A SATELLITE DERIVED MAP OF ECOLOGICAL SYSTEMS

IN THE EAST GULF COASTAL PLAIN, USA

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A SATELLITE DERIVED MAP OF ECOLOGICAL SYSTEMS IN THE EAST GULF COASTAL PLAIN, USA

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Kevin James Kleiner, son of Thomas and Lynette Kleiner, was born on December 1, 1969 in Waukegan, Illinois. He graduated from Grayslake Community High School in 1987 and completed a bachelor of science degree in Mechanical Engineering at the University of Illinois at Urbana-Champaign in May, 1993. He is currently employed by Auburn University as a Research Assistant in the School of Forestry and Wildlife Sciences. On February 11, 1995 he married Carol Johnston, daughter of Merle and Robert Johnston. They have two daughters, Sipsey Grace and Abbott Lucile (Abbey).

THESIS ABSTRACT

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Land cover mapping via remote sensing is an important tool for conservation and land management. A critical component to land cover mapping is defining the classification. A classification scheme must be sufficiently detailed to meet the goals to which the map will be applied yet simple enough to accurately map the classification units with the available data and classification methods.

This thesis describes the methods and presents the results and accuracy assessment of a map of NatureServe's Ecological Systems in the East Gulf Coastal Plain, USA derived using Landsat ETM+ imagery. A combination of remote sensing techniques and classification methods was used to generate a 50 class land cover map.

Of 43 Ecological Systems existing in the East Gulf Coastal Plain, 25 were mapped and an additional 8 modified system classes were mapped. The remaining 17 mapped land cover classes were composed of anthropogenic classes and land cover lacking vegetation.

Additionally, an accuracy assessment of the land cover map was performed and interpreted by assessing the causes of error. In this land cover map, a majority of the errors are caused by either fuzzy boundaries between class definitions or a lack of spatial data that can reliably separate classes. This error analysis provides insight into the utility of the classification scheme when mapping with remotely sensed data.

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INTRODUCTION

The management and conservation of biodiversity is a topic of ever increasing concern. As the human population continues to grow, our encroachment into and modification of natural environments increases. The negative consequences of this trend include reductions in the population sizes and available habitats for other organisms (Primack, 2002). To better understand how our environment is changing and make decisions regarding how limited resources should be applied, accurate land cover maps depicting existing vegetation are needed.

Vegetation Classification

Classification is the process of creating multiple groups of objects where there is greater similarity among objects within a single group than among objects in different groups. This can be a useful organizing procedure provided the utility gained from the new groups outweighs the information lost from generalizing and ignoring differences between things in the same group (James, 1985). Because of the variability and complexity seen in nature, plant ecologists have long been classifying vegetation into simpler, discrete units. But from the earliest days of ecology, there has been debate about whether this is even feasible. In the early 1900's, leading plant ecologists thought a species response to habitat was the dominant force in structuring vegetation (Noy-Meir, 1987). Some ecologists believed that plant species tended to cluster together in repeating patterns, while others were unconvinced. Clements, an early believer in the existence of communities, is credited with establishing this idea as the organismic view. He stressed positive interactions among plants as a second major force in structuring vegetation (Clements, 1920). These interactions increase the probability that a species will be near another species with which it has a positive association. The continuum view put forth by Gleason (1926), however, argued that species affinities transition gradually in response to changes in the environment. Gleason stressed individual responses of species to the environment, random events from dispersal, and disturbance (Noy-Meir, 1987). From his perspective, attempts at community classification are unproductive.

In Europe a more quantitative approach to understanding vegetation was developing in the early 1900's. Braun-Blanquet developed the idea of the diagnostic species as defining a community (Noy-Meir, 1987). Du Rietz (1928) tried to link empirical data with a causal theory of plant communities. According to him:

1. combinations of some species are found more frequently than others
2. associations, as defined by dominants, exist in fairly discrete units, even across continuous habitat transitions.

3. when an association is sampled with quadrants of set size, the frequency of species has a U-shaped distribution. Most species are either very frequent or very rare.

Du Rietz thought that competition was responsible for the sharp association boundaries.

As sampling methods were developed to meet statistical requirements, it became apparent that sampling bias and subjectivity were responsible for much of the disagreement between philosophies. Whittaker (1952) showed that when using truly random sampling, vegetation is largely continuous with some clustering of sites and species. Goodall (1966) stressed positive interactions and evolutionary adaptations of secondary species (facilitation) and the unusually large importance of some species (keystone species). Whittaker and Levin (1977) looked at communities from a broader scale and emphasized the concepts of patches and mosaics. This renewed an appreciation of scale as being fundamentally important to understanding communities.

Despite the many advances, both quantitative and causal, there has been no great theoretical advancement or general hypotheses of plant communities. This may reflect the realization that ecological processes are too complex to expect broad scale, general patterns and therefore, the classical theories are inadequate. This does not reject the idea of the community as being a useful concept, but rather accepts the notion that, despite rigid sampling efforts, community descriptions are inherently subjective and are best treated as working hypotheses rather than clearly defined entities. It is also worth noting that some communities are much better defined, with distinct boundaries, but others have more subtle transitions. No general theory exists because there are many kinds of communities.

Given that nearly a century of effort has gone into quantitative community classification without any unified theory, it should come as no surprise that there are different approaches to community classification. Although they likely have continuous boundaries, communities do exist and have measurable attributes. These include physiognomy, life form, canopy coverage, species composition, species richness, and species proportion (Barbour et al., 1999). Vegetation classification attempts to place similar sampled units together, clearly separating them from other sampled units.

There are different approaches to classification, both conceptual and statistical (Barbour et al., 1999). Dominance based classification looks at only one or two dominant species. These are frequently overstory dominants, but it is also common to create a classification using one overstory dominant and one forb dominant. With this approach all other species are excluded from the classification. Another approach is classifying sampling units into communities based on the entire flora. Quantitative techniques such as the Braum-Blanquet releve' technique are used to create different vegetation orders (Poore, 1955). Classification can also be performed hierarchically, creating multiple classification levels. This is the approach taken by the National Vegetation Classification Standard (NVCS) in an attempt to standardize vegetation classification nationally (Grossman et al., 1998). As an example, the NVCS classification of the longleaf pine woodland is shown below:

Class II : Woodland

II.A : Evergreen woodland

II.A.1 : Tropical or subtropical broadleaved evergreen woodland

II.A.1.N : Natural / Semi-natural

II.A.1.N.a : Tropical or subtropical broadleaved evergreen woodland

CES203.375 : Longleaf Pine woodland

Ecosystem Classification

When choosing a classification scheme the map producer should consider both the end user and map production methods. What is the intended use of the map? What is the desired final or minimum class accuracy of the map? Are the desired classes even mappable? If the intended use of the land cover map is conservation of biodiversity, then classes should be constructed which are ecologically meaningful (Pearlstine et al., 1998; Schultz, 1967). This could be accomplished with an ecosystem classification, a classification approach which seeks to integrate climate, soil, landform, and vegetation into the class definitions (Kimmins, 2004). An ecosystem classification would have additional benefits as well. It would reduce the focus on individual species management, widely recognized as an inferior approach to conservation (Primack, 2002). To the extent that an ecosystem classification facilitated conservation and management of ecosystems, it would help ensure the continued existence of ecosystem processes and evolution (Bailey, 1996).

Many conservation organizations are currently using ecosystem classifications to help fulfill their missions of protecting and conserving biodiversity (Grumbine, 1994). The Gap Analysis Program (GAP) is a USGS funded program whose goal is to identify gaps in existing conservation reserves. Focusing primarily on vertebrates, the analysis is accomplished by spatially mapping an ecosystem classification, using this classification as a surrogate for vertebrate habitat, and determining how much of each species habitat is currently conserved (Csuti and Kiester, 1996). NatureServe, formerly part of the Nature Conservancy, is a private, nationwide conservation organization with extensive botanical field experience. They have spent many years developing community classifications (Brussard and Tull, 2007).

Although different ecosystem classifications exist (Eyre, 1980; FNAI, 1990; Jennings, 1997), GAP has chosen NatureServe's Ecological Systems as the mapping units for the next generation of GAP land cover mapping. Ecological Systems are a nationally consistent classification and represent NatureServe's assessment of the ecological management units within the United States (Comer et al., 2003). This classification was generated by vegetation ecologists and relies primarily on vegetation, often herbaceous vegetation, as the diagnostic characteristics of a system. These systems are more specifically defined in Comer et al. (2003) as follows:

> A terrestrial ecological system is defined as a group of plant community types that tend to co-occur within landscapes with similar ecological processes, substrates, and/or environmental gradients. A given terrestrial ecological system will typically manifest itself at intermediate geographic scales of 10s to 1,000s of hectares and persist for 50 or more years.

It is not strictly a vegetation classification scheme because it attempts to identify environmental processes which facilitate the existence of a particular community.

The Ecological Systems classification scheme is, to some degree, a climax or potential vegetation classification scheme (Comer et al., 2003). It does not provide a complete description of current vegetation, which vertebrate modeling requires. A prime example of this is the longleaf pine woodland. This is a fire maintained community that historically accounted for much of the East Gulf Coastal Plain (Frost, 1993). Due to timber harvesting and fire suppression, much of this area currently does not contain longleaf, even though this is the historically dominant vegetation.

Due to the fact that Ecological Systems describe climax vegetation, modifications were created to reflect actual vegetation. For the longleaf example, to better describe actual vegetation, we created two modifiers for this region: the loblolly modifier and the hardwood modifier. These 3 classes, loblolly modifier, hardwood modifier, and true longleaf, better describe current vegetation that exists on lands that were once longleaf woodlands.

Vegetation Mapping Via Remote Sensing

Maps, with vegetation depicted on them, have been in existence since at least the 15^{th} century (Küchler and Zonneveld, 1988). Initially, vegetation was added to maps to better convey locations and relationships between places (Küchler, 1967). Only later were vegetation maps recognized as useful by themselves. As distant travel became more common, scientists inquired about the distribution and mechanisms behind large scale vegetation patterns (Barbour et al., 1999). Schimper created the first modern vegetation map of the world in 1898. This map described vegetation life form and the classification scheme would be recognizable today as a form of global ecological land units (Küchler, 1967). In the United States, Shantz and Zon created the first map of pre-European vegetation in 1923 (Küchler, 1967). This classification of major forest and grassland types is still in use today.

Over time, our ability to make more precise maps has increased along with our need for better maps. In the 1930s, the federal government began to inventory land resources in an effort to buy land and retire it from agricultural use (Lins and Kleckner, 1996). Although ground surveys were used, this early fine scale mapping was the first large extent implementation of air photo interpretation for the purpose of land cover mapping in the United States. The first national map derived from aerial photography was created in the 1940s by Marschner (Anderson, 1967). This was a morphological or life form vegetation classification and was eventually published in 1950 under the title *Major Land Uses in the United States* (Marschner, 1950). In the 1950s, as urban expansion increased, local agencies began using land cover mapping to monitor urban growth. By the 1980s federal agencies became interested in increasing the thematic resolution in land cover mapping and using it to catalog and map biodiversity (Lins and Kleckner, 1996).

Remote sensing is currently the most efficient tool available for large extent land cover mapping (Gaydos, 1996). Many satellites are currently in orbit measuring the reflectance of energy from the earth's surface. These measurements are made continuously and consistently, relayed back to earth for storage, and provide a reliable record of earth surface reflectance. Different surface types reflect light differently, both in terms of intensity and wavelength (Jensen, 1986). Image analysts use these differences in reflectance to make inferences about land cover and create land cover maps.

Satellite image derived land cover mapping has been in existence since the 1970's (Lins and Kleckner, 1996). Initial focus was on separating broad categories of land use and land cover. Although these terms are frequently used interchangeably, land use appropriately refers to ownership and activity on the land whereas land cover describes the natural or anthropogenic substance covering the earth's surface (Avery and Berlin, 1992). Anderson et al. (1976, see Table 1) created a hierarchical system in which the first level distinguishes general land cover classes including urban, agriculture, water, rangeland and forest. Level 2 is more detailed and breaks each level 1 class into multiple classes. For example, agriculture gets separated into crop and pasture, orchards, confined feeding operations, and other agricultural land. Recognizing the need for large area land cover mapping, the USGS created the national land cover dataset (NLCD) based upon circa 1992 Landsat TM imagery. Covering the conterminous US at a grain of 30 meters, this was the first large area, fine grain land cover map (Vogelmann et al., 2001).

Although the Anderson et al. (1976) classification scheme forms the basis for much of the land cover classification performed today, for many applications these classes are not sufficiently detailed. While classes of land use are rather detailed, natural vegetation classes are broad. There are 7 urban classes in Anderson et al. (1976) level 2 classification but only 3 classes of forest lands. These natural vegetation classes may be too general for some purposes

The US Geological Survey's Gap Analysis Program (GAP) has been mapping land cover since 1987, specifically for the purposes of vertebrate modeling. As mentioned earlier, GAP projects have been initiated in all states except Alaska and projects are complete in 41 states (Gap Analysis Program, 2007). From these efforts several conclusions can be drawn: (1) we are frequently pushing and exceeding the limit of what can be discerned in the imagery (Pearlstine et al., 1998), (2) there is a tradeoff between thematic resolution and accuracy (the more classes mapped the less accurate the map will be) (Pearlstine et al., 1998), and (3) if states do not collaborate regarding their choice of map units then edge matching at state boundaries becomes a significant problem (Stoms, 2000). The first conclusion provides motivation for incorporating additional information beyond just spectral data into land cover mapping (Bolstad and Lillesand, 1992a; Hutchinson, 1982). The second and third conclusions emphasize the importance of selecting an appropriate classification scheme.

Remote Sensing Classification Methods

Satellite image classification has been a rapidly developing field for many years. Large increases in personal computing power have turned a process which once could only be performed on central mainframes into a much more variable and flexible endeavor (Gaydos, 1996). Attempting to catalog all approaches to image classification is a thesis by itself but I will cover the common ones. First, approaches can be broken into patch based and pixel based classification (Definiens Imaging, Inc., 2005). Image pixels are a digital information storage construct with no corresponding structure on the ground (Fisher, 1997). Delineating the image initially into patches is appealing because this is how land cover actually exists spatially.

Regardless of whether classifying pixels or patches, the next step is to decide whether to use training data (supervised classification) or a multidimensional clustering algorithm (unsupervised classification). These need not be done exclusively and in fact are often done in sequence.

When performing a supervised classification there are many methods that can be chosen including discriminant analysis, logistic regression, and decision trees (McDermid et al., 2005; Schowengerdt, 2007). More advanced software packages or independent modeling enables one to create heuristic algorithms or model building (ERDAS, Inc., 1997). External statistical packages allow one to create a statistically rigorous model.

Depending on the classification scheme, methods can produce comparable output or widely different results (Schowengerdt, 2007). Therefore, selection of a method is to a large extent dependent on the desired output. In remote sensing methodological studies, the desired output is often a statistical model relating spectral reflectance to cover type. In practical applications, such as land cover mapping, the desire is to balance the demand for complete methods documentation and repeatability with the need to produce the most accurate map possible. In this case, it is useful to think of classification in terms of how explicitly the classification algorithm can be defined.

The optimal product would be a defensible statistical model mapping all classes. There are limitations here though for several reasons. There may be insufficient training data to produce a reliable statistical model. The statistical model may produce a map which does not attain the desired accuracy. And finally, although there has been tremendous progress in the last 30 years, computer vision or pattern recognition algorithms are not yet sufficiently complex to match what humans can visually interpret in images (Overington, 1992). Classification via remote sensing began using manual interpretation of aerial imagery and today there is still a place for image interpretation in remote sensing analysis.

Manual interpretation should be used after more rigorous modeling has failed. A framework for producing a classification can be outlined as follows:

1. A data driven predictive model. Again, this is optimal and should tried first.

2. A producer defined model. This should be partially data driven but will not be a statistical model. Instead, the producer decides upon thresholds to create classes. This is the classical GIS information extraction technique and is often referred to as overlay analysis.
3. The last option is to simply recode known areas to a particular class. This is not predictive but can still be useful if a rare class with known patch extents must be included in the map. This is often referred to as "burning in."

All of these techniques are widely used in current land cover mapping efforts (Lillesand, 1994; McDermid et. al, 2005). The amount of information and utility provided to the end user of the classification decreases as the method moves from 1 to 3.

A final and more recent approach has been the inclusion of other spatial data layers in addition to satellite imagery to help inform the classifier (Hutchinson, 1982; Estes, 1985; Bolstad and Lillesand, 1992b). Often referred to as ancillary data, incorporation of data layers such as soils, ecoregions, and geology can improve classification if they are sufficiently correlated with the vegetation in the classification scheme (Loveland et al., 2002; Franklin et al., 1986; Bolstad and Lillesand, 1992a).

OBJECTIVES

This study will assess the utility of Ecological Systems as a classification scheme from a remote sensing perspective. It will start with the premise of using Ecological Systems as a mapping scheme and will not address the question of the validity of Ecological Systems as an ecological classification.

A map of Ecological Systems would be useful to land managers for planning, conservation organizations wanting to purchase land or easements, or landscape ecologists trying to understand patterns and trends across the landscape. For this reason the creation of quality land cover maps and understanding how to improve future maps are important endeavors.

My goal in this study is to map Ecological Systems in the East Gulf Coastal Plain (Fenneman, 1938; Homer et al., 2004) (see Figure 1). This study area was chosen to coincide with the study area of the ongoing Alabama Gap Analysis Project (AL-GAP, 2006). A list of Ecological Systems occurring within the East Gulf Coastal Plain (Comer et al., 2003) is provided in Table 2. Through the process of mapping these systems I will assess their mapping accuracy and, therefore, their utility as mapping units from a remote sensing perspective.

METHODS

Due to the complexity of the classification scheme, the creation of the land cover map followed a complex process. Figure 2 is a schematic of the general work flow. The description of methods will follow the general headings in the left hand side of this figure: Data Development, Ecological Systems Mapping, and Anthropogenic Class Mapping.

The final hybrid classification scheme consists of 4 types of classes: original NLCD 2001 classes, refined anthropogenic classes, Ecological Systems, and modified

Ecological Systems. The list of all 50 classes in the map and corresponding class type is shown in Table 3.

Data Development

Data used to create the map fell into 4 categories: point data identifying the location of Ecological Systems on the ground, satellite imagery, ancillary data used to enhance the accuracy of the classification, and an initial land cover classification (NLCD 2001). Each of these data development steps is described in detail below.

ECOLOGICAL SYSTEMS TRAINING DATASET

Point data were accumulated from a variety of sources (Table 4) to create an Ecological Systems training dataset. Some of these data were collected specifically in conjunction with the AL-GAP mapping project while other datasets were not. The data collected for the AL-GAP project by external personnel (Rob Evans, Al Schotz, Milo Pyne, from Table 4) contained, at minimum, the GPS coordinates and an assigned Ecological System at all sample points. Other datasets were either previous classifications that I subsequently assigned to Ecological Systems or databases of field plots (NatureServe) or locations of rare species (state heritage programs). If possible, I assigned plots and rare species locations to an Ecological System and this assignment was reviewed by Milo Pyne of NatureServe. Points that could not be confidently assigned to an Ecological System were not included in the final training dataset. These points were overlaid on satellite imagery and assessed for whether they occurred on land use edges or whether there was land use change between image dates. Points which occurred on edges or on sites where there was obvious change were excluded from the final training dataset.

Field data were also collected by AL-GAP. In most of these plots, additional information beyond GPS location and Ecological System was collected. This included relative tree densities, estimated basal areas, landscape position, whether the plot was in a wetland, and other information relevant to an ecological classification. Data from each source were merged and the final Ecological Systems training dataset contained approximately 3200 points.

SATELLITE IMAGERY

The base layer for the production of this land cover map was Landsat Enhanced Thematic Mapper plus imagery (Landsat ETM+). This is satellite imagery with a pixel resolution of 30 meters. All imagery was geometrically corrected by USGS's Center for Earth Resources and Observation Science (EROS) and has a maximum spatial error of +/- 30 meters (1 pixel) (Huang et al., 2002). I chose a minimum mapping unit for most classes of 900 square meters (1 pixel). Thirty meter cell resolution was also used in all other data development.

Three seasonal mosaics were used with each mosaic requiring 21 satellite scenes (63 images total), see Figure 3. Image acquisition dates (i.e., date when the data was acquired by the satellite) ranged from 07/30/1999 to 06/23/2003. Although I had image mosaics for all 3 seasons from the NLCD 2001 mapping, there was significant spectral variance between scenes in these mosaics. Because the Ecological Systems classification is more detailed with greater spectral overlap between classes, it was decided that a better normalized mosaic was needed.

For this reason additional scenes were acquired and the scenes were normalized and mosaicked using no change block regression as described in Hogland (2005). In this technique, digital numbers (DNs) are altered in a slave scene to better match the master scene through linear regression, change detection, and block averaging.

NLCD

An initial classification (NLCD 2001) using the same source imagery (Homer et al., 2004) was previously created (Grand et al., 2004) and this was used as the first stage of classification. The NLCD 2001 classes are shown in Table 5. The NLCD 2001 map was created using Classification and Regression Trees (CART) (Breiman et al., 1984; Quinlan, 1993). The NLCD methods developed nationally are described in Homer et al. (2004) and methods and results specific to Alabama are fully described in Grand et al. (2004). The vegetated classes in the initial classification were refined to create the map of Ecological Systems, as the remainder of the methods will discuss.

ANCILLARY DATA

For many Ecological Systems, spectral information, alone, is insufficient to accurately identify them. Furthermore, the Ecological Systems concept incorporates environmental factors into the classification scheme. One would expect that if environmental variables can be modeled spatially, these would be important predictive data layers. Therefore, spatial data from other sources, hereafter referred to as ancillary data, were incorporated into the mapping process (see Table 6) to increase classification accuracy. Ancillary data were incorporated at multiple stages and for specific Ecological Systems where a data layer was thought to potentially improve the classification.

The following data layers were created: National Wetlands Inventory (NWI), Black Belt soils, matrix system boundaries, blackwater range, brackish water boundary, landform model, and modified stream layers. Additionally, several anthropogenic classes required ancillary data. Data layers identifying quarries, clear cuts and utility swaths were created. More specific methods for each ancillary data layer are described below.

NATIONAL WETLANDS INVENTORY (NWI)

The national wetlands inventory (NWI) is a US Fish and Wildlife Service mapping program which identifies and categorizes wetlands within the United States (USFWS, 2007). These maps, generally created via manual interpretation of air photos at a scale of 1:80000, were created prior to the advent of widespread digital mapping. The Fish & Wildlife Service is currently working to digitize these maps but at the start of the AL-GAP project, there were very few digital maps in the EGCP. Therefore, AL-GAP initiated the task of collecting existing digital NWI maps, digitizing paper NWI maps, later contracting out the digitizing of paper maps, and the eventual assembling them into a statewide digital data layer. NWI follows the Cowardin (1979) wetland classification scheme, which is quite detailed. Furthermore, attribution of polygons is a large portion of the work involved in map digitization. Recognizing this, AL-GAP decided to only code the digitized maps as wet or nonwet.

Once the NWI layer was assembled, pixels were recoded to separate riparian wetlands from nonriparian wetlands. This was accomplished in several ways. Pixels were recoded to riparian or nonriparian based upon patch size, shape factor, National Hydrography Dataset (NHD) (USGS, 2001) overlay, and manual editing. Generally, large patches of pixels corresponded to the large river floodplains. A threshold of 3000 pixels was chosen above which all patches were considered riparian. Shape factor is a landscape metric which essentially is a ratio of the perimeter of the patch to the perimeter of a circle of equal area. The larger the shape factor, the more linear and convoluted the patch (Forman and Godron, 1986). A threshold of 2.4 was chosen above which all pixels within the patch were identified as riparian. Finally, the NWI layer was overlaid with the NHD layer. Any patches which intersected the NHD layer were identified as riparian. These methods were insufficient in the lower coastal plain because a much larger percentage of the area is identified as wet in the NWI. In the lower coastal plain, NWI was recoded to riparian only where it coincided with NHD pixels. Finally, manual editing further identified smaller riparian areas.

There were several 1:24000 topograhic quadrangle maps for which recent NWI maps did not exist. In these instances, older 1:40000 maps were digitized and inserted. The final result was a thematic raster layer covering the entire extent of the EGCP identifying NWI wetlands as either riparian or nonriparian.

BLACK BELT SOILS

Soil type is recognized to be one of the dominant forces controlling vegetation patterns (Barbour et al., 1999). This is especially true in the Black Belt, an area containing patches of extremely alkaline soil relative to surrounding areas (Wilson, 1981; Harper, 1920). There are several classes in the Ecological Systems classification specific to the Black belt, and it was thought that a detailed soil layer would be especially useful in identifying these systems. STATSGO, the statewide and courser grain soil map (NRCS, 2006a), was assessed and deemed not sufficiently useful. The SSURGO mapping program, on the other hand, is a county level soil mapping program which produces maps with greater spatial and thematic detail (NRCS, 2006b).

Again, the problem was one of data not being in digital format. Roughly half of the counties in the black belt had digital soils maps. AL-GAP digitized the parts of the remaining and available counties which intersected the Black Belt as defined by Omernik's Ecoregion map unit 65a, blackland prairie (Omernik, 1998).

For each county within the Black Belt, soil surveys were accessed through SoilDataMart (NRCS, 2006b) and soil types were assessed for their Black Belt vegetation affinity. This was done by looking at 2 attributes, pH concentration and suggested timber species. Three categories were created: high affinity (pH greater than 7 and *Juniperus virginiana* the recommended timber species), some affinity (pH greater than 7 but other timber species recommended), and no affinity (pH less than or equal to 7). Polygons were recoded to category, rasterized, and all counties merged. There were 2 counties in the Black Belt lacking county level soil surveys: Lowndes County, AL and Lowndes County, MS. For these, the coarser scale STATSGO data were incorporated. The result was a thematic layer identifying the location of Black Belt soil types.

MODIFIED MATRIX SYSTEM RANGES

The concept of matrix as the spatial distribution of an Ecological System is especially important for the purpose of mapping. A matrix system is the primary vegetation type in an area; the background or matrix within which other Ecological Systems are embedded (Comer et al., 2003). Conceptually, for a given location, there can only be one matrix vegetation type. In reality though, there is not a hard line where one matrix system ends and another begins. It has been shown that vegetation in the Southeastern US transitions along a gradient (Carter et al., 1999; Skeen et al., 1993). The problem with mapping this is that the matrix systems, to some extent, represent historical or potential vegetation. So no specific line can be identified on a map.

There are two ways of dealing with this. One can identify a best guess of where this line is and 1) let that line stand, however obvious, in the final map or 2) find a way to blur this line and better intergrade the matrix systems. I chose to do the latter, but in a way that reflects current vegetation and is therefore defensible. For each boundary between matrix types the final separation was created using Omernik's ecoregions, spectral data (NLCD 2001), and image objects generated in Ecognition. Ecognition is patch based, image processing and classification software (Definiens Imaging, Inc., 2005). It enables the user to generate image objects (i.e., patches) based upon the similarity of image pixels adjacent to one another. The precise algorithm used in Ecognition is proprietary but it is at minimum using DN value and a texture measure to generate the image objects (Definiens Imaging, Inc., 2005). Omernik's ecoregions were the primary data layer upon which initial matrix system ranges were delineated. TM imagery was then used as input to create image objects. Objects were classified by the relative composition of NLCD 2001 pine, hardwood, and mixed forest types. Finally, manual recoding was performed to re-label interior objects not immediately adjacent to the primary boundary. In this manner the initial boundaries were modified and better reflected both the fine scale features in the imagery and the transition in relative forest type, from pine along the coast and eastern edge of the mapping zone to more hardwood dominance further north and west. The final distribution of matrix system ranges is shown in Figure 4. The matrix system range map is particularly important for understanding the Ecological Systems classification. Each matrix Ecological System only exists within its range and no other matrix system can exist within another range. These areas are mutually exclusive and this layer had significant influence in the classification.

BLACKWATER RANGE

Coastal plain blackwater streams are characterized by high acidity and high dissolved organic carbon concentrations which give rise to their dark color. Having headwaters frequently in swamps, bogs, or marshes, and low stream velocities increases dissolved organic carbon. Flowing over mostly sandy soils reduces dissolved mineral concentrations and buffering capacity. These factors combine to reduce biological productivity (Smock and Gilinsky, 1992).

The range of blackwater streams was created by expert review. Dr. George Folkerts, a biology professor at Auburn University with extensive field experience in Alabama and Mississippi, was enlisted to identify which streams in the coastal plain had significant blackwater influence.

FRESHWATER/BRACKISH BREAK

This layer was created from a land cover classification created by the National Oceanic and Atmospheric Administration's (NOAA) Coastal Change and Analysis Program (CCAP) (NOAA, 2007). The circa 2001 CCAP classification scheme is similar to NLCD but wetlands are further separated according to whether they are palustrine or estuarine. These wetland classes provided the basis for generating a spatial layer showing which coastal areas were fresh and which were brackish.

First, wetland pixels were extracted from the land cover. This raster layer was then vectorized and polygons were generalized using the generalize option in Arcgis. Finally, smaller polygons (less than approximately 23000 m^2 or 25 pixels) were removed, nodata values were filled with adjacent values, and the vector layer was converted back to a raster layer.

MODIFIED HYDROGRAPHY

This ancillary layer was created by the Southeast Regional Gap Analysis Project (SEReGAP). The National hydrography dataset (NHD) consists of the delineated streams taken from the 1:24000 quad maps (USGS, 2001). But between adjacent quads there is inconsistency as to which order streams are identified. To remedy this inconsistency, a stream network was created from the National Elevation Dataset (NED) (USGS, 2006a). First, 1:100000 stream digital line graphs (DLGs) were incorporated into the digital elevation model (DEM) to force drainage. This was accomplished by rasterizing the DLGs, overlaying this raster onto the DEM, and subtracting 25 meters from the elevation at each pixel. Then the ARC/Info flow accumulation command was run to create a stream network. Flow accumulation produces a raster layer showing the number of cells which provide surface flow to each cell. This layer was visually compared to the more detailed portions of the NHD and a cutoff value was chosen where they best matched (personal communication, Matt Rubino, SEReGAP). The final output was a binary raster layer showing where streams exist.

LANDFORM MODEL

This ancillary layer was created by SEReGAP. The National Elevation Dataset (NED) DEM and modified hydrography layer were used to create landform categories following the methods in Anderson et al. (1998). For each twelve digit hydrologic unit code (HUC) (Seaber et al., 1987), a landscape position model was generated using a 30 by 30 square kernel. Then slope, aspect, and landscape position were integrated into discrete categories. In the EGCP, SEReGAP used a subset of the Anderson et al. (1978) landform categories. The 13 landform classes in this model are shown in Table 7 (Anderson et al., 1998).

QUARRIES

The quarries layer was created by manually digitizing around mines identified from a USGS coverage (Geonames, 2006) of mine locations obtained from SEReGAP. Additional mines were located through visual inspection of the TM mosaics.

CLEAR CUTS

A clear cut layer was created by comparing the NLCD 2001 classification to the older NLCD 1992 classification (USGS, 2007). Pixels that had changed from forest in the 1992 classification to either scrub/shrub or herbaceous in the 2001 classification were identified. This layer was further modified to remove small clear-cut patches and fill in non clear-cut pixels within larger clear-cut patches.

UTILITY SWATHS

Larger gas and power line right of ways were identified from existing coverages and in the satellite imagery. A national power line arc coverage (USCB, 2007) and a more detailed Mississippi Power lines coverage (MARIS, 2007) were overlaid on the TM imagery. Arcs were moved to spatially match locations in the imagery. Additional gas and power lines were visually identified in the imagery. Arcs were buffered by 30 meters and the resultant buffers were rasterized to produce a binary raster layer.

Ecological Systems Mapping

An important step in creating the map was finalizing the map legend by deciding which Ecological Systems would be mapped. Throughout the mapping process, and in consultation with the vertebrate modeling side of the project, the list of Ecological Systems (Table 2) to be mapped was narrowed down from an initial 39 Ecological Systems in the East Gulf Coastal Plain (Comer et al., 2003) to 23 Ecological Systems and 8 Ecological System modifications (31 total). Ecological systems were not mapped if they existed in patches too small to be identified remotely (less than 3 by 3 pixels or 90 by 90 meters) or if it was clear from preliminary examination that I had insufficient predictive data to map them.

Due to the complexity of the Ecological Systems classification scheme, it was clear that a single classification technique would not be sufficient to accurately map the Ecological Systems. Instead, a process evolved where multiple techniques were applied sequentially. This included image processing, GIS analysis, and spectral classification techniques including image subsetting, decision trees, spatial queries, logistic regression, unsupervised classifications (clustering), and direct image interpretation. A schematic of this process is shown in Figure 5. Essentially, classification techniques were applied, starting with a decision tree classifier, the most objective and statistically rigorous, and ending with manual image interpretation, the most subjective. After each classification step, the output model (decision tree output) or map (spatial query) was assessed. If the accuracy was acceptable, that model or map became final for that Ecological System and was incorporated into the final classification. Otherwise, the next most desirable classification technique was performed.

The first step (Figure 5) was to subset the image into subzones which would be mapped separately. Image subsetting is especially useful when mapping large areas (Lillesand, 1994). This is beneficial because it reduces: 1) the variability within individual ecological systems, 2) the affect of changing land use patterns, and 3) the number of classes in each zone. By breaking a large heterogeneous area into several smaller and more homogeneous areas, spectral variability within classes can be reduced. Six subzones were identified based upon physiography, ecoregions, and primary land cover type (see Figure 6).

After subsetting, a decision tree was generated using 80% of the training data, the image mosaics, and ancillary data. Decision trees were generated using See5 version 1.4. See5's tree generation algorithm identifies a threshold for each attribute (data layer) which maximizes class separations, compares changes in entropy for each attribute, and selects the attribute and threshold which minimizes global entropy (Quinlan, 1993). The accuracy of the decision tree was assessed using the remaining 20% of the training data. Initial decision trees for each of the 6 subzones are shown in Appendix 1.

Decision trees were created for two purposes. First, in several subzones the accuracy of the decision trees was sufficiently high (>75%) that these trees were used to classify their respective subzones. In these subzones the decision trees provided objective and fully documented and reproducible classification methods. In other subzones, where the accuracy of the decision trees were poor, the decision trees were inspected for unanticipated correlations that could provide insight into potential mapping approaches.

The second approach to classification (Figure 5) was spatial queries. In this method, multiple ancillary data layers or ancillary and satellite data were spatially intersected to define classes. For example, several Ecological Systems endemic to the Black Belt region were identified by intersecting the Black Belt soils data layer with the NLCD classification. This approach is not necessarily data driven but it is well documented and therefore repeatable.

The third approach to classification (Figure 5) was individual systems classification. At this stage focus moved away from mapping a subregion and instead I was concerned with only a single class. In one instance (longleaf pine), a statistically rigorous model was developed for a single class (Hogland, 2005). In general, however, at this stage of the classification framework an increasing amount of subjectivity necessarily enters the mapping process making repeatability difficult.

The final approach to classification was manual image interpretation. In this stage classes are mapped by visual interpretation, often with the aid of digital orthoquads (DOQs) (USGS, 2006b) or other ancillary imagery. Classes are identified manually and often rely on texture, context, or other aspects of visual identification which are difficult to quantify and codify in an algorithm. While this approach can be very subjective it is not necessarily less accurate than automated procedures.

SUBZONE METHODS

The mapping zone was divided into smaller mapping areas using a combination of ecoregions (Omernik, 1998) and Ecological System ranges. In this manner, a large heterogeneous area, was divided into 6 smaller relatively homogeneous areas. These were barrier, coastal, flatwoods, riverine, black belt, and upland (see Figure 6). A brief description of mapping methods for each subset follows:

Barrier

This subset contains 4 Ecological Systems with relatively distinct spectral signatures. In this subzone the initial CART model was acceptable and was used to classify the Ecological Systems.

Coastal

This subset contains 4 Ecological Systems. In the final CART model, two Ecological Systems (Maritime forest and Tidal Swamp) were combined. Post processing was performed on the resulting map to eliminate speckle of systems where they were obviously misclassified. This was accomplished by clumping individual classes, identifying patches with 2 or fewer pixels, and recoding these pixels to the majority class in a 3x3 kernel. In some instances, larger patches were recoded if it was clear from visual inspection that they were misidentified. As an example, the water edge of a beach-ocean interface can be misclassified as vegetation when it is clearly not when looking at other imagery. In this instance the vegetation patch would be coded water. Finally, the two combined systems were separated using the Freshwater/Brackish break ancillary layer and proximity to water.

Flatwoods

The flatwoods subzone has 9 Ecological Systems contained within it. Because of this larger number and the fact that many of these are wetlands with overlapping spectral ranges, the CART model was unable to separate them. Spatial queries were also unsuccessful because of a lack of ancillary data that could separate systems. For example, DEM derived layers have little predictive power because this area of the lower coastal plain has little relief. High resolution soil maps would probably have been useful for separating isolated wetlands, but these were unavailable. The final classification was produced subsetting the subzone by hydrologic regime using the NLCD 2001, TM mosaics, and the NWI layer. Vegetated classes from the NLCD were divided into uplands, riparian corridors, and isolated wetlands. Within each of these categories, Ecological Systems were identified by sequentially identifying classes, removing these pixels from the pool of unclassified pixels, and advancing to another Ecological System. Specific methods are described in the Individual Systems Classification section below.

Riverine

Conceptually, this is the large river floodplain ecoregion (65p) as identified by Omernik (1998). Spatially, it was delineated using the NLCD 2001 woody wet class (90). Large river floodplain is the only Ecological System in this subzone.

Black Belt

Ecological Systems in this subzone were mapped primarily by spatial queries. The NLCD, Black Belt soils, and Matrix system ranges were overlaid. Each combination of attributes from the various data layers were assigned to the most likely Ecological System. For example, a pixel mapped as deciduous forest in the NLCD and occurring on a soil type with a high affinity for Black Belt vegetation would be labeled as the Limestone Forest Ecological System. The major exception to the rule was Dry Chalk Bluff, which was mapped separately as described below in the Individual Systems Classification section.

Upland

Ecological Systems in this subzone were mapped primarily by spatial queries. Data layers used included NLCD, NWI, modified matrix system ranges, Blackwater range, and the landform model. The matrix Ecological Systems in this subzone were labeled by simply intersecting the NLCD and modified matrix system ranges. For example, any deciduous forest in the NLCD that fell within the Southern Loess Bluff Forest matrix system range was labeled the Southern Loess Bluff Forest Ecological System. The exception was the Longleaf Pine Ecological System which is described in the Individual Systems Classification section below.

POST PROCESSING

In all subzones there was additional post processing to further refine the classification. Classes were reviewed individually. Large areas which were clearly misclassified when comparing the classification to satellite imagery were either filtered or manually recoded. In the coastal subzone, for example, isolated pixels of Brackish tidal marsh (class 250) were initially classified in grasslands not immediately adjacent to the coast. These were recoded via a majority filter.

INDIVIDUAL SYSTEMS CLASSIFICATION

As stated earlier, several classes were mapped independently from the other classes in a subzone. The methods used for identifying classes individually are briefly described below:

EGCP Dry Chalk Bluff – These were mapped by selecting pixels in the cliff class of the landform model within a 5x5 window buffer of water (class 1). These are bluffs occurring along the major rivers in the Black Belt. Although a 3x3 window conceptually makes more sense (only bluffs immediately adjacent to water would be selected), a 5x5 window was chosen to allow for potential misregistration between the satellite imagery and the DEM. Only bluff pixels not greater than 2 pixels (60 meters) away from water are mapped as Dry Chalk Bluff .

EGCP Interior Upland Longleaf Pine Woodland - Open understory modifier - This system was the subject of intense study by Hogland (2005). Using logistic regression, he produced separate maps predicting the probability of occurrence of longleaf at each pixel, along with other land cover and forest types. I combined these separate probability layers to produce a single classification based upon which class was most likely to occur (maximum likelihood). The longleaf maximum likelihood was "burned" into the final upland classification. For further information on this class or method see Hogland (2005) or to access these probability layers see AL-GAP (2006).

EGCP Black Belt Calcareous Prairie and Woodland – Herbaceous modifier – This was mapped according to a spatial query and further limited to remove extrapolation outside the training set. The NLCD 2001 class scrub/shrub (55) was subjected to a series of unsupervised classifications to identify potential prairie. This was combined with class 71 (herbaceous /grassland) and pasture (83). This sum was intersected with Black Belt soils. Finally, extrapolation beyond the prairie training points in the original point dataset was removed by selecting pixels which only fell within the range for the IR bands (4,5,6) in the spring, summer, and fall mosaics corresponding to the locations of these training points.

EGCP Nonriverine Basin Swamp – This class was mapped in several different ways. First, they were identified by visually locating bay swamps on topographic maps, digital orthographic quarter quads (DOQQs), and satellite imagery. These were then manually digitized on the satellite imagery. Second, larger nonriparian clumps from the NWI layer were visually examined on satellite imagery and assigned to this class, if appropriate.

EGCP Southern Loblolly-Hardwood Flatwoods – The challenge for this class was defining a range. Although it doesn't readily appear in Omernik's ecoregion map, it is a distinct forest type in older state forest assessments (Dunston, 1910; Harper, 1943) and it is a distinct ecoregion in the Keys et al. (1995) ecoregion map. However, the spatial resolution of the Keys et al. ecoregion map was too course. A range was created through expert review (Milo Pyne, NatureServe) by identifying STATSGO soil types with an affinity for this forest type. Soil polygons were selected and clipped to the spatial extent of the Keys et al. ecoregion. Within this range, a series of unsupervised classifications was performed to identify this class. This Ecological System exists within a mosaic of pine plantation and riparian hardwood. Unsupervised classifications were visually interpreted using DN values, texture, and DOQ comparison.

EGCP Nonriverine Cypress Dome – This class was created by first manually defining a spatial range. Cypress domes exist in fairly distinct regions of the Florida panhandle, where they are in a matrix of pine flatwoods, and southern Alabama, where they exist in a matrix of agriculture on the Citronelle Formation (Osbourne, 1989). In each case, the range was created by delineating a polygon on the satellite imagery.

Cypress domes are also all circular and they have a fairly narrow size range so they are easily identified by shape or clumping and identifying manually. NLCD wetlands within the range were identified. These wetlands were clumped and riparian wetlands were removed. Of the remaining clumps, larger (greater than 30 pixels) and smaller (less than 5 pixels) ones were eliminated. The middle sized clumps were refined with an unsupervised classification and visual examination of the satellite imagery.

EGCP Jackson Prairie and Woodland – This class was manually burned in. Known occurrences from the original point dataset (see Table 4) were overlaid on DOQs and the prairie patches were digitized.

Anthropogenic Class Mapping

Not every pixel in the EGCP can correctly be attributed to an Ecological System. This is obviously true for land cover types such as water, urban, and agriculture. But there were also nonnatural vegetated land cover classes which AL-GAP decided to recognize, independent of NatureServe's Ecological Systems classification. Some of these classes were unaltered NLCD 2001 classes and others were more specific land use classes, from here on referred to as anthropogenic classes. Included in the anthropogenic class category are several nonvegetated but not truly anthropogenic classes such as water and unconsolidated shore.

Methods for mapping the anthropogenic classes are described below. More detailed explanations of the national guidelines for NLCD 2001 methods can be found in Homer et al. (2004) and Yang et al. (2003). Descriptions of methods and results specific to Alabama can be found in Grand et al. (2004) and Lee and Robinson (2004).

Open Water (Fresh) – Water (class 11) in the NLCD2001 classification and fresh in the Freshwater/brackish break ancillary layer.

Open Water (Brackish/Salt) – Water (class 11) in the NLCD2001 classification and brackish in the Freshwater/brackish break ancillary layer.

Open Water (Aquaculture) – This is a subset of what was originally Open Water (Fresh). In Alabama and Mississippi (exclusive of the Mississippi Alluvial Valley), commercial aquaculture facilities exist primarily in the Black Belt. In this area, water pixels were clumped. Riparian (patches greater than 150 pixels) and small patches (less than 10 pixels) were removed. The remaining clumps of pixels were visually examined to determine if they were aquaculture facilities. Aquaculture ponds are usually rectangular in shape and clumped. DOQs were also consulted when clump identity was unclear.

Developed Open Space – Taken directly from NLCD 2001, class 21.

Low Intensity Developed – Taken directly from NLCD 2001, class 22.

Medium Intensity Developed – Taken directly from NLCD 2001, class 23.

High Intensity Developed – Taken directly from NLCD 2001, class 24.

Bare Soil – This is a subset of the NLCD2001 Barren class (31). It occurs primarily in Eglin Air Force Base along targets and ranges and is also scattered within agriculture.

Quarry/Strip Mine/Gravel Pit – This class was created using the Quarries ancillary data layer.

Unconsolidated Shore (Lake/River/Pond) – This class is a subset of the NLCD2001 Unconsolidated Shore class (32) consisting of inland pixels adjacent to water.

Unconsolidated Shore (Beach/Dune) – This class is a subset of the NLCD2001 Unconsolidated Shore class (32) consisting of coastal pixels adjacent to water.

Evergreen Plantations – This class was created using image objects. The leaf off TM mosaic was subset by Omernik's level 4 ecoregions (Omernik, 1998). Within each ecoregional subset, image objects were generated and classified within eCognition. A training set was created by visually identifying plantation objects and nonplantation objects. eCognition then uses a nearest neighbor classification routine. After several trials, classification performed best when TM band 4 average value and TM band 4 standard deviation were selected as classification attributes. Upon completion of the automated classification routine, the classified objects were visually compared to the leaf off mosaic and recoded if I disagreed with the eCognition classification. I identified plantations visually using bands 4, 5, and 6. Important characteristics for visual recognition were average DN value, low patch texture (high degree of homogeneity), and patch shape (linear edges increased likelihood of the patch being a plantation).

Ecoregion subsets were then merged back together. Care was taken to map this class conservatively (errors of commission were avoided at the expense of increasing omission errors), especially in the lower coastal plain.

Successional Shrub/Scrub (Clear cut) – Shrub/Scrub (class 52 in NLCD 2001) was intersected with the Clear cut ancillary layer.

Successional Shrub/Scrub (Utility swath) – Shrub/Scrub (class 52 in the NLCD2001) was intersected with the Utility Swath ancillary layer.

Successional Shrub/Scrub (Other) – This class is the remaining pixels of Shrub/Scrub from the NLCD 2001 class 52 after class 125 and 126 and all Ecological System classes had been mapped.

Pasture/Hay – This is a subset of the NLCD 2001 Pasture/Hay class (81). A small fraction of NLCD 2001 Pasture/Hay class was eventually recoded to several Ecological Systems.

Row Crop – Taken directly from NLDC 2001, class 82.

Accuracy Assessment

Providing the accuracy assessment of a land cover map is an important part of mapping (Congalton and Green, 1999). An accuracy assessment lets the end user know if the map will be acceptable for his or her intended use. As land cover mapping has evolved, so have assessment methods. The traditional way of reporting assessment is with an independent set of samples where the true land cover can be compared to the mapped land cover. Often, accuracy is reported as a single value. But because there is often a wide range in accuracy among classes, a single value usually provides little information (Congalton and Green, 1999). A better way of reporting accuracy is with a cross tabulation table (SAS/STAT, 2007) which is known as an error matrix in the remote sensing literature (Jensen, 1986). This table shows the true class and the mapped class for all accuracy assessment points. It provides information on both the accuracy of each class and where confusion between classes exists. If a statistical measure is desired, Kappa is used to provide a measure of new information in the map (Cohen, 1960; Congalton, 1981). This is the difference between the error matrix accuracy and what one would expect with a randomly generated land cover map (Rosenfield and Fitzpatrick-Lins, 1986).

The data used to create the accuracy assessment for this classification came from multiple sources. Assessment data were withheld from the initial Ecological Systems training dataset. DOQs were used for interpreting points. Finally, field work was performed to collect additional point data. A decision was made to obtain a minimum of

25 points per class. This was not an optimal number (Congalton and Green, 1999), but one I arrived at when considering the existence of the initial accuracy dataset and our available resources for collecting additional data.

If there were 25 points for a particular class in the withheld Ecological Systems training dataset then no further points were collected. The second step, if needed, was to collect additional points from digital orthoquads (DOQs). Three DOQs per ecoregion were selected randomly for a total of 15. Within the extent of each DOQ footprint, the land cover map was processed to remove edge pixels and clump land cover patches. Patches greater than 9 pixels were then randomly selected by class, and a single point within each randomly selected patch was randomly generated. These points were then manually interpreted from the DOQs and TM imagery. Several Ecological System classes could not be confidently identified using manual interpretation of DOQs (Florida panhandle beach vegetation, dune and coastal grassland, Black Belt prairie, Limestone forest, and Longleaf pine woodland). These classes required additional field work. This was accomplished by either walking transects through areas on public lands for coastal classes, or selecting patches visible from roads of patches occurring on private land.

The final assessment dataset contained 1,268 points. Four classes do not have an accuracy assessment reported. Successional shrub/scrub utility swath (126) was not assessed because its incorporation was entirely dependant upon the utility swath ancillary data layer, which has unknown accuracy. The issue with the other three classes (Bare soil (17), Quarry/Strip Mine/Gravel Pit (18), and the Ecological System EGCP Jackson Prairie and Woodland (134)) is that only known occurrences were incorporated into the map, and so for these classes, there is no prediction of occurrence. Finally, a Kappa coefficient was calculated (Congalton and Green, 1999). This can be interpreted as the accuracy of the classification above that which could be expected from chance.

RESULTS

A map of the final Ecological Systems land cover map is shown in Figure 7. A list of class area and percent area is shown in Table 8. The class accounting for the largest area is the Loblolly modifier of the Upland Longleaf Pine Woodland (15.7%). The only other class accounting for at least 10 percent of the area is Pasture/Hay (11.4%). Classes accounting for between 5 and 10 percent of the area include: Interior Shortleaf Pine-Oak Forest - Mixed Modifier, Row Crop, and Small Stream and River Floodplain Forest. Finally, 29 of the 50 mapped classes each account for less than 1 percent of the area mapped. Although this is a relatively small area, these classes account for many of the mapped Ecological Systems which represent rare and diverse communities.

Classes were mapped via multiple methods as shown in Figure 5. Table 9 lists the final mapping method for each of the 50 classes. Five classes were mapped via CART. These classes were generated exclusively with spectral data. Twenty-six classes were mapped using spatial queries and ancillary data. Twelve classes were mapped individually, and of these 12, 7 required manual image interpretation. The remaining 7 classes were incorporated directly from the NLCD 2001 map without any additional processing.

The contingency table (error matrix) from the accuracy assessment is shown in Table 10. For the entire classification, the average user's accuracy is 56% and the area adjusted user's accuracy is 48%. The area adjusted accuracy weights the accuracy of each class by the percentage of area occupied by that class (Congalton and Green, 1999). It is worth reiterating here that these average numbers have little meaning when it comes to assessing the quality of the map. They are provided according to convention. Much more insight can be gleaned from looking at the error matrix, identifying individual class accuracies, and when a class has low accuracy, understanding which classes it is confused with.

The Kappa coefficient is also a useful measure for assessing the accuracy of a classification (Kalkhan et al., 1996). The Kappa coefficient for this classification is 0.56. Kappa can theoretically range from -1 to +1 but negative values indicate negative correlation, meaning that you would be better off with a completely random classification. Landis and Koch (1977) categorize Kappa values as follows:

> 0.8	strong agreement
0.4 – 0.8	moderate agreement
< 0.4	poor agreement

According to their definitions, this classification has moderate agreement.

Another informative approach to classification accuracy assessment is an inspection of each class individually. This is provided in Appendix 2. I have included a brief description of the confidence I have in each class, what is really being mapped, and potential ways of improving the classification for certain classes.

DISCUSSION

The classification procedure shown in Figure 4 is a hierarchy of classification methods. There is decreasing objectivity and repeatability as one moves through the methods from the top to bottom. Ideally, one would want a single, data driven model that would generate rules to create a classification. This is preferred because it would be 1) parsimonious, 2) objective, 3) repeatable, and 4) would enable error estimates at the pixel rather than class level. This is strong motivation for creating a single, statistically valid classification (the first classification approach in Figure 4).

However, there are other considerations. Users demand land cover maps with both thematic complexity (many classes) and high accuracy. Additionally, we lack the ability to create algorithms as sophisticated as human vision. Put simply, we can see more information in remotely sensed imagery than we can currently program computers to recognize. These considerations provide motivation to move down the classification hierarchy and utilize methods requiring a greater degree of input from the image analyst. This approach is less parsimonious, less objective, less repeatable, and allows for error estimates at the class level only. The recognition of this tradeoff deserves greater attention in the land cover mapping literature than it currently receives. The methods used to create this land cover map illustrate this tradeoff.

As previously stated, the area adjusted average user's accuracy is 48%. This means if one randomly selected pixels from the map, they would be accurate 48% of the time. It is hoped that the full error matrix in Table 10 along with the discussion of each class in Appendix 2 will provide a more useful assessment regarding whether classes may be appropriate for a particular purpose.

Another way to better understand the classification and assess its utility for a given purpose is to view how these classes would collapse back to the NLCD 2001. Table 11 shows the relationship between each class in the Ecological Systems map and the percentage of area which is covered in each NLCD 2001 class. As can be seen, while there is not a perfect hierarchical relationship, where each systems class exists within a single NLCD class, there is a high degree of fidelity between most Ecological Systems classes and a single NLCD class.

If an Ecological Systems class is deemed to be of insufficient accuracy by the user after reviewing the NLCD comparison and the accuracy assessment error matrix, several options exist. A user can 1) combine Ecological System classes based upon class accuracy and which class/classes there is confusion with or 2) recode all classes which are sufficiently contained within an NLCD class back to that NLCD class. An end user of this map can use this relationship to pick and choose Ecological Systems from the system map based upon their classification accuracy. A hybrid map can than be created which would include portions of both the NLCD 2001 and the Ecological Systems map. This new map would have greater overall accuracy than the Ecological Systems map and more thematic resolution (more classes) than the NLCD 2001 map.

After generating the map and accuracy assessment it can be instructive to revisit class definitions. Classes may have been mapped in such a way that they only partially captured the original class definition. The accuracy assessment could indicate that a class contains more or less variability than desired. Although unlikely, it is even conceivable that a class is entirely mapped incorrectly. Table 12 lists final descriptions for each class. This is not an attempt to redefine Ecological Systems or suggest an improved classification scheme. Rather, the goal is to inform the potential user what the mapmaker believes is a concise and accurate class description of what has been mapped.

Errors in a land cover map can be caused by many reasons and it is important to look at error source. This helps in understanding how to improve future classifications. Congalton and Green (1999) divide mapping error into 4 major categories: reference data error, sensitivity of classification scheme to observer variability, inappropriate use of remote sensing technologies, and mapping error. They point that in practice, inappropriate use of technique and mapping error are often difficult to separate. The purpose of separating them is to attempt to identify errors essentially due to mapping naiveté, where a more experienced person could produce a better map.

To better assess issues causing error in my classification, I expanded the mapping error to 3 categories. I based this decision upon which 2 classes were confused and how those 2 classes were mapped. The 3 new categories were spectral (class confusion likely spectral confusion), ancillary data model (class confusion caused by ancillary layer predicting incorrectly), or ancillary manual. This last class was chosen when the error was the result of manual interpretation or a manual delineation between classes. The aquaculture class, for example, was produced by manually identifying an area containing a high concentration of aquaculture facilities, and then identifying those facilities. If an aquaculture reference point was mapped as open water, it would be a manual ancillary data layer error.

Table 13 lists the types of errors and their frequency. Twelve percent of the errors were due to reference data error. These errors were primarily either land cover change or interpreter error (mislabeled reference point). Twenty percent of the error was from sensitivity of classification scheme to observer variability. The error in this category is caused by two things: poorly defined matrix system boundaries and poorly defined class boundaries due to the continuous nature of many ecological systems. This error can be directly attributed to the classification scheme. Twenty percent of the error is attributable to ancillary data map error. Error in this category is between classes where ancillary data is the primary predictive layer separating the classes. Ten percent of the error is attributed to manual delineation using ancillary data. In this category, ancillary data is not being used in a strictly predictive fashion. Rather, ancillary data is modified to, for example, limit the potential spatial range of a class. Finally, 6% of the error is attributed to inappropriate use of remote sensing technology. I reserved this category to apply to cases where classes are poorly mapped, and I lacked a method to map a system with reasonable accuracy. Spectral mapping error accounts for 32% of the overall error. This category accounts for cases where there is likely confusion due to spectral similarity between classes. As the number of classes in a classification scheme increases, it should be expected that spectral confusion increases. This is simply due to the fact that one is trying to divide up a fixed spectral range into smaller and smaller categories.

Analyzing the mapping error more critically, one can view errors from ancillary data as spectral errors. Ancillary data were used to separate classes where spectral data was insufficient. So if ancillary data had not been used, error attributed to ancillary data would have been attributed to a spectral cause. Spectral error would have been (32% +

20% + 10%) or 62% of the error and is an indication of the extent of error attributable to the incomplete predictive power of spectral information alone.

This number 62% is interesting in 2 respects. On one hand it seems very large. This by far is the primary cause of error and reducing this component of the error would significantly improve the map. Alternatively, it appears low. In an ideal classification, all error would be due to spectral confusion. In this instance, however, nearly 40% of the error can be attributed to other problems: issues with the classification system, reference data error, and inappropriate use.

In addition to creating the classification and developing mapping methods, the other objective of this thesis is to determine whether NatureServe's Ecological System classification is a realistic target classification scheme in the EGCP, given existing satellite imagery and ancillary data. Although I cannot address this question statistically, through the process of mapping and performing an accuracy assessment I have enough information to begin addressing this question. First, it is important to remember that only 25 of 39 (64 %) Ecological Systems were mapped in the EGCP (Table 2). The other 16 systems were excluded because it was determined that I did not have ancillary data to spatially model them (this includes classes designated small patch). Had these been included, accuracy would have been poorer. Second, there is an accuracy assessment providing estimates of users and producers class accuracies. In an effort to reduce the complexity of the error matrix, I categorized the individual systems user's accuracy into four categories: <25%, 26-50%, 51-75%, >75%. The percentage of systems in each category is shown in Figure 8. Although this is easier to interpret, much information is lost because one can no longer see what classes the system is confused with. It is also important to note that the acceptable accuracy for a system is application dependant and probably system dependent. But we can glean several things from this figure. Approximately a quarter (29%) of the systems were mapped well (accuracy > 75%), nearly two thirds (62%) of the systems were mapped moderately well (accuracy ≥ 51%), and approximately one third (38%) were mapped poorly (accuracy < 50%). Within this last class, I would recommend limiting my use of these classified Ecological Systems to applications where I was well aware of the potential implications of the limited accuracy.

A final Systems assessment can be performed by revisiting the cause of errors in the accuracy assessment. Referring to Table 13, 12 percent of error is attributed to reference data error. These errors were independent of the classification scheme. Six percent of the error is attributed to inappropriate use of technology. In this category, error exists because there was not an effective way to classify the Ecological System. This can be attributed to the decision to map a particular Ecological System. Twenty percent of the error was due to classification sensitivity. This category can rightfully be attributed to the classification scheme. Finally, summing the different map error types totals 62%. This is the error due to incomplete ability to predict the systems based upon existing data (dependant variables). From this assessment it is clear that much of the error is attributable to the classification scheme and a lack of data to predict the Ecological Systems with a high degree of accuracy.

For a land cover map to be useful it must have reasonably high accuracy. An absolute number cannot be chosen because what is useful is situation or application dependant. Further, land cover classes need to be chosen which have distinct boundaries. This requirement will minimize inaccuracies in reference point labeling and increase map accuracy and error estimates. A third and underappreciated aspect, is that data layers must exist or be generated that have the ability to accurately predict the class. A classification system may be very useful for categorizing existing vegetation when one is taking plots on the ground. But if spatial data, either spectral or ancillary, does not exist that can separate the classes and predict them with reasonable accuracy across a mapping zone, the vegetation classification system may have limited utility from a remote sensing perspective. All three of these issues were relevant in this map and limited the accuracy of this classification.

CONCLUSION

Despite a century of intense study, the classification of vegetation remains a challenging task today. When classifying vegetation via remote sensing, there is the additional task of relating vegetation to spectral reflectance. These issues are further complicated when mapping complex classification schemes over large areal extents.

Despite these challenges, I produced a reasonably accurate, Ecological Systems vegetation classification of the East Gulf Coastal Plain containing 50 classes. Although objectivity and repeatability were an initial goal, mapping was only accomplished by incorporating ancillary data, mapping sequentially in smaller subzones, and utilizing a variety of classification methods.

Error analysis indicates a substantial portion (62%) of the error in the classification is due to overlapping class boundaries, matrix systems representing pre-

European vegetation and therefore having unknowable ranges, and data layers lacking sufficient predictive capability. If the purpose of the Ecological Systems classification is to provide a classification system that can be mapped remotely, future work should focus on refining the classification scheme to one with more discrete boundaries that can be better modeled with existing geospatial data.

Table 1. Anderson Land Cover Classification System (from Anderson et al., 1976).

Level 1	Level 2
1 Urban	11 Residential
	12 Commercial
	13 Industrial
	14 Transportation and Utilities
	15 Industrial and Commercial
	16 Mixed Urban
	17 Other Urban
2 Agriculture	21 Cropland and Pasture
	22 Orchards
	23 Confined Feeding Operations
	24 Other Agricultural Land
3 Rangeland	31 Herbaceous Rangeland
	32 Shrub and Brush Rangeland
	33 Mixed Rangeland
4 Forest Land	41 Deciduous Forest Land
	42 Evergreen Forest Land
	43 Mixed Forest Land
5 Water	51 Streams and Canals
	52 Lakes
	53 Reservoirs
	54 Bays and Estuaries
6 Wetland	61 Forested Wetland
	62 Nonforested Wetland
7 Barren Land	71 Dry Salt Flats
	72 Beaches
	73 Sandy Areas other than Beaches
	74 Bare Exposed Rock
	75 Strip Mines, Quarries, and Gravel Pits
	76 Transitional Areas
	77 Mixed Barren Land
8 Tundra	81 Shrub and Brush Tundra
	82 Herbaceous Tundra
	83 Bare Ground Tundra
	84 Wet Tundra
	85 Mixed Tundra
9 Perennial Snow or Ice	91 Perenniel Snowfields
	92 Glaciers

Table 2. List of Ecological Systems occurring within the East Gulf Coastal Plain (from Comer et al., 2003). An asterisk denotes the system was not mapped.

NatureServe Code	Ecological System Name
*CES202.338	Alabama Ketona Glade and Woodland
*CES202.349	Allegheny-Cumberland Sandstone Box Canyon and Rockhouse
*CES202.357	Southern Interior Sinkhole Wall
*CES203.078	Southern Coastal Plain Herbaceous Seepage Bog
CES203.192	East Gulf Coastal Plain Treeless Savanna and Wet Prairie
CES203.251	Southern Coastal Plain Nonriverine Cypress Dome
*CES203.258	Southeastern Coastal Plain Interdunal Wetland
CES203.266	Florida Panhandle Beach Vegetation
*CES203.275	Southern Coastal Plain Spring-run Stream Aquatic Vegetation
CES203.299	East Gulf Coastal Plain Tidal Wooded Swamp
CES203.303	Mississippi Sound Salt and Brackish Tidal Marsh
CES203.375	East Gulf Coastal Plain Near-Coast Pine Flatwoods
CES203.384	Southern Coastal Plain Nonriverine Basin Swamp
*CES203.385	East Gulf Coastal Plain Interior Shrub Bog
CES203.476	East Gulf Coastal Plain Southern Mesic Slope Forest
CES203.477	East Gulf Coastal Plain Northern Mesic Hardwood Slope Forest
CES203.478	East Gulf Coastal Plain Black Belt Calcareous Prairie and Woodland
*CES203.479	South-Central Interior / Upper Coastal Plain Flatwoods
CES203.481	East Gulf Coastal Plain Northern Loess Bluff Forest
CES203.482	East Gulf Coastal Plain Northern Loess Plain Oak-Hickory Upland
CES203.483	East Gulf Coastal Plain Northern Dry Upland Hardwood Forest
CES203.489	East Gulf Coastal Plain Large River Floodplain Forest
CES203.492	East Gulf Coastal Plain Dry Chalk Bluff
CES203.493	Southern Coastal Plain Blackwater River Floodplain Forest
*CES203.494	Southern Coastal Plain Oak Dome and Hammock
CES203.496	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland
CES203.500	East Gulf Coastal Plain Dune and Coastal Grassland
*CES203.501	Southern Coastal Plain Hydric Hammock
CES203.502	East Gulf Coastal Plain Limestone Forest
CES203.503	East Gulf Coastal Plain Maritime Forest
*CES203.504	East Gulf Coastal Plain Southern Depression Pondshore
*CES203.505	Southern Coastal Plain Seepage Swamp and Baygall
CES203.506	East Gulf Coastal Plain Interior Shortleaf Pine-Oak Forest
*CES203.534	Panhandle Florida Limestone Glade
*CES203.554	East Gulf Coastal Plain Northern Seepage Swamp
CES203.555	East Gulf Coastal Plain Jackson Prairie and Woodland
CES203.556	East Gulf Coastal Plain Southern Loess Bluff Forest
CES203.557	East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods
*CES203.558	East Gulf Coastal Plain Northern Depression Pondshore
CES203.559	East Gulf Coastal Plain Small Stream and River Floodplain Forest
*CES203.560	Southern Coastal Plain Dry Upland Hardwood Forest
*CES202.691	Central Interior Highlands Calcareous Glade and Barrens
*CES203.353	East Gulf Coastal Plain Jackson Plain Prairie and Barrens

Table 3. Map legend, class type, and subzone.

Class No.	Class Name	Class Type[a]	Mapping Subzones[b]
1	Open Water (Fresh)	Anth	Fl, Ri, Bb, Up
2	Open Water (Brackish/Salt)	Anth	Ba, Co, Fl, Up
3	Open Water (Aquaculture)	Anth	Bb
4	Developed Open Space	NLCD	all
5	Low Intensity Developed	NLCD	all
6	Medium Intensity Developed	NLCD	all
7	High Intensity Developed	NLCD	all
12	Florida Panhandle Beach Vegetation	EcSy	Ba
17	Bare Soil	Anth	Co, Fl, Up
18	Quarry/Strip Mine/Gravel Pit	Anth	all
32	East Gulf Coastal Plain Dry Chalk Bluff	EcSy	Bb
35	Uncon. Shore (Lake/River/Pond)	Anth	all
36	Uncon. Shore (Beach/Dune)	Anth	Ba, Co
44	Interior Shortleaf Pine-Oak Forest - Hardwood modifier	MoES	Up
45	Limestone Forest	EcSy	Bb
46	Northern Dry Upland Hardwood Forest	EcSy	Up
47	Northern Loess Bluff Forest	EcSy	Up
48	Northern Loess Plain Oak-Hickory Upland - Hardwood Modifier	EcSy	Up
49	Northern Mesic Hardwood Forest	EcSy	Bb, Up
50	Southern Loess Bluff Forest	EcSy	Up
51	Southern Mesic Slope Forest	EcSy	Fl, Bb, Up
62	Interior Upland Longleaf Pine Woodland - Offsite Hardwood Modifier	MoES	Up
69	Black Belt Calcareous Prairie and Woodland - Woodland Modifier	MoES	Bb
71	Evergreen Plantations	Anth	Fl, Bb, Up
79	Maritime Forest	EcSy	Co
80	Northern Loess Plain Oak-Hickory Upland - Juniper Modifier	MoES	Up
94	Interior Upland Longleaf Pine Woodland - Loblolly Modifier	MoES	Up
95	Interior Upland Longleaf Pine Woodland - Open Understory Modifier	EcSy	Up
101	Northern Dry Upland HardwoodForest - Offsite Pine Modifier	MoES	Up
106	Interior Shortleaf Pine-Oak Forest - Mixed Modifier	EcSy	Up
125	Successional Shrub/Scrub (Clear Cut)	Anth	all
126	Successional Shrub/Scrub (Utility Swath)	Anth	all
127	Successional Shrub/Scrub (Other)	NLCD	all

132	Black Belt Calcareous Prairie and Woodland - Herbaceous Modifier	EcSy	Bb
134	Jackson Prairie and Woodland	EcSy	Up
143	Dune and Coastal Grassland	EcSy	Ba
148	Pasture/Hay	NLCD	all
149	Row Crop	NLCD	all
157	Large River Floodplain Forest - Forest Modifier	EcSy	Ri
158	Small Stream and River Floodplain Forest	EcSy	Fl, Bb,Up
163	Blackwater River Floodplain Forest	EcSy	Co, Fl, Up
179	Nonriverine Basin Swamp	EcSy	Fl, Up
186	Near-Coast Pine Flatwoods - Offsite Hardwood Modifier	MoES	Fl
187	Near-Coast Pine Flatwoods - Open Understory Modifier	EcSy	Fl
189	Southern Loblolly-Hardwood Flatwoods	EcSy	Up
195	Nonriverine Cypress Dome	EcSy	Fl, Up
206	Tidal Wooded Swamp	EcSy	Ma, Fl
233	Treeless Savanna and Wet Prairie	EcSy	Co, Ma
238	Large River Floodplain Forest - Herbaceous Modifier	MoES	Ri
250	Salt and Brackish Tidal Marsh	EcSy	Ba, Co

a. Class types: Anth = Anthropogenic, NLCD = National Land Cover Dataset, EcSy = Ecological System, MoES = Modified Ecological System
b. Occurs in mapping subzones: Ba = Barrier, Co = Coastal, Fl = Flatwoods, Ri = Riverine, Bb = Black Belt, Up = Upland, all = occurs in all subzones

Table 4. Sources of point data for training.

Alabama Natural Heritage Program, ALNHP-VEG database
Alabama Natural Heritage Program, DOQ interpretation by Al Schotz
AL-GAP field data (Hogland and Kleiner)
Eglin Air Force Base, field plots
Mississippi Natural Heritage Program, vegetation database
NatureServe, GAP targeted field points collected by Rob Evans
NatureServe, National Forest plots collected by Milo Pyne
Ron Wieland (formerly of the Mississippi State Museum) through NatureServe, personal collection
The Nature Conservancy - Alabama Chapter, known prairie localities from Georgia Pierson

Table 5. National Land Cover Dataset (NLCD) 2001 legend in the East Gulf Coastal Plain (from Homer et al., 2004).

Class Number	Class Name
11	Water
21	Developed, Open Space
22	Developed, Low Intensity
23	Developed, Medium Intensity
24	Developed, High Intensity
31	Barren Land (Rock/Sand/Clay)
32	Unconsolidated Shore
41	Deciduous Forest
42	Evergreen Forest
43	Mixed Forest
52	Shrub/Scrub
71	Grassland/Herbaceous
81	Pasture/Hay
82	Cultivated Crops
90	Woody Wetlands
95	Emergent Herbaceous Wetlands

Table 6. Ancillary data used.

Data Layer	Original Source Data	Creator*
NLCD 2001	circa 2000 ETM+ imagery	AL-GAP
NWI	NWI maps (USFWS)	AL-GAP
Soils	Surgo Soil Maps (NRCS)	AL-GAP
Blackwater Range	Expert Review	AL-GAP
Fresh/Brackish break	SECAP land cover	AL-GAP
Modified Hydrography	NHD and NED	SEReGAP
Landform Model	National Elevation Dataset (NED)	SEReGAP
Quarries and Mines	circa 2000 ETM+ imagery	AL-GAP
Clear Cuts	NLCD 1992 and NLCD 2001	AL-GAP
Utility Swaths	circa 2000 ETM+ imagery	AL-GAP
Ecological System Ranges	Omernik Ecoregions	NatureServe
Modified Matrix System Ranges	Omernik Ecoregions	AL-GAP

*AL-GAP – Alabama Gap, SEReGAP – Southeast Region Gap

Table 7. Landform classes of the landform model within the East Gulf Coastal Plain (modified from Anderson et al., 1998).

Flat summit/ridge
Slope crest
Cove/ravine – North/Northeast
Cove/ravine – South/Southwest
Steep slope - North/Northeast
Steep slope – South/Southwest
Sideslope - North/Northeast
Sideslope – South/Southwest
Moist flat
Slope bottom
Stream
Lake/river

Table 8. Area and percent area for each class (percent area rounded to 0.1%).

Class Number	Class Name	Area km^2	% Area
1	Open Water (Fresh)	3185	1.4
2	Open Water (Brackish/Salt)	6203	2.6
3	Open Water (Aquaculture)	127	0.1
4	Developed Open Space	10404	4.4
5	Low Intensity Developed	3321	1.4
6	Medium Intensity Developed	1042	0.4
7	High Intensity Developed	344	0.1
12	Florida Panhandle Beach Vegetation	19	<0.1
17	Bare Soil	239	0.1
18	Quarry/Strip Mine/Gravel Pit	96	<0.1
32	Dry Chalk Bluff	3	<0.1
35	Unconsolidated Shore (Lake/River/Pond)	59	<0.1
36	Unconsolidated Shore (Beach/Dune)	72	<0.1
44	Interior Shortleaf Pine-Oak Forest - Hardwood Modifier	10807	4.6
45	Limestone Forest	197	0.1
46	Northern Dry Upland Hardwood Forest	2331	1.0
47	Northern Loess Bluff Forest	1875	0.8
48	Northern Loess Plain Oak-Hickory Upland - Hardwood Modifier	1915	0.8
49	Northern Mesic Hardwood Forest	3379	1.4
50	Southern Loess Bluff Forest	1871	0.8
51	Southern Mesic Slope Forest	4580	2.0
62	Interior Upland Longleaf Pine Woodland - Offsite Hardwood Modifier	8992	3.8
69	Black Belt Calcareous Prairie and Woodland - Woodland Modifier	81	<0.1
71	Evergreen Plantations	10249	4.4
79	Maritime Forest	359	0.2
80	Northern Loess Plain Oak-Hickory Upland - Juniper Modifier	277	0.1
94	Interior Upland Longleaf Pine Woodland - Loblolly Modifier	36794	15.7
95	Interior Upland Longleaf Pine Woodland - Open Understory Modifier	2362	1.0
101	Northern Dry Upland Hardwood Forest - Offsite Pine Modifier	243	0.1
106	Interior Shortleaf Pine-Oak Forest - Mixed Modifier	14936	6.4
125	Successional Shrub/Scrub (Clear Cut)	16939	7.2
126	Successional Shrub/Scrub (Utility Swath)	863	0.4
127	Successional Shrub/Scrub (Other)	7593	3.2

132	Black Belt Calcareous Prairie and Woodland - Herbaceous Modifier	64	<0.1
134	Jackson Prairie and Woodland	0*	<0.1
143	Dune and Coastal Grassland	39	<0.1
148	Pasture/Hay	26775	11.4
149	Row Crop	18087	7.7
157	Large River Floodplain Forest - Forest Mod	6854	2.9
158	Small Stream and River Floodplain Forest	18130	7.7
163	Blackwater River Floodplain Forest	6266	2.7
179	Nonriverine Basin Swamp	288	0.1
186	Near-Coast Pine Flatwoods - Offsite Hardwood Modifier	252	0.1
187	Near-Coast Pine Flatwoods - Open Understory Modifier	4282	1.8
189	Southern Loblolly-Hardwood Flatwoods	487	0.2
195	Nonriverine Cypress Dome	58	<0.1
206	Tidal Wooded Swamp	229	0.1
233	Treeless Savanna and Wet Prairie	269	0.1
238	Large River Floodplain Forest - Herbaceous Modifier	305	0.1
250	Salt and Brackish Tidal Marsh	481	0.2

* This class occupied only 545 pixels, just less than 0.5 km^2.

Table 9. Class Name and Classification Method (corresponding to Figure 5).

Class Num	Class Name	Classification Method
1	Open Water (Fresh)	spatial query with ancillary data
2	Open Water (Brackish/Salt)	spatial query with ancillary data
3	Open Water (Aquaculture)	manual image interpretation
4	Developed Open Space	decision tree classifier (NLCD)[1]
5	Low Intensity Developed	decision tree classifier (NLCD)[1]
6	Medium Intensity Developed	decision tree classifier (NLCD)[1]
7	High Intensity Developed	decision tree classifier (NLCD)[1]
12	Panhandle Beach Vegetation	decision tree classifier
17	Bare Soil	manual image interpretation
18	Quarry/Strip Mine/Gravel Pit	spatial query with ancillary data
32	Dry Chalk Bluff	individual system mapping[3]
35	Uncon. Shore (Lake/River/Pond)	manual image interpretation
36	Uncon. Shore (Beach/Dune)	manual image interpretation
44	Shortleaf Pine-Oak Forest - Hardwood modifier	spatial query with ancillary data[3]
45	Limestone Forest	spatial query with ancillary data[2]
46	N. Dry Upland Hardwood Forest	spatial query with ancillary data[3]
47	Northern Loess Bluff Forest	spatial query with ancillary data[3]
48	N. Loess Plain Upland - Hardwood Modifier	spatial query with ancillary data[3]
49	Northern Mesic Hardwood Forest	spatial query with ancillary data[2]
50	Southern Loess Bluff Forest	spatial query with ancillary data[3]
51	Southern Mesic Slope Forest	spatial query with ancillary data[2]
62	Longleaf Pine Woodland - Offsite Hardwood Modifier	spatial query with ancillary data[3]
69	Black Belt Woodland	spatial query with ancillary data[2]
71	Evergreen Plantations	individual class mapping
79	Maritime Forest	decision tree classifier
80	N. Loess Plain Upland - Juniper Modifier	spatial query with ancillary data[3]
94	Longleaf Pine Woodland - Loblolly Modifier	spatial query with ancillary data[2]
95	Longleaf Pine Woodland	individual system mapping
101	N. Dry Upland Hardwood Forest - Offsite Pine Modifier	spatial query with ancillary data[3]
106	Shortleaf Pine-Oak Forest - Mixed Modifier	spatial query with ancillary data[3]
125	Succ. Shrub/Scrub (Clear Cut)	spatial query with ancillary data[2]
126	Succ. Shrub/Scrub (Utility Swath)	spatial query with ancillary data[2]
127	Succ. Shrub/Scrub (Other)	decision tree classifier (NLCD)
132	Black Belt Prairie	individual system mapping[3]

134	Jackson Prairie and Woodland	manual image interpretation
143	Dune and Coastal Grassland	decision tree classifier
148	Pasture/Hay	decision tree classifier (NLCD)
149	Row Crop	decision tree classifier (NLCD)
157	Large River Floodplain Forest	spatial query with ancillary data[3]
158	Small Stream Floodplain Forest	spatial query with ancillary data[2]
163	Blackwater Floodplain Forest	spatial query with ancillary data[2]
179	Nonriverine Basin Swamp	manual image interpretation
186	Pine Flatwoods - Offsite Hardwood Modifier	spatial query with ancillary data[3]
187	Pine Flatwoods	spatial query with ancillary data[3]
189	S. Loblolly-Hardwood Flatwoods	individual system mapping[3]
195	Nonriverine Cypress Dome	manual image interpretation
206	Tidal Wooded Swamp	spatial query with ancillary data[2]
233	Treeless Savanna and Wet Prairie	decision tree classifier
238	Large River Floodplain Forest - Herbaceous Modifier	spatial query with ancillary data[3]
250	Salt and Brackish Tidal Marsh	decision tree classifier[3]

[1] NLCD (CART) denotes the class was taken directly from the NLCD 2001 classification (which was also created using CART).

[2] The modified matrix System ranges were the only ancillary data used. This layer was combined with the NLCD 2001 to produce the class.

[3] Ancillary data layers other than the modified matrix System ranges were used to produce the class.

Table 10. Contingency Table (Error Matrix) from the accuracy assessment. Correct class listed vertically and predicted class listed horizontally.

		1	2	3	4	5	6	7	12	17	18	32	35	36	44	45	46	47	48	49	50	51	62	69	71	79	80	94	95	101	106	125	126	127	132	134	143	148	149	157	158	159	163	179	186	187	189	195	206	233	238	250	Tot	Users Acc
Open Water (Fresh)	1	19		5													1																						1									1					27	0.70
Open Water (Brackish/Salt)	2		25						1					1																																						1	28	0.89
Open Water (Aquaculture)	3	1		24																																																	25	0.96
Developed Open Space	4				9	12	2													1	1			1							1							2			1												30	0.30
Low Intensity Developed	5					6	19																												1		2						1										29	0.21
Medium Intensity Developed	6						7	19																																													26	0.27
High Intensity Developed	7				1			19																																													20	0.95
Florida Panhandle Beach Vegetation	12								9					2																							11																22	0.41
Bare Soil	17																																																				0	---
Quarry/Strip Mine/Gravel Pit	18																																																				0	---
Dry Chalk Bluff	32	2										4			1																				1																		8	0.50
Uncon. Shore (Lake/River/Pond)	35												18																														1										19	0.95
Uncon. Shore (Beach/Dune)	36								19					22												1											7																49	0.45
Shortleaf Pine-Oak Forest - Hard.	44														27	1				6		3									3	1															1						42	0.64
Limestone Forest	45															10					1		5	4				2				2									2												26	0.38
N. Dry Upland Hard. Forest	46														1		18			2										3		2																					26	0.69
N. Loess Bluff Forest	47																	21			4											1									1												27	0.78
N. Loess Plain Upland - Hardwood	48														8				11	1							1																										21	0.52
N. Mesic Hardwood Forest	49																			7									1		1																						9	0.78
S. Loess Bluff Forest	50														2						22				1						1	1																					27	0.81
S. Mesic Slope Forest	51														1							7						2			1																						11	0.64
Longleaf Pine Wdlnd - Offsite Hard	62					1																6	17					4				1						1		1													31	0.55
BB Woodland	69																						1	15				1				2		1																			20	0.75
Evergreen Plantations	71																	1					2	1	20			3															1										28	0.71
Maritime Forest	79				1																					20			1								1				1		1		2	3		1	9	1			41	0.49
N. Loess Plain Upland - Juniper Mod.	80																			1					2		14							2																			19	0.74
Longleaf Pine Wdlnd - Loblolly Mod.	94																			2		4	5					34	6		2										2					1		1		1			58	0.59
Longleaf Pine Woodland	95																					1						17	12																								30	0.40
N. Dry Upland Hard. - Offsite Pine	101																			2					5					18																							25	0.72
Shrtlf Pine-Oak Forest - Mixed	106														5					3		3	1					1	1		31																2						47	0.66
Succ. Shrub/Scrub (Clear Cut)	125					1									2			2			2								2		2	7		9				1	1		1									3			33	0.21
Succ. Shrub/Scrub (Utility Swath)	126																																																				0	---
Succ. Shrub/Scrub (Other)	127			1	2	1									1						1											2		2	1			7	3		1									3			25	0.08
BB Prairie	132																																		1			8	2														11	0.09
Jackson Prairie and Woodland	134																																																				0	---
Dune and Coastal Grassland	143																									1											11															2	14	0.79
Pasture/Hay	148				3	1	1					1																						2				9	9		1									2		1	30	0.30
Row Crop	149					1	1							1																		2		1				6	9		1												22	0.41
Large River Floodplain Forest	157					1														1			3									1		2						34	1			2					12	3			60	0.57
Small Stream Floodplain Forest	158															2				1		1																			8			1			5						18	0.44
Miss Lower Floodplain Forest	159																				3																																3	---
Blackwater River Floodplain Forest	163																					2	1					3				1		2						1	4		13	8	1	4		6	2	1			49	0.27
Nonriverine Basin Swamp	179																											1																36		1		3					41	0.88
Pine Flatwoods - Offsite Hardwood	186																																										11	1	7	6							25	0.28
Pine Flatwoods	187					2																			1	1															1		7	1	1	15		2	4	2		5	42	0.36
S. Loblolly-Hardwood Flatwoods	189																								3						6	2									1						15						27	0.56
Nonriverine Cypress Dome	195																																															10					10	1.00
Tidal Wooded Swamp	206																									3																				1			2	2			8	0.25
Treeless Savanna and Wet Prairie	233																																													1				11		3	15	0.73
Large RiverForest - Herb. Modifier	238																																	6				3	6												10		25	0.40
Brackish Tidal Marsh	250																									1											1													3		34	39	0.87
	Gran	22	25	30	16	26	30	38	29	0	0	5	18	26	48	13	19	24	11	27	34	27	35	21	32	27	15	68	23	21	48	25	0	27	4	0	33	37	31	36	26	0	35	49	11	32	23	24	29	32	10	46		**0.56**
Producers Accuracy		0.9	1	0.8	0.6	0.2	0.2	0.5	0.3	---	---	0.8	1	0.8	0.6	0.8	0.9	0.9	1	0.3	0.6	0.3	0.5	0.7	0.6	0.7	0.9	0.5	0.5	0.9	0.6	0.3	---	0.1	0.3	---	0.3	0.2	0.3	0.9	0.3	---	0.4	0.7	0.6	0.5	0.7	0.4	0.1	0.3	1	0.7	**0.57**	

Table 11. Percentage of Ecological System class area occurring within NLCD class.

	Water	Developed, Open Space	Developed, Low Intensity	Developed, Medium Intensity	Developed, High Intensity	Barren Land	Unconsolidated Shore	Deciduous Forest	Evergreen Forest	Mixed Forest	Shrub/Scrub	Grassland/Herbaceous	Pasture/Hay	Cultivated Crops	Woody Wetlands	Emergent Herb. Wetlands
Open Water (Fresh)	99														1	
Open Water (Brackish/Salt)	100															
Open Water (Aquaculture)	99															
Developed Open Space		98									2					
Low Intensity Developed			100													
Medium Intensity Developed				100												
High Intensity Developed					100											
Florida Panhandle Beach Vegetation	3	1	8	1			77				1	8		2		
Bare Soil						93	2						2	2		
Quarry/Strip Mine/Gravel Pit						99					1					
Dry Chalk Bluff	5	2						49	6	5	23	1	5	1	2	1
Unconsolidated Shore (Lake/River/Pond)							100									
Unconsolidated Shore (Beach/Dune)		4	2				84				1	3	1	3		
Interior Shortleaf Pine-Oak Forest - Hardwood Modifier								96		1	3				1	
Limestone Forest	1							54	1	6	8				25	5
Northern Dry Upland Hardwood Forest								83		11	3				2	
Northern Loess Bluff Forest								88	2	4	3				2	
Northern Loess Plain Oak-Hickory Upland - Hardwood								80		11	6				3	
Northern Mesic Hardwood Forest								80		18	2				1	
Southern Loess Bluff Forest								73	4	18	2				2	
Southern Mesic Slope Forest								31	43	24	1				1	
Interior Upland Longleaf Pine Woodland - Offsite Hard.								96			2				1	
Black Belt Calcareous Prairie and Woodland - Wdlnd									60	33	7				1	
Evergreen Plantations									100							
Maritime Forest	2							1	75	2	7			1	7	4
Northern Loess Plain Oak-Hickory Upland - Offsite Pine									97		3					
Interior Upland Longleaf Pine Woodland - Loblolly Mod.								2	66	27	3				3	
Interior Upland Longleaf Pine Woodland		5						1	71	3	8	9			1	
Northern Dry Upland Hardwood Forest - Offsite Pine									99		1					
Interior Shortleaf Pine-Oak Forest								7	48	38	3				3	
Successional Shrub/Scrub (Clear Cut)											95	4				
Successional Shrub/Scrub (Utility Swath)								13	12	6	33	2	24		7	2
Successional Shrub/Scrub (Other)											96	3				
Black Belt Calcareous Prairie and Woodland - Herb.											29	2	69			
Jackson Prairie and Woodland		9						13	6	5	55	5	3		3	1
Dune and Coastal Grassland	1	2	8	1			10	2	13		39	14		5	2	2
Pasture/Hay											1	1	98			
Row Crop														100		
Large River Floodplain Forest - Forest Modifier								14	6	7	2				70	1
Small Stream and River Floodplain Forest								17	1	9	3				62	6
Blackwater River Floodplain Forest								6	29	22	3				38	3
Nonriverine Basin Swamp	2	1						3	45	4	5	1	1	1	38	1
Near-Coast Pine Flatwoods - Offsite Hardwood								98							2	
Near-Coast Pine Flatwoods									78	11	2				6	1
Southern Loblolly-Hardwood Flatwoods								2	72	20	1				5	
Nonriverine Cypress Dome	1	1						2	25	2	7		1	3	54	3
Tidal Wooded Swamp	2							1	22	3	2				68	2
Treeless Savanna and Wet Prairie							1		9		14	30	4	5	5	32
Large River Floodplain Forest - Herbaceous Modifier											43	10				46
Salt and Brackish Tidal Marsh	7								3		5	2	1		9	73

Table 12. Final class descriptions.

Class Number	Class Name	Description
1	Open Water (Fresh)	Open Water (Fresh)
2	Open Water (Brackish/Salt)	Open Water (Brackish/Salt)
3	Open Water (Aquaculture)	Aquaculture ponds
4	Developed Open Space	Low impervious urban areas : parks, golf courses, cemeteries
5	Low Intensity Developed	Low density urban: older residential neighborhoods
6	Medium Intensity Developed	Medium density urban: dense residential
7	High Intensity Developed	High density urban
12	Florida Panhandle Beach Vegetation	Frontal dune vegetation (*Uniola paniculata*)
17	Bare Soil	Unvegetated
18	Quarry/Strip Mine/Gravel Pit	Quarries
32	Dry Chalk Bluff	Cliffs along major rivers and tributaries where they dissect the Black Belt
35	Unconsolidated Shore (Lake/River/Pond)	Sand bars along larger streams and rivers, primarily in the lower coastal plain
36	Unconsolidated Shore (Beach/Dune)	Beach sand, completely unvegetated
44	Interior Shortleaf Pine-Oak Hardwood Modifier	Hardwood dominated uplands within the historic range of the mixed Forest - shortleaf pine - oak forest
45	Limestone Forest	Upland hardwoods on calcareous soils, only mapped in the black belt
46	Northern Dry Upland Hardwood Forest	Upland hardwoods east of loess influence, soils drier and less fertile
47	Northern Loess Bluff Forest	Mesic hardwood forests specific to the loess bluffs

48	Northern Loess Plain Oak-Hickory Upland - Hardwood Modifier	Upland hardwood forests within the area of loess influence
49	Northern Mesic Hardwood Forest	Hardwood forests on slopes
50	Southern Loess Bluff Forest	Mesic hardwood forests specific to the bluffs, within the range of southern magnolia
51	Southern Mesic Slope Forest	Hardwood forests on slopes, within the range of southern magnolia
62	Interior Upland Longleaf Pine Woodland - Offsite Hardwood Modifier	Hardwood dominated uplands, fire suppressed, within historic system range longleaf
69	Black Belt Calcareous Prairie Woodland - Woodland Modifier	Fire suppressed, cedar dominated grasslands in the black belt
71	Evergreen Plantations	Young dense managed pine
79	Maritime Forest	Coastal forests affected by wind and salt spray, both broadleaved and needle leaved
80	Northern Loess Plain Oak-Hickory Upland - Juniper Modifier	Offsite evergreen dominated stands in the northern loess plain
94	Interior Upland Longleaf Pine Woodland - Loblolly Modifier	Disturbed, loblolly dominant, within the historic longleaf system range
95	Interior Upland Longleaf Pine Woodland - Open Understory Modifier	Open pine woodlands, including longleaf woodlands
101	Northern Dry Upland Hardwood Forest -Offsite Pine Modifier	Offsite evergreen dominated stands east of the loess plain and north of the shortleaf pine - oak forest range
106	Interior Shortleaf Pine-Oak Forest - Mixed Modifier	Mixed and evergreen dominant upland forests within the historic shortleaf pine - oak system
125	Successional Shrub/Scrub (Clear Cut)	Deforested areas, succeeding to shrub

126	Successional Shrub/Scrub (Utility Swath)	Shrub or grass along utility right of ways
127	Successional Shrub/Scrub (Other)	Transitional shrubland
132	Black Belt Calcareous Prairie and Woodland - Herbaceous Modifier	Grasslands in the Black Belt
134	Jackson Prairie and Woodland	Known Jackson prairies patches
143	Dune and Coastal Grassland	Dune vegetation on the back slopes of dunes extending to Maritime forest
148	Pasture/Hay	Pasture and Hay
149	Row Crop	Row Crop
157	Large River Floodplain Forest - Forest Modifier	Floodplain forests along the major rivers (Chattahoochee, Choctawhatchee, Yellow, Escambia, Alabama, Cahaba, Tombigbee, Warrior, Pascagoula, and Pearl)
158	Small Stream and River Floodplain Forest	Floodplain forests along smaller streams and rivers
163	Blackwater River Floodplain Forest	Floodplain forests in the lower coastal plain within a delineated blackwater range
179	Nonriverine Basin Swamp	Bay swamps, containing both broadleaved and needle-leaved tree species, with minimal stream connectivity in the lower coastal plain
186	Near-Coast Pine Flatwoods - Offsite Hardwood Modifier	Hardwood dominated uplands in the coastal flatwoods range, fire suppressed
187	Near-Coast Pine Flatwoods - Open Understory Modifier	Evergreen forests in the coastal flatwoods range
189	Southern Loblolly-Hardwood Flatwoods	Mature loblolly and hardwood stands on flat or gentle slopes, restricted to interior flatwoods subsection, immediately south of the black belt
195	Nonriverine Cypress Dome	Cypress dominant depressional wetlands in the lower coastal plain
206	Tidal Wooded Swamp	Riparian freshwater swamps, forested, receiving daily flooding from tidal fluctuations
233	Treeless Savanna and Wet Prairie	Wet grasslands within the coastal flatwoods range

238	Large River Floodplain Forest - Herbaceous Modifier	Herbaceous vegetation within historic floodplains of the large rivers
250	Salt and Brackish Tidal Marsh	Coastal marsh

Table 13. Error types and frequency by error type.

Error Type	Frequency	Percentage
Reference data error	69	12
Inappropriate use of a technology	34	6
Classification scheme	116	20
Mapping error - ancillary data	112	20
Mapping error – spectral	181	32
Mapping error - manual with ancillary data	56	10
Total	568	100

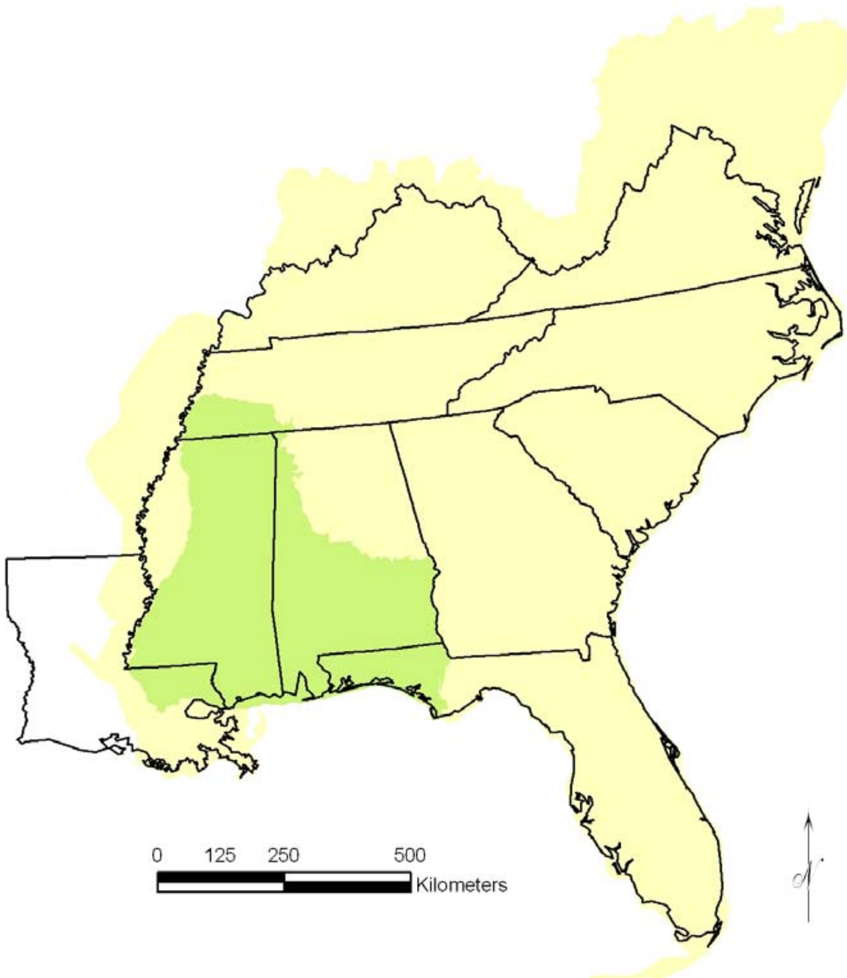

Figure 1. The East Gulf Coastal Plain (after Homer et al., 2004).

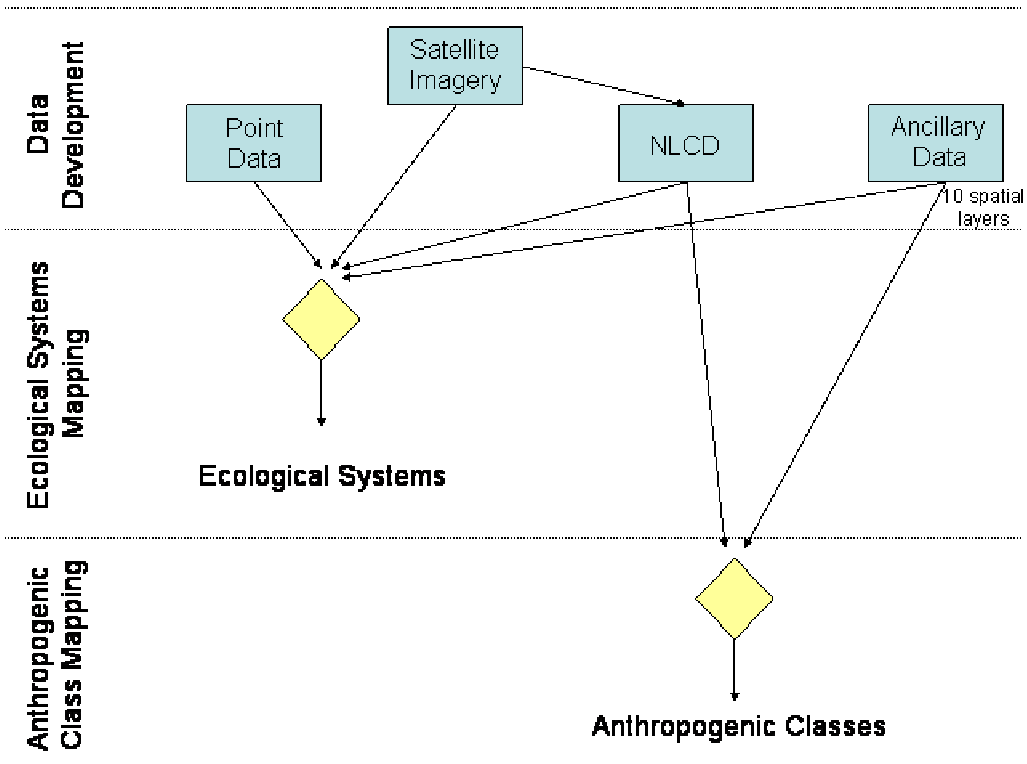

Figure 2. Schematic of classification methods and structure of methods discussion.

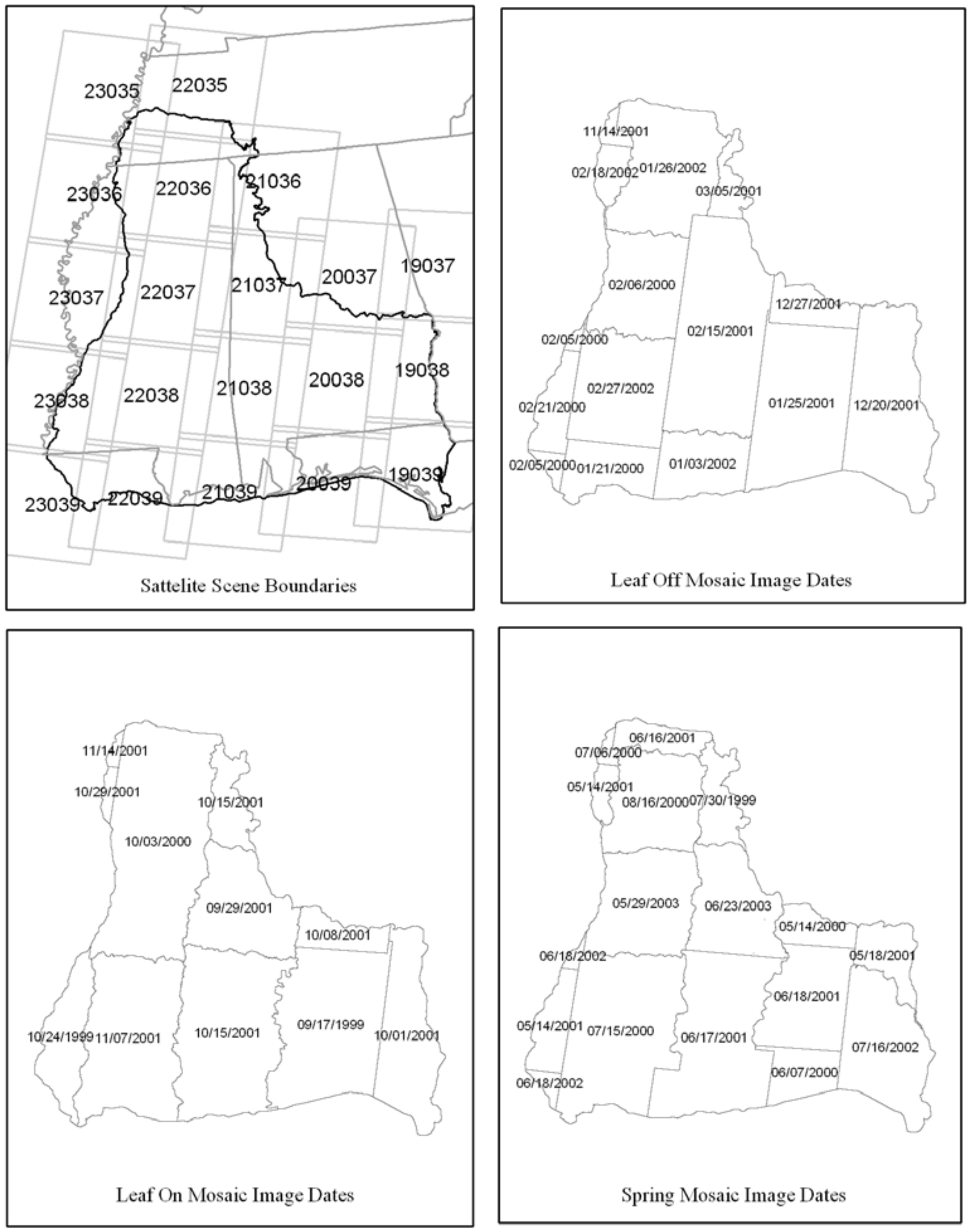

Figure 3. Scene boundaries and seasonal image mosaic boundaries with image dates.

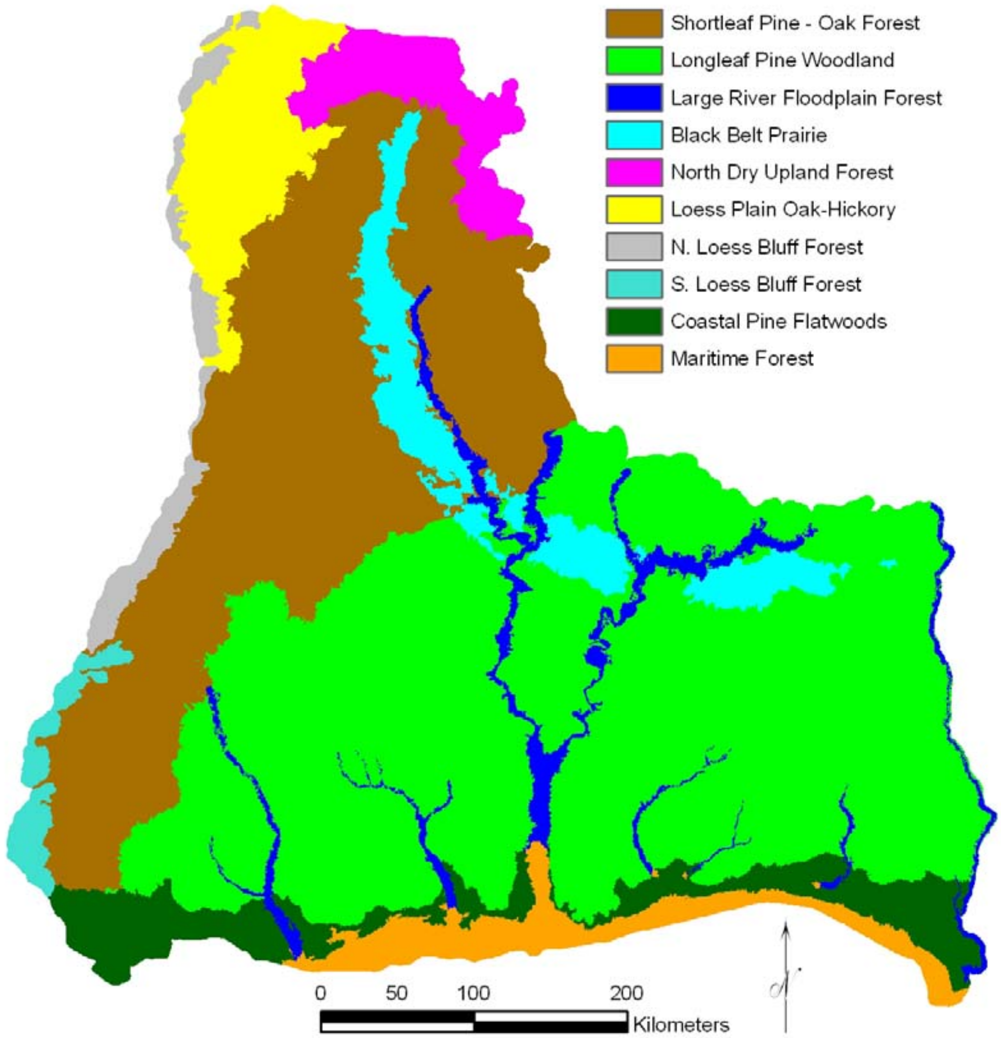

Figure 4. Map of matrix system ranges in the East Gulf Coastal Plain.

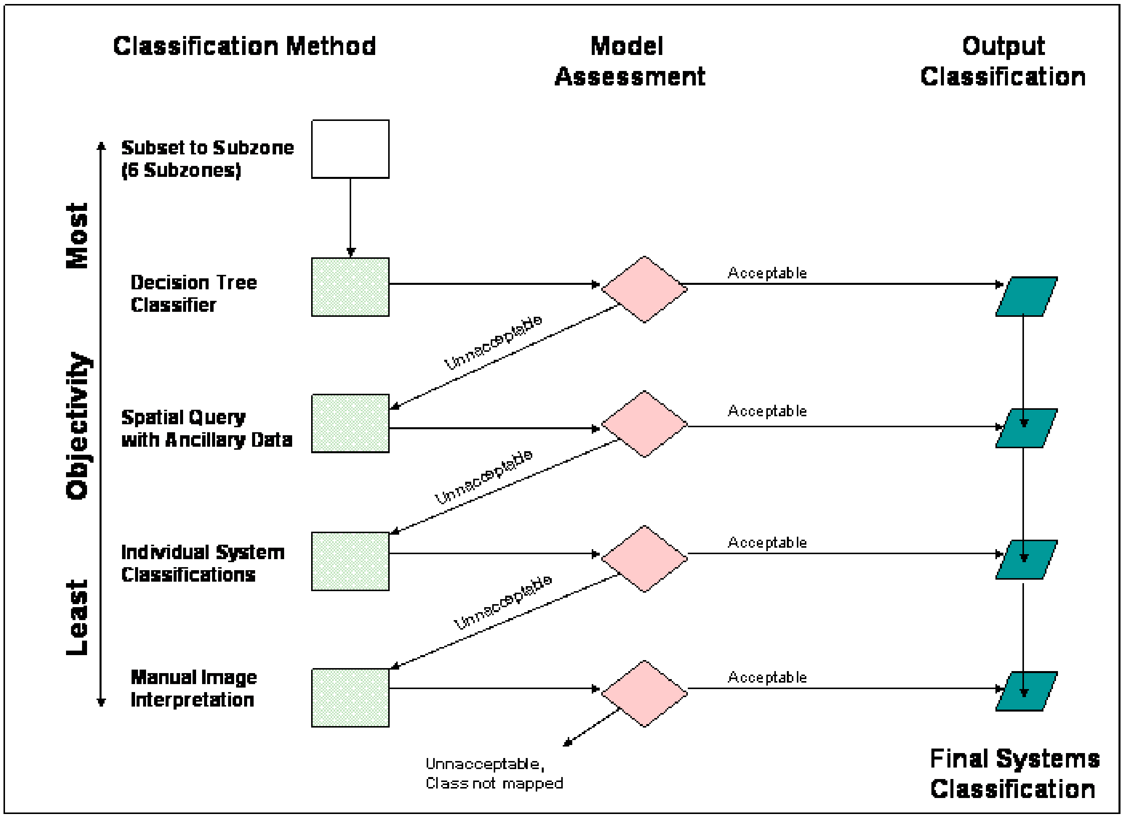

Figure 5. Diagram of the classification procedure for Ecological Systems.

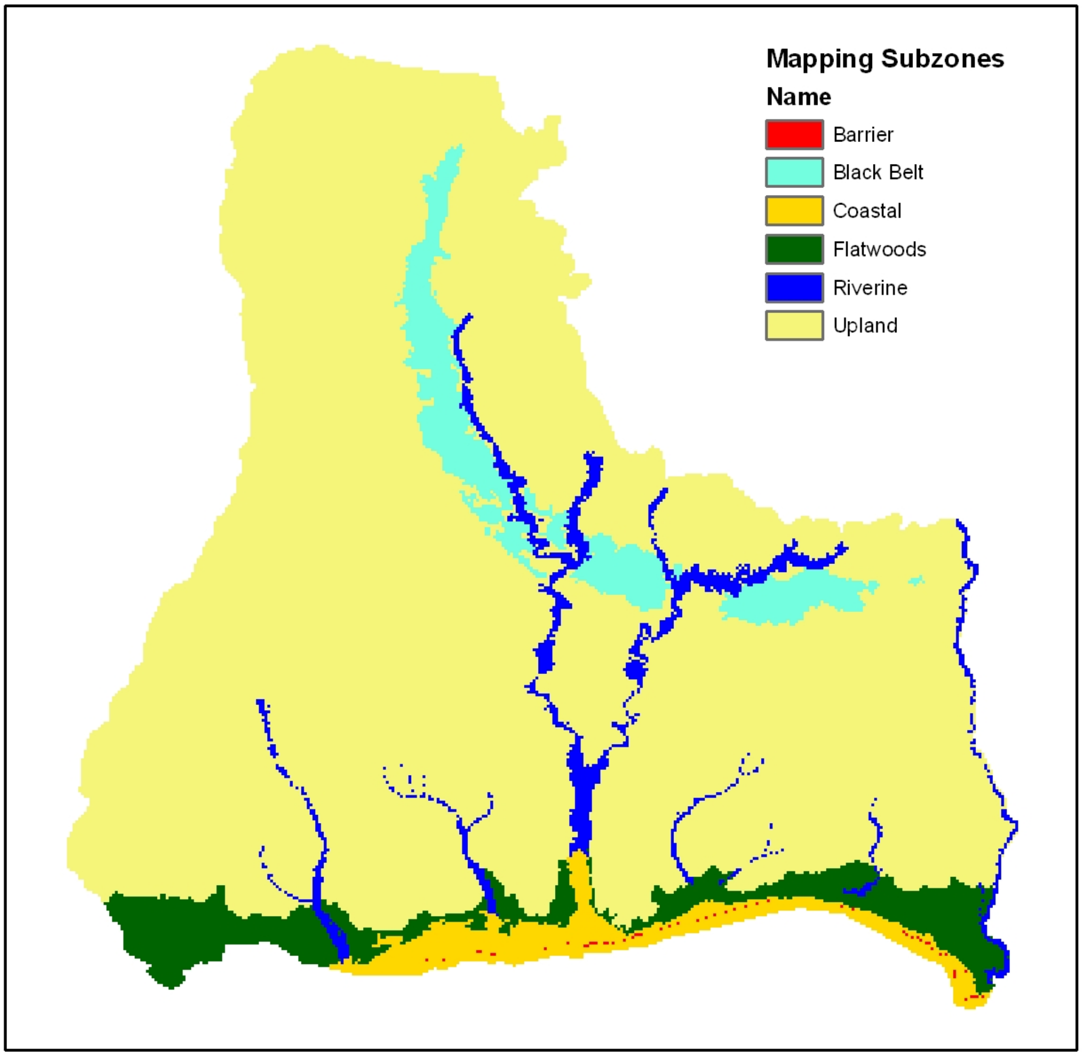

Figure 6. Map of subzone locations in the East Gulf Coastal Plain. Each of the six areas was mapped separately.

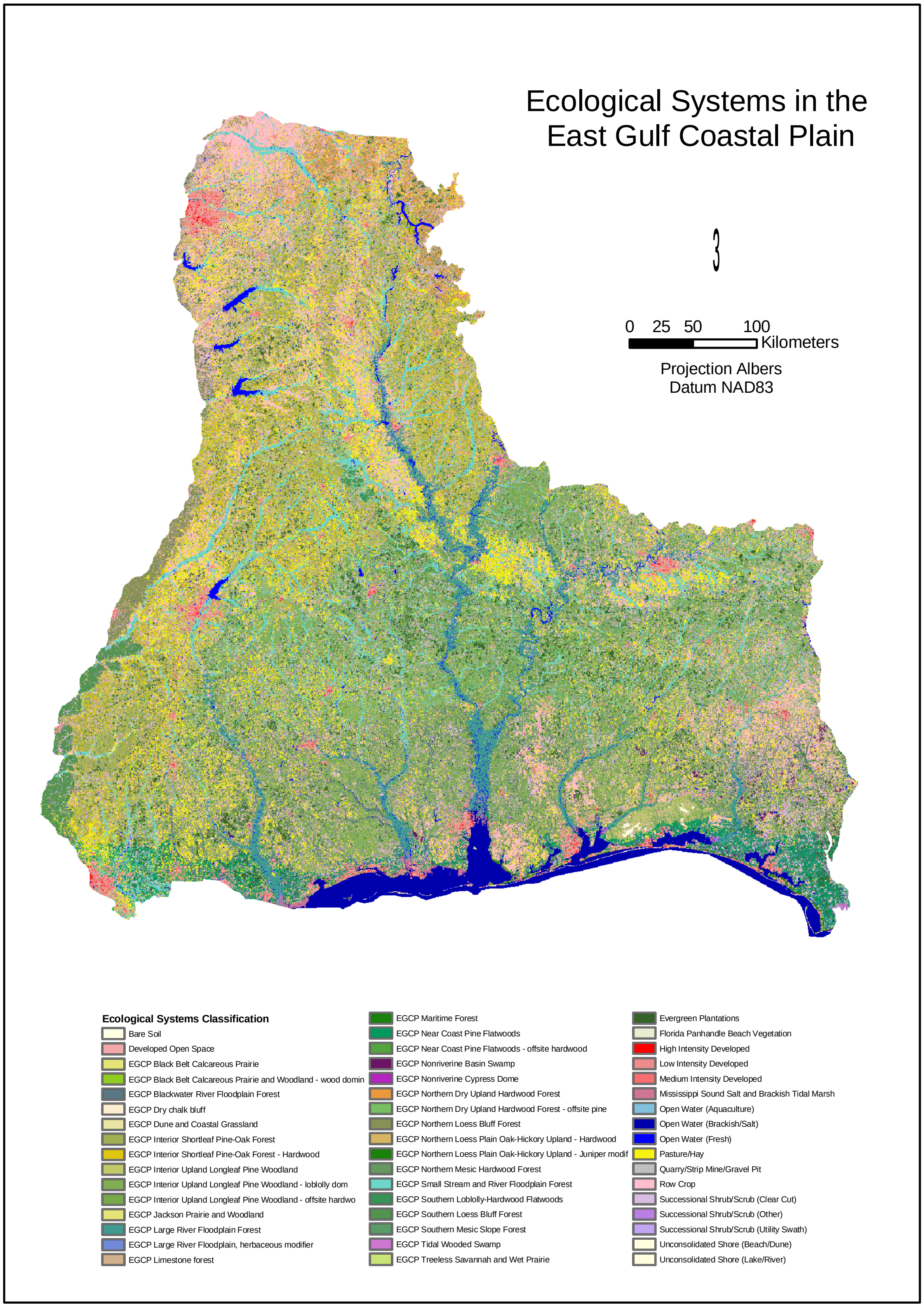

Figure 7. Ecological Systems land cover map (legend also shown in Table 3).

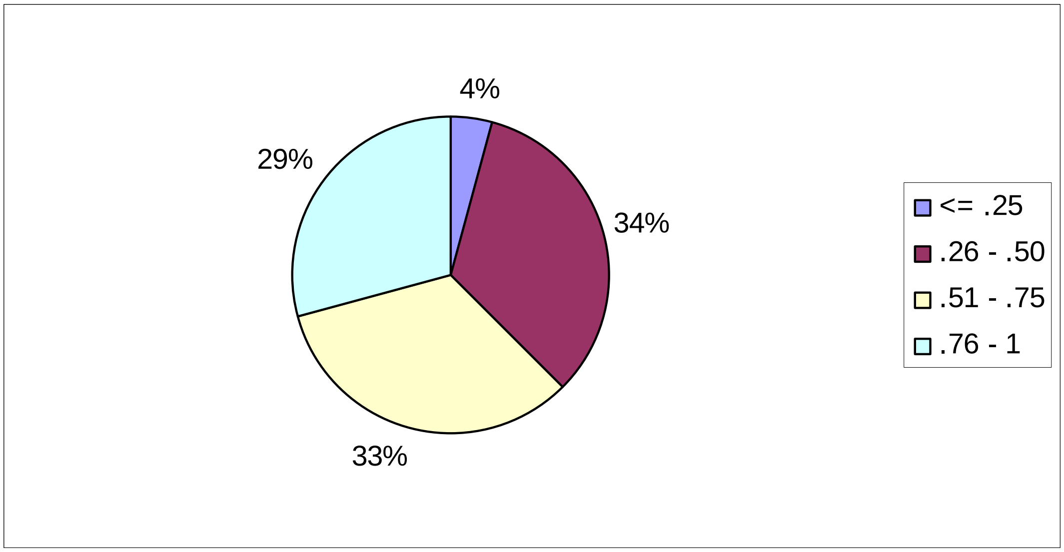

Figure 8. Percentage of Ecological Systems user's accuracies by category.

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APPENDIX 1

Initial CART Models

One interprets a CART model as follows: In the Barrier subset, the initial separation is performed from the fall mosaic, band 2. If this value is greater than 81, pixels are coded to 266 (Florida Panhandle Beach Vegetation). At this split 106 training points were classified as 266, 93 correctly and 13 incorrectly. The second split, on the remainder of the dataset is on the fall mosaic, band 3. If the pixel value is less than or equal to 34, it is classed as 503 (Maritime Forest). At this split 100 training points were classed as 503, 87correctly and 13 incorrectly. The remainder of the training data is recursively portioned according to the rest of the decision tree.

Barrier subset

```
fall02 > 81: 266 (93/13)
fall02 <= 81:
:...fall03 <= 34: 503 (87/13)
    fall03 > 34:
    :...fall04 <= 51: 303 (151/14)
        fall04 > 51:
        :...fall05 <= 59:
            :...tc02 <= 177: 500 (21/3)
            :   tc02 > 177: 503 (7/2)
```

```
fall05 > 59:
:...fall02 > 53: 500 (42/9)
    fall02 <= 53:
    :...fall05 > 67: 303 (37/8)
        fall05 <= 67:
        :...fall01 <= 66: 500 (18/7)
            fall01 > 66: 303 (7/2)
```

Barrier subset key:

266	Florida Panhandle Beach Vegetation
303	Salt and Brackish Tidal Marsh
500	Dune and Coastal Grassland
503	Maritime Forest

Coastal subset

```
fall03 <= 33:
:...wtc02 <= 180: 2990 (19)
:   wtc02 > 180: 5030 (22/1)
fall03 > 33:
:...wint04 > 75:
    :...fall01 <= 62: 1920 (8/1)
```

```
    :   fall01 > 62: 5030 (8/1)
    wint04 <= 75:
    :...wtc02 > 171: 1920 (13/5)
        wtc02 <= 171:
        :...fall05 > 78: 1920 (12/2)
            fall05 <= 78:
            :...fall01 > 63: 3030 (45/1)
                fall01 <= 63:
                :...fall05 <= 54: 3030 (8/1)
                    fall05 > 54:
                    :...fall02 <= 47: 1920 (15/4)
                        fall02 > 47: 3030 (5)
```

Coastal subset key:

1920 Treeless Savannah and Wet Prairie

2990 Tidal Wooded Swamp

3030 Salt and Brackish Tidal Marsh

5030 Maritime Forest

Flatwoods subset

```
fall02 > 42:
:...wint01 <= 56:
```

```
:   :...fall01 <= 64: 1920 (6/2)
:   :   fall01 > 64: 2990 (12/2)
:   wint01 > 56:
:   :...fall03 > 35: 1920 (77/21)
:       fall03 <= 35:
:       :...fall04 <= 53: 2990 (5/1)
:           fall04 > 53:
:           :...fall05 > 59: 5590 (8/2)
:               fall05 <= 59:
:               :...fall04 <= 61: 1920 (11/5)
:                   fall04 > 61: 3750 (9/5)
fall02 <= 42:
:...fall04 <= 47:
    :...wint06 <= 30:
    :   :...wint01 > 55: 5590 (10/1)
    :   :   wint01 <= 55:
    :   :   :...fall02 <= 36: 5600 (9/3)
    :   :       fall02 > 36: 3840 (7/1)
    :   wint06 > 30:
    :   :...wint02 > 45: 1920 (5/3)
    :       wint02 <= 45:
    :       :...fall02 <= 36: 3840 (6/3)
    :           fall02 > 36: 2510 (70/20)
    fall04 > 47:
    :...fall01 <= 53:
```

```
:...wint06 > 25: 5600 (59/18)
:   wint06 <= 25:
:   :...wint02 <= 36: 3840 (6)
:       wint02 > 36: 5050 (5/1)
fall01 > 53:
:...wint04 > 75: 5050 (44/8)
    wint04 <= 75:
    :...wint01 > 63: 5590 (16/2)
        wint01 <= 63:
        :...fall05 <= 44: 5050 (6/2)
            fall05 > 44:
            :...wint02 <= 40: 3840 (10/6)
                wint02 > 40:
                :...wint03 > 45: 5050 (5/3)
                    wint03 <= 45:
                    :...wint06 <= 31: 3840 (9/4)
                        wint06 > 31:
                        :...fall04 <= 57: 2990 (41/8)
                            fall04 > 57: 5590 (7/3)
```

Flatwoods subset key:

1920 Treeless Savanna and Wet Prairie

2510 Nonriverine Cypress Dome

2990 Tidal Wooded Swamp

3750 Near-Coast Pine Flatwoods

3840 Nonriverine Basin Swamp

5050 Southern Seepage Swamp

5590 Small Stream and River Floodplain Forest

5600 Dry Upland Hardwood Forest

Riverine subset

```
wint03 > 46: 3030 (36/1)
wint03 <= 46:
:...fall04 > 49:
    :...wint03 <= 44: 2990 (37/3)
    :   wint03 > 44: 4890 (3)
    fall04 <= 49:
    :...wintc1 <= 41:
        :...falltc3 <= 164: 4890 (35/1)
        :   falltc3 > 164: 2990 (6/2)
        wintc1 > 41:
        :...wintc2 <= 169: 3030 (7/1)
            wintc2 > 169: 2990 (10/3)
```

Riverine subset key:

2990 Tidal Wooded Swamp

3030 Salt and Brackish Tidal Marsh

4890 Large River Floodplain Forest

Black Belt subset

```
sprn02 <= 31:
:...wint01 > 59: 5590 (48/8)
:   wint01 <= 59:
:   :...sprn03 <= 18: 5590 (11/1)
:       sprn03 > 18: 4781 (6/1)
sprn02 > 31:
:...wint03 <= 37: 4920 (2)
    wint03 > 37:
    :...fall02 <= 41: 5020 (4/2)
        fall02 > 41: 4781 (57/3)
```

Black Belt subset key:

4781 Black Belt Calcareous Prairie

4920 Dry Chalk Bluff

5020 Limestone Forest

5590 Small Stream and River Floodplain Forest

Upland subset

```
mxrng in {7,18}: 4962 (0)
mxrng = 0: 4810 (6/4)
mxrng = 2: 5590 (4/1)
mxrng = 4: 4760 (8/3)
mxrng = 5: 4830 (3/2)
mxrng = 6: 4770 (9/6)
mxrng = 8: 5560 (7/2)
mxrng = 9: 5560 (11/2)
mxrng = 17: 2510 (6/4)
mxrng = 15:
:...wint06 <= 30: 5590 (8/1)
:   wint06 > 30:
:   :...wint04 <= 66: 2510 (55/2)
:       wint04 > 66: 3840 (5/2)
mxrng = 1:
:...nlcd in {11,22,24,32,71,81,82,95}: 5061 (0)
:   nlcd = 21: 4770 (3/1)
:   nlcd = 42: 5061 (89/15)
:   nlcd = 52: 5061 (6/3)
:   nlcd = 90: 5590 (16/5)
```

```
:   nlcd = 41:
:   :...wint04 > 65: 4760 (20/9)
:   :   wint04 <= 65:
:   :   :...wint04 <= 58: 4770 (35/12)
:   :       wint04 > 58:
:   :       :...wint06 <= 48: 4760 (8/3)
:   :           wint06 > 48: 4770 (14/3)
:   nlcd = 43:
:   :...wint04 <= 57: 4770 (6/3)
:       wint04 > 57:
:       :...fall05 <= 48: 5062 (6/2)
:           fall05 > 48:
:           :...wint04 <= 61: 5061 (7/2)
:               wint04 > 61:
:               :...fall04 > 66: 4760 (5)
:                   fall04 <= 66:
:                   :...wint06 <= 37: 4760 (5/1)
:                       wint06 > 37: 5061 (9/5)
mxrng = 3:
:...nlcd in {11,22,24,32}: 4962 (0)
    nlcd = 21: 4960 (6/3)
    nlcd = 52: 4960 (16/10)
    nlcd = 71: 4962 (2)
    nlcd = 81: 4930 (1)
    nlcd = 82: 4961 (1)
```

```
nlcd = 95: 3840 (1)
nlcd = 41:
:...fall05 > 53: 4760 (24/7)
:   fall05 <= 53:
:   :...wint06 <= 36: 4760 (8/4)
:       wint06 > 36: 4964 (9/3)
nlcd = 43:
:...wint05 <= 57:
:   :...fall04 <= 55: 4962 (9/3)
:   :   fall04 > 55: 4963 (5/2)
:   wint05 > 57:
:   :...wint05 <= 63: 4760 (6/2)
:       wint05 > 63: 3840 (6/4)
nlcd = 90:
:...fall04 <= 48: 3840 (26/4)
:   fall04 > 48:
:   :...wint04 <= 54: 4963 (7/3)
:       wint04 > 54: 4760 (20/12)
nlcd = 42:
:...fall06 <= 19:
    :...wint06 > 26: 4960 (5/4)
    :   wint06 <= 26:
    :   :...wint06 <= 21:
    :       :...fall05 <= 38: 4963 (9/3)
    :       :   fall05 > 38: 3840 (5)
```

```
:       wint06 > 21:
:       :...fall04 <= 52: 4962 (7/2)
:           fall04 > 52: 4963 (11/4)
fall06 > 19:
:...wint04 <= 61:
    :...fall04 <= 45: 3840 (9/5)
    :   fall04 > 45:
    :   :...fall06 <= 23: 4963 (10/7)
    :       fall06 > 23:
    :       :...fall05 <= 48: 4961 (5/2)
    :           fall05 > 48: 4962 (5/2)
    wint04 > 61:
    :...fall04 > 57:
        :...wint06 > 29: 4960 (16/9)
        :   wint06 <= 29:
        :   :...wint05 > 53: 4962 (8/4)
        :       wint05 <= 53:
        :       :...wint04 > 75: 4963 (21/7)
        :           wint04 <= 75:
        :           :...fall06 <= 20: 4963 (8/2)
        :               fall06 > 20:
        :               :...fall04 <= 59: 4962 (11/4)
        :                   fall04 > 59: 4963 (5/2)
        fall04 <= 57:
        :...wint06 > 29:
```

```
:...fall06 <= 24: 4963 (14/6)
:   fall06 > 24: 4962 (58/23)
wint06 <= 29:
:...fall04 > 55:
    :...wint04 <= 70: 3840 (6/3)
    :   wint04 > 70: 4963 (10/4)
    fall04 <= 55:
    :...wint05 > 50: 4962 (25/6)
        wint05 <= 50:
        :...wint04 > 69: 4962 (53/26)
            wint04 <= 69:
            :...wint06 <= 26:
                :...wint05 <= 42: 4963 (9/3)
                :   wint05 > 42: 4962 (26/7)
                wint06 > 26:
                :...wint06 <= 27: 4961 (5/2)
                    wint06 > 27: 4963 (8/3)
```

Upland subset key:

2510 Nonriverine Cypress Dome

3840 Nonriverine Basin Swamp

4760 Southern Mesic Slope Forest

4770 Northern Mesic Slope Forest

4810 Northern Loess Bluff Forest

4830 Northern Dry Upland Hardwood Forest

4930 Blackwater River Floodplain Forest

4960 Interior Upland Longleaf Pine Woodland

4962 Interior Upland Longleaf Pine Woodland – Loblolly Modifier

4963 Interior Upland Longleaf Pine Woodland – Hardwood Modifier

5061 Interior Shortleaf Pine-Oak Forest

5062 Interior Shortleaf Pine-Oak Forest – Hardwood Modifier

5560 Southern Loess Bluff Forest

5590 Small Stream and River Floodplain Forest

APPENDIX 2

Discussion Of Classification Accuracy By Class

1. Open Water (Fresh) – Although the listed user's accuracy is 70%, the true accuracy is certainly higher. If all water classes are combined, accuracy is 92%.

2. Open Water (Brackish/Salt) – Accuracy of this class is dependant upon how good the brackish/fresh split is. In reality, there is not a single line but a transitional gradient and the location of this gradient moves with time (when more freshwater is coming downriver the gradient moves further towards the confluence. This transition is not captured in this accuracy assessment so the accuracy of this class may be questionable.

3. Open Water (Aquaculture) – This class has an extremely small spatial extent and is patchy; aquaculture facilities tend to be clumped. For this classification the Black Belt region was the primary focus for identifying aquaculture facilities. Therefore, aquaculture facilities existing elsewhere in the mapping zone are less likely to be identified and, correspondingly, have a lower accuracy.

4. Developed Open Space - see class 7, High Intensity Developed.

5. Low Intensity Developed - see class 7, High Intensity Developed.

6. Medium Intensity Developed – see class 7, High Intensity Developed.

7. High Intensity Developed – These four urban classes were taken directly from the NLCD 2001 map, where impervious surface was mapped using higher resolution imagery and regression trees (Yang et al., 2003). Developed Open Space (class 4) is characterized by less than 20% impervious surface, while low intensity developed (5), medium intensity developed (6), and high intensity developed (7) are characterized by 21-50%, 51-80%, and greater than 80% impervious surface, respectively. Interestingly, as can be seen in the confusion matrix, there is a consistent pattern of an urban class being confused with the urban class of immediately less impervious surface. If this trend were to hold with a larger dataset, it could be argued that the regression model was inaccurate but precise, and simply shifting thresholds would increase the accuracy. Additionally, in the initial NLCD 2001 map all urban classes were assessed as 1 class with an accuracy of 70%. Combining all 4 classes in this assessment yields an accuracy of 98%.

12. Florida Panhandle Beach Vegetation – Although this Ecological System has a low accuracy of 41%, it is primarily confused with the EGCP Dune and Coastal Grassland, an immediately adjacent Ecological System. Furthermore, there are no EGCP Dune and Coastal Grassland points identified as Florida Panhandle Beach Vegetation. So while the accuracy is low, it is conservatively mapped and is usually one of two Ecological Systems.

17. Bare Soil – This class consists primarily of the target areas on Eglin Air Force Base. It was produced via manual image interpretation. I had no accuracy assessment points so class accuracy was not assessed.

18. Quarry/Strip Mine/Gravel Pit – This class was not assessed for accuracy. Quarries were visually identified from DOQs and satellite imagery starting with a point file of known quarries from EPA. Satellite imagery was further inspected for the location of quarries. There may be borrow pits that have succeeded to more natural swampy areas but care was taken to exclude anything with a significant amount of vegetation. There also should be no error of inclusion: all mapped quarries should be quarries, but it is likely that not all quarries are mapped. There is no predictive model for this class so an accuracy assessment would be uninformative.

32. East Gulf Coastal Plain Dry Chalk Bluff – This Ecological System has a user's accuracy of 50% and this is likely accurate. What is mapped in this class are steep cliffs (as defined from the landform model) adjacent to water and primarily in the Black Belt. It was not mapped spectrally so confusion potentially exists with many other classes.

35. Unconsolidated Shore (Lake/River/Pond) – This class is primarily sand bars along larger rivers in the lower coastal plain. One important point is that the size of the sand bar is often determined by the river stage and most of the rivers have regulated flow. Therefore sand bar size will be influenced by whether the upstream dam was releasing water at the time the image was taken. There are also limestone sink pond shores in eastern Florida in this class.

36. Unconsolidated Shore (Beach/Dune) – This class consists of the coastal beach line. There is significant confusion between this class and the Ecological System Florida Panhandle Beach Vegetation. This confusion is logical because the beach vegetation class consists of beach grasses of varying density overlying sand.

44. Interior Shortleaf Pine-Oak Forest - Hardwood Modifier – This system has a reported accuracy of 64% but all confusion is between other hardwood forested types. Most confusion is with other mesic hardwood types.

45. Limestone Forest – This Ecological System has a low reported accuracy of 38%. Greatest confusion is with the Interior Upland Longleaf Pine Woodland - Offsite Hardwood Modifier. Because the separation between these 2 systems was accomplished with a soils map, it suggests this is the primary cause of error. However, without the soils map, its unlikely this class would have been mapped at all.

46. Northern Dry Upland Hardwood Forest – This Ecological System has a reasonable accuracy of 69%. It is a matrix system in the north of the mapping zone where pine begins to be replaced by more hardwoods. Confusion is with other forest types.

47. Northern Loess Bluff Forest – This is a spatially defined matrix Ecological System along the northwestern edge of the map zone. Few other Ecological Systems reside within its extent and it is primarily contiguous forest. It has a correspondingly high accuracy of 78% but this is likely underestimated. A greater number of accuracy assessment points would likely lead to an increased estimate of accuracy.

48. Northern Loess Plain Oak-Hickory Upland - Hardwood Modifier – The loess plain is a transition zone from the western bluffs of deep loess soil to the poorer quality soils which exist eastward as the loess effect diminishes. The vague transition is captured in the accuracy of this class, 52%. The primary source of confusion is with the EGCP Interior Shortleaf Pine-Oak Forest – Hardwood modifier, the hardwood matrix system immediately east. If these classes were merged, the accuracy would be 73%. The difference in error is the result of not having a clearly defined line, but rather a transition.

49. Northern Mesic Hardwood Forest – The user's accuracy of this class is stated as 78%, but this is misleading. The producer's accuracy is 26%. This large difference and their relative sizes suggests that the class has a fairly low degree of inclusion, but a high degree of exclusion. The map under predicts the distribution of this forest type considerably. Mapping of this class relied on landform and here may lay the problem. The quality of DEM combined with the fact that there is little relief in the coastal plain make landform a less than satisfactory predictor for this class. In more mountainous parts of the Southeast landform has been used by GAP projects to map ecologically similar classes. I overestimated the utility of landform as a predictive mapping tool for this Ecological System in the EGCP..

50. Southern Loess Bluff Forest – Accuracy for this Ecological System is 81%. As with the northern loess bluff, this is likely a low estimate.

51. Southern Mesic Slope Forest - The user's accuracy of this class is stated as 64%, but this is misleading. The producer's accuracy is 26%. This large difference and their relative sizes suggests that the class has a fairly low degree of inclusion, but a high degree of exclusion. The map considerably under predicts the distribution of this forest type. As with the Northern Mesic Hardwood Forest, the mapping of this class relied on landform which is problematic.

62. Interior Upland Longleaf Pine Woodland - Offsite Hardwood Modifier - This class has an accuracy of 55%. Confusion is primarily with the mesic slope hardwood type and loblolly type. Because a mixed forest class is not in our classification system for this area, spectral confusion is the source this error.

69. East Gulf Coastal Plain Black Belt Calcareous Prairie and Woodland - Woodland Modifier – This class is successional evergreen (*Juniperus virginiana*) in the Black Belt. Conceptually, these were likely prairies historically, but, due to fire suppression, have become wooded. Accuracy is 71% and, because it is successional class, confusion is primarily with scrub/shrub classes.

71. Evergreen Plantations – Accuracy is estimated at 71% for this class. For this classification, not everything planted or in rows is considered plantation. The intent was to map young, dense, intensively managed pine. Identifying plantations in the northern part of the zone, where the background or matrix vegetation is hardwood, is relatively straightforward. In the southern third of the zone, however, nearly all vegetation is evergreen and much of the forested lands are planted. This makes identifying plantations significantly more difficult. In general, I think this class is under represented (there are greater errors of exclusion than inclusion), but this is not captured in the accuracy assessment. Additionally, accuracy likely increases as one advances from south to north.

79. Maritime Forest – The accuracy of this class is 49%. This may be partly explained by the fact that this is a broad class covering diverse vegetation types. Contained within this class are both live oak hammocks and coastal pine.

80. East Gulf Coastal Plain Northern Loess Plain Oak-Hickory Upland - Juniper Modifier – The accuracy of this class is 74%. It is evergreen forest in the loess plain.

94. East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland - Loblolly Modifier – This class contains the largest area of forested lands in the Longleaf matrix range of the EGCP. It is the secondary growth forest following the initial logging of the longleaf woodland. It includes a greater mature, planted pine and naturally seeded pine. Accuracy is 59% with confusion primarily with true longleaf, mesic slope forest types, and the hardwood modifier of the longleaf ecosystem.

95. East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland - Open Understory Modifier – This is the true longleaf Ecological System. Accuracy is 40%, with nearly all confusion being with the loblolly modifier. Because of the nature of the land cover modeling, the accuracy of this class is likely much greater on public lands. Additionally, field checks revealed that although this class does not always contain longleaf, it is consistently mature, open pine woodland. Potentially, accuracy can be improved by 1) incorporating more training data from private lands, 2) including finer grain a priori probability estimates, and 3) stratifying classification by soil type.

101. East Gulf Coastal Plain Northern Dry Upland Hardwood Forest - Offsite Pine Modifier – The accuracy of this class is 72%, confusion is primarily with plantations.

106. East Gulf Coastal Plain Interior Shortleaf Pine-Oak Forest - Mixed Modifier – The accuracy of this class is 66%, but all confusion is with other forested types.

125. Successional Shrub/Scrub (Clear Cut) – The accuracy of this class is 21%. The greatest confusion is with class 127 Successional Shrub/Scrub (Other). Combining these 2 classes would produce an accuracy of 34%. In the NLCD 2001 map there is a scrub/ shrub class with an accuracy of 65%. Reasons for the initial Ecological Systems accuracy being low (21%) include: a large number of classes, difficulty identifying the class in DOQs, and shrub/scrub being a successional, temporally transitional class. Due to the temporal nature of successional classes, one would expect spectral overlap between the successional class and a large number of other classes. Additionally, edge or mixed pixels, which have multiple land cover classes in the pixel are frequently mapped as scrub/shrub. Essentially, scrub/shrub is not a well defined, discrete class, but rather a combination of temporally transitional land cover and mixed pixel effects.

126. Successional Shrub/Scrub (Utility Swath) - This class was created from digitized line work. Only known occurrences are mapped so the accuracy was not assessed.

127. Successional Shrub/Scrub (Other) – The accuracy of this class is 8%. Confusion is primarily with row crop. Due to the low accuracy of the 2 assessed shrub/scrub classes, all 3 shrub/scrub classes should be lumped into a single class or removed from the classification entirely. For further discussion see class 125, Successional Shrub/Scrub (Clear Cut).

132. East Gulf Coastal Plain Black Belt Calcareous Prairie and Woodland - Herbaceous Modifier – The accuracy of this class is 9%. This is the true black belt prairie ecological system. Of 11 sites that were field checked, only 1 had native prairie vegetation on it. However, this class was consistently unmanaged old field. For the remaining 10 points, 8 (80%) were unmanaged old field with native *Andropogon sp.* and other grasses as the dominant vegetation. This class contains 2 ground cover types that are potentially useful: unmanaged grassland and what can more accurately be referred to as potential prairie sites.

134. East Gulf Coastal Plain Jackson Prairie and Woodland – Only known localities of this class were incorporated into the map. There is no predictive model so no accuracy assessment was performed.

143. East Gulf Coastal Plain Dune and Coastal Grassland – The user's accuracy of this class is 79%. However, the producer's accuracy is only 33% so there is considerable under prediction. It is a subset of what is truly this class on the ground. In the producer's accuracy, confusion is with the Florida panhandle beach vegetation Ecological System and unconsolidated shore, both of which are to be expected.

148. Pasture/Hay – Accuracy is 30%, but this is likely an underestimate. Including row crop would increase the accuracy to 60%. The initial NLCD 2001 has a pasture accuracy of 63% and this is likely closer to the true accuracy. There are at least two issues causing reduced accuracy. First, there are more classes in the Ecological Systems classification than in the NLCD 2001 classification (46 vs. 12 assessed classes). Confusion between the additional grassland classes, likely to be confused with pasture, reduces accuracy. Second, 30 points were identified in this accuracy assessment as pasture, compared to 95 in the nlcd2001 map. A smaller sample size may be misrepresenting the actual accuracy.

149. Row Crop – Accuracy is 41%. See the discussion in class 148.

157. East Gulf Coastal Plain Large River Floodplain Forest - Forest Modifier – The accuracy of this class is 57%. Confusion is primarily with the Tidal Wooded Swamp Ecological System. Combining these classes would increase accuracy to 77%. The producer's accuracy is 94% so the spatial extent of this class is potentially exaggerated. The initial floodplain forest class in the NLCD 2001, which this class was extracted from, was developed using a DEM model in which the floodplain was over predicted (Grand et al., 2004). Although steps were taken to further refine the floodplain extent, some of the NLCD 2001 error has propagated into this map.

158. East Gulf Coastal Plain Small Stream and River Floodplain Forest – Accuracy for this class is estimated as 44%. Curiously, it is confused mostly with class 189 East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods which has a restricted range. This is likely just a sampling artifact. All confusion is with other forested classes, primarily forested wetlands.

163. Southern Coastal Plain Blackwater River Floodplain Forest – This class was separated from class 158 EGCP Small Stream and River with the blackwater ancillary data layer. The accuracy of this class is 27%. Confusion is primarily with other forested wetland types. Although there is confusion between this class and class 158, there was no attempt to fully assess the quality of blackwater/brownwater break.

179. Southern Coastal Plain Nonriverine Basin Swamp – The accuracy of this class is 88%. **This is likely an overestimate of accuracy but it is also likely that their true extent is underestimated in this map.** This class was identified via a hybrid classification scheme including directly incorporating known localities. After the accuracy assessment, it was observed that several of these assessment points were in these known areas. To maintain objectivity, no points were added or removed.

In general, basin swamps are a difficult class to map. In springtime imagery they are visually recognizable, but creating a computer algorithm to identify them proved unsuccessful. Additionally, accessing them in the field is challenging as they tend not to have road access. My opinion is that most of the patches of basin swamp in the map are in fact basin swamp, but this is an underestimate of their true areal extent.

186. East Gulf Coastal Plain Near-Coast Pine Flatwoods - Offsite Hardwood Modifier – This class is the fire suppressed, deciduous hardwood modification of the coastal flatwoods. The accuracy of this class is estimated as 28%. Confusion is primarily with 163 Southern Coastal Plain Blackwater River Floodplain Forest, a broad-leafed evergreen system, but also 186 East Gulf Coastal Plain Near-Coast Pine Flatwoods – Open Understory Modifier. Difficulty mapping this system was driven by the fact that, in the lower coastal plain, even deciduous trees have a short leafless season and catching this in imagery is difficult.

187. East Gulf Coastal Plain Near-Coast Pine Flatwoods - Open Understory Modifier - This is the true coastal pine flatwoods. The estimated accuracy is 36%. Confusion is primarily with class163 Southern Coastal Plain Blackwater River Floodplain Forest, class 250 Brackish Tidal Marsh, and class 206 Tidal wooded swamp. The tidal marsh confusion is troubling, but confusion with the other forest types is reasonable. The accuracy of this class is likely substantially underestimated here.

189. East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods – The accuracy of this class is 56%, confusion being primarily with class 106 Interior Shortleaf Pine-Oak Forest – mixed modifier. The error matrix also lists confusion with Evergreen Plantations and it is likely that this is where the bulk of the confusion truly exists.

195. Southern Coastal Plain Nonriverine Cypress Dome – The user's accuracy of this class is 100%. Cypress Domes are easily identified where they exist either in a matrix of pine or agriculture. The producer's accuracy is 42%, suggesting they are under represented. It is likely that both of these values are accurate. Therefore, high accuracy where they are predicted, but they account for a larger percentage of the landscape (there are more of them) than is depicted in this map.

206. East Gulf Coastal Plain Tidal Wooded Swamp – The user's accuracy of this class is estimated to be 25%, but only 8 points were identified as this class. The producer's accuracy is 07% with the vast majority of confusion being between large river floodplain and maritime forest. This Ecological System is perhaps the one I have the least confidence that we have spatial data for input into a model to generate a predicted distribution. As described by NatureServe (Comer et al., 2003), it is riparian freshwater swamp that gets daily inundation from the rising and falling of the tide and its corresponding 'backing up' of riverine discharge. It was mapped using a brackish/freshwater break derived from a CCAP classification and is dependent upon the accuracy of that classification. Additionally, all known assessment points were from the Mobile delta. Therefore, the 25% accuracy may not be representative elsewhere.

233. East Gulf Coastal Plain Treeless Savanna and Wet Prairie – The user's accuracy is 73% and the producer's accuracy is 34% so there may be substantial errors of exclusion. Confusion is with both forested and grassland classes which matches the definition of this class as a seral stage, maintained by fire, between a full grassland and a forested flatwood (FNAI, 1990).

238. East Gulf Coastal Plain Large River Floodplain Forest - Herbaceous Modifier – The user's accuracy of this class is 40% and the producer's accuracy is 100%. There are likely more errors of inclusion than exclusion. Confusion exists with class 127 Successional Shrub/Scrub (Other), class 148 Pasture/Hay and class 149 Row Crop. The method of identifying this class involved identifying areas of shrub, pasture, or row crop within the large river subset. So error could potentially be reduced with manual interpretation and recoding.

250. Mississippi Sound Salt and Brackish Tidal Marsh – The accuracy of this class is 87%. Confusion is primarily with class 233 Treeless Savanna and Wet Prairie as these are adjacent and spectrally similar systems. Because this class is limited to the coastline, its extent can easily be identified. Therefore while the accuracy estimate is high it is also likely accurate.

APPENDIX 3

Source Code Used To Create The Final Ecological Systems Classification

```
COMMENT "Generated from graphical model:
c:/kevin/kevin/thesis/final/megamodel.gmd";
#
# set cell size for the model
#
SET CELLSIZE MIN;
#
# set window for the model
#
SET WINDOW 418860, 1438200 : 1064490, 784740 MAP;
#
# set area of interest for the model
#
SET AOI NONE;
#
# declarations
#
```

Integer RASTER n1_flatwoods_work2 FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/flatwoods_work2.img";

Integer RASTER n2_new_sys_range FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/new_sys_range.img";

Integer RASTER n3_mesic_model_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/mesic_model.img";

Integer RASTER n4_nlcd_s9 FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/mapwork/nlcd_s9.img";

Integer RASTER n6_step01a FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/step01a.img";

Integer RASTER n7_new_sys_range_no_lobflat FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/new_sys_range_no_lobflat.img";

Integer RASTER n11_bw_range FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/bw_range.img";

Integer RASTER n12_cypdome_final FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/cypdome_final.img";

Integer RASTER n15_nwi_2class FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/nwi_2class.img";

Integer RASTER n16_nbs_final FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/nbs_final.img";

Integer RASTER n19_lob_flat_classified_subset_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/lob_flat_classified_subset.img";

Integer RASTER n21_nlcd_s9 FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/mapwork/nlcd_s9.img";

Integer RASTER n22_longleaf_maxlik FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/longleaf_maxlik.img";

Integer RASTER n25_maggra FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/maggra";

Integer RASTER n28_model_01 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/model_01.img";

Integer RASTER n29_fall_tc FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/images/john_normal/fall_tc.img";

Integer RASTER n31_tc_fall71_sub FILE NEW IGNORE 0 ATHEMATIC 8 BIT UNSIGNED INTEGER "g:/output/tc_fall71_sub.img";

Integer RASTER n32_winter_tc FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/images/john_normal/winter_tc.img";

Integer RASTER n34_tc_wint71_sub FILE NEW IGNORE 0 ATHEMATIC 8 BIT UNSIGNED INTEGER "g:/output/tc_wint71_sub.img";

Integer RASTER n36_diff_tc_green_norm FILE NEW USEALL ATHEMATIC 8 BIT SIGNED INTEGER "g:/output/diff_tc_green_norm.img";

Integer RASTER n38_model_2_temp1 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/model_2_temp1.img";

Integer RASTER n39_eglin FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/eglin";

Integer RASTER n41_model_2 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/model_2.img";

Integer RASTER n43_c90_wet_clump FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/c90_wet_clump.img";

Integer RASTER n47_sieve_1 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/sieve_1.img";

Integer RASTER n50_buf_clumps FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/buf_clumps.img";

Integer RASTER n51_model_2a FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/model_2a.img";

Integer RASTER n53_donuts FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/donuts.img";

Integer RASTER n57_non_singles FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/non_singles.img";

Integer RASTER n62_rc_90 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/rc_90.img";

Integer RASTER n65_single_pixels FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/single_pixels.img";

Integer RASTER n67_recode_ind_pixels FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/recode_ind_pixels.img";

Integer RASTER n71_mesic_model_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/mesic_model.img";

```
Integer RASTER n72_temp1 FILE NEW USEALL THEMATIC BIN DIRECT
DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/temp1.img";
Integer RASTER n74_mesic_subset FILE NEW IGNORE 0 THEMATIC BIN DIRECT
DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/mesic_subset.img";
Integer RASTER n76_new_sys_range_no_lobflat FILE OLD NEAREST NEIGHBOR
AOI NONE "z:/kevin/ancillary_working/new_sys_range_no_lobflat.img";
Integer RASTER n78_draft_90mod FILE NEW IGNORE 0 THEMATIC BIN DIRECT
DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/draft_90mod.img";
Integer RASTER n86_model_3 FILE NEW IGNORE 0 THEMATIC BIN DIRECT
DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/model_3.img";
Integer RASTER n88_pshore_aoi FILE OLD NEAREST NEIGHBOR AOI NONE
"z:/kevin/ancillary_working/pshore_aoi";
Integer RASTER n90_z_46_metamodel_091306 FILE NEW USEALL THEMATIC BIN
DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/z_46_metamodel_091306.img";
Integer RASTER n91_ccap_brack FILE OLD NEAREST NEIGHBOR AOI NONE
"z:/kevin/ancillary_working/ccap_brack";
Integer RASTER n92_new_sys_range FILE OLD NEAREST NEIGHBOR AOI NONE
"z:/kevin/ancillary_working/new_sys_range.img";
Integer RASTER n94_bbsoils FILE OLD NEAREST NEIGHBOR AOI NONE
"z:/kevin/soils/bbsoils.img";
Integer RASTER n95_z46_step3 FILE NEW IGNORE 0 THEMATIC BIN DIRECT
DEFAULT 8 BIT UNSIGNED INTEGER "g:/z46_step3.img";
```

Integer RASTER n96_z46spring_refl FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/images/spring/z46spring_refl.img";

Integer RASTER n97_winterall FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/images/john_normal/winterall.img";

Integer RASTER n98_c96 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/c96.img";

Integer RASTER n101_clump FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/bb/clump.img";

Integer RASTER n105_sieve_2 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/bb/sieve_2.img";

Integer RASTER n108_bufclump FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/bb/bufclump.img";

Integer RASTER n109_nwi_2class_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/nwi_2class.img";

Integer RASTER n111_donuts FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/bb/donuts.img";

Integer RASTER n117_recode_96_from_nwi FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/recode_96_from_nwi.img";

Integer RASTER n118_j137 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/j137.img";

Integer RASTER n123_recode_96_from_smstrm FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/recode_96_from_smstrm.img";

Integer RASTER n128_sieve_10 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/bb/sieve_10.img";

Integer RASTER n131_prairie FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/prairie.img";

Integer RASTER n133_c55_pot_bbprairie FILE OLD NEAREST NEIGHBOR AOI NONE "g:/blackblet/55_bust/c55_pot_bbprairie.img";

Integer RASTER n134_z_46_metamodel_062806 FILE OLD NEAREST NEIGHBOR AOI NONE "g:/z_46_metamodel_062806.img";

Integer RASTER n136_water_in_bb FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/water_in_bb.img";

Integer RASTER n137_bb4 FILE OLD NEAREST NEIGHBOR AOI NONE "g:/blackblet/drychalkbluff/bb4";

Integer RASTER n140_water_buffer FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/water_buffer.img";

Integer RASTER n142_z46_landforms FILE OLD NEAREST NEIGHBOR AOI NONE "f:/landform/z46_landforms";

Integer RASTER n143_stpslp_adj_wat_step1 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/stpslp_adj_wat_step1.img";

Integer RASTER n147_step1_buffer FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/step1_buffer.img";

Integer RASTER n151_water_buf_3x3 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/water_buf_3x3.img";

Integer RASTER n152_landform_steep_slp_adja_water FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/landform_steep_slp_adja_water.img";

Integer RASTER n154_donut_bluff FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/donut_bluff.img";

Integer RASTER n156_donut_water FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/bb/donut_water.img";

Integer RASTER n158_matrix_range_in_blackbelt FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/matrix_range_in_blackbelt.img";

Integer RASTER n162_jacprai FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/last_minute_edits/jacprai";

Integer RASTER n163_blk_to_smstm FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/last_minute_edits/blk_to_smstm";

Integer RASTER n164_strm_to_lgriv FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/last_minute_edits/strm_to_lgriv";

Integer RASTER n165_ccap_to_overwrite_nlcd_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE

"z:/kevin/systems_final/last_minute_edits/ccap_to_overwrite_nlcd.img";

Integer RASTER n167_bb_063006 FILE OLD NEAREST NEIGHBOR AOI NONE "g:/bb_063006.img";

Integer RASTER n168_z46_step4 FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/z46_step4.img";

Integer RASTER n170_bw_fix FILE OLD NEAREST NEIGHBOR AOI NONE "f:/temp/bw_fix.img";

Integer RASTER n172_z46_temp2 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/z46_temp2.img";

Integer RASTER n175_cypdom_edge_to_rc FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/las_minute_2/4_models/cypdom_edge_to_rc.img";

Integer RASTER n176_excess_96_in_la FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/las_minute_2/4_models/excess_96_in_la.img";

Integer RASTER n177_nbas_edge_to_rc FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/las_minute_2/4_models/nbas_edge_to_rc.img";

Integer RASTER n178_96fin_rc_to_blk_and_smstrm FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/las_minute_2/4_models/96fin_rc_to_blk_and_smstrm.img";

Integer RASTER n179_meslp_recode_final FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/las_minute_2/4_models/meslp_recode_final.img";

Integer RASTER n181_z46_step5 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/z46_step5.img";

Integer RASTER n182_water_in_forest_with_rc_class FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/systems_final/las_minute_2/4_models/water_in_forest_with_rc_class.img";

Integer RASTER n185_96fin FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/las_minute_2/96fin.img";

Integer RASTER n187_96_fin_clump FILE NEW IGNORE 0 THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/las_minute_2/96_fin_clump.img";

Integer RASTER n190_96fin_buf FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "g:/output/las_minute_2/96fin_buf.img";

Integer RASTER n193_z46_step4_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "g:/z46_step4.img";

Float RASTER n198_96fin_bw_cnt FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/output/las_minute_2/96fin_bw_cnt.img";

Float RASTER n200_96fin_clump_hist FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/output/las_minute_2/96fin_clump_hist.img";

Float RASTER n201_96fin_per_touch_bw FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/output/las_minute_2/96fin_per_touch_bw.img";

Float RASTER n203_96fin_bw_cnt_float FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/output/las_minute_2/96fin_bw_cnt_float.img";

Integer RASTER n206_bw_to_change_25 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/las_minute_2/bw_to_change_25.img";

Integer RASTER n209_z46_step4_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "g:/z46_step4.img";

Float RASTER n213_96fin_smstrm_cnt FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/96fin_smstrm_cnt.img";

Float RASTER n215_96fin_per_touch_smstrm FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/output/las_minute_2/96fin_per_touch_smstrm.img";

Float RASTER n217_96fin_smstrm_cnt_float FILE NEW USEALL ATHEMATIC FLOAT DOUBLE "g:/output/las_minute_2/96fin_smstrm_cnt_float.img";

Integer RASTER n220_sm_strm_to_change_25 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "g:/output/las_minute_2/sm_strm_to_change_25.img";

Integer RASTER n221_96fin_rc_to_blk_and_smstrm FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "z:/kevin/systems_final/las_minute_2/4_models/96fin_rc_to_blk_and_smstrm.img";

Integer RASTER n225_clump FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "c:/97_catfishponds/clump.img";

Integer RASTER n227_lowval FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "c:/97_catfishponds/lowval.img";

Integer RASTER n233_highval FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "c:/97_catfishponds/highval.img";

Integer RASTER n235_middle FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "c:/97_catfishponds/middle.img";

Integer RASTER n236_clump_final FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "c:/97_catfishponds/clump_final.img";

Integer RASTER n238_clump FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_final/clump.img";

Integer RASTER n241_j96_sp FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j96_sp.img";

Integer RASTER n243_j96_sp_clump FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "f:/asap/j96_sp_clump.img";

Integer RASTER n245_j136 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j136.img";

Integer RASTER n247_j221 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j221.img";

Integer RASTER n249_j137 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j137.img";

Integer RASTER n253_step6 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/step6.img";

Integer RASTER n254_t25_final_fn FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_final/t25_final_fn";

Integer RASTER n255_new_sys_range_no_lobflat FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/new_sys_range_no_lobflat.img";

Integer RASTER n256_bw_range FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/bw_range.img";

Integer RASTER n258_j96 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j96.img";

Integer RASTER n260_j96_clump FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "f:/asap/j96_clump.img";

Integer RASTER n264_sieve_100 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "f:/asap/sieve_100.img";

Integer RASTER n268_j136buf FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j136buf.img";

Integer RASTER n269_j137buf FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j137buf.img";

Integer RASTER n270_j221 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/j221.img";

Integer RASTER n274_change_136 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/change_136.img";

Integer RASTER n277_change_137 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/change_137.img";

Integer RASTER n280_change_221 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/change_221.img";

Integer RASTER n281_step6 FILE OLD NEAREST NEIGHBOR AOI NONE "f:/asap/step6.img";

Integer RASTER n283_step7 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/step7.img";

Integer RASTER n297_choctaw_10_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_lgriv_mouthfix/choctaw_10.img";

Integer RASTER n298_escambia_10_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_lgriv_mouthfix/escambia_10.img";

Integer RASTER n299_mobile_10_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_lgriv_mouthfix/mobile_10.img";

Integer RASTER n300_pascagoula_10_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_lgriv_mouthfix/pascagoula_10.img";

Integer RASTER n301_pearl_10_RC_Org FILE OLD NEAREST NEIGHBOR AOI NONE "c:/96_lgriv_mouthfix/pearl_10.img";

Integer RASTER n303_step9 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/step9.img";

Integer RASTER n304_max_slope_in_clump FILE OLD NEAREST NEIGHBOR AOI NONE "f:/asap/final/max_slope_in_clump.img";

Integer RASTER n305_new_sys_range_no_lobflat FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/new_sys_range_no_lobflat.img";

Integer RASTER n306_j96_to_rc_from_hydro FILE OLD NEAREST NEIGHBOR AOI NONE "f:/asap/final/j96_to_rc_from_hydro.img";

Integer RASTER n307_j96_clump FILE OLD NEAREST NEIGHBOR AOI NONE "f:/asap/slopmax/j96_clump.img";

Integer RASTER n308_nlcd_s8_new FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/mapwork/nlcd_s8_new.img";

Integer RASTER n310_j96_clump FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 32 BIT UNSIGNED INTEGER "f:/asap/final/j96_clump.img";

Integer RASTER n316_nwhdmaxinclump FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/final/nwhdmaxinclump.img";

Integer RASTER n318_j96_to_rc_from_hydro FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/final/j96_to_rc_from_hydro.img";

Integer RASTER n319_bw_range FILE OLD NEAREST NEIGHBOR AOI NONE "z:/kevin/ancillary_working/bw_range.img";

Integer RASTER n320_z46_newhydro FILE OLD NEAREST NEIGHBOR AOI NONE "f:/asap/z46_newhydro.img";

Integer RASTER n322_hyd_buf_5x5 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "f:/asap/final/hyd_buf_5x5.img";

Integer RASTER n325_step9 FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "c:/97_catfishponds/step9.img";

Integer RASTER n328_z46_ecol_systems_class FILE NEW USEALL THEMATIC BIN DIRECT DEFAULT 8 BIT UNSIGNED INTEGER "c:/z46_ecol_systems_class.img";

INTEGER MATRIX n48_Low_Pass;

INTEGER MATRIX n68_Custom_Integer;

INTEGER MATRIX n106_Custom_Integer;

INTEGER MATRIX n138_Low_Pass;

FLOAT MATRIX n144_Low_Pass;

```
FLOAT MATRIX n189_Low_Pass;

FLOAT MATRIX n191_Output;

FLOAT MATRIX n207_Output;

FLOAT MATRIX n250_Low_Pass;

FLOAT MATRIX n286_Output;

FLOAT MATRIX n290_Output;

FLOAT MATRIX n294_Output;

INTEGER MATRIX n311_Low_Pass;

FLOAT MATRIX n312_Output;

INTEGER TABLE n45_Output;

INTEGER TABLE n55_Output;

INTEGER TABLE n103_Output;

INTEGER TABLE n113_Output;

INTEGER TABLE n120_Output;

INTEGER TABLE n126_Output;

INTEGER TABLE n196_Output;

INTEGER TABLE n211_Output;

INTEGER TABLE n228_Output;

INTEGER TABLE n231_Output;

INTEGER TABLE n262_Output;

INTEGER TABLE n284_Output;

INTEGER TABLE n288_Output;

INTEGER TABLE n292_Output;
```

```
INTEGER TABLE n314_Output;

#

# addition variables to recode n3_mesic_model_RC

#

INTEGER TABLE n3_recode;

#

# addition variables to recode n19_lob_flat_classified_subset_RC

#

INTEGER TABLE n19_recode;

#

# addition variables to recode n71_mesic_model_RC

#

INTEGER TABLE n71_recode;

#

# addition variables to recode n109_nwi_2class_RC

#

INTEGER TABLE n109_recode;

#

# addition variables to recode n165_ccap_to_overwrite_nlcd_RC

#

INTEGER TABLE n165_recode;

#

# addition variables to recode n193_z46_step4_RC
```

```
#

INTEGER TABLE n193_recode;

#

# addition variables to recode n209_z46_step4_RC

#

INTEGER TABLE n209_recode;

#

# addition variables to recode n223_memory

#

INTEGER TABLE n223_recode;

#

# addition variables to recode n297_choctaw_10_RC

#

INTEGER TABLE n297_recode;

#

# addition variables to recode n298_escambia_10_RC

#

INTEGER TABLE n298_recode;

#

# addition variables to recode n299_mobile_10_RC

#

INTEGER TABLE n299_recode;

#
```

```
# addition variables to recode n300_pascagoula_10_RC
#
INTEGER TABLE n300_recode;
#
# addition variables to recode n301_pearl_10_RC
#
INTEGER TABLE n301_recode;
#
# load matrix n48_Low_Pass
#
n48_Low_Pass = MATRIX(3, 3:
        1, 1, 1,
        1, 1, 1,
        1, 1, 1);
#
# load matrix n68_Custom_Integer
#
n68_Custom_Integer = MATRIX(3, 3:
        1, 1, 1,
        1, 0, 1,
        1, 1, 1);
#
# load matrix n106_Custom_Integer
```

```
#
n106_Custom_Integer = MATRIX(3, 3:
        1, 1, 1,
        1, 1, 1,
        1, 1, 1);
#
# load matrix n138_Low_Pass
#
n138_Low_Pass = MATRIX(5, 5:
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1);
#
# load matrix n144_Low_Pass
#
n144_Low_Pass = MATRIX(3, 3:
        1, 1, 1,
        1, 1, 1,
        1, 1, 1);
#
# normalize matrix n144_Low_Pass
```

```
#
if (global sum ($n144_Low_Pass) NE 0)
	{n144_Low_Pass = $n144_Low_Pass / global sum ($n144_Low_Pass);}
#
# load matrix n189_Low_Pass
#
n189_Low_Pass = MATRIX(3, 3:
	1, 1, 1,
	1, 1, 1,
	1, 1, 1);
#
# normalize matrix n189_Low_Pass
#
if (global sum ($n189_Low_Pass) NE 0)
	{n189_Low_Pass = $n189_Low_Pass / global sum ($n189_Low_Pass);}
#
# load matrix n250_Low_Pass
#
n250_Low_Pass = MATRIX(3, 3:
	1, 1, 1,
	1, 1, 1,
	1, 1, 1);
#
```

```
# normalize matrix n250_Low_Pass
#
if (global sum ($n250_Low_Pass) NE 0)
        {n250_Low_Pass = $n250_Low_Pass / global sum ($n250_Low_Pass);}
#
# load matrix n311_Low_Pass
#
n311_Low_Pass = MATRIX(5, 5:
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1,
        1, 1, 1, 1, 1);
#
# load recode table for n3_mesic_model_RC
#
n3_recode = TABLE(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0);
#
# load recode table for n19_lob_flat_classified_subset_RC
#
n19_recode = TABLE(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

```
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 165, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0);
#
# load recode table for n71_mesic_model_RC
#
n71_recode = TABLE(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1);
#
# load recode table for n109_nwi_2class_RC
#
n109_recode = TABLE(0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0);
#
# load recode table for n165_ccap_to_overwrite_nlcd_RC
#
n165_recode = TABLE(0, 1, 2, 3, 4, 21, 84, 83, 83, 9, 143, 143, 55, 96, 96, 96, 16, 17,
18, 36, 34, 13, 96);
#
# load recode table for n193_z46_step4_RC
#
```

n193_recode = TABLE(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0);

#

load recode table for n209_z46_step4_RC

#

n209_recode = TABLE(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0);

#

load recode table for n223_memory

#

n223_recode = TABLE(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0);

#

load recode table for n297_choctaw_10_RC

#

n297_recode = TABLE(0, 121, 114, 121, 221, 121, 221, 114, 121, 121, 221);

#

load recode table for n298_escambia_10_RC

#

n298_recode = TABLE(0, 121, 114, 114, 121, 121, 221, 221, 121, 221, 222);

#

load recode table for n299_mobile_10_RC

#

n299_recode = TABLE(0, 114, 121, 114, 221, 221, 221, 121, 114, 114, 114);

#

load recode table for n300_pascagoula_10_RC

#

n300_recode = TABLE(0, 114, 114, 114, 114, 221, 221, 221, 121, 121, 114);

#

load recode table for n301_pearl_10_RC

#

```
n301_recode = TABLE(0, 121, 221, 221, 221, 114, 121, 121, 221, 221, 114);

#

# recode n3_mesic_model_RC_Org

#

#define n3_mesic_model_RC LOOKUP($n3_mesic_model_RC_Org, $n3_recode)

#

# recode n19_lob_flat_classified_subset_RC_Org

#

#define n19_lob_flat_classified_subset_RC

LOOKUP($n19_lob_flat_classified_subset_RC_Org, $n19_recode)

#

# recode n71_mesic_model_RC_Org

#

#define n71_mesic_model_RC LOOKUP($n71_mesic_model_RC_Org, $n71_recode)

#

# recode n109_nwi_2class_RC_Org

#

#define n109_nwi_2class_RC LOOKUP($n109_nwi_2class_RC_Org, $n109_recode)

#

# recode n165_ccap_to_overwrite_nlcd_RC_Org

#

#define n165_ccap_to_overwrite_nlcd_RC

LOOKUP($n165_ccap_to_overwrite_nlcd_RC_Org, $n165_recode)
```

```
#
# recode n193_z46_step4_RC_Org
#
#define n193_z46_step4_RC LOOKUP($n193_z46_step4_RC_Org, $n193_recode)
#
# recode n209_z46_step4_RC_Org
#
#define n209_z46_step4_RC LOOKUP($n209_z46_step4_RC_Org, $n209_recode)
#
# recode n223_memory_Org
#
#define n223_memory LOOKUP($n223_memory_Org, $n223_recode)
#
# recode n297_choctaw_10_RC_Org
#
#define n297_choctaw_10_RC LOOKUP($n297_choctaw_10_RC_Org, $n297_recode)
#
# recode n298_escambia_10_RC_Org
#
#define n298_escambia_10_RC LOOKUP($n298_escambia_10_RC_Org,
$n298_recode)
#
# recode n299_mobile_10_RC_Org
```

```
#
#define n299_mobile_10_RC LOOKUP($n299_mobile_10_RC_Org, $n299_recode)
#
# recode n300_pascagoula_10_RC_Org
#
#define n300_pascagoula_10_RC LOOKUP($n300_pascagoula_10_RC_Org,
$n300_recode)
#
# recode n301_pearl_10_RC_Org
#
#define n301_pearl_10_RC LOOKUP($n301_pearl_10_RC_Org, $n301_recode)
#
# function definitions
#
n322_hyd_buf_5x5 = FOCAL MAX ( $n320_z46_newhydro , $n311_Low_Pass ) ;
n6_step01a = CONDITIONAL { ( $n7_new_sys_range_no_lobflat == 4 and
$n21_nlcd_s9 == 41 ) 221 ,  ( $n7_new_sys_range_no_lobflat == 4 and $n21_nlcd_s9 ==
42 ) 221 , ( $n7_new_sys_range_no_lobflat == 4 and $n21_nlcd_s9 == 43 ) 221, (
$n7_new_sys_range_no_lobflat == 4 and $n21_nlcd_s9 == 90 ) 221, (
$n7_new_sys_range_no_lobflat == 4 and $n21_nlcd_s9 == 71 ) 222 ,   (
$n7_new_sys_range_no_lobflat == 4 and $n21_nlcd_s9 == 52 ) 222 ,  (
$n7_new_sys_range_no_lobflat == 4 and $n21_nlcd_s9 == 95 ) 222 ,  ( $n15_nwi_2class
== 10 and $n21_nlcd_s9 == 41 and $n11_bw_range == 0) 137 , ( $n15_nwi_2class ==
```

10 and $n21_nlcd_s9 == 43 and $n11_bw_range == 0) 137 , ($n15_nwi_2class == 10 and $n21_nlcd_s9 == 90 and $n11_bw_range == 0) 137 , ($n15_nwi_2class == 10 and $n21_nlcd_s9 == 95 and $n11_bw_range == 0) 137 , ($n15_nwi_2class == 10 and $n21_nlcd_s9 == 41 and $n11_bw_range == 1) 136 , ($n15_nwi_2class == 10 and $n21_nlcd_s9 == 43 and $n11_bw_range == 1) 136 , ($n15_nwi_2class == 10 and $n21_nlcd_s9 == 90 and $n11_bw_range == 1) 136 , ($n15_nwi_2class == 10 and $n21_nlcd_s9 == 95 and $n11_bw_range == 1) 136 , ($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 41 and $n25_maggra == 1) 145 , ($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 42 and $n25_maggra == 1) 145 , ($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 43 and $n25_maggra == 1) 145 , ($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 90 and $n25_maggra == 1) 145 ,($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 41) 163 , ($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 43) 163 , ($n7_new_sys_range_no_lobflat NE 8 and $n7_new_sys_range_no_lobflat NE 9 and $n3_mesic_model_RC == 1 and $n21_nlcd_s9 == 90) 163 , ($n15_nwi_2class == 12 and $n21_nlcd_s9 == 52) 96 , ($n15_nwi_2class == 12 and $n21_nlcd_s9 == 71) 96 , ($n15_nwi_2class == 12 and $n21_nlcd_s9 == 41) 96 , ($n15_nwi_2class == 12 and $n21_nlcd_s9 == 42) 96 , ($n15_nwi_2class == 12

and $n21_nlcd_s9 == 43) 96 , ($n15_nwi_2class == 12 and $n21_nlcd_s9 == 90) 96, ($n15_nwi_2class == 12 and $n21_nlcd_s9 == 95) 96, ($n7_new_sys_range_no_lobflat == 9 and $n21_nlcd_s9 == 41) 211, ($n7_new_sys_range_no_lobflat == 9 and $n21_nlcd_s9 == 42) 211, ($n7_new_sys_range_no_lobflat == 9 and $n21_nlcd_s9 == 43) 211, ($n7_new_sys_range_no_lobflat == 9 and $n21_nlcd_s9 == 90) 211, ($n7_new_sys_range_no_lobflat == 8 and $n21_nlcd_s9 == 41) 201, ($n7_new_sys_range_no_lobflat == 8 and $n21_nlcd_s9 == 42) 201, ($n7_new_sys_range_no_lobflat == 8 and $n21_nlcd_s9 == 43) 201, ($n7_new_sys_range_no_lobflat == 8 and $n21_nlcd_s9 == 90) 201, ($n7_new_sys_range_no_lobflat == 7 and $n21_nlcd_s9 == 41) 191 , ($n7_new_sys_range_no_lobflat == 7 and $n21_nlcd_s9 == 43) 191 , ($n7_new_sys_range_no_lobflat == 7 and $n21_nlcd_s9 == 42) 192 , ($n7_new_sys_range_no_lobflat == 6 and $n21_nlcd_s9 == 41) 181 , ($n7_new_sys_range_no_lobflat == 6 and $n21_nlcd_s9 == 43) 181 , ($n7_new_sys_range_no_lobflat == 6 and $n21_nlcd_s9 == 42) 182 , ($n7_new_sys_range_no_lobflat == 1 and $n21_nlcd_s9 == 42) 161 , ($n7_new_sys_range_no_lobflat == 1 and $n21_nlcd_s9 == 43) 161 , ($n7_new_sys_range_no_lobflat == 1 and $n21_nlcd_s9 == 41) 162 , ($n7_new_sys_range_no_lobflat == 3 and $n21_nlcd_s9 == 42) 143 , ($n7_new_sys_range_no_lobflat == 3 and $n21_nlcd_s9 == 43) 143 , ($n7_new_sys_range_no_lobflat == 3 and $n21_nlcd_s9 == 41) 144 , ($n4_nlcd_s9 > 0) $n4_nlcd_s9 } ;

```
n28_model_01 = CONDITIONAL { ($n12_cypdome_final > 0 ) 135 , ( $n16_nbs_final > 0 ) 134 , ($n19_lob_flat_classified_subset_RC > 0 ) $n19_lob_flat_classified_subset_RC , ($n1_flatwoods_work2 > 0 ) $n1_flatwoods_work2 , ($n7_new_sys_range_no_lobflat == 3 and $n22_longleaf_maxlik > 0 ) 141 , ($n6_step01a == 52 ) 55 , ( $n6_step01a > 0 ) $n6_step01a } ;
n34_tc_wint71_sub = EITHER $n32_winter_tc(2) IF ( $n28_model_01 == 71 ) OR 0 OTHERWISE ;
n31_tc_fall71_sub = EITHER $n29_fall_tc(2) IF ( $n28_model_01 == 71 ) OR 0 OTHERWISE ;
n36_diff_tc_green_norm = EITHER ( GLOBAL MEAN ( $n31_tc_fall71_sub ) - $n31_tc_fall71_sub )  /  GLOBAL SD ( $n31_tc_fall71_sub )  - ( GLOBAL MEAN ( $n34_tc_wint71_sub ) - $n34_tc_wint71_sub )  /  GLOBAL SD ( $n34_tc_wint71_sub ) IF ($n28_model_01 == 71) OR 99 OTHERWISE ;
n38_model_2_temp1 = CONDITIONAL { ($n36_diff_tc_green_norm == 99 )  0 , ($n36_diff_tc_green_norm <=  -1 ) 53 , ($n36_diff_tc_green_norm >= 1 ) 53 , ($n39_eglin == 1 and $n36_diff_tc_green_norm == 0 ) 141 , ($n39_eglin == 0 and $n36_diff_tc_green_norm ==  0 ) 55 };
n41_model_2 = EITHER $n38_model_2_temp1 IF ( $n38_model_2_temp1 > 0 ) OR $n28_model_01 OTHERWISE ;
n51_model_2a = CONDITIONAL { ( $n41_model_2 == 96 ) 96 , ( $n41_model_2 == 121 ) 121 , ( $n41_model_2 == 136 ) 136 , ( $n41_model_2 == 137 ) 137 , ( $n41_model_2 == 221 ) 221 ,  ( $n41_model_2 > 0 ) 1 } ;
n72_temp1 = EITHER 90 IF ( $n41_model_2 == 90 ) OR 0 OTHERWISE ;
```

```
n74_mesic_subset = EITHER $n72_temp1 IF ( $n71_mesic_model_RC == 1 ) OR 0
OTHERWISE ;
n43_c90_wet_clump = CLUMP ( $n74_mesic_subset , 8 ) ;
n45_Output = SIEVETABLE ( 2 , HISTOGRAM ( $n43_c90_wet_clump )  ) ;
WRITE $n45_Output TO "g:/output/hist2.tbl";
n47_sieve_1 = LOOKUP ( $n43_c90_wet_clump, $n45_Output ) ;
n65_single_pixels = EITHER 1 IF ( $n43_c90_wet_clump > 0 and $n47_sieve_1 == 0 )
OR 0 OTHERWISE ;
n67_recode_ind_pixels = EITHER FOCAL MAJORITY ( $n41_model_2 ,
$n68_Custom_Integer )  IF ( $n65_single_pixels == 1) OR 0 OTHERWISE ;
n50_buf_clumps = FOCAL MAX ( $n47_sieve_1 , $n48_Low_Pass ) ;
n53_donuts = EITHER 0 IF ( $n47_sieve_1 > 0 ) OR $n50_buf_clumps OTHERWISE ;
n55_Output = ZONAL MAX ( $n53_donuts , $n51_model_2a ) ;
WRITE $n55_Output TO "g:/output/s90_adj.tbl";
n57_non_singles = EITHER LOOKUP ( $n47_sieve_1 , $n55_Output ) IF (
$n47_sieve_1 > 0 ) OR 0 OTHERWISE;
n62_rc_90 = CONDITIONAL { ($n67_recode_ind_pixels > 0) $n67_recode_ind_pixels ,
($n57_non_singles == 1 ) 96 , ($n57_non_singles > 0 ) $n57_non_singles } ;
n78_draft_90mod = CONDITIONAL { ($n74_mesic_subset == 0 AND $n72_temp1 ==
90 AND $n76_new_sys_range_no_lobflat == 1) 161 , ($n74_mesic_subset == 0 AND
$n72_temp1 == 90 AND $n76_new_sys_range_no_lobflat == 3 ) 143 ,
($n74_mesic_subset == 0 AND $n72_temp1 == 90 AND
$n76_new_sys_range_no_lobflat == 6) 181 , ($n74_mesic_subset == 0 AND
```

```
$n72_temp1 == 90 AND $n76_new_sys_range_no_lobflat == 7) 191,
($n74_mesic_subset == 0 AND $n72_temp1 AND $n76_new_sys_range_no_lobflat ==
15 ) 131 , ($n62_rc_90 > 0 ) $n62_rc_90} ;
n86_model_3 = EITHER $n78_draft_90mod IF ( $n78_draft_90mod > 0 ) OR
$n41_model_2 OTHERWISE ;
n90_z_46_metamodel_091306 = CONDITIONAL { ( $n86_model_3 == 32 ) 34 ,
($n86_model_3 == 142 ) 144 , ($n86_model_3 == 95 ) 96 , ($n86_model_3 == 11 and
$n91_ccap_brack == 1) 14 , ( $n86_model_3 == 11 and $n91_ccap_brack == 0 ) 13 , (
$n86_model_3 == 83 and $n88_pshore_aoi == 1 ) 96 , ( $n86_model_3 > 0 )
$n86_model_3 } ;
n136_water_in_bb = EITHER 1 IF ( $n137_bb4 == 1 and
$n90_z_46_metamodel_091306 == 13 ) OR 0 OTHERWISE ;
n151_water_buf_3x3 = FOCAL MAX ( $n136_water_in_bb , $n144_Low_Pass ) ;
n156_donut_water = EITHER 0 IF ( $n136_water_in_bb == 1 ) OR
$n151_water_buf_3x3 OTHERWISE ;
n140_water_buffer = FOCAL MAX ( $n136_water_in_bb , $n138_Low_Pass ) ;
n143_stpslp_adj_wat_step1 = CONDITIONAL { ($n140_water_buffer == 1 and
$n142_z46_landforms == 10) 1 , ($n140_water_buffer == 1 and $n142_z46_landforms
== 11) 1  } ;
n147_step1_buffer = FOCAL MAX ( $n143_stpslp_adj_wat_step1 , $n144_Low_Pass ) ;
n154_donut_bluff = EITHER 0 IF ( $n143_stpslp_adj_wat_step1 == 1 ) OR
$n147_step1_buffer OTHERWISE ;
```

```
n152_landform_steep_slp_adja_water = EITHER 1 IF ( $n154_donut_bluff == 1 and
$n156_donut_water == 1 and $n90_z_46_metamodel_091306 NE 13 ) OR
$n143_stpslp_adj_wat_step1 OTHERWISE ;
n131_prairie = CONDITIONAL { ( $n92_new_sys_range == 5 and
$n90_z_46_metamodel_091306 == 71 and $n94_bbsoils == 2 and
$n96_z46spring_refl(4) > 93 and $n96_z46spring_refl(4) < 123 and
$n96_z46spring_refl(5) > 57 and $n96_z46spring_refl(5) < 91 and
$n96_z46spring_refl(6) > 21 and $n96_z46spring_refl(6) < 48 and $n97_winterall(4) >
56 and $n97_winterall(4) < 74  and $n97_winterall(5) > 67 and $n97_winterall(5) < 106
and $n97_winterall(6) > 41 and $n97_winterall(6) $n90_z_46_metamodel_091306 93
and $n96_z46spring_refl(4) < 123 and $n96_z46spring_refl(5) > 57 and
$n96_z46spring_refl(5) < 91 and $n96_z46spring_refl(6) > 21 and
$n96_z46spring_refl(6) < 48 and $n97_winterall(4) > 56 and $n97_winterall(4) < 74  and
$n97_winterall(5) > 67 and $n97_winterall(5) < 106 and $n97_winterall(6) > 41 and
$n97_winterall(6) < 66 ) 1, ($n133_c55_pot_bbprairie == 1 and $n94_bbsoils == 2 and
$n96_z46spring_refl(4) > 93 and $n96_z46spring_refl(4) < 123 and
$n96_z46spring_refl(5) > 57 and $n96_z46spring_refl(5) < 91 and
$n96_z46spring_refl(6) > 21 and $n96_z46spring_refl(6) < 48 and $n97_winterall(4) >
56 and $n97_winterall(4) < 74 and $n97_winterall(5) > 67 and $n97_winterall(5) < 106
and $n97_winterall(6) > 41 and $n97_winterall(6) < 66 ) 1
} ;
n118_j137 = EITHER 1 IF ( $n90_z_46_metamodel_091306 == 137 ) OR 0
OTHERWISE ;
```

```
n98_c96 = EITHER 1 IF ( $n92_new_sys_range == 5 and
$n90_z_46_metamodel_091306 == 96 ) OR 0 OTHERWISE ;
n101_clump = CLUMP ( $n98_c96 , 8 ) ;
n126_Output = SIEVETABLE ( 10 , HISTOGRAM ( $n101_clump )  ) ;
WRITE $n126_Output TO "g:/output/bb/size.tbl";
n128_sieve_10 = LOOKUP ( $n101_clump, $n126_Output ) ;
n103_Output = SIEVETABLE ( 2 , HISTOGRAM ( $n101_clump )  ) ;
WRITE $n103_Output TO "g:/output/bb/list.tbl";
n105_sieve_2 = LOOKUP ( $$n101_clump, $n103_Output ) ;
n108_bufclump = FOCAL MAX ( $n105_sieve_2 , $n106_Custom_Integer ) ;
n111_donuts = EITHER 0 IF ( $n105_sieve_2 > 0 ) OR $n108_bufclump OTHERWISE ;
n120_Output = ZONAL MAX ( $n111_donuts , $n118_j137 ) ;
WRITE $n120_Output TO "g:/output/bb/zonmax_smstrm.tbl";
n123_recode_96_from_smstrm = EITHER LOOKUP ( $n105_sieve_2 , $n120_Output )
IF ( $n105_sieve_2 > 0 ) OR 0 OTHERWISE;
n113_Output = ZONAL MAX ( $n111_donuts , $n109_nwi_2class_RC ) ;
WRITE $n113_Output TO "g:/output/bb/zonmax_nwi.tbl";
n117_recode_96_from_nwi = EITHER LOOKUP ( $n105_sieve_2 , $n113_Output ) IF (
$n105_sieve_2 > 0 ) OR 0 OTHERWISE;
n95_z46_step3 = CONDITIONAL { ( $n152_landform_steep_slp_adja_water == 1 )
173, ( $n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 41 and
$n94_bbsoils == 2 ) 174, ( $n92_new_sys_range == 5 and $n131_prairie == 1 ) 171,
($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 42 and $n94_bbsoils
```

== 2) 172, ($n92_new_sys_range == 5 and <raster> == 43 and $n94_bbsoils == 2) 172 , ($n92_new_sys_range == 5 and <raster> == 90 and $n94_bbsoils == 2) 174 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 90 and $n94_bbsoils == 2) 174 , ($n92_new_sys_range == 5 and $n117_recode_96_from_nwi == 1) 137 , ($n92_new_sys_range == 5 and $n123_recode_96_from_smstrm == 1) 137, ($n92_new_sys_range == 5 and $n128_sieve_10 > 0) 137, ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 41 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 1) 162 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306== 41 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 3) 144 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 41 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 6) 181 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 42 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 1) 161 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 42 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 3) 143 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 42 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 6) 182 , ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 43 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 1) 161, ($n92_new_sys_range == 5 and $n90_z_46_metamodel_091306 == 43 and $n94_bbsoils < 2 and $n158_matrix_range_in_blackbelt == 3) 143 , ($n92_new_sys_range == 5 and

```
$n90_z_46_metamodel_091306 == 43 and $n94_bbsoils $n90_z_46_metamodel_091306
0 ) $n90_z_46_metamodel_091306
 } ;
n172_z46_temp2 = CONDITIONAL { ( $n95_z46_step3 == 137 and $n170_bw_fix ==
1 ) 136 , ( $n95_z46_step3 == 136 ) 136 , ( $n95_z46_step3 == 221 ) 221, (
$n95_z46_step3 == 137) 137, ( $n95_z46_step3 > 0 ) $n95_z46_step3 } ;
n168_z46_step4 = CONDITIONAL { ( $n163_blk_to_smstm == 1 and
$n172_z46_temp2 == 136 ) 137 , ($n162_jacprai == 1) 151 , ($n164_strm_to_lgriv == 1
and $n172_z46_temp2 == 136 ) 221 , ( $n164_strm_to_lgriv == 2 and $n172_z46_temp2
== 137 ) 221 , ( $n165_ccap_to_overwrite_nlcd_RC > 0 )
$n165_ccap_to_overwrite_nlcd_RC, ( $n167_bb_063006 == 81 ) 83 ,
($n172_z46_temp2 == 81 ) 83, ( $n167_bb_063006 == 82 ) 84 , ( $n172_z46_temp2 ==
82 ) 84 , ($n167_bb_063006 > 0 ) $n167_bb_063006 , ($n172_z46_temp2 > 0 )
$n172_z46_temp2
 } ;
n185_96fin = EITHER 1 IF ( $n168_z46_step4 == 96 ) OR 0 OTHERWISE ;
n187_96_fin_clump = CLUMP ( $n185_96fin , 8 ) ;
n200_96fin_clump_hist = LOOKUP ( $n187_96_fin_clump , HISTOGRAM (
$n187_96_fin_clump )  ) ;
n190_96fin_buf = FOCAL MAX ( $n187_96_fin_clump , $n189_Low_Pass ) ;
n207_Output = SUMMARY ( $n190_96fin_buf , $n209_z46_step4_RC ) ;
WRITE $n207_Output TO "g:/output/las_minute_2/96_fin_smstrm.mtx";
n211_Output = ZONAL MAJORITY COUNT ( $n207_Output, IGNORE 0 ) ;
```

```
WRITE $n211_Output TO "g:/output/las_minute_2/96fin_zm_smstrm.tbl";

n213_96fin_smstrm_cnt = LOOKUP ( $n187_96_fin_clump , $n211_Output ) ;

n217_96fin_smstrm_cnt_float = $n213_96fin_smstrm_cnt;

n215_96fin_per_touch_smstrm = EITHER ( $n217_96fin_smstrm_cnt_float/
$n200_96fin_clump_hist  * 100 ) IF ( $n200_96fin_clump_hist > 0 ) OR 0 OTHERWISE
;

n220_sm_strm_to_change_25 = EITHER 1 IF ( $n215_96fin_per_touch_smstrm > 25 )
OR 0 OTHERWISE ;

n191_Output = SUMMARY ( $n190_96fin_buf , $n193_z46_step4_RC ) ;

WRITE $n191_Output TO "g:/output/las_minute_2/96_fin_bw.mtx";

n196_Output = ZONAL MAJORITY COUNT ( $n191_Output, IGNORE 0 ) ;

WRITE $n196_Output TO "g:/output/las_minute_2/96fin_zm_bw.tbl";

n198_96fin_bw_cnt = LOOKUP ( $n187_96_fin_clump , $n196_Output ) ;

n203_96fin_bw_cnt_float = $n198_96fin_bw_cnt;

n201_96fin_per_touch_bw = EITHER ( $n203_96fin_bw_cnt_float/
$n200_96fin_clump_hist  * 100 ) IF ( $n200_96fin_clump_hist > 0 ) OR 0 OTHERWISE
;

n206_bw_to_change_25 = EITHER 1 IF ( $n201_96fin_per_touch_bw > 25 ) OR 0
OTHERWISE ;

n221_96fin_rc_to_blk_and_smstrm = CONDITIONAL { ($n206_bw_to_change_25 ==
1) 136 , ( $n220_sm_strm_to_change_25 == 1 ) 137 } ;

n181_z46_step5 = CONDITIONAL { ( $n175_cypdom_edge_to_rc > 0 )
$n175_cypdom_edge_to_rc , ( $n177_nbas_edge_to_rc > 0 ) $n177_nbas_edge_to_rc , (
```

```
$n176_excess_96_in_la > 0 ) $n176_excess_96_in_la , (
$n178_96fin_rc_to_blk_and_smstrm > 0 ) $n178_96fin_rc_to_blk_and_smstrm ,  (
$n179_meslp_recode_final > 0 ) $n179_meslp_recode_final ) , (
$n182_water_in_forest_with_rc_class > 0) $n182_water_in_forest_with_rc_class,  (
$n168_z46_step4 > 0 ) $n168_z46_step4} ;
#define n223_memory Float(EITHER 1 IF ( $n181_z46_step5 == 11 ) OR 0
OTHERWISE )
n253_step6 = CONDITIONAL { ( $n254_t25_final_fn == 2) 221 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 1 ) 161 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 3 ) 143 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 5 ) 174 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 6 ) 181 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 7 ) 191 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 15 ) 134 ,
( $n254_t25_final_fn == 3  and $n255_new_sys_range_no_lobflat == 17 ) 111 ,
( $n254_t25_final_fn == 4  and $n256_bw_range == 1 ) 136 ,
( $n254_t25_final_fn == 4  and $n256_bw_range == 0 ) 137 ,
( $n254_t25_final_fn == 5 )  45 ,
( $n254_t25_final_fn == 7 ) 53 ,
( $n254_t25_final_fn == 8 ) 134 ,
( $n254_t25_final_fn == 9 ) 121,
( $n254_t25_final_fn == 10 ) 136 ,
( $n254_t25_final_fn == 11 ) 135 ,
```

```
( $n181_z46_step5 > 0 ) $n181_z46_step5
 } ;
n258_j96 = EITHER 1 IF ( $n253_step6 == 96 ) OR 0 OTHERWISE ;
n260_j96_clump = CLUMP ( $n258_j96 , 8 ) ;
n262_Output = SIEVETABLE ( 100 , HISTOGRAM ($n260_j96_clump ) ) ;
WRITE $n262_Output TO "f:/asap/sievtab.tbl";
n264_sieve_100 = LOOKUP ( $n260_j96_clump , $n262_Output ) ;
n249_j137 = EITHER 1 IF ( $n253_step6 == 137 ) OR 0 OTHERWISE ;
n269_j137buf = FOCAL MAX ( $n249_j137 , $n250_Low_Pass ) ;
n247_j221 = EITHER 1 IF ( $n253_step6 == 221 ) OR 0 OTHERWISE ;
n270_j221 = FOCAL MAX ( $n247_j221 , $n250_Low_Pass ) ;
n245_j136 = EITHER 1 IF ( $n253_step6 == 136 ) OR 0 OTHERWISE ;
n268_j136buf = FOCAL MAX ( $n245_j136 , $n250_Low_Pass ) ;
n241_j96_sp = EITHER 1 IF ( $n260_j96_clump > 0 and $n264_sieve_100 == 0 ) OR 0
OTHERWISE ;
n243_j96_sp_clump = CLUMP ( $n241_j96_sp , 8 ) ;
n294_Output = SUMMARY ( $n243_j96_sp_clump , $n270_j221 ) ;
WRITE $n294_Output TO "f:/asap/sum221.mtx";
n292_Output = ZONAL MAX ( $n294_Output ) ;
WRITE $n292_Output TO "f:/asap/zm221tab.tbl";
n280_change_221 = LOOKUP ($n243_j96_sp_clump , $n292_Output ) ;
n290_Output = SUMMARY ( $n243_j96_sp_clump , $n269_j137buf ) ;
WRITE $n290_Output TO "f:/asap/sum137.mtx";
```

```
n288_Output = ZONAL MAX ( $n290_Output ) ;

WRITE $n288_Output TO "f:/asap/zm137tab.tbl";

n277_change_137 = LOOKUP ( $n243_j96_sp_clump , $n288_Output ) ;

n286_Output = SUMMARY ( $n243_j96_sp_clump, $n268_j136buf ) ;

WRITE $n286_Output TO "f:/asap/zm136.mtx";

n284_Output = ZONAL MAX ( $n286_Output ) ;

WRITE $n284_Output TO "f:/asap/zm136tab.tbl";

n274_change_136 = LOOKUP ( $n243_j96_sp_clump , $n284_Output ) ;

n283_step7 = CONDITIONAL { ( $n274_change_136 == 1 and $n281_step6 == 96 )
136, ( $n277_change_137 == 1 and $n281_step6 == 96 ) 137 ,  ( $n280_change_221 ==
1 and $n281_step6 == 96 ) 221 , ( $n281_step6 > 0 ) $n281_step6
} ;

n303_step9 = CONDITIONAL { ( $n297_choctaw_10_RC > 0 ) $n297_choctaw_10_RC
, ( $n298_escambia_10_RC > 0 ) $n298_escambia_10_RC , ( $n299_mobile_10_RC > 0
) $n299_mobile_10_RC , ( $n300_pascagoula_10_RC > 0 ) $n300_pascagoula_10_RC ,
( $n301_pearl_10_RC > 0 ) $n301_pearl_10_RC ,
($n306_j96_to_rc_from_hydro == 136 ) 136,
($n306_j96_to_rc_from_hydro == 137 ) 137,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and $n308_nlcd_s8_new
== 83 ) 83 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and $n308_nlcd_s8_new
== 84 ) 84 ,
```

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( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and $n308_nlcd_s8_new
== 55 ) 83 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 1 ) 161 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 3 ) 143 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 5 ) 174 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 6 ) 181 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 7 ) 191 ,
( $n307_j96_clump > 0 and $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 15 ) 131 ,
 ($n307_j96_clump > 0 and  $n304_max_slope_in_clump > 0 and
$n305_new_sys_range_no_lobflat == 17 ) 111 ,
( $n283_step7 > 0 ) $n283_step7
} ;
n325_step9 = EITHER 1 IF ( $n303_step9 == 96 ) OR 0 OTHERWISE ;
n310_j96_clump = CLUMP ( $n325_step9 , 8 ) ;
n312_Output = SUMMARY ( $n310_j96_clump , $n322_hyd_buf_5x5 ) ;
WRITE $n312_Output TO "f:/asap/final/newhydmat.mtx";
n314_Output = ZONAL MAX ( $n312_Output ) ;
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```
WRITE $n314_Output TO "f:/asap/final/newhydzm.tbl";

n316_nwhdmaxinclump = LOOKUP ( $n310_j96_clump , $n314_Output ) ;

n318_j96_to_rc_from_hydro = CONDITIONAL { ( $n316_nwhdmaxinclump > 1 and
$n319_bw_range == 1 ) 136 ,  ( $n316_nwhdmaxinclump > 1 and $n319_bw_range == 0
) 137
} ;

n225_clump = CLUMP ( $n223_memory , 8 ) ;

n231_Output = SIEVETABLE ( 2000 , HISTOGRAM ($n225_clump) ) ;

WRITE $n231_Output TO "c:/97_catfishponds/sievetablarge.tbl";

n233_highval = LOOKUP ( $n225_clump , $n231_Output ) ;

n228_Output = SIEVETABLE ( 50 , HISTOGRAM ($n225_clump)  ) ;

WRITE $n228_Output TO "c:/97_catfishponds/sievetab.tbl";

n227_lowval = LOOKUP ( $n225_clump , $n228_Output ) ;

n235_middle = CONDITIONAL { ( $n227_lowval > 0 and $n225_clump > 0 and
$n233_highval == 0 ) 1
 } ;

n236_clump_final = CLUMP ( $n235_middle , 8 ) ;

n328_z46_ecol_systems_class = CONDITIONAL { ( $n236_clump_final > 0 ) 3, (
$n221_96fin_rc_to_blk_and_smstrm > 0 ) $n221_96fin_rc_to_blk_and_smstrm, (
$n318_j96_to_rc_from_hydro > 0 ) $n318_j96_to_rc_from_hydro, ($n325_step9 > 0 )
$n325_step9
} ;

QUIT;
```