imagery to actual probabilities of that species occurring.

METHODS

Data Acquisition

Call Counts

Bobwhite call count data for a set of permanent routes in Virginia were available in digital format for 1990-93 (Chapter 3). The individual routes were split into stops using a custom Advanced Revelation (Ver 3.12, Revelation Technologies, One Tech Drive, Andover Tech Center, Andover, MA 01810) program made available by A. B. Jones III of the Virginia Department of Game and Inland Fisheries. This program used route starting points and a specified distance to break the routes into stops that approximated stop location. The stop-level data were entered into a database, and an average was computed for the 4 years. I felt a span of years would remove spurious effects of variation in bobwhite detection during a particular year, should they exist. The span of years also provided a good indication of the abundance of bobwhite along the route prior to the date of the imagery. The mean number of bobwhite heard for each stop was the suggested index to the bobwhite population (M. Fies pers. comm.). Each of the individually identified stops was labeled with the average number of bobwhite heard. Only those stops falling in the Landsat TM scene row 15 path 34 were retained for this section.

Landsat Thematic Mapper

An April 11, 1992 6 band Landsat TM image (row 15 path 34) centered on Richmond, VA was used for this analysis (Figure 4-1). Spectral variation between dates precluded working with more than 1 scene at a time, hence this analysis is only representative of this particular scene. Six bands of raw information (bands 1-5,7) were used in addition to 2 other data themes that were made available from combinations of these original 6 bands. A Normalized Difference Vegetation Index (NDVI) was calculated from the normalized ratio of band 3 to band 4 (Rouse et al. 1974, Tucker 1979). I also calculated the first transformation of the tasseled cap transformation, or the soil brightness index. This transformation applied a set of coefficients to each of the raw Landsat TM bands producing an index to bare soil brightness.

Measurements of the spatial texture of a data theme or themes are often used to define the context surrounding a pixel. A single pixel does not exist on the landscape; rather, the adjacent pixels influence the attributes of that pixel. To account for the location of bobwhite not directly on the stop location I calculated the mean and standard deviation of each of the data themes in a 13-pixel circle or approximately 400-meter radius circle. Four hundred meters is generally the standard distance that most birds can be heard from road based-call counts (Peterjohn et al. 1996), and in Virginia, bobwhite within this distance are thought to be counted (M. Fies. pers. comm.). The degree of vegetation heterogeneity at the landscape level is well approximated by examining the standard deviation for the NDVI (Hepinstall and Sader 1997). I used the mean and standard deviation for each of the 8 bands because each provided potential information about the habitat around the stop. Sixteen output grids were created, a mean and standard deviation for the brightness values in the 6 raw bands and 2 indices.

Stop-level information was extracted from each of the 16 data layers. The values for the 13-pixel circular landscape and the average bobwhite call count for that stop were combined in a Microsoft Excel database and imported into SAS (SAS Institute 1990), a statistical software package, for model development.

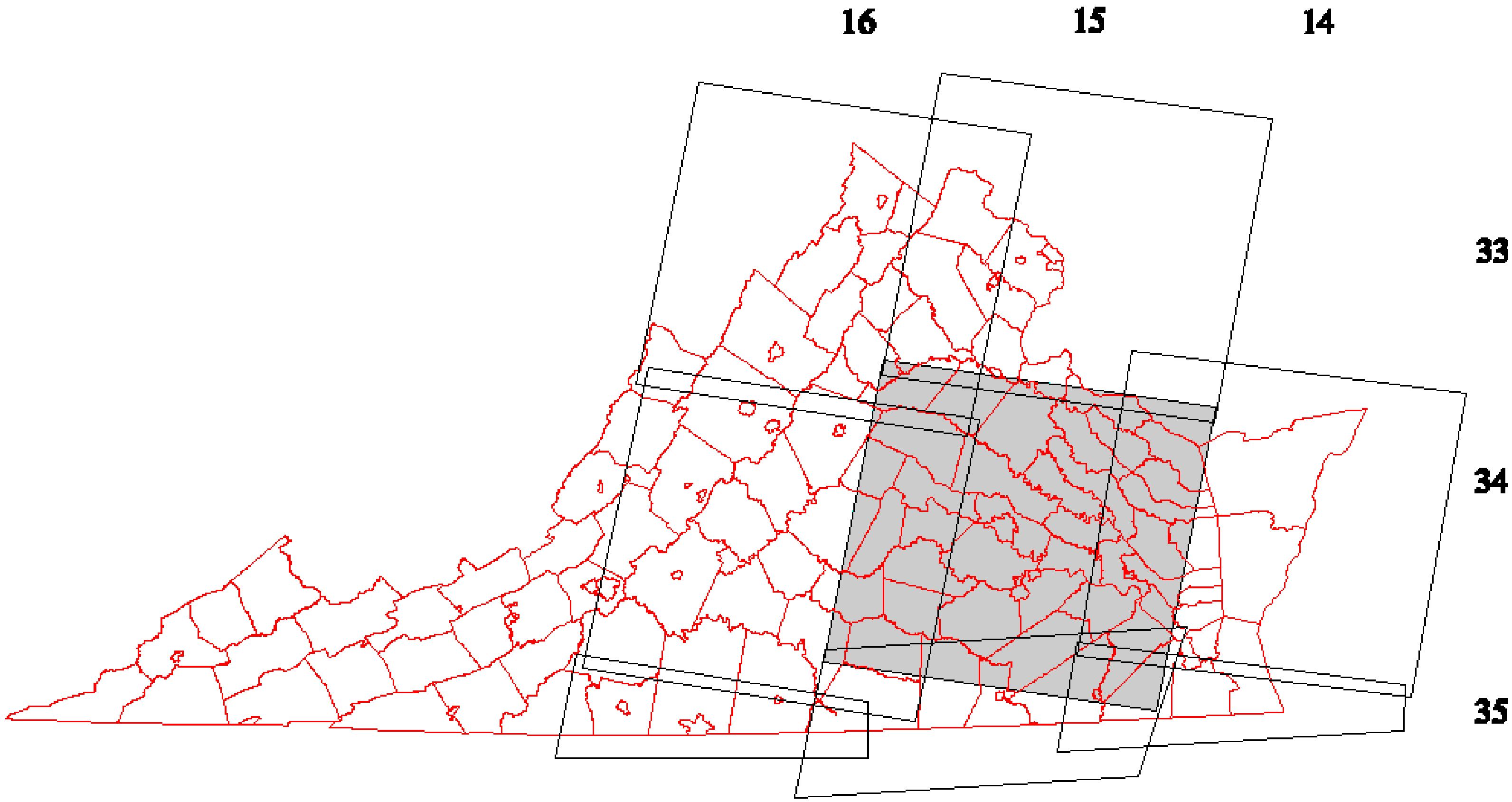


Figure 4-1. Virginia country boundaries with extents of Landsat TM scenes, showing scene 15/34 (shaded) where this phase of the study was conducted.

Modeling

Data Usage

The 346 buffered stops contained within this scene were randomly split into 2 groups. For this phase, stop level information was more applicable than route level information, so I used individual stops for this analysis. The first group contained 248 stops and would be used to develop the models. The second group contained 98 stops and was reserved for validation of the models.

High/Low Population Model

All modeling exercises used an alpha = 0.2. This level is appropriate when modeling (R. H. Giles pers. comm).

Model Building

Stops with an average call count greater than 1.0 bobwhite indicated habitats supporting high populations while stops with counts less than 1.0 indicated low bobwhite abundance. This number is equivalent to 10 bobwhite per route, or the threshold used in Chapter 3. Of the 248 modeled data stops, 110 (44%) were in the high category, and 138 (56%) were in the low category (Figure 4-2). I used a logistic regression model to predict the probability of an area supporting a high bobwhite population based on the means and standard deviations of the raw imagery at a stop.

Model Verification

The independent set of 98 routes was tested using the logistic regression coefficients produced by the model. If a stop had an average greater than or equal to 1.0 bobwhite heard, and the predicted probability was above 0.6, then the model was deemed correct. Conversely, if the model had an average below 1.0 and a probability below 0.6, it was also deemed correctly classified. If there were mixed results between the actual number and the probability threshold (e.g., greater than 1.0 bobwhite heard and a probability below 0.6 or a probability above 0.6 and fewer than 1.0 bobwhite heard) then the model was deemed incorrectly classified. Finally, Pearson product-moment correlation coefficients were calculated between the final logistic probability for a stop and its bobwhite call count to analyze how well the model fit the actual data.

Presence/Absence Mode

Model Building

Fifty-eight stops did not detect bobwhite in any year, so a true presence/absence model logistic regression model could be calculated. After analyzing the distribution of these zero counts between the previous modeled and tested data, it was determined that a similar percentage of each use category had zero counts (28.5% of the modeled stops and 27.6% of the independent stops). I used the same 248 stops to build the model as the high/low model, while retaining the same 98 stops to validate this model.

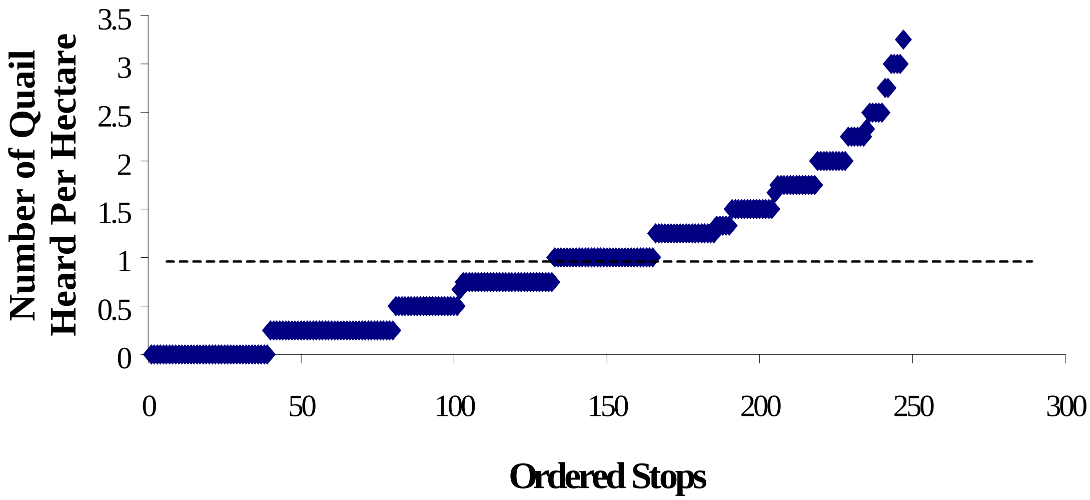


Figure 4-2. Graph showing ordered stop level data, with a line at the split used to differentiate between high and low populations.

Model Verification

The model coefficients were used in a logistic regression model on the independent, verification set of data. Like the high/low model, the presence/absence model was deemed correct if it predicted a probability greater than 0.6 and the stop had an average greater than 0 or if the probability was below 0.6 with an average of 0 bobwhite. Mixed results indicated the stop was incorrectly classified. Pearson correlation coefficients were also calculated between the logistic probability and call count data.

Model Application

Applying the logistic regression coefficients for each model to the original imagery generated two maps depicting the quality of habitat. The significant coefficients from the high/low model were applied to the raw TM imagery to predict the probability of an area supporting a high bobwhite population. Similarly, when the coefficients from the presence/absence model were applied to the entire scene, the probability of that landscape supporting some number of bobwhite is shown.

RESULTS

Modeling

High/Low Population Model

Model Building

Of 18 variables that entered into the stepwise logistic regression model, 4 were significant in predicting high or low population abundance (Table 4-1). This model had a concordance of 70.9% and accurately predicted 65.7% of the modeled data (163/248 stops). Figure 4-3 shows the 2-scene area classified using this logistic regression model.

Model Verification

The resultant high/low population logistic regression equation was applied to the remaining 98 routes to assess how the model performed. Of the 98 stops, the model accurately predicted 64 (65.3%) stops (Table 4-2). The correlation coefficients between the actual stop count and the logistic probability for the 98 independent stops was 0.166, and when all 346 stops were examined, this correlation coefficient was 0.345.

Presence/Absence Model

Model Building

Of the 18 variables entered into the stepwise logistic regression model, only three were significant in predicting bobwhite presence (Table 4-3). This model had a concordance of 69.2% and accurately predicted 83.1% of the modeled data (206/248

Table 4-1. Logistic regression parameter estimation for 4 variable model predicting high/low bobwhite populations in eastern Virginia, 1990-1993.

Variable	Parameter Estimates	SE	χ^2	P
Intercept	-5.8081	1.4880	15.2357	0.0001
Mean band 4	0.0326	0.0210	2.3961	0.1216
Mean band 5	0.0264	0.0135	3.8414	0.0500
Standard deviation band 2	-0.3673	0.1513	5.8931	0.0152
Standard deviation band 7	0.2393	0.0665	12.9462	0.0003

Table 4-2. Logistic regression classification table for bobwhite population abundance for the modeled and independent sets of bobwhite call count stops, eastern Virginia, 1990-1993.

	Predicted Population Abundance					
	Modeled Data (n=248)			Independent Data (n=98)		
Observed Population Abundance	High	Low	Percent Correct	High	Low	Percent Correct
High	58	52	52.7%	14	24	36.8%
Low	29	109	79.0%	14	46	76.7%
Percent Correct	66.7%	67.7%	67.3%	50.0%	65.7%	61.2%

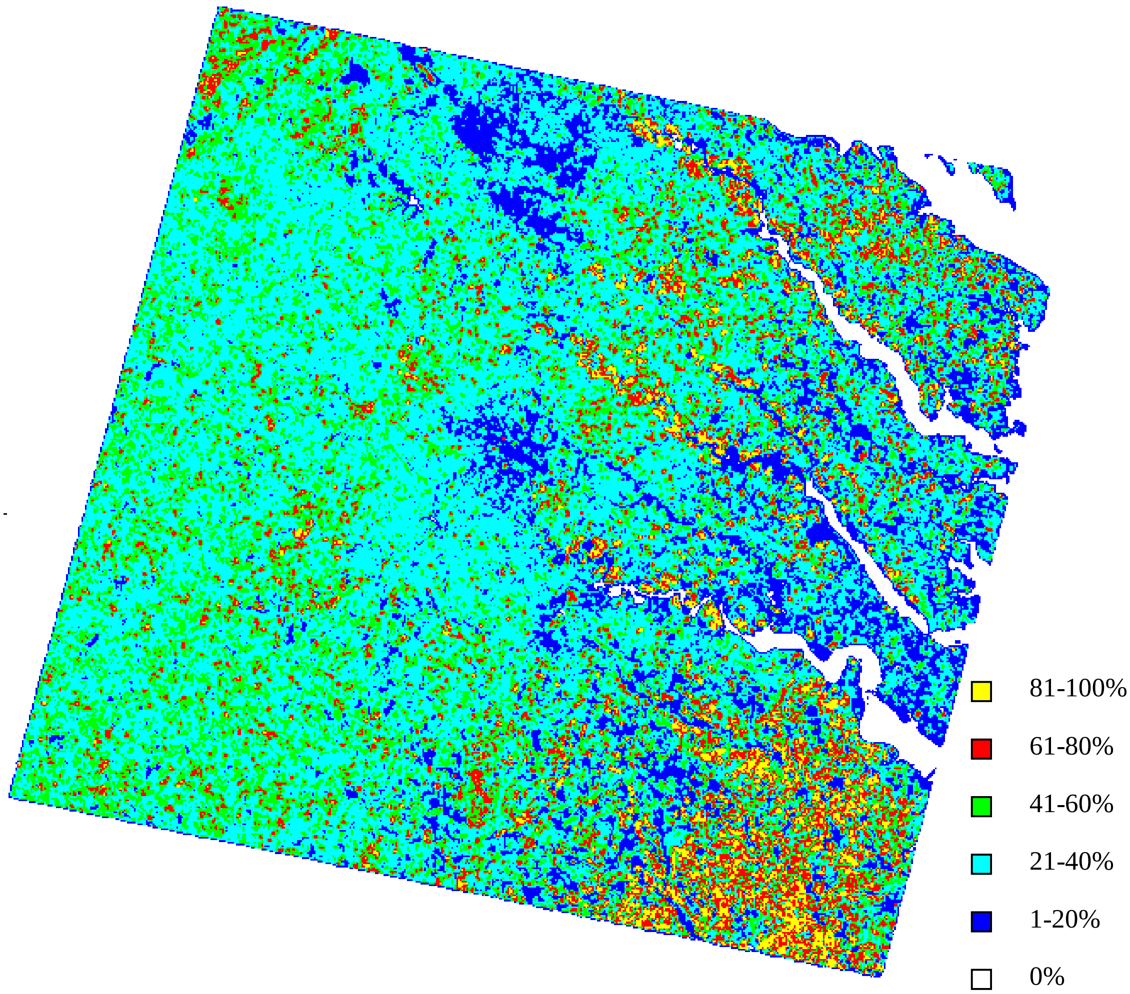


Figure 4-3. Percent probability map of a landscape supporting high numbers of bobwhite based on high/low population logistic regression model, Virginia 1990-1993.

Table 4-3. Logistic regression parameter estimation for 3 variable model predicting presence/absence for bobwhite populations in eastern Virginia, 1990-1993.

Variable	Parameter Estimates	SE	χ^2	P
Intercept	3.3075	4.2915	0.5940	0.4409
Mean band 1	-0.1383	0.0806	2.9408	0.0864
Mean Soil Brightness Index	0.0624	0.0242	6.6603	0.0099
Standard deviation band 5	0.0732	0.0346	4.4699	0.0345

Table 4-4. Logistic regression classification table for bobwhite presence/absence model showing the modeled and independent sets of bobwhite call count stops, eastern Virginia, 1990-1993.

	Predicted Population Abundance					
	Modeled Data (n=248)			Independent Data (n=98)		
Observed Population Abundance	High	Low	Percent Correct	High	Low	Percent Correct
High	206	0	100.0%	81	1	99.6%
Low	42	0	0.0%	15	1	1.7%
Percent Correct	83.1%	0%	83.1%	83.4%	50.0%	82.8%

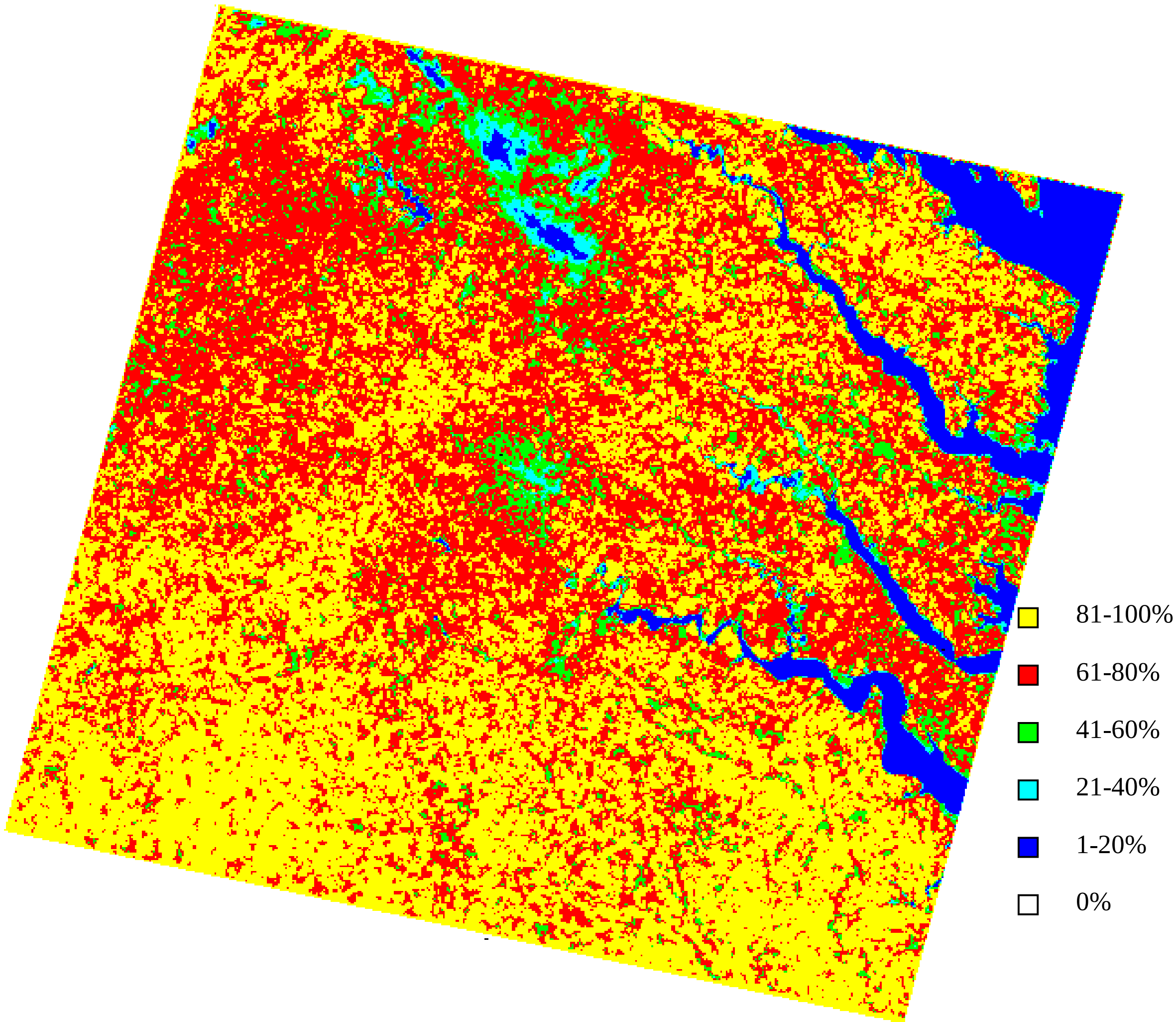


Figure 4-4. Percent probability map of a landscape supporting some number of bobwhite based on presence/absence logistic regression model, Virginia 1990-1993.

stops). Figure 4-4 shows an example of an area classified using this logistic regression model.

Model Verification

The resultant presence/absence logistic regression equation was applied to the remaining 98 routes to assess how the model performed. Of the 98 stops, the model accurately predicted 82 (83.7%) stops (Table 4-4). The correlation coefficients between the actual stop count and the logistic probability for the 98 independent stops was 0.294, and when all 346 stops were examined, this correlation coefficient was 0.344.

Model Application

Coefficients for each model were applied to the corresponding raw bands to generate probability maps for the entire Landsat TM scene. The high/low population model (Figure 4-3) depicts the probability that the 13-pixel circular landscape surrounding that pixel is capable of supporting a high bobwhite population. This model predicts 6.99% of the TM scene being able to support a high population of bobwhite.

The presence/absence model generated a prediction map (Figure 4-4) showing the probability that the 13-pixel landscape surrounding that pixel of supporting any bobwhite. This map predicts 90.31% of the scene can support some quantity of bobwhite.

DISCUSSION

High/Low Population Model

The high/low population model contained 4 variables and the intercept (Table 4-1). Two of the variables were means and two were standard deviations for spectral bands within a 13-pixel radius circle of a call count stop. The stepwise logistic regression model shows the means of bands 4 and bands 5 as significant in predicting high or low population abundance. Bands 4 and 5 are extremely useful in vegetation cover delineation and identification (Lillesand and Kiefer 1994). The predictability of high or low population abundance was positively associated with the means of both bands 4 and 5. The standard deviation of bands 2 and 7 were significant variables. Band 2, like bands 4 and 5, offers some information for vegetation discrimination. The negative association with the variation in the 13-pixel circle may be explained by the avoidance by bobwhite of small, very heterogeneous areas on the landscape. Band 7 has been described as being useful for the discrimination of rocks and minerals (Lillesand and Kiefer 1994). A positive association with the standard deviation of band 7 may be expressing some of the bare soil characteristics important to bobwhite. The standard deviation of band 7, expressing mid-infrared radiation, may be expressing differences in water content in soils and vegetation, indicating potential heterogeneous areas.

The high/low population model performed reasonably well when applied to the independent set of data. One potential problem may be anomalies in the reference data, but given the sample size reserved for validation it is doubtful that there are that many outliers in the data. Rather, there may be more information at these stops than what I included as bobwhite habitat usage. A model such as this may not be able to accurately represent the existing information. The prediction rate of the independent and modeled data indicates this problem. Both the independent and modeled data had a moderate accuracy rate (65.3% and 67.3%, respectively). This result and the correlation coefficients support the idea that there is a more detailed bobwhite-habitat relationship than can be expressed with this model. The low correlation coefficients between the actual data and predicted probabilities show that the model is not performing as well as it could.

Presence/Absence Population Model

The presence/absence model contained three significant variables and the intercept. The mean of band 1, the mean of the soil brightness index, and the standard deviation of band 5 were significant predictors of bobwhite presence. The negative association between bobwhite numbers and the mean of band 1 may indicate the split between soil and vegetation. The positive association of bobwhite numbers with the mean soil brightness index may be expressing the bobwhite’s need for bare soil. Finally, the standard deviation of band 5 may be expressing some of the association with vegetation cover types. Band 5 is very useful in discriminating between various vegetation cover types, and the standard deviation may be expressing some of the bobwhite’s need for a heterogeneous matrix, or their need for edge type habitats. Hepinstall and Sader (1997) reported bands 4 and 5 and, to a lesser degree, the spatial variance measure for the NDVI layer as important predictors of bird presence.

This model performed better than the high/low population model. When compared to the independent data, this model accurately predicted 83.7% of the independent data and 83.1% of the modeled data. It is reasonable to presume that models should be better able to differentiate between presence/absence conditions more readily than between the relatively similar population levels. In addition, there is more likely to be some confusion between population levels than between sites supporting bobwhite populations and those where bobwhite are absent.

One issue to consider with this model is the tendency for the model to predict areas with the potential of supporting some number of bobwhite. Much of the 2-scene area has a probability > 60% of supporting some number of bobwhite. The remaining areas, including water bodies and urban areas that are not typically considered bobwhite habitats, had a percentage > 0%. Based upon the model, few areas can even have a value of zero, which contrasts to the high/low model, where some areas (especially water bodies) had a zero probability of high bobwhite numbers. Generally, few areas are predicted as supporting high bobwhite numbers, but much of the area is predicted as supporting some number of bobwhite.

The Pearson product-moment correlation coefficients were also higher for this model than the high/low population model (0.294 and 0.166, respectively). The coefficient for the presence/absence model for all the stops was similar to the high/low population model (0.344 and 0.345, respectively).

Models

This study utilized spatial texture methods, following Hepinstall and Sader (1997), and a single-species approach, like Aspinall and Veitch (1993). Both previous studies used Bayesian conditional probabilities to model suitability for birds, but the format outlined was not appropriate for our discrete data (B. Noble and J. Huffman pers. comm., Virginia Polytechnic Institute and State University Statistical Consulting Center). To evaluate the pixels surrounding a stop without using Bayesian modeling, I explored the use of spatial texture measures. For each of the bands, I included all the values for the surrounding 530 pixels, calculating means and standard deviations for each. These spatial windows account for any of the potential locations where a bobwhite call may have originated and incorporate the information for the window into one statistic. Finally, by using a 4 year mean of bobwhite heard, I eliminated the potential spurious effects of a particular year. In contrast, Hepinstall and Sader (1997) relied upon one year of BBS data to develop their models.

This method provides a reliable way of examining landscape characteristics across a large area and producing a map of probabilities of high population abundance or population presence based on current imagery. Temporal issues are very important when modeling a species that associates with transitional or edge habitats. The land cover map of bobwhite habitats (Chapter 2) is now 7 years old, reducing the effectiveness of management decisions made using it. Using the raw imagery method, it is feasible it extract the data for at each of the stops, perform the calculations, and develop a model in a few hours. Applying the model to a full Landsat scene took 75 hours on a Pentium 200 personal computer. Thus, within a week of acquiring new imagery, a predictive map is available as input for management and research decisions.

This modeling method has some limitations. Certainly, it is difficult to manage for a particular mean and standard deviation of a Landsat TM band. Modeling populations using raw, remotely-sensed imagery removes the time consuming and costly step of habitat mapping, while estimating occurrence of a species. In contrast, more traditional habitat mapping takes the raw imagery and puts an individual pixel into a habitat class based upon the reflectance in each band at that pixel. This step relies on a mean and the standard deviation of the points surrounding the mean. These land cover/land use maps are then clustered using landscape characteristics, proximity to other classes, or other measures depending upon the species. By mapping species associations from a classified land cover map, researchers are effectively classifying the data twice, and may be propagating errors.

This technique has the potential for targeting continued research by identifying areas with high potential for supporting the elevated bobwhite numbers. Once identified, these areas most likely to support high bobwhite numbers could be examined more closely using any of the higher resolution sensors rapidly coming into service (Wynne and Carter 1997).

CHAPTER 5- CONCLUSIONS

Remote sensing and geographic information systems were employed to generate and analyze habitat maps for bobwhite. First, 4 band combinations and classification algorithms were tested using 3 classification schemes. This analysis showed that careful selection of the algorithm and band combinations improves classification accuracy and categorical specificity. Additionally, abundant reference data are invaluable when attempting any remote sensing effort. Collecting ground reference data early in the project is as important as any other phase of the study, and should never be overlooked when starting a project such as this.

A method was devised to use ground reference data to classify remotely-sensed images into some habitat classes that have infrequently been identified using remotely-sensed images. This hybrid method maintains characteristics of both supervised and unsupervised algorithms. In eastern Virginia, this method yielded an overall accuracy of 79.2% which was significantly better than 12 of the other 14 classification algorithms and band combinations ($\underline{P} < 0.05$). The final band combination and algorithm was applied to the set of 8 scenes making up the study area. A mosaic of these scenes was created and the accuracy of the overall map was verified. The result was a map of habitats important to bobwhite in the eastern portion of Virginia.

Exploring the spatial arrangements of the habitats delineated in the first phase, I described the arrangements and landscape measures of habitats that may be influencing bobwhite populations in eastern Virginia. The relationships were built using bobwhite call count data and tested using an independent set of the call count data. The models were applied on the portions of the 2 Landsat TM scenes making up the study area for this phase. Pattern recognition (PATREC) and logistic regression modeling techniques were used in this phase to describe the relationships between bobwhite abundance and 19 landscape metrics. Using the models developed, one can identify limiting factors on a landscape and seek solutions to improve the quality of the landscape for bobwhite, or explain the reasons for the existing population declines.

Finally, I explored the possibilities of modeling levels of population abundance from raw, remotely-sensed imagery. Such models eliminate the costly and time-consuming step of image interpretation. As indicated, much reference data is necessary to successfully complete any image classification. Image interpretation, image classification, and the collection of reference data are all time consuming. The method I devised takes raw imagery and predicts levels of population abundance based on models using existing count information. This method is species-independent, and can be applied to most any species.

When classifying the raw imagery (Chapter 2), I sought classes thought to be important to bobwhite or comprising a major portion of the landscape. I ignored potential differences in habitats not identified as bobwhite habitats (i.e., I made no attempt to subdivide the deciduous forest class into finer level classes, whereas more specific classes have been used by numerous state Gap Analysis Programs). As such, the classified images generated as part of phase 1 would be of little use to other researchers. For example, this map would not be as specific as needed for elk habitat delineation, and elk researchers would need to perform a separate classification.

The raw image modeling method has great potential as a resource-monitoring tool for wildlife managers. With this technique, the researcher is essentially using population data to identify better habitats and seek out similar areas on the landscape. Supervised classification uses information provided by the analyst to find similar areas on the landscape. Similarly, unsupervised classification uses digital numbers to clump the image into spectral classes, which are later recoded into information classes. Both supervised and unsupervised classification methods cluster the data. If spatial analyses or models (i.e. Chapter 3) are then used on the classified image, additional clumping and changing may occur, leading to conclusions drawn on data far removed from the original data. The raw image modeling method skips the middle step and uses available biological information to rapidly predict levels of population abundance. Shortly after acquiring new population data or new imagery, a model can be developed to predict populations based on existing conditions.

LITERATURE CITED

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer. 1976. A land use and land cover classification system for use with remote sensor data. U.S. Geological Service Professional Paper 964. Washington, D.C. 28pp.

Aspinall, R., and N. Veitch. 1993. Habitat mapping from satellite imagery and wildlife survey data using a Bayesian modeling procedure in a GIS. Photogrammetric Engineering & Remote Sensing 59:537-543.

Baker, J. B. and O. G. Langdon. 1990. *Pinus taeda* Loblolly Pine. Pages 497-512 *in* Burns, R. M. and B. H. Honkala, eds. Silvics of North America, Volume 1, Conifers. Agriculture Handbook 654. USDA Forest Service US Government Printing Office. Washington. D.C.

Barnes, T. G., L. A. Madison, J. D. Sole, and M. J. Lacki. 1995. An assessment of habitat quality for northern bobwhite in tall fescue-dominated fields. Wildlife Society Bulletin 23:231-37.

Bauer, M. E., T. E. Burk, A. R. Ek, P. R. Coppin, S. D. Lime, T. A. Walsh, D. K. Walters, W. Befort, and D. F. Heinzen. 1994. Satellite inventory of Minnesota forest resources. Photogrammetic Engineering and Remote Sensing 60:287-98.

Berry, K. H. 1986. Introduction: Development, testing, and application of wildlife-habitat models. Pages 3-4 *in* Verner, J., M. L. Morrison, and C. J. Ralph, eds. Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates University of Wisconsin Press, Madison, Wisconsin. 469pp.

Boroski, B. B., R. H. Barett, I. C. Timossi, and J. G. Kie. 1996. Modeling habitat suitability for black-tailed deer (*Odocoileus hemionus columbianus*) in heterogeneous landscapes. Forest Ecology and Management 88:157-165.

Brady, S. J. 1988. Potential implications of sodbuster on wildlife. Transactions of the North American Wildlife and Natural Resources Conference 53:239-248.

Brennan, L. A. 1991. How can we reverse the northern bobwhite population decline. Wildlife Society Bulletin 19:544-55.

______. 1993. Strategic plan for quail management and research in the United States: Introduction and background. Pages 160-169 *in* K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Parks, Pratt, Kansas.

_____. 1994. Broad scale population declines in four species of North American quail: An examination of possible causes. Pages 44-50 *in* Sustainable Ecological Systems: Implementing an Ecological Approach to Land Management. General Technical Report RM-247. Fort Collins, Colorado: USDA, Forest Service, Rocky Mountain Forest and Range Experiment Station.

Brown, D. E., A. Sands, S. Clubine, and C. E. Braun. 1993. Strategic plan for quail management and research in the United States: issues and strategies: Grazing and Range Management. Pages 176-177 *in* K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Parks, Pratt, Kansas.

Buckner, R. C. and L. P. Bush. 1979. Preface. Pages xiii-xiv *in* Buckner, R. C. and L. P. Bush, eds. Tall Fescue. American Society of Agronomy. Madison, Wisconsin.

Burger Jr., L. W., E. W. Kurzejeski, T. V. Dailey, and M. R. Ryan. 1990. Structural characteristics of vegetation in CRP fields in northern Missouri and their suitability as bobwhite habitat. Transactions of the 55th North American Wildlife and Natural Resources Conference 55:74-83.

Burns, J. C. and D. S. Chamblee. 1979 Adaption. Pages 9-30 *in* R. C. Buckner and L. P. Bush, eds. Tall Fescue. American Society of Agronomy. Madison, Wisconsin.

Cantu, R., and D. D. Everett. 1982. Reproductive success and brood survival of bobwhite quail as affected by grazing practices. Pages 79-83 *in* F. Schitoskey Jr., E. C. Schitoskey, and L. G. Talent, eds. Proceedings of the Second National Quail Symposium. Oklahoma State University, Stillwater, Oklahoma.

Capel, S., J. A. Crawford, R. J. Robel, L. W. Burger Jr., and N. W. Sotherton. 1993. Strategic plan for quail management and research in the United States: Issues and strategies: Agricultural practices and pesticides. Pages 172-173 *in* K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Parks, Pratt, Kansas.

Carter, K. K. and A. G. Snow Jr. 1990. *Pinus virginiana* Virginia Pine. Pages 513-519 *in* Burns, R. M. and B. H. Honkala, eds. Silvics of North America, Volume 1, Conifers. Agriculture Handbook 654. USDA Forest Service US Government Printing Office. Washington. D.C.

Church, K. E., J. R. Sauer, and S. Droege. 1993. Strategic plan for quail management and research in the United States: Issues and strategies: Population trends of quails in North America. Pages 44-54 *in* K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Parks, Pratt, Kansas.

Cline, G. A. 1988. Habitat relationships of bobwhite quail and cottontail rabbits on agricultural lands in Halifax county, Virginia. MS Thesis. Virginia Polytechnic Institute and State University, Blacksburg Virginia. 99pp.

Congalton, R. G. and K. Green. 1999. Assessing the accuracy of remotely sensed Data: principles and practices. Lewis Publishers. Boca Raton, Florida. 137pp.

Cox, J. 1994. Relationships between land cover and the abundance of breeding birds recorded along Florida’s Breeding Bird Survey routes. Pages 286-294 *in* Proceedings of the Annual Conference of Southeastern Fish and Wildlife Agencies. 48:286-294.

Crist, E. P. and R. C. Cicone. 1984. Application of the tasseled cap concept to simulated Thematic Mapper data. Photogrammetric Engineering and Remote Sensing 50:343-352.

_____ and R. J. Kauth. 1986. The tasseled cap de-mystified. Photogrammetric Engineering and Remote Sensing 52:81-86

Dai, X. L. and S. Khorram. 1998. The effects of image misregistration on the accuracy of remotely sensed change detection. IEEE Transactions on Geoscience and Remote Sensing 36:1566-1577.

Dailey, T. V. 1989. Modeling bobwhite quail habitat relationships on 4 central Missouri wildlife management areas. Missouri Department of Conservation, Federal Aid in Wildlife Restoration Project W-13-R-43, Final Report.

Davidson, C. 1998. Issues in measuring landscape fragmentation. Wildlife Society Bulletin 26:32-37.

Droege, S. 1990. The North American Breeding Bird Survey. Pages 1-4 *in* J. R. Sauer, and S. Droege, eds. Survey designs and statistical methods for the estimation of avian population trends. USFWS Biological Report, Washington D.C.

_____, and J. R. Sauer. 1990. Northern bobwhite, gray partridge, and ring-necked pheasant population trends (1966-1988) from the North American Breeding Bird Survey. Pages 2-20 *in* K. E. Church, R. E. Warner, and S. J. Brady, eds. Perdix V: Gray Partridge and Ring-Necked Pheasant Workshop. Kansas Department of Wildlife and Parks, Emporia, Kansas.

Dubuc, L. J., W. B. Krohn, R. B. Owen Jr. 1990. Predicting occurrence of river otters by habitat on Mount Desert Island, Maine. Journal of Wildlife Management 54:594-599.

Duda, R. O. and P. E. Hart. 1973. Pattern classification and scene analysis. Wiley Publishers Inc. New York, New York 482 pp.

Edwards, C., M. G. Smith, and R. N. Peterson. 1985. The changing distribution of farms by size: A Markov analysis. Agricultural Economics Research 37:1-16.

Edwards, W. R. 1972. Quail, land use, and weather in Illinois, 1956-1970. Pages 174-183 *in* J. A. Morrison and J. C. Lewis, eds. Proceedings of the First National Bobwhite Quail Symposium. Oklahoma State University, Stillwater, Oklahoma. 390pp.

Exum, J. H., R. W. Dimmick, and B. L. Dearden. 1982. Land use and bobwhite populations in an agricultural system in west Tennessee. Pages 6-11 *in* F. Schitoskey Jr., E. C. Schitoskey, and L. G. Talent, eds. Proceedings of the Second National Quail Symposium. Oklahoma State University, Stillwater, Oklahoma.

Felix III, A. C., T. L. Sharik, and B. S. McGinnes. 1986. Effects of pine conversion on food plants of northern bobwhite quail, eastern wild turkey, and white-tailed deer in the Virginia piedmont. Southern Journal of Applied Forestry 10:47-52.

Fies, M. L., I. L. Kenyon Jr., and J. V. Gwynn. 1992. Effects of changing land use patterns on bobwhite quail habitat in Virginia. Virginia Journal of Science 23(1B): 143-55.

Flather, C. H., and T. W. Hoekstra. 1989. An analysis of the wildlife and fish situation in the United States: 1989-2040. General Technical Report RM-178. USDA Forest Service, Rocky Mountain Forest and Range Experiment Station. Fort Collins, Colorado. 146pp.

Frohn, R. C. 1998. Remote sensing for landscape ecology. Lewis Publishers, Boca Raton, Florida. 88pp.

Gale, F. 1995. Farm numbers continue to drop. Agricultural Outlook Digest, Jan-Feb 215:2-5.

Gaudette, M. T. 1986. Modeling winter habitat for white-tailed deer in southwestern Virginia. M.S. Thesis. Virginia Polytechnic Institute and State University, Blacksburg, Virginia. 68pp.

Gopal, S. and C. Woodcock. 1994. Theory and methods for accuracy assessment of thematic maps using fuzzy sets. Photogrammetric Engineering and Remote Sensing 60:181-188.

Grubb, T. G. 1988. Pattern recognition- a simple model for evaluating wildlife habitat. USDA Forest Service Rocky Mountain Forest and Range Experiment Station, RM-487: USDA Forest Service Rocky Mountain Forest and Range Experiment Station, RM-487, Fort Collins, Colorado.

Guthery, F. S. 1997. A Philosophy of Habitat Management for Northern Bobwhites. Journal of Wildlife Management 61:291-301.

Hall, L. S., P. R. Krausman, and M. L. Morrison. 1997. The habitat concept and a plea for standard terminology. Wildlife Society Bulletin 25:173-182.

Hanowski, J. M., and G. J. Niemi. 1995. A comparison of on- and off-road bird counts: do you need to go off road to count birds accurately? Journal of Field Ornithology 66:469-483.

Hansen, M. H., T. Frieswyk, J. F. Glover, and J. F. Kelly. 1992. The eastwide forest inventory data base: users manual. General Technical Report. NC-151. USDA Forest Service North Central Forest Experimental Station, St. Paul, Minnesota. 48 pp.

Hays, R. L. and A. H. Farmer. 1990. Effects of the CRP on wildlife habitat: Emergency haying in the Midwest and pine plantings in the Southeast. Transactions of the North American Wildlife and Natural Resources Conference 55:30-39.

Heitmeyer, M. E. 1980. Foods of bobwhites in northeastern Missouri related to land use. Missouri Academy of Science 14:51-60.

Hepinstall, J. A., and S. A. Sader. 1997. Using Bayesian statistics, Thematic Mapper satellite imagery, and Breeding Bird Survey data to model bird species probability of occurrence in Maine. Photogrammetric Engineering and Remote Sensing 63:1231-1237.

Herr, A. M. and L. P. Queen. 1993. Crane habitat evaluation using GIS and remote sensing. Photogrammetic Engineering and Remote Sensing 59:1531-38.

Homer, C. G., T. C. Edwards, R. D. Ramsey, and K. P. Price. 1993. Use of remote sensing methods in modeling sage grouse winter habitat. Journal of Wildlife Management 57:78-84.

Hunter, J. E., R. J. Gutierrez, and A. B. Franklin. 1995. Habitat configuration around spotted owl sites in northwestern California. Condor 97:684-693.

Kauth, R. J. and G. S. Thomas. 1976. The tasseled cap- a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. Pages 41-51 *in* Proceedings of the Symposium on Machine Processing of Remotely Sensed Data. Purdue University, West Lafayette, Indiana.

Jackson, J. 1990. Bobwhite quail and the southern pine plantation. Forest Farmer 49:22-23.

Jensen, J. R. 1996. Introductory digital image processing: a remote sensing perspective. 2nd edition. Prentice Hall, Upper Saddle River, New Jersey. 316pp.

Johnsgard, P. A. 1988. The Quails, Partridges, and Francolins of the World. Oxford University Press, Oxford, United Kingdom. 264pp.

Kauth, R. J. and G. S. Thomas. 1976. The tasseled cap- A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. Pages 41-51 *in* Proceedings of the Symposium on Machine Processing of Remotely Sensed Data. Purdue University, West Lafayette, Indiana.

Keller, M. E., and S. H. Anderson. 1992. Avian use of habitat configurations created by forest cutting in southeastern Wyoming. Condor 94:55-65.

Keyser, A. J., G. E. Hill, and E. C. Soehren. 1998. Effects of forest fragment size, nest density, and proximity to edge on the risk of predation to ground-nesting passerine birds. Conservation Biology 12:986-994.

Kling, C. L. 1980. Pattern recognition for habitat evaluation. M.S. Thesis. Colorado State University, Fort Collins, Colorado 244 pp.

Knick, S. T. and D. L. Dyer. 1997. Distribution of black-tailed jack rabbit habitat determined by GIS in southwestern Idaho. Journal of Wildlife Management 61:75-85.

Kurzejeski, E. W., and J. B. Lewis. 1985. Application of PATREC modeling to wild turkey management in Missouri. Pages 269-283 *in* J. Earl, and M. C. Kennamer, eds. Proceedings of the Fifth National Wild Turkey Symposium. Des Moines, Iowa.

Kuvlesky Jr., W. P., B. D. Leopold, P. D. Curtis, J. L. Roseberry, and T. Hutton. 1993. Strategic plan for quail management and research in the United States: issues and strategies: Population Dynamics and Effects of Hunting. Pages 180-181 *in* K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Parks, Pratt, Kansas.

Langner, L. L. and C. H. Flather. 1994. Biological diversity: Status and trends in the United States. General Technical Report RM-244. USDA Forest Service, Rocky Mountain Forest and Range Experiment Station. Fort Collins, Colorado. 24pp.

Lehmann, V. W. 1937. Increasing quail by improving their habitat. Texas Cooperative Wildlife Service. Austin, Texas. 44pp.

Lillesand, T. M. and R. W. Kiefer. 1994. Remote sensing and image interpretation. 3rd edition. John Wiley and Sons, Inc, New York, New York. 750 pp.

_____, J. Chipman, D. Nagel, H. Reese, M. Bobo, and R Goldmann. 1998. Upper Midwest Gap Analysis Program image processing protocol. Report prepared for the U.S. Geological Survey, Environmental Management Technical Center, Onalaska, Wisconsin, June 1998. EMTC 98-G001. 25 pp. + Appendixes A-C.

Loveland, T. R., and D. M. Shaw. 1996. Multi-resolution land characterization: Building collaborative partnerships. Pages 79-85 *in* J. M. Scott and a. F. W. D. T. H. Tear, editors. Gap analysis: A landscape approach to biodiversity planning. American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland.

McGarigal, K., and B. J. Marks. 1995. FRAGSTATS: Spatial pattern analysis programs for quantifying landscape structure. U.S. Forest Service General Technical Report PNW-351, Pacific Northwest Forest Experiment Station, Portland Oregon.

McGowan, D. P. Jr. and D. L. Otis. 1998. Population demographics of two local South Carolina mourning dove populations. Journal of Wildlife Management 62:1443-1451.

McInteer Jr., J. F. 1986. Virginia's bobwhite quail. Virginia Commission of Game and Inland Fisheries. Richmond, Virginia. 36pp.

Meseke, C. A. 1992. Nest site selection of the northern bobwhite on central Illinois grasslands. American Zoologist 32:101A.

Michener, W. K., J. B. Atkinson, P. F. Houhoulis, P. M. Johnson, R. N. Smith, J. W. Jones. 1998. Northern bobwhite quail: responses to landscape configuration. Technical Papers, 64th Annual Meeting of the American Society for Photogrammetry and Remote Sensing. Tampa, Florida. 10pp.

Mickelson Jr., J. G, D. L. Civco, and J. A. Silander, Jr. 1998. Delineating forest canopy species in the northeastern United States using multi-temporal TM imagery. Photogrammetric Engineering and Remote Sensing 64:891-904.

Montopoli, G. J., and D. A. Anderson. 1991. A logistic regression model for the cumulative effects of human intervention on bald eagle habitat. Journal of Wildlife Management 55:290-293.

Morrison, M. L., I. C. Timossi, and K. A. With. 1987. Development and testing of linear regression models predicting bird-habitat relationships. Journal of Wildlife Management 51:247-253.

Morton, D. D. 1998. Land cover of Virginia from Landsat Thematic Mapper imagery. MS Thesis. Virginia Polytechnic Institute and State University, Blacksburg Virginia 253pp.

Natural Resources Council. 1982. Impacts of emerging agricultural trends on fish and wildlife habitat. National Academy Press. Washington, D.C. 303pp.

O'Neill, R. V., J. R. Krummel, R. H. Gardner, G. Sugihara, B. Jackson, D. L. DeAngelis, B. T. Milne, M. G. Turner, B. Zygmunt, S. W. Christensen, V. H. Dale, R. L. Graham. 1988. Indices of landscape pattern. Landscape Ecology 1:153-162.

Peterjohn, B. G., J. R. Sauer, and C. S. Robbins. 1996. Population trends from the North American breeding bird survey. Pages 3-39 *in* D. F. Stotz, J. W. Fitzpatrick, and T. A. Parker, eds. Neotropical Birds: Ecology and Conservation.

Reading, R. P. and R. Matchett. 1997. Attributes of black-tailed prairie dog colonies in north-central Montana. Journal of Wildlife Management 61:664-673.

Robbins, C. S., D. K. Dawson, and B. A. Dowell. 1989. Habitat area requirements of breeding forest birds of the middle Atlantic states. Wildlife Monographs 103. 34pp.

Robinson, I. R. and F. S. Barkalow. 1979. Bobwhite quail foods in Pocosin habitat converted to pine. Journal of Wildlife Management 43:515-21.

Roseberry, J. L. 1993. Bobwhite and the "new biology". K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Parks, Pratt, Kansas.

______ and L. M. David. 1994. The Conservation Reserve Program and northern bobwhite population trends in Illinois. Transactions of the Illinois State Academy of Science 87:61-70.

______ and W. D. Klimstra. 1984. Population ecology of the bobwhite. Southern Illinois University Press, Carbondale, Illinois . 259pp.

______, B. G. Peterjohn, and W. D. Klimstra. 1979. Dynamics of an unexploited bobwhite population in deteriorating habitat. Journal of Wildlife Management 43:306-15.

______, B. J. Richards, and T. P. Hollenhorst. 1994. Assessing the potential impact of Conservation Reserve Program lands on bobwhite habitat using remote sensing, GIS, and habitat modeling. Photogrammetic Engineering and Remote Sensing 60:1139-43.

_____ and S. D. Sudkamp. 1998. Assessing the suitability of landscapes for northern bobwhite. Journal of Wildlife Management 62:895-902.

______, and A. Woolf. 1995. Final Report W-106-R Cooperative Upland Wildlife Project (Phase II). Federal Aid in Wildlife Restoration Report to Illinois Department of Natural Resources. 139pp.

Rosene, W. 1969. The bobwhite quail: Its life and management. Rutgers University Press, New Brunswick, New Jersey. 418pp.

Rouse, J.W., R.H. Haas, J.A. Schell, D.W. Deering, and J.C. Halan. 1974. Monitoring the Vernal Advancement and Retrogradation (Greenwave Effect) of Natural Vegetation. NASA/GSFC Type III Final Report, Greenbelt, MD. 371pp.

SAS Institute Inc. 1990. SAS/STAT user's guide. Version 6.0. SAS Inst. Inc. Cary, North Carolina. 1686 pp.

Sauer, J. R., J. E. Hines, G. Gough, I. Thomas, and B. G. Peterjohn. 1997. The North American Breeding Bird Survey results and analysis. Version 96.4. Patuxent Wildlife Research Center, Laurel, Maryland <http://www.mbr-pwrc.usgs.gov/bbs/bbs.html>

Schamberger, M. and J. O'Neal. 1984. Concepts and constraints of habitat model testing. Pages 5-10 *in* Verner, J., M. L. Morrison, and C. J. Ralph, eds. Wildlife 2000: Modeling habitat relationships of terrestrial vertebrates. University of Wisconsin Press, Madison, Wisconsin. 469pp.

Schulz, P. A. and F. S. Guthery. 1988. Effects of short duration grazing in northern bobwhites: A pilot study. Wildlife Society Bulletin 16:18-24.

Scott, T. G. 1985. The bobwhite thesaurus. International Quail Foundation, Edgefield, South Carolina. 306pp.

Sherburne, S. S. and J. A. Bissonette. 1994. Marten subnivean access point use: response to subnivean prey levels. Journal of Wildlife Management 58:400-405.

Sole, J. D. 1995. Changes in vegetation and bobwhite quail and eastern cottontail rabbit use in a converted fescue field. Transactions of the Kentucky Academy of Science 56:1-8.

Space Imaging. 1998. Space Imaging Website. <http://www.spaceimage.com/>

Stanton, B. F. Changes in farm size and structure in American agriculture in the twentieth century. Pages 42-70 *in* A. Hallam, ed. Size, Structure, and the Changing Face of American Agriculture. Westview Press, Boulder, Colorado .

Stauffer D. F., G. A. Cline, and M. J. Tonkovich. 1990. Evaluating potential effects of CRP on bobwhite quail in piedmont Virginia. Pages 57-67 *in* Transactions of the 55th North American Wildlife and Natural Resources Conference.

Stelly, M. 1979. General forward. Page xi *in* Buckner, R. C. and L. P. Bush, eds. Tall fescue. American Society of Agronomy. Madison, Wisconsin.

Stoddard, H. L. 1931. The Bobwhite Quail: Its Habitat, Preservation and Increase. Charles Scribners Sons, New York, New York .559pp.

Tall Timbers. 1995. Game bird research report, Pages 16-21 *in* Krier, M., T., L. A. Brennan, and S. Liggett, eds. Tall Timbers Annual Report. Tall Timbers Research Inc. Tallahassee Florida.

Thomas, J. W. 1980. Wildlife-habitat modeling—cheers, fears, and introspection. Pages xix-xxv *in* Verner, J., M. L. Morrison, and C. J. Ralph, eds. Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates. University of Wisconsin Press, Madison, Wisconsin. 469pp.

Tonkovich, M. J. 1995. Field evaluation of the northern bobwhite Habitat Suitability Index with Implications for the Conservation Reserve Program. Ph.D. Dissertation. Virginia Polytechnic Institute and State University, Blacksburg Virginia. 217pp.

Tucker, C. J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of the Environment: 8:127-150.

U. S. Department of Commerce, Bureau of the Census. 1978. Census of agriculture: Geographic area series-Part 46 Virginia. US Government Printing Office. Washington, District of Columbia.

_____. 1982. Census of agriculture: Geographic area series-Part 46 Virginia. US Government Printing Office. Washington, District of Columbia.

_____. 1987. Census of agriculture: Geographic area series-Part 46 Virginia. US Government Printing Office. Washington, District of Columbia.

_____. 1992. Census of agriculture: Geographic area series-Part 46 Virginia. US Government Printing Office. Washington, District of Columbia.

United States Geological Survey, 1996. US GeoData Digital Line Graphs. United States Geological Survey FS-078-96.

Vance, D. R. 1976. Changes in land use and wildlife populations in southeastern Illinois. Wildlife Society Bulletin 4:11-15.

Wallace, A. 1994. Evolution of the low income per acre--large number of acres per farm-highly mechanized--monoculture--not too sustainable agriculture. Communications in Soil Science and Plant Analysis 25:61-66.

Wells, R., and K. Sexson. 1982. Evaluation of bobwhite quail surveys in Kansas. Pages 19-30 *in* F. Schitoskey Jr., E. C. Schitoskey, and L. G. Talent, eds. Proceedings of the Second National Bobwhite Quail Symposium. Oklahoma State University, Stillwater, Oklahoma.

Whiting Jr., R. M., and D. L. Sloan. 1993. Activity patterns and habitat use of northern bobwhite females in 2 grazing systems. Pages 131-136 *in* K. E. Church, and T. V. Dailey, eds. Quail III: National Quail Symposium. Kansas Department of Wildlife and Park, Pratt, Kansas.

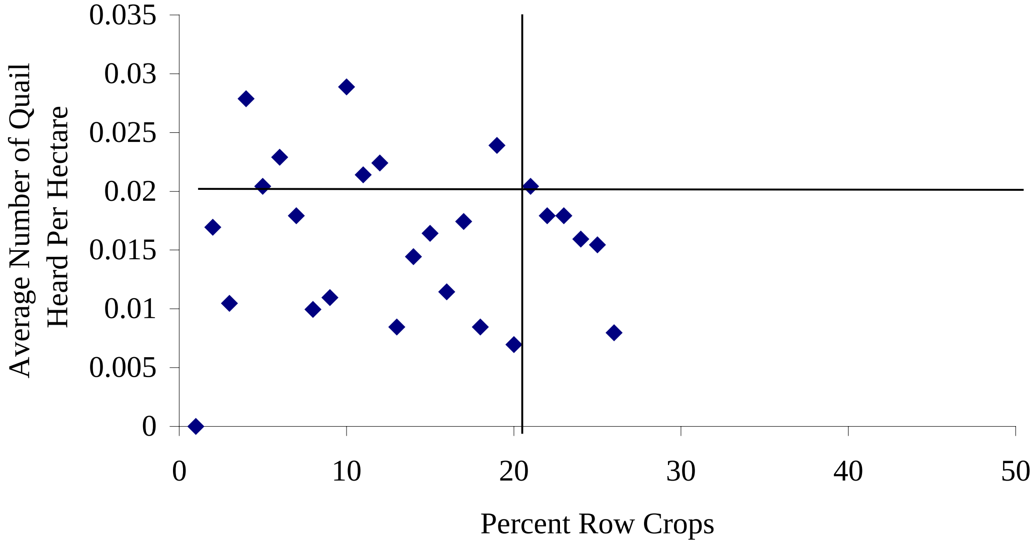
Williams, G. L., K. R. Russell, and W. K. Seitz. 1978. Pattern recognition as a tool in the ecological analysis of habitat. Pages 521-531 *in* Classification, inventory, and analysis of fish and wildlife habitat: Proceedings of a national symposium. U.S. Fish and Wildlife Service Biological Services Program FWS/OBS-78/76.

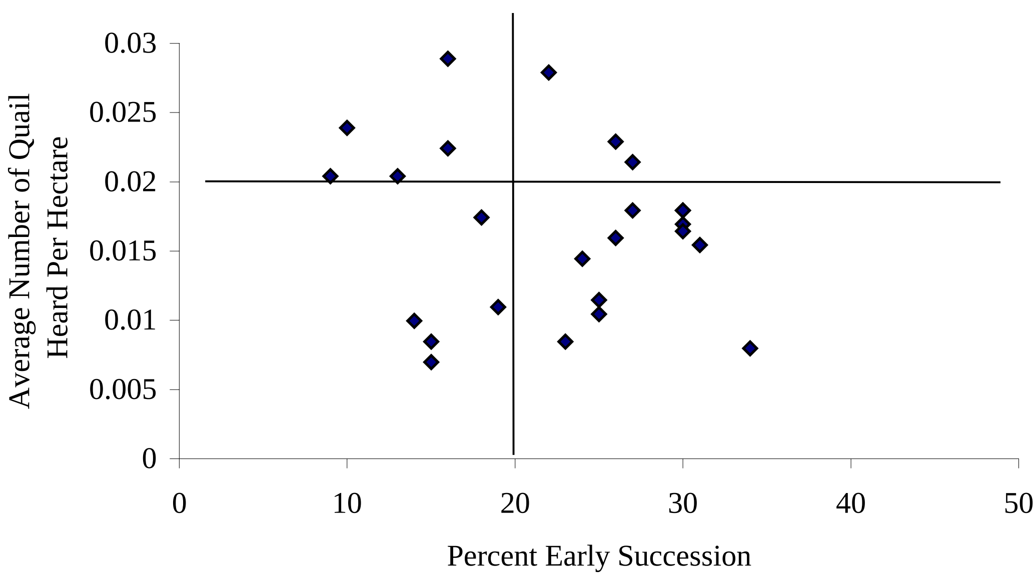
Williamson, J. F. 1981. Dynamic classification: Conceptual development and applications in wildlife management. Ph.D. Dissertation, Virginia Polytechnic Institute and State university, Blacksburg, Virginia. 231pp.

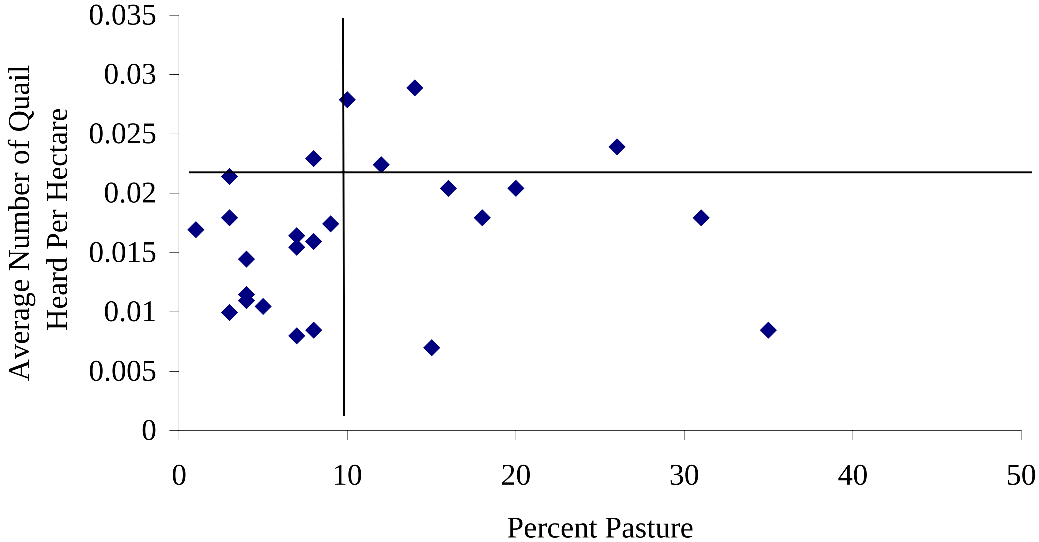
Wynne, R.H., and D. B. Carter. 1997. Will remote sensing live up to its promise for forest management? Journal of Forestry 95(10):23-26.

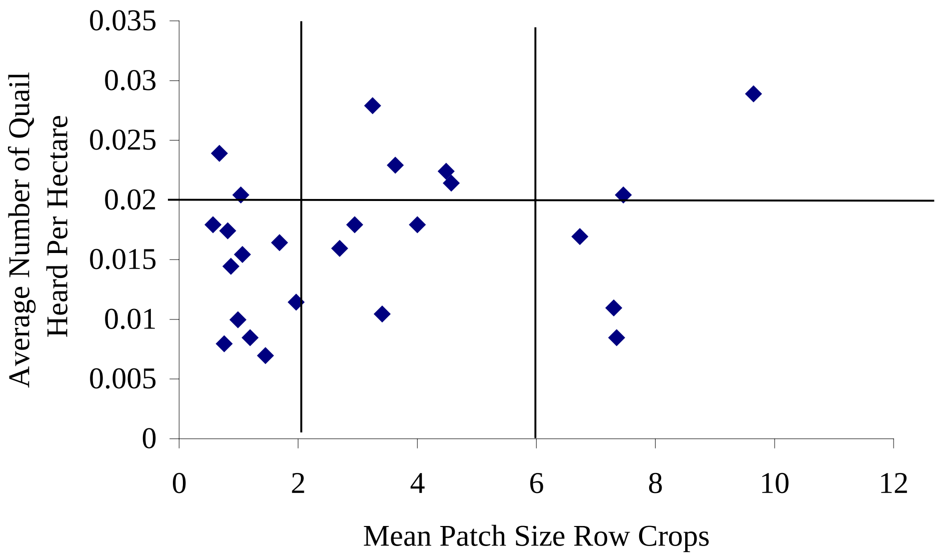
Zar, J. H. 1984. Biostatistical analysis. 2nd Edition. Prentice-Hall Inc. Englewood Cliffs, New Jersey. 718pp.

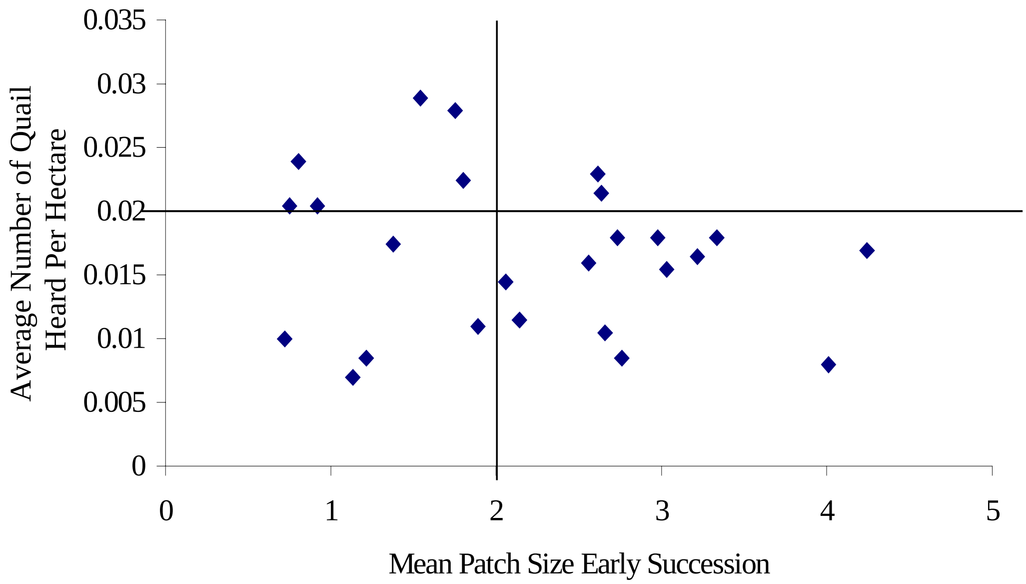
Appendix A. Scatterplots showing splits in data used for PATREC modeling.

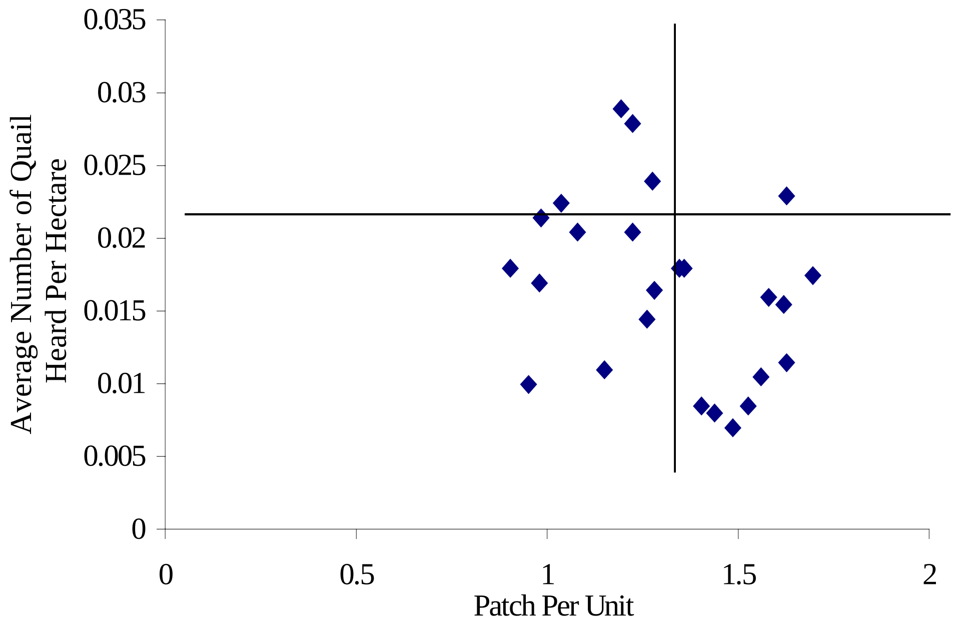





0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
10
20
30
40
50
Average Number of Quail
Heard Per Hectare
Percent Pasture


0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
2
4
6
8
10
12
Average Number of Quail
Heard Per Hectare
Mean Patch Size Row Crops


0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Average Number of Quail Heard Per Hectare
0
1
2
3
4
5
Mean Patch Size Early Succession


0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Average Number of Quail Heard Per Hectare
0
0.5
1
1.5
2
Patch Per Unit

Vita

Garrett Lauren Schairer was born in Syracuse, NY to August G. and Shirley I. Schairer. After graduating from Liverpool High School, he attended the University of Maine. While in Maine he studied Wildlife Ecology and Forestry. He spent his junior year at the University of Montana in Missoula, Montana. In May 1996, he earned his Bachelor of Science in Wildlife Ecology. In August of 1996, he came to Virginia Polytechnic Institute and State University to pursue a Master of Science degree. While at Virginia Tech, he was active with the Student Chapter of The Wildlife Society, serving as the student representative to the State chapter of The Wildlife Society from 1996 to 1998.