OBJECT-ORIENTED APPROACHES TO

MAPPING CHANNEL HABITAT ON THE LOWER CONGO RIVER

by

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(Under the Direction of Marguerite Madden)

ABSTRACT

Information about large river channels is required for assessments of ecologically and economically important fish assemblages, but field mapping can be an expensive and time-consuming process. Classification of fluvial fish habitats using remotely sensed images is a potential alternative. This study examines whether widely available satellite images can be used to map habitat on the Lower Congo River in Western Africa using an object-oriented approach. One Landsat 7 image and three ASTER images of the river were classified using object-oriented techniques and the results were compared to existing topographic maps. Although insufficient ground truth data were available for a numerical accuracy assessment, the habitat maps produced from the ASTER images correctly identified all major turbulent areas, islands, and rock formations.   This study concludes that an object-oriented approach provides procedural benefits over pixel-based approaches, and that the ability to incorporate spatial context is a major advantage in habitat classification.

INDEX WORDS: ASTER, Landsat, Congo, habitat, rivers, object-oriented classification

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CHAPTER 1 – INTRODUCTION

Large rivers play an important part in both ecosystems and human societies around the world. For humans, rivers provide transportation, food, water, and power, while for flora and fauna they provide essential habitat. Large rivers also exhibit high levels of biodiversity, which in turn delivers a number of economic and environmental benefits (Pimentel et al. 1997). Riparian corridors, for example, host a large number of diverse species and play a substantial role in controlling environmental processes such as flooding and water quality (Naiman et al. 1993). Species richness has also been shown to increase with river size, particularly in the tropics (Allan and Flecker 1993).

Large river ecosystems currently face a number of threats, many of which are caused by human activity. These threats include habitat loss and degradation, construction of levees and dams, contaminant introduction, destruction of wetlands, logging, fire suppression, species extinctions, species introductions, and overharvesting (Allan and Flecker 1993, Johnson et al. 1995, Kouamelan et al. 2003). The effect of many of these threats is the reduction of habitat heterogeneity, and a resulting decline in diversity and abundance of fishes.

Despite the importance of large rivers and the serious threats they face, we know little about them in comparison with small streams and lakes, and as a result, our theoretical understanding of large river ecosystems is quite weak (Johnson et al. 1995). Taxonomic information about the species inhabiting large rivers, for example, is far from complete. This is

particularly true in the tropics, where our lack of knowledge constitutes the largest gap in our global understanding of aquatic vertebrates (Allan and Flecker 1993).

A key step in broadening our understanding of large river ecosystems is the study of the features that make up their physical environment. Current theories assume that the physical environment exhibits powerful controls on biological structure (Johnson et al. 1995), and a number of studies support this contention (Lammert and Allan 1999, Kouamelan 2003, Walters et al. 2003). The traditional method of characterizing fluvial habitat in streams and rivers is to use field mapping teams to measure a number of physical parameters; but this method can be costly and time-consuming, while limited accessibility makes some large rivers difficult and dangerous to map. As a result, some researchers have suggested that remote sensing and geographic information systems (GIS) may be useful in mapping and understanding fluvial habitats (Johnson et al. 1995).

One example of such an approach comes from ichthyological research conducted by the American Museum of Natural History (AMNH) on the Lower Congo River in Western Africa. Despite the river's tremendous size and the diversity of its ichthyofauna, surprisingly little is known about the basin's fish assemblages and habitat. For this reason, AMNH proposed a research program in 2004 to study the Lower Congo River's fish species. In order to gather information about the fish assemblages of the Lower Congo and test a number of hypotheses about evolutionary divergence among ichthyofauna in the basin, AMNH proposed to send an ichthyology field team to the Democratic Republic of Congo in the Summer of 2005 to collect specimens. A lack of adequate information about the spatial locations and extents of aquatic habitats suitable for sustaining fish assemblages within the channel, however, made planning for the expedition difficult. In need of a timely and cost-effective way to increase their

understanding of the Congo's aquatic habitat, AMNH turned to remote sensing. To this end, manual interpretation techniques were used to identify major rapids and pools on satellite image data from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). This initial success, however, raised the question of whether it was possible to obtain more detailed information about river channel habitats, both quickly and economically, using remotely-sensed images and a new approach to image classification known as object-oriented classification, which combines the advantages of traditional spectrally-based image classifications with the spatial context provided by a GIS.

This study will attempt to determine whether an object-oriented approach can be used to map channel-scale habitat on a large tropical river like the Lower Congo using widely-available satellite data. The following chapter, Chapter 2, will describe the context of the problem further by reviewing literature on remote sensing of fluvial systems, fluvial habitat classification, and object-oriented classification. Chapter 3 lays out the study's purpose and research objectives, and Chapter 4 will provide a brief description of the study area. Chapter 5 addresses the data sets and methods used, while Chapter 6 provides a discussion of the studies results. Finally, Chapter 7 summarizes the conclusions of the study.

CHAPTER 2 - LITERATURE REVIEW

2.1 Problem Context

Human beings in general (and scientists in particular) seem compelled to classify people, places, objects, and even ideas. For instance, we classify students by grades, cities by size, and biological organisms by physical characteristics. We place these phenomena into groups for a variety of reasons. First and foremost, classification helps us think about complex systems by carving them up into smaller parts – "creating order out of chaos" (Goodwin 1999). Second, systems of classification help us to communicate information about objects by creating standard units with consistent and logical names. Third, categorization helps us to describe systems in numerical terms by facilitating the use of statistical and spatial descriptors and procedures, such as mean, range, variance, clusters, and pattern analysis. The fourth (and perhaps most elegant) reason for classification is that occasionally a classification system meshes so well with theory that it helps to explain, and not just describe, natural events or processes – as the Periodic Table of Elements does in chemistry (Goodwin 1999).

For these reasons, it is clear that classification plays an important role in our understanding of the world around us, and as a result much of the natural world has been classified by humans, with rivers being no exception. Although numerous classification systems exist for rivers, these systems can generally be divided into two types: form-based (or morphological), and process-based (Goodwin 1999, Legleiter and Goodchild 2005). As the names imply, form-based systems rely on observations and measurements of existing channel forms, while process-based systems attempt to classify rivers based on the physical processes

that create them, such as sedimentation and erosion.   Both approaches require that various

aspects of the channel itself be classified and/or quantified in some way. For example, Rosgen

(1994) uses measurements of entrenchment, gradient, width/depth ratio, sinuosity, and sediment

size to classify channels into a number of major and minor categories. Each classification

system defines its own set of parameters, though they often overlap. One of the more traditional

and widely used methods of classifying channel elements is the visual classification of habitat

types at the channel scale (Kaufmann 2000). This method uses visual observations to classify a

channel into habitat elements such as cascades, falls, rapids, pools, riffles, and runs. While this

method of classification is less quantitative and more subjective than many other methods, it is

also easily understood and easily implemented.

The classification systems mentioned above, as well as the data used to drive them, are

used in a variety of fields. River classification is used in river navigation, engineering (Basson,

Rosgen 1994), channel restoration (Legleiter et al. 2004, Rosgen 1994), and water resource

management (Rosgen 1994). This information is also used to predict channel change and to

assess and forecast human impacts on rivers (Basson, Marcus 2002, Legleiter 2003, Legleiter et

al. 2004, Legleiter and Goodchild 2005). These systems of measurement and classification are

particularly useful, however, in environmental sampling (Fitzpatrick 1998, EPA 2000, Mertes

2002) and fisheries and wildlife management (Gorman and Karr 1978, Richards et al. 1997,

Rosgen 1994, Legleiter and Goodchild 2005, Legleiter 2003, Legleiter et al. 2004). For

example, the Environmental Protection Agency's (EPA) Environmental Monitoring and

Assessment Program (EMAP) is charged with monitoring the ecological condition of natural

resources, including rivers, to provide information to policy-makers and decision-makers. As a

result, the EPA has compiled detailed protocols for monitoring the ecological condition of both

non-wadeable rivers (EPA 2000) and wadeable streams (Kaufmann 1999), an important part of which is characterizing physical habitat. Differences in channel habitat are in large part responsible for differences in aquatic species composition and abundance, and provide a variety of conditions for diverse assemblages, while human changes to habitat can adversely affect riverine ecosystems (Gorman and Karr 1978, EPA 2000). For these reasons, habitat mapping is an important part of ecological monitoring and resources management.

Although information about the physical features of rivers is obviously of use to a variety of people and organizations, gathering such data is often a costly and time-consuming affair. The process often relies on measurements made by field teams, and habitat classifications in particular depend on subjective decisions made in the field (Kaufmann 2000; Marcus et al. 2003). Time, cost, and accessibility can make such field measurements prohibitively difficult. Much of the Lower Congo, for example, is unnavigable, and would be impossible to map from a boat. In other cases, information about a channel is desired before travel to the field is possible, or because field measurements are impossible for logistical reasons. Habitat classification using remotely-sensed data offers a unique solution to these problems.

For example, information can be extracted from remotely-sensed images in much less time and at a fraction of the cost, provided that high-quality image data are available. Furthermore, the synoptic perspective provided by remotely-sensed images gives a view that is not available to ground-based field teams, and such a perspective can sometimes reveal new insights. In addition, although images may lack the detail seen by field teams, they can be less subjective in their record of observations because of their reliance on well-defined physical parameters, as opposed to human intuition (Marcus et al. 2003).

Remote sensing of rivers is not a new idea by any means. Aerial photographs have long been used to study river channels since after World War II (Legleiter 2003, Paine and Kiser 2003, Roberts et al. 1997), and the advent of satellite platforms has allowed broader and more frequent monitoring of fluvial systems (Legleiter 2003). As sensors have grown more sophisticated in their ability to record both spatial and spectral detail, researchers have become increasingly successful at classifying river channel habitats using remotely-sensed data (Legleiter 2003, Marcus et al. 2003, Legleiter and Goodchild 2005). However, most research to date has been accomplished using traditional pixel-based methods, which attempt to classify the individual picture elements of an image, but do not take into account any information about adjacent pixels or the spatial relationships between pixels (Lillesand and Kiefer 2003).

New algorithms and software now make it possible to consider the spatial context of pixels during the classification process – an approach known as *object-oriented classification*. In a process called image segmentation, an object-oriented classifier groups like pixels together based on rule sets, and these groups of pixels are in turn identified as objects, such as houses or parking lots (Blaschke et al. 2000). Such an object-based approach could prove useful in classifying river channel habitats, since such habitats are often at least partially defined by shape and spatial context. For example, pools often have a shape that differs from the rest of the channel, and rapids are often bracketed both upstream and downstream by calmer stretches of water. Object-oriented techniques have already been used to successfully improve land use and land cover classifications (Blaschke et al. 2000, Geneletti and Gorte 2003). These successes suggest that such an approach might also be useful in improving automated classifications of river channel habitats.

2.2 Review of Similar Studies

Remote Sensing of Fluvial Systems

Passive Remote Sensing of Fluvial Systems

A wide range of passive sensors have been used to study fluvial systems in a number of ways. Perhaps one of the broadest of these applications has been in mapping riverine landscapes, where the unique synoptic perspective and wide coverage of satellite-based sensors has allowed researchers to further their studies of the relationships between channels, catchment basins, and floodplains (Mertes 2002). In addition to this broad-scale mapping of fluvial systems, passive sensors have been used to quantify the physical properties of water within river channels. Legleiter et al. (2004), for example, examined the physical basis and feasibility of using optical sensors for assessing stream depth, concluding that some hyperspectral sensors can be well suited to measuring stream depths of up to three meters depending on water clarity, with the potential for mapping pools and riffles. Such sensors have also been used to assess the water quality of rivers, including estimation of algal densities and sediment loads using optical and infrared data, and to record and analyze the thermal properties of water (Mertes 2002). The Forward Looking Infrared system, or FLIR, has been shown to be capable of generating detailed maps of water temperature, which can be an important habitat discriminator for some species of fish (Mertes 2002).

Passive sensors have also been widely used in the particular area of channel-scale habitat mapping, although the majority of research has focused on small rivers and streams, most likely because smaller channels are more prevalent, more accessible, and easier to sample (Johnson et al. 1995). For example, Roberts et al. (1997) proposed using airborne multispectral digital

imagery and aerial photographs to identify and monitor salmon habitat in British Columbia, Canada, and provides a detailed discussion of more than 30 habitat parameters which can be measured using aerial photo interpretation and standard photogrammetric techniques. However, the increased information content of high-resolution, hyperspectral imagery may provide an advantage over more traditional aerial photographs, and recent research has focused on these types of data. Marcus et al. (2003) studied the feasibility of using 1-meter, 128-band imagery to map habitat, depths, and woody debris in mountain streams, obtaining overall classification accuracies for habitats between 69% and 86%, depending on the order of the stream. Legleiter (2003) used the same data to compare spectrally-defined habitat classes with those mapped in the field, finding that while some field-mapped habitat classes could be linked to spectral classes, other parts of the channel could not be easily classified based solely on spectral characteristics. This difficulty in characterizing transition areas between habitat units has led to the application of fuzzy classification methods to images acquired by passive sensors. In fuzzy classification, pixels are not required to belong to only one class; rather, they are assigned a possibility for membership in every class. Legleiter and Goodchild (2005) successfully applied this approach, in conjunction with hydraulic modeling, to both hyperspectral and multispectral data, resulting in an alternative, more realistic way of looking at channel-scale habitat classification.

Experience has shown that spectral resolution of a passive sensor also plays an important role in the remote sensing of channel habitats. A study in 2000 cited by Marcus et al. (2003), saw very low overall accuracies (10-53%) using 4-band, 1-meter data on small channels in Montana and Wyoming. Though much of the error was likely caused by difficulties with co-registration of the images, the authors still noted the need for greater spectral resolution. In contrast, Marcus (2002) was able to achieve an 85% overall classification accuracy using 128-

band, 1-meter hyperspectral imagery from the Probe1 sensor on the Lamar River in Wyoming, and Goovaerts (2002) increased that accuracy to 97% using the statistical technique of indicator kriging. In the same study, Marcus improved overall classification accuracies by almost 18% by using 128-band images as opposed to 4-band images. Another 2002 study, cited in Marcus et al. (2003), saw accuracies rise by 7.2% when using 128 bands instead of 8 bands. Marcus postulates that "both the improved spectral and enhanced spatial resolution provided by HSRH [High Spatial Resolution Hyperspectral] imagery appear necessary to accurately map in-stream habitats" (Marcus et al. 2003:364). It is important to note, however, that all of the research cited here was conducted on streams and small rivers, and it is unclear whether the need for hyperspectral data applies to larger rivers as well.

In an effort to better understand the physical basis for the remote sensing of channel habitat, Legleiter et al. (2004) used a hand-held spectrometer along Soda Butte Creek in Yellowstone National Park, to study the interaction between electromagnetic reflectance and stream channel elements, such as water depth and substrate. The results indicated that depth measurements in particular, which can be used to map pools and riffles, can be made using a ratio-based model, but that this is generally only feasible in shallow waters (about 1-3 meters). They concluded that "high radiometric sensitivity, fine spatial resolution, and a large number of spectral bands are highly desirable, if not necessary, for stream studies" (507). Once again, however, these studies are based on relatively shallow, narrow streams, and the conditions which require high spectral resolution in small streams may not be present or important in large rivers. For example, although hyperspectral data are preferable for estimating depth in shallow streams, the greater depths of large rivers make it impossible to accurately gauge water depth. Thus, hyperspectral data may not be a prerequisite for habitat classification on larger rivers.

This study differs from previous research in its data resolution, classification methods, and channel scale, and therefore the conclusions drawn from the existing literature on habitat classification using passive sensors have limited relevance. That habitat units like rapids, runs, and pools have been classified in remotely-sensed images of the appropriate scale indicates that these features can be identified, but the differences between small and large fluvial systems may require changes in how this is accomplished. Large channels may show increased channel depths, stronger turbulence, greater volume of flow, larger bed particle size, increased tributary inputs, and reduced effects of overhanging vegetation. These differences from smaller channels will influence both the habitat classification system and the methods of identification.

Active Remote Sensing of Fluvial Systems

As noted above, active remote sensing systems produce their own electromagnetic radiation. The most widely recognized of these systems are radar and LIDAR, both of which operate in the microwave portion of the electromagnetic spectrum. Radar has been used extensively to map elevations using two different techniques: radargrammetry (altimetry), which uses the offsets in separate radar images to compute elevations; and interferometry, which analyzes the phases of radar signals to find elevations (Elachi and van Zyl 2006, Henderson and Lewis 1998). The Shuttle Radar Topography Mission (SRTM) flown by NASA in 2000, for example, used interferometry to collect elevation data for most of the earth's surface at a horizontal resolution of 90 meters and a vertical resolution of 1 meter.   In terms of fluvial environments, radar altimetry and interferometry are commonly used to quantify the elevation of water surfaces, in some cases to the centimeter scale (Mertes 2002). The Laser Radar or Light Detection and Ranging system (LIDAR) is being increasingly used for topographic mapping

because of its fine vertical resolution, which is generally below one meter, and less than 10 centimeters in some cases (Mertes 2002), although coverage is generally limited and can be costly. Elevation data can also be useful for mapping of habitat channel because it allows comparison of gradient changes. This can be used, for example, to differentiate between a fall and a rapid, which may be indistinguishable with only spectral information.

Fluvial Habitat Classification

As noted previously, fluvial classification is normally accomplished through the use of field teams. Two of the most detailed protocols for mapping rivers in the field are provided by Fitzpatrick (1998) and Kaufmann (2000), published by USGS and the EPA, respectively. Each of these manuals covers in detail the protocols for obtaining a wide array of physical measurements of streams and rivers. These parameters include, among others, various types of channel dimensions, measures of channel gradient, channel substrate size and type, habitat complexity and cover, riparian vegetation cover, and drainage basin characteristics. The measurements for wadeable streams are generally made from the bank and from the stream channel itself, while those for non-wadeable rivers are made from the bank and from boats. In addition to these quantitative measurements, teams also prepare maps based on visual observation of generic channel features such as cascades, falls, rapids, pools, riffles, and runs. The EPA refers to these features as habitat units, while USGS uses the name geomorphic channel units (GCUs). This study uses the term *habitat unit* because of the study's ties to ichthyologic research; but it is important to note that the use of habitat units is not strictly confined to habitat description. The term GCU emphasizes the fact that these features are intimately tied to the geomorphology of the river.

Although some of the visual features of these mapping systems, such as rapids and runs, can be identified from remotely sensed images, many of the other variables, such as bankfull width and bed particle size, are impossible to quantify from a satellite image. For this reason, it is important to consider how physical variables affect fish assemblages in fluvial systems, and which of these variables might be measured from widely-available imagery and data sets. Much of the research in the area of abiotic controls on species composition is centered on streams much smaller than the Congo, most likely because these streams are much more accessible and easier to sample than a large tropical river (Johnson et al. 1995). Although it is difficult to tell how these variables might affect fish assemblages in larger rivers, these studies may still be useful, however, in thinking about what physical parameters might affect fish assemblages; and there is at least some evidence that geomorphic variables may predict species composition regardless of stream size (Walters et al. 2003).

Stream slope may be considered the dominant abiotic factor in controlling fish assemblages, and slope is intimately related to the physical variables of depth, turbulence, bed material size, and water velocity (Walters et al. 2003, D'Angelo et al. 1997). Slope affects fish assemblages in two ways: by altering the benthic habitat, and by acting as a barrier to dispersal of some species. While it is unknown whether the former method is of great importance on the Congo, the second must surely be given the volume and power of the river, making it an important factor in evolutionary studies. Slope may be calculated from a DEM, but this method is a weak correlate to survey measurements (Walters et al. 2003).

Thalweg variation, or the change in the change in the channel's centerline depth, is related to variations in both depth and turbulence, and has also been found to be an important factor in species composition. Although thalweg measurements cannot be made for a river as

deep as the Congo using satellite imagery, this connection to depth and turbulence might be exploited. Walters et al. (2003) found direct, continuous measures of pools and riffles to be poor predictors of species composition in comparison to thalweg measurements, but Lammert and Allan (1999), in contrast, found a strong correlation between fish abundance and measures of channel morphology, including percent pool and percent run. This suggests that while measures of turbulence and depth may not be as accurate as thalweg measurements, they may still be useful in characterizing channel habitat. In some cases, turbulence may be used on its own to identify habitat for particular species adapted to life in the rapids (Schelly and Stiassny 2004). Additionally, the churning action of rapids increases oxygen content in neighboring pools, which may increase the use of fish habitat in these pools.

Two additional related factors which influence fluvial habitat are bed material and water velocity. Average particle size of bed material has been shown to be a strong predictor of species composition (Walters et al. 2003), and although this information cannot be obtained from ASTER or Landsat images, it is once again strongly correlated with stream slope and the presence of riffles and pools (which are in turn measures of turbulence and depth). Water velocity, too, plays a role in habitat creation and species distribution (Kouamelan et al. 2003), with some species of fish being attracted to low velocity areas because they require less energy than maintaining a position in faster moving water (Jackson et al. 1999). Again, velocity cannot be directly measured from satellite images, but relative assessments of velocity can be made based on spatial relationships to channel obstructions and channel curvature.

Several other factors identifiable from digital image data may affect channel habitat, including bank cover, geology and topography, connectivity, and habitat heterogeneity. Lammert and Allan (1999) demonstrated that fish assemblages show a strong relationship to

some types of nearby landuse, particularly within 100 meters of the channel, and overhanging

vegetation can affect the amount of sunlight that areas near the bank receive. Urban areas in

particular may have powerful effects on nearby stream habitat (Walters et al. 2003). In terms of

geology and topography, some underlying geologic formations may be more conducive to the

development of pool-riffle structures than others (Jackson et al. 2001), and streams with

extensive topographic relief close to the channel bed may be limited in the amount of sunlight

and discharge they receive (D'Angelo et al. 1997). Turbulence, too, may be associated with

topography where elevation changes cause rapid drops in the channel. Connectivity can have

profound impacts on species composition by preventing or encouraging movement of fishes:

steep cascades and waterfalls may limit the range of some species, while connections with

tributaries may encourage the movement of others species and create habitat conditions that

promote diversity (Walters et al. 2003, Jackson et al. 2001, Rice et al. 2001). Finally, habitat

heterogeneity throughout the channel's length can encourage diversity of species by improving

conditions for both foraging and escape from predation (Jackson et al. 2001).

Object-Oriented Classification of Fluvial Systems

Image interpretation can generally be approached in one of two ways: 1) a purely manual

approach in which a human interpreter classifies an image based on visual cues and expertise

knowledge; or 2) using some sort of automated technique, such as a supervised classification,

which is guided and augmented by the user. In the case of fluvial habitat classification,

automated techniques provide three advantages over manual interpretation. The first advantage

is reduced time for classification. Although an investment of time is needed for the construction

of training areas or rule sets, classification proceeds relatively quickly once such parameters are

defined, and the time savings increase as more images are added to the classification process. The second advantage is repeatability. Although a level of subjectivity is involved in the definition of training sites and rule sets, automated techniques in general provide more repeatable and less subjective results than human interpreters, which is often of importance in legal matters. The third advantage is that it is often easier for a computer to sort through and synthesize the multiple data sets associated with multi- and hyperspectral data than it is for a human interpreter. For these reasons, automated techniques can be an important tool for the interpreter attempting to quantify a riverine system.

Automated classification techniques have traditionally been pixel-based, meaning they classify a pixel as a member of a group based primarily on that pixel's spectral characteristics (see Lillesand and Kiefer 2003). For example, many of the studies cited in this proposal used a maximum likelihood classifier, which uses statistical probability to assign a pixel to a class based on the pixel's spectral characteristics. Researchers have developed powerful variations of these pixel-based algorithms: Goovaerts (2002), for example, used a statistical technique called indicator kriging to incorporate some spatial elements in a maximum likelihood classification of river channel habitat units. In general, however, pixel-based techniques have not taken into account the sort of spatial information, such as shape or spatial relationship to other pixels, which a human interpreter processes almost automatically. Object-oriented classifiers attempt to correct this deficiency by incorporating spatial information into their analyses. Two of the most widely available object-oriented software available today are Visual Learning Systems' Feature Analyst and Definiens Imaging's eCognition.

Feature Analyst is a type of object-oriented software which incorporates an iterative, machine learning process to "learn" from the user and refine its classifications (Visual Learning

Systems 2004). The classification process is similar to a traditional, pixel-based supervised classification, in that the process relies on user-defined examples of each class, called training sets. Feature Analyst, however, possesses several advantages over a purely pixel-based classification. First, Feature Analyst is object-based. It classifies not only individual pixels, but can also recognize groups of pixels as distinct objects. Second, unlike a pixel-based classification, the software takes into account shape and spatial context (the position of a pixel or object relative to other objects). Third, the software's iterative learning process allows it to refine its classifications based on user feedback. These advantages make Feature Analyst considerably more powerful than traditional methods of feature extraction, while its training-set approach makes it easy to use with little operator training.

Unlike Feature Analyst, which is a plug-in for existing software, eCognition is a stand-alone software package that performs multiresolution image segmentations and object-oriented image classification (Definiens Imaging 2004, Benz et al. 2004). While eCognition supports sample-based classifications in a way similar to Feature Analyst, it also has the ability to accept segmentation and classification parameters (known as "membership functions") *a priori*. The user defines a series of rules that govern the image segmentation and classification, and these rules can then be saved and applied to subsequent images. The program also utilizes a fuzzy classification system, such as that employed by Legleiter et al. (2005). These additional features make eCognition a powerful analytical tool, and for this reason, eCognition is employed in this study.

Object-oriented classification has already been used to conduct and improve landuse/landcover classifications (Schiefer 2001, Elbert and Helmschrot 2004). For example, Blaschke et al. (2000) used Landsat TM and SPOT panchromatic images for an area near

Salzburg, Austria in conjunction with various GIS data layers to compare per-pixel classifications with context-based classifications (performed with eCognition). Although they did not report numerical differences in classification accuracy, the context-based classifications resulted in more homogeneous classified areas, with fewer isolated pixels (the "salt and pepper effect"). Similarly, Geneletti and Gorte (2003) used a combination of black-and-white orthophotos and Landsat TM images of Northern Italy in a comparison of pixel-based and object-oriented classifications. Their results showed that object-oriented classification provided an increase in overall classification accuracy. Though there seems to be little published research to date concerning the use of object-oriented classification to assess channel habitat, the method has been shown to be of use in coastal and riparian environments. Jordan and Manglass (2005) used Feature Analyst to successfully automate coastal feature mapping, and Rolim and Lingau (2002) obtained favorable results using eCognition to monitor riparian areas. These successes suggest that such an approach might prove feasible for mapping channel habitat in large rivers.

CHAPTER 3 – RESEARCH OBJECTIVES

The specific hypothesis to be tested in this study is that channel habitat in large rivers can be mapped using medium resolution, multispectral imagery, using object-oriented classification techniques. This study differs from previous research in two major ways: its data set selection and its classification approach. With regard to data set selection, one of the major objectives of this study is to test whether inexpensive, widely available image data can be used to map habitat on large rivers, a question which is particularly relevant for researchers who have limited funding or who are conducting research in remote corners of the world. As has been shown, much of the current research in habitat mapping uses high resolution hyperspectral data for the simple reason that they provide the spatial and spectral detail that is essential in mapping small streams. Such data, however, have disadvantages as well, perhaps the greatest being their limited availability and cost. These data are typically collected from airborne sensors, which necessarily limits the spatial and temporal coverage of the data and increases the cost of collection.

In contrast, medium-resolution multispectral imagery, such as that provided by Landsat and ASTER, is widely available for most of the world over large periods of time. In many cases, Landsat and ASTER data are freely given to researchers, and data can be directly downloaded via the internet. Even when the data are not free, images from the Landsat Enhanced Thematic Mapper Plus (ETM+) cost on the order of $600; and ASTER images are only $60 from the United States Geological Survey (USGS). Because ASTER and Landsat are satellite-based

sensors, they return to an area over and over on a regular basis, while imagery from airborne sensors is generally collected only once. This repetitive imaging can be particularly useful in the tropics, where frequent cloud cover makes clear images difficult. In addition, high resolution hyperspectral images have much higher data volumes than medium resolution multispectral images. Although with today's fast computers and large storage capacities this is less of a problem, high data volume can still create challenges for data transfer and analysis. For these reasons, this study uses ASTER and Landsat data. The necessary trade-off in using this type of data is that it can only be used for larger rivers.

The second major objective of this study is to test whether an object-oriented classification approach can offer procedural advantages that traditional classification techniques cannot. Object-oriented classifiers have already been shown to improve the accuracy of land cover classifications; but do they offer any methods of analysis that would be impossible for pixel-based approaches? This procedural aspect of the study is important, particularly because adequate ground truth data from the Lower Congo are not available to conduct a traditional accuracy assessment. In this case, the degree that an object-oriented approach will increase the accuracy of a habitat classification cannot be tested, but what can be tested instead is whether such an approach can offer new ways of approaching the problem. There is certainly reason to believe that object-oriented approaches contribute to habitat suitability analysis of large rivers. The ability to use spatial information in addition to spectral information opens up a number of possibilities in defining how an image is classified to define aquatic habitats..

This study will attempt to answer the following research questions.

- Can objects representing habitat units be extracted from medium-resolution multi-spectral satellite imagery?

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- Assuming that multiple object scales will be used for analysis, what scales should be used for segmentation?

- Once an image has been segmented, can its objects be classified as habitat units?

- How reliable is the resulting classification?

- Can object-oriented methods developed with data at one resolution be applied to coarser-resolution data?

- Does an object-oriented approach provide procedural advantages over traditional approaches?

- What guidelines can be established for future habitat classifications using object-oriented methods?

CHAPTER 4 - STUDY AREA

The study area for this project is located in the Democratic Republic of Congo in western Africa, along a section of the Lower Congo River. This portion of the Congo River flows southwest from the town of Kinshasa to the Atlantic Ocean, and accounts for the last 500 kilometers of the river's length (see Figure 4.1). In contrast to the Middle Congo, which descends only 300 meters over the 2000 kilometers upstream of Kinshasa and reaches widths of 15 kilometers in some places, the Lower Congo and its tributaries are narrow, steep, and distinguished by a large number of waterfalls and rapids. In the 350 kilometers from Kinshasa to Matadi, for example, the river drops some 270 meters and passes through three distinct sections: the *Cataractes Nord*, 133 kilometers long with 30 rapids; the *Bief Centrale Navigable*, 129 kilometers long with alternating sections of rapids and reaches; and the *Cataractes Sud*, 88 kilometers long with 23 chutes and rapids and an incredible 100 meters of elevation change (Robert 1946). This turbulence makes much of the Lower Congo unnavigable; but the river's relative isolation, along with its relatively unchanged geology since the Pleistocene, are in large part responsible for the incredible diversity of ichthyofauna in the region (Beadle 1981). It is the relationship between the river's natural barriers and the diversity of endemic fish species that is the focus of study for the AMNH ichthyology team, and which in turn drove the need for channel habitat mapping along the Lower Congo.

The stretch of river used for analysis in this study runs approximately 340 kilometers from the cities of Brazzaville and Kinshasa in the northeast to the town of Matadi in the

southwest (see Figure 4.1). Although the river flows through the Democratic Republic of Congo throughout this length, at times it forms the border with the countries of Congo and Angola (see Figure 4.2). Geologically, this portion of the river can be split into three sections: the upper third, composed primarily of sandstones, and which roughly corresponds to the Cataractes Nord; the middle third, composed mainly of carbonates, which generally follows the Bief Centrale Navigable; and the bottom third, composed of a series of metamorphic layers, and which approximately coincides with the Cataractes Sud (Dadet 1966, Lepersonne 1974). The yearly mean flow volume past Brazzaville-Kinshasa is generally between 35,000 and 45,000 m^3/s. Although the flow volume is fairly stable compared to many seasonal rivers, the Lower Congo does exhibit seasonal variations in its flow, with low flow occurring around June to August, and high flow occurring around November and December. The low flow volume is generally about one half of the high flow volume (Systeme d'Observation du Cycle Hydrologique 2006).

The climate for the study area is typical for the tropics, with high rainfall, except in the dry season, and warm temperatures year-round. Average annual precipitation at Kinshasa, for example, is 1,358 mm, with a low of 3 mm in July and August, and a high of 222 mm in November. The average annual low temperature at Kinshasa is 20.7 degrees Celsius, while the average high temperature is 30.4 degrees Celsius (BBC Weather 2006). Vegetation in the study area is primarily medium to high shrubland with short herbaceous vegetation and sparse trees, although woodland areas dominate in the areas just south of Kinshasa and Brazzaville (Africover 2004). Ground photographs indicate that grasses are also extensive in the area, and large numbers of fires in the dry season most likely contribute to the maintenance of these grasses (Gardiner 2006).

Figure 4.1. Democratic Republic of the Congo and the Lower Congo River.
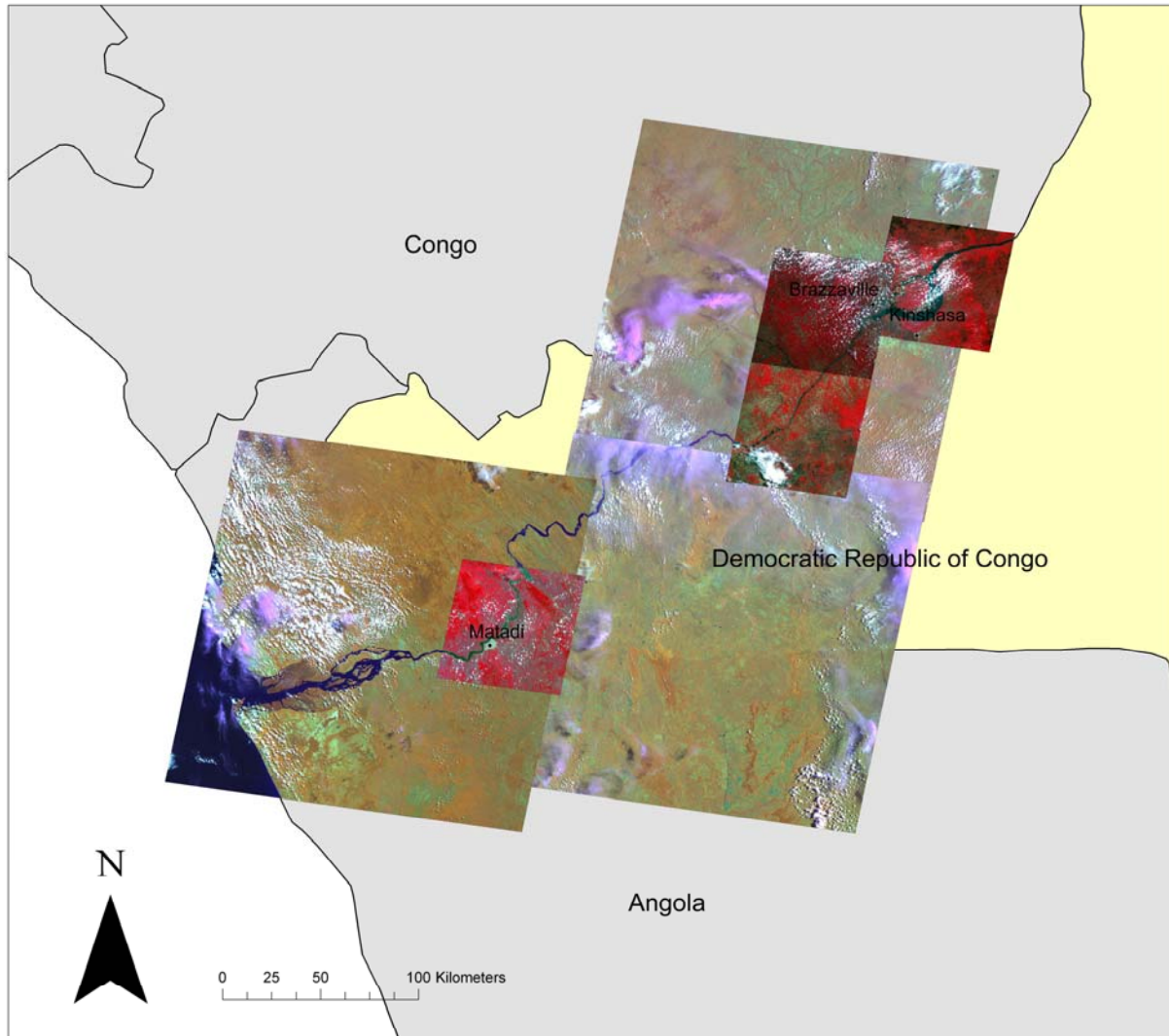
Figure 4.2. Study area. The three large images are Landsat ETM+ 4-5-3 images, while the smaller images are ASTER images in a 3-2-1 band combination.

CHAPTER 5 - DATA AND METHODS

5.1 Data Sources

Digital Data

Four ASTER images were used as the primary image data for this study (see Table 5.1). Although Landsat ETM+ data were also used, the ASTER images provide higher spatial resolution in the visible and near infrared (VNIR) bands (15 meters for the latter as opposed to 30 meters for the former - see Table 5.1 for a comparison). A typical ASTER scene is also higher in spectral resolution, being composed of a total of 14 bands, as opposed to the 8 bands of Landsat ETM+. In this study, however, only the first three ASTER Bands (green, red, and near infrared) were used, as the remaining bands have lower spatial resolutions and offer little additional information useful for discriminating between habitat units. The scenes were obtained as L1B products, meaning that they contain radiometrically calibrated and geometrically coregistered data for all channels. The stated geopositional accuracy of ASTER L1B products is plus or minus 50 meters. The images were provided by the American Museum of Natural History. For ease of reference, the images are labeled Tiles A1 through A4, and can be seen in Figures 5.1 through 5.4

The ASTER images were orthocorrected using the ASTERDTM 2.2 program produced by SulSoft. ASTERDTM is a plug-in for the Environment for Visualizing Images (ENVI) software produced by Research Systems, Inc., and the module automatically extracts digital elevation values from an ASTER L1A or L1B stereo pair to create a digital terrain model

(DTM). The DTM is then used to orthocorrect the bands in the image, with a final x/y error of plus or minus 50 meters.

Three images from the ETM+ sensor aboard the Landsat 7 satellite were also available for this study (see Table 5.1). Much of the river channel in two of the Landsat scenes was partially obscured by clouds, however, so that only one Landsat scene was used in the classification procedures. True-color images of the cloudy scenes were used to aid in visual interpretation of the ASTER images. In order to use the classification criteria developed for the ASTER images with the Landsat data, only three of the eight available ETM+ Bands were used. As with ASTER, these were the green, red, and near-infrared bands (NIR), all with a spatial resolution of 30 meters. These scenes were taken from the Landsat GeoCover dataset, which provides orthorectified images with a geopositional accuracy of plus or minus 50 meters. The images were provided free of charge by the Global Land Cover Facility (GLCF, website at http://www.landcover.org) at the University of Maryland. These images will be referred to as Tiles E1 through E3. An image subset of the scene used on classification (Tile E3) can be seen in Figure 5.5.

Also provided by GLCF were three Digital Elevation Models (DEMs) from the SRTM dataset. These DEMs are based on the "unfinished" 3 arc-second DEM of the world produced by the United States Geologic Survey (USGS). In order to create images based on the World Reference System 2 (WRS-2), the data were resampled by GLCF using the nearest neighbor technique. The horizontal resolution of the DEM is 90 meters, with a vertical resolution of less than 1 meter.

The spatial resolution of image data is particularly important in mapping channel scale habitat units. A common rule of thumb in remote sensing is that nine pixels in a three-by-three

square are required to identify an object on the ground (Jordan 2005). Similarly, a general

guideline for habitat mapping is that each habitat unit must be at least as long as the channel is

wide (Kaufmann 2000), and that a habitat unit should be at least 50% of the channel width

(Fitzpatrick et al. 1998). Based on these requirements, the minimum necessary resolution for

mapping habitat units in a channel is approximately 1/6 of the channel width (see Figure 5.6).

Since a large channel with a width of 500 meters would require a resolution of at least 83 meters,

a river of this size should be easily mapped with a medium-resolution sensor such as Landsat or

ASTER. Likewise, small streams with widths of 1-3 meters would require imagery with sub-

meter resolution. This method of estimating required spatial resolution makes the assumption

that the channel is not obscured from the sensor's view by overhanging vegetation – an

assumption often not met in small streams, but generally valid for large rivers. At the narrowest

part of the study area, the Lower Congo River is approximately 500 meters wide, and thus a

minimum spatial resolution of 83 meters is required. ASTER and ETM+ both provide greater

spatial resolutions in the VNIR bands, and should therefore provide sufficient detail for mapping

habitat units in the study area. It should be noted that Legleiter et al. (2004) suggest a less

rigorous guideline that resolution should be at least one-half the mean channel width. This study

uses the more rigorous 9-pixel rule mentioned above.

Ancillary Data

Additional information for this study was supplied by a number of ancillary data sets,

including digital photographs, textual descriptions, diagrams, topographic maps, and geologic

maps. The ground photographs were taken by the AMNH field team in July of 2005 near

sampling sites along the river. Some of the photos are referenced using coordinates from a

Geographic Positioning System (GPS). These photos were an invaluable aid in gaining a sense

of what the river actually looks like from the ground and in developing the land cover

classification. The textual descriptions and river profile diagrams were translated from the

original French in Robert's *Le Congo Physique* (1946), and these sources were also useful in

interpreting images of the river. The topographic maps are a set of seven black and white maps

at 1:100,000 scale, printed by the U.S. Army Map Service in 1942 and based on a set of Belgian

maps dated 1934. The maps cover the entire study area, with the exception of a small stretch of

river approximately 65 kilometers north of Matadi. The geologic maps (Dadet 1966, Lepersonne

1974), produced by French and Belgian researchers between 1966 and 1974, are at the much

broader scales of 1:500,000 and 1:2,000,000. The maps provide very basic information about the

geology of the area, and proved useful for placing the river in a geologic context.

5.2 Description of Methods

Physical Habitat Variables

While remotely sensed image data provide synoptic information that can be used for

riverine habitat classification, they cannot provide the detailed measurements, such as thalweg

depth or bed particle size, that well-trained field observers can. For this reason, remotely sensed

classifications generally complement, but do not replace, field observations for physical habitat

assessments of rivers. In some areas, however, field observations may be impractical for reasons

of safety and accessibility. The Lower Congo, for example, is completely unnavigable for at

least two-thirds of its length, making collection of data from a boat unsafe along much of the

channel. The number of roads in the area is also limited, which can make access to the river

difficult. Of the numerous physical parameters that may affect fluvial fish assemblages (see

Walters et al. 2003 for a comprehensive list), only a few can be assessed in any useful way using

satellite data; but these parameters can nevertheless provide useful information about aquatic

habitats.

Four variables were selected for classification in this study: presence of whitewater,

presence of islands and shallows, bank cover, and water depth,. As discussed previously,

turbulence, approximated here by the presence or absence of whitewater, is related to several

factors which predict fish assemblages, including thalweg depth and bed particle size, and

turbulence also plays in important role in the limitation of dispersal. Based on visual

interpretation of the images, areas with whitewater reflect higher in the green and red bands than

areas without whitewater, and show a higher brightness overall. The presence of islands and

shallows is the second factor, which is itself tied to depth. Bank vegetative cover, including

island cover, is the third variable that will be classified. By using the spectral reflectance values

of the land adjacent to the river channel, we can determine the land cover on the river's banks.

Banks with trees will have a higher probability of providing overhead cover for some portion of

the channel (albeit a small one, given the channel's width).

The final variable, water depth, is also tied to many of the same factors as turbulence.

Although some techniques have been proposed for estimating depth in streams and shallow

rivers (Winterbottom and Gilvear 1997, Legleiter et al 2004), the effectiveness of such

techniques on different types of rivers using different types of sensors is still being explored

(Legleiter and Roberts 2005). Four major factors affect the reflectance of radiation in water:

bottom depth, substrate type, suspended sediment concentration, and surface turbulence

(Winterbottom and Gilvear 1997, Legleiter et al 2004). Deeper water tends to show greater

radiation absorption, particularly in the infrared bands, making infrared suitable for identifying

only very shallow areas. Substrates with differing albedos also affect radiance, with lighter

colored substrates (such as limestone) returning higher values than darker colored substrates.

Suspended sediment concentration tends to cause scattering, although the impact is smallest in

the infrared. Surface turbulence also tends to increase reflectance as turbulence increases,

affecting all wavelengths equally. Because near-infrared bands appear to be the most sensitive to

changes in depth, and in order to minimize any effects from sediment, the infrared band will be

used to assess water depth by identifying the shallowest areas in the channel.

The variables of slope, geology, topography, connectivity, and water velocity were also

considered for analysis in this study, but time constraints and methodological problems

precluded their use. These issues will be discussed in Chapters 6 and 7.

Object-Oriented Classification

The process of object-oriented classification differs from that of traditional pixel-based

classification in a number of ways. This section describes some of the key object-oriented

concepts referred to in this study. For simplicity and uniformity, these concepts are discussed in

the context and vocabulary of eCognition, though they may be referred to differently in other

software packages.

Image Segmentation

The first step in the process of object-oriented classification is to create relatively

homogeneous groups of pixels known as objects. In eCognition, this process is referred to as

multi-resolution image segmentation. The procedure uses a bottom-up, region-growing algorithm

in conjunction with user-specified parameters to create image objects with minimal heterogeneity, which can then be classified based on a variety of object characteristics.

The most important of the user-specified parameters is the *scale factor*, which controls the size of the resulting image objects. Small scale factors produce small image objects, while large scale factors produce large objects. The segmentation process is referred to as "multiresolution segmentation" because it can be performed any number of times on the same image using different scale factors, thus producing different *object levels* containing objects of different scales. The process is an iterative one which builds from each previous segmentation. If an image is segmented with a small scale factor and then with a large scale factor, the second segmentation uses the original image objects as a basis for the new, larger objects. The original small objects become *subobjects* which are wholly contained within the new, larger *superobjects*. Because of this dependency on previous iterations, the direction of segmentation (large to small or small to large) can affect the shape of the resulting image objects at each level.

An advanced form of image segmentation featured in eCognition is *classification-based segmentation*, which allows information from previous classifications to be used in the segmentation process. This procedure can be used either to fuse objects of the same class to create larger superobjects, or to further segment larger objects of a single class into smaller subobjects. For example, an image can be segmented and its objects classified as *water* and *land*. Using classification-based segmentation, all adjoining *water* objects can be fused to create larger objects. The *land* objects, on the other hand, could be segmented into even smaller objects using a smaller scale factor without affecting the water objects. As will be seen in the classification procedures, classification-based segmentation is a powerful tool.

Object-Based Classification

Before the image objects can be classified, a *class hierarchy* must be created. A class hierarchy is simply the classification system to be used for the image arranged in a hierarchical form. As with many other computer-based hierarchies, higher elements are known as *parents*, while lower elements are referred to as *children*. Parent classes in eCognition must be fully defined by their child classes: in other words, if the parent class *water* is composed of the child classes *whitewater* and *not whitewater*, all objects classified as *water* must also be classified as either *whitewater* or *not whitewater*. In addition, child classes inherit all of the characteristics of their parent classes, so that if *water* is defined as all objects with a mean value of 49 or less in ASTER Band 3, then the child classes of water must meet this requirement as well.

Once the image objects and class hierarchy have been created, the objects can then be classified based on a wide variety of object characteristics, such as mean pixel value, area, shape, neighboring objects, or distance to neighboring objects. In eCognition, each of these object characteristics is known as a *feature*, and the set of all features that define a class is known as the class's *feature space*. For example, if the class *water* can be differentiated from all other classes using only ASTER Band 3, then ASTER Band 3 is the feature space of the class *water*. The specific values for each feature in an object's feature space can be defined in one of two ways: using either membership functions or nearest neighbor samples. Membership functions allow the user to define the criteria for class membership, as in the example above where water is defined as all objects with a mean value of 49 or less in ASTER Band 3. The nearest neighbor method of classification, also known as "click and classify," allows the user to select sample objects for each class and have membership functions automatically generated. (The name nearest neighbor is somewhat confusing, since it is also the name of an image processing

resampling procedure. In this case it refers to a procedure similar to the training set procedure

used in pixel-based classifications). An additional benefit of the nearest neighbor method is that

its feature space can be optimized, meaning that the software can compute the most effective

feature space for differentiating classes.

Some of the most useful and powerful features available in eCognition are part of a group

called *class-related features* because they allow the use of spatial context. As with

classification-based segmentations, class-related features refer to previous classifications for

their value. An example of a class-related feature would be "border to neighboring object,"

which returns a value based on the length of an objects border with another object of a specified

class. We could, for example, specify that the class *bank* is any object which shares a border of

at least 1 pixel with any object classified as *water*. Obviously, such a feature will require more

than one classification, as its value cannot be calculated until all of the *water* objects have been

identified. These class-related features make it possible to define classes by their relationships to

other classes, which would be completely impossible using traditional pixel-based methods.

Despite their power, however, these features add time to the classification process because of

their requirement of multiple iterations, so they must be used judiciously.

Finally, eCognition also allows the use of fuzzy classification. Whereas many traditional

classification systems use a binary membership function (a pixel either does or does not belong

to a class), eCognition can compute partial percentage membership values for each object. These

values give the possibility of that object's membership to each class in the class hierarchy. A

value of 1.0 means the object definitely belongs to that class, while a value of 0.0 means that the

object definitely does not belong to that class. Values in between indicate varying degrees of

possibility of membership. Unless specified otherwise, an object is assigned to the class for

which it has the highest membership value. The default membership threshold is 0.1, so that objects are only assigned to a class if at least one their membership values is greater than this threshold. Objects that do not meet this requirement remain unclassified. As Legleiter and Goodchild (2005) showed, fuzzy classification is particularly useful for classifying features with indefinite boundaries and transition areas, such as habitat units.

Scale Factors and Membership Functions

The determination of appropriate scale factors, membership functions, and feature space is essential to the segmentation process. This section describes how these values were selected for this study.

Determination of Scale Factor

The choice of scale factor is an important first decision in the segmentation process, as it controls the size of the image objects. Image objects that are too large may hide useful information, while image objects that are too small may provide excessive details that require significant processing time for segmentation. Definiens recommends using an image object size which is comparable to the phenomena being classified – in other words, if you want to classify buildings, use building-sized objects. When multiple object levels are required, however, the user must decide which level should be the base segmentation level.

In order to test how scale factor and direction of segmentation affect the resulting riverine objects, a test image was segmented at three different scale factors in each of three different directions, for a total of nine image segmentations. The smallest scale factor was 10, which produced objects small enough to represent small islands and subtle spectral differences in the

water surface. The second scale factor was 35, which produced objects on a scale appropriate to the customary minimum mapping unit used in habitat classification. The third scale factor was 70, which produced large objects comparable to reaches. The three directions were top-down (70-35-10), bottom-up (10-35-70), and middle-out (35-10-70). Once the segmentations were performed, each image was examined to determine whether and how the resulting image objects differed from one another, and which were most appropriate for habitat classification.

Although the top-down, bottom-up, and middle-out segmentations all produced fairly similar objects, there were some differences. Figure 5.7 illustrates how slightly different image objects were produced at the same scale depending on the direction of segmentation. The advice of Definiens would suggest that a scale factor of 35 would be most appropriate, since this creates objects which are comparable to the minimum mapping unit. Close inspection of the border between the river channel and bank, however, reveals that this interface is not well delineated at this scale. In order to differentiate between the bank and the river, a small scale factor in the vicinity of 5 or 10 is needed. Therefore, the bottom-up approach is most desirable for this type of habitat mapping.

A variety of scale factors are used throughout the study. These values were generally arrived at through trial and error. For each segmentation, scale factors were selected which produced meaningful image objects for each class. In several cases, multiple object scales were used in the same image. For example, in the advanced classifications discussed below, the river and its banks were segmented at a scale factor of 15, while the landcover was segmented at a scale factor of 30 in the same image. This allowed object sizes to be tailored to specific classes and image regions.

Definition of Membership Functions and Feature Space

In many of the classifications discussed below, membership functions are used to define certain classes. The most notable of these are the *water* and *river* classes. Both of these classes were defined in part by their reflectance in ASTER Band 3, since water typically has a very low reflectance in the NIR bands. Definiens's documentation suggests using a DN value of less than 50 to identify water in this spectral region. This is a very general guideline, however, since a variety of factors, such as lighting conditions, water quality, and sensor type can affect the reflectance values. The DN value 49 in ASTER Band 3 was therefore used as a starting point for identifying water. This number was then adjusted up or down based on the ASTER Band 3 reflectance of the shallowest known water body in each image until a satisfactory classification of water was achieved. A similar relationship was defined for water depth using ASTER Band 3 reflectance. DN values closer to the minimum value for water were classified as deep, while those closer to the maximum value for water were classified as shallow.

The nearest neighbor feature space for most classes was defined using ASTER Bands 1, 2, and 3, as well as mean object brightness. The only exceptions to this rule were the classes *whitewater* and *not whitewater* in the advanced classifications. These classes were defined using only ASTER Bands 1 and 2, and object brightness.

Classification Development

This project can be divided into three stages of development, each building off the previous one and each progressively more complex. The first stage involved a simple mask of the river channel and a classification of whitewater within the channel. The second stage was expanded to include classification of land cover surrounding the river and on its islands, as well

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as whitewater within the channel. The third stage involved the most advanced classification

procedures, including three object levels and numerous class-related features.

Stage 1 - Classifying Whitewater through Masking

In the first stage of development, the river channel was masked and classified in terms of

the degree of whitewater. This stage of classification focused on the following methodological

issues: differentiating water from other classes; differentiating the river channel from other

bodies of water; identifying islands; classifying land cover on islands; identifying shallow areas

(shoals); and classifying areas of whitewater. A subset of ASTER Tile A3 was chosen for

testing to minimize cloud cover and because it contained representative samples of all desired

objects. The class hierarchies and workflow for the entire process can be seen in Figures 5.8 and

5.9.

Since the results of the image segmentation tests revealed that a bottom-up segmentation

scheme provided the best results, the image was segmented in eCognition once again using a

scale factor of 10. The resulting objects were then classified as either *water* or *not water* based

on their reflectance in ASTER Band 3. *Water* objects were defined using a fuzzy membership

function, where all objects with a mean digital number (DN) value of 48 or lower in ASTER

Band 3 were given a membership value of 1.0 (total membership), and all objects with a mean

DN of 49 or higher were assigned a membership value of 0 (no membership). Mean DN values

between 48 and 49 were given partial membership values between 0 and 1. Objects with a

partial membership of 0.1 or higher were assigned to the class *water*. The class *not water* was

defined as the inverse of the function for *water*. This classification resulted in all objects within

the river channel being classified as *water*, but a large number of other small objects throughout

the image were also classified as *water*. In order to distinguish the main channel from these unwanted *water* objects, all adjacent *water* objects were combined into larger objects. This resulted in one large *water* object representing the main channel, and a number of smaller unwanted *water* objects outside the main channel. The classes *water* and *not water* were then replaced with two new classes: *channel* and *not channel*. The class *channel* was defined using the same membership function as water, with an additional function which required that all members of the class *channel* have an area of 5000 pixels or more. No partial membership was allowed for this class – all objects were assigned a membership value of either 1 or 0. The class *not channel* was once again defined as the inverse of *channel*. The image was then classified again, and as only the main channel had an area greater than 5000 pixels, it became the only member of *channel*. The remaining *water* objects, all with areas less than 5000 pixels, were assigned to the class *not channel*.

At this point in the classification, the image consisted of a number of objects classified as either part of the main river channel or not. All islands were included in the class *not channel*. To distinguish islands from the other *not channel* objects, all adjacent *not channel* objects were combined into larger objects. This consolidated the left and right banks of the river into single objects, and each island, no matter what its size, was also transformed into a single object. The classes *channel* and *not channel* were then replaced with four new classes arranged in a hierarchy: *river*, *not river*, *islands*, and *not islands*. *River* and *not river* were defined similarly to *water* and *not wate*r. *Islands* were defined as objects with areas less than 5000 pixels belonging to the class *not river*, while *not islands* were defined as having areas greater than 5000 pixels. The image was classified for a third time, and since the only *not river* objects with areas greater than 5000 pixels were the left and right banks, the banks were classified as *not islands* and all

smaller *not river* objects were classified as *islands*. (Note: Although area was chosen as the distinguishing feature between *islands* and *not islands*, eCognition also allows the use of a function called *rel border*, which measures the fraction of an object's border which is adjacent to another specified class of objects. This function is closer to the intuitive definition of *islands*, but its class-related nature requires multiple classification iterations. To avoid this unnecessary complication, area was chosen as the distinguishing feature.)

At this point, the image was composed of large-scale objects: the river channel, the banks, and islands. In order to create smaller objects for habitat classification, each of the objects belonging to the classes *river* and *islands* was segmented further using a small scale factor. This created a new level of smaller image objects within the river channel and its islands, resulting in an image with two object levels – Level 1, with small *river* and *islands* subobjects, and Level 2, with the *river* and *islands* superobjects. The old class hierarchy was removed, and a new one was created. This new class hierarchy subdivided *river* into *whitewater* and *not whitewater*, both defined by fuzzy membership functions based on overall object brightness. The class *islands* was subdivided into three classes based on three possible island land covers: *vegetation*, *exposed sand*, and *shoals* (shallow water over sand or rock). Because of the complexity of distinguishing these classes, they were defined using sample objects and eCognition's automated standard nearest neighbor classifier. Level 1 was then classified using the new class hierarchy. All adjacent objects of the same class on Level 1 were combined, and the level was classified once more with the new objects. This produced a final habitat classification with each object receiving a fuzzy membership value for each class.

Stage 2 - Classifying Whitewater and Land Cover

In the second stage of development, the class hierarchy was expanded to include land cover classes for the entire image. Islands were not differentiated from other land masses, nor was the river channel distinguished from other bodies of water. For procedural reasons, shallows (*shoals)* were again considered to be part of the class *not water*. This stage of classification focused on distinguishing differing land and bank cover types. The full Tile A3 was used for testing this time, not merely a subset.

The land cover classes were created based on analysis of the image data in conjunction with the DEM, the Landsat true-color images, and with ground photographs of the area taken by the AMNH ichthyology team in July 2005. In general, trees are confined to low areas such as draws, and grasses and shrubs predominate elsewhere. Although landcover data is available for this area through the Africover program, it is not well correlated with the imagery, and therefore it was not used.

The full class hierarchy for Stage 2 can be seen in Figure 5.10. The classes *whitewater* and *not whitewater* were again defined using a membership function based on brightness, while the remaining classes were defined using the nearest neighbor classifier. The feature space of the nearest neighbor classifier contained the mean values of all three ASTER Bands, as well as the mean brightness value for each object. Only two or three sample objects were selected for each class. (While a pixel-based classifier generally requires upwards of 20 sample pixels, object-based classification uses fewer samples because each object is composed of a number of pixels already.) In order to help distinguish between certain spectrally similar classes, a number of class-related features were introduced. Because *shoals* and *grasslands* were spectrally similar, any object classified as *shoals* was required to share a border of at least one pixel with an object

classified as *water*. Similarly, because *sand* and *clouds* are almost identical spectrally, *sand* carried the additional requirement that it share a border of at least one pixel with *water* or *shoals*.

Two object levels were created during the segmentation process, although only one was used for the final classification. In the previous stage, several objects near the river-land interface were noticed to include portions of both the bank and the river. To prevent this from happening again, the image was segmented with a scale factor of 5, thus creating smaller objects and providing a better boundary between water and land. These objects were too small for land cover and habitat classification, however. The objects were therefore classified as *water* and *not water*, and a classification-based segmentation was then performed to create a new object level with a scale factor of 15. This created superobjects based on the previously classified subobjects, ensuring that the borders of the larger objects more closely followed the water-land divide. Once this was accomplished, the image was classified in three iterations with class-related features. The workflow for the entire stage can be seen in Figure 5.11.

Stage 3 - Advanced Classifications

The third level of methodological development combines the lessons learned in the first two stages and focuses on classifying objects using contextual features. For example, land cover classes were classified differently depending on whether they occurred on an island, in the river, or on the river bank. The entire process is composed of four successive class hierarchies and 21 separate processing steps. As in the previous stage, the entire Tile A3, not merely a subset, was used for testing.

Although four separate class hierarchies are required for classification, all are variants of the final class hierarchy shown in Figure 5.7. The hierarchy is composed of three levels, one for

each of the object levels used during classification. On level two of this newest classification system, a distinction is made between *islands* (objects surrounded by *river*), *banks* (objects adjacent to *river*), and *land* (objects not adjacent to *river*). This information is used in level one, where it is used to further classify land cover as being on an island, a bank, or the land. Level one also makes a distinction between *river* and *water* that was not made in earlier classifications. Depth and presence of whitewater are separated, so that whitewater is measured using ASTER Bands 1 and 2, while relative depth is approximated using ASTER Band 3.

The segmentation and classification process is complicated, requiring 21 steps. A number of different scale factors are used during the process to create appropriately-sized objects for the different classes. Several classes are defined by class-related features linking subobjects to superobjects, so that all three object levels are necessary for the final classification. The image is first classified at a small scale factor in order to fully differentiate between the river channel and its banks, and the resulting objects are classified as *water* or *not water*. The objects are then segmented again using a classification-based segmentation to create larger objects in order to decrease the processing time for an object fusion. The objects are again classified as *water* or *not water*, and objects of the same class are fused. This object level is then classified using the Level 3 hierarchy as shown in Figure 5.7. The objects classified as *not islands* are then segmented with a moderate scale factor, and this new object level is then classified using the Level 2 hierarchy. Finally, the objects classified as *river* and *banks* are segmented with a scale factor smaller than that used in Level 2, and this newest object level is classified using the Level 1 hierarchy. The full workflow for this classification can be seen in Figure 5.8.

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Automating Tasks

One of the primary advantages of classifying images using an automated procedure is that the process can be repeated on multiple images. The eCognition software makes it possible to record procedural steps and apply them to new images using *protocols*. Once Tile A3 was classified using the advanced classification procedure, the steps were recorded in a protocol, and the procedure was applied to Tiles A1, A2, and A4.

Classifying Habitat in Landsat Images

Despite the fact that ASTER provides higher resolution than Landsat ETM+ in some bands, Landsat data has a number of advantages. First, Landsat images are widely available free of charge for researchers. Second, Landsat scenes cover a broad area, so that only three separate scenes are needed to cover the entire Lower Congo (see Figure 4.2). This is particularly useful in the Lower Congo study area, because frequent cloud cover renders many of the available ASTER images unusable. Third, because of the long duration of the Landsat mission, Landsat provides superb temporal availability and continuity, with image data dating back to 1972 for the Landsat Multispectral Scanner (MSS) and 1984 for the Landsat Thematic Mapper TM. ASTER, in contrast, first began imaging in February of 2000. Fourth, Landsat ETM+ provides collects data in the blue band, which ASTER does not. For these reasons, the final protocols developed for the ASTER images were tested on a subset of a Landsat image, Tile E3. A subset, rather than the entire image, was used because the large size of the image and the small scale factor required to delineate the channel and bank required too much processing power and time. Therefore, a subset of the image was chosen which roughly corresponded to Tile A3.

5.3 Statistical Analysis

Two sets of statistical measures were used to assess the classification accuracy: best classification statistics and classification stability statistics. The "best classification" for any object is defined as the highest membership value for that object. The best classification statistics in eCognition are computed based on the highest membership value for each object, and the central tendency, variance, and range for each class are reported. The classification stability statistics are concerned with the difference between the best and second-best class membership values for each class. Once again, these statistics provide measures, by class, of central tendency, variance, and range for these differences.   It is important to note that these statistics do not assess accuracy with respect to ground truth – instead, they describe how closely image objects correspond to the proposed classification criteria, and how separable these objects are based on these criteria. Because no ground truth data are available for the study area at this time, a traditional accuracy assessment and error matrix were not prepared. Instead, the classified image was visually compared to the original image data, as well as to existing topographic maps, photos, and textual descriptions of the river, to provide a qualitative assessment of the classification accuracy.

Table 5.1. Image and elevation data sets used in this study. Sources of data are the American Museum of Natural History (AMNH) and the Global Land Cover Facility at the University of Maryland (GLCF, http://glcf.umiacs.umd.edu/index.shtml). Scenes are given tile numbers as a way to quickly refer to images used in the study.

| Sensor	Date	Resolution	ID #	WRS2 Path/Row	Tile #	Source
ASTER	2003/7/18	15m VNIR 30m SWIR 90m TIR	AST_L1B.003:2017611718	182/63	A1	AMNH
ASTER	2000/9/18	15m VNIR 30m SWIR 90m TIR	AST_L1B.003:2016603537	182/63	A2	AMNH
ASTER	2000/09/18	15m VNIR 30m SWIR 90m TIR	AST_L1B.003:2016603609	182/63	A3	AMNH
ASTER	2005/3/24	15m VNIR 30m SWIR 90m TIR	AST_L1B.003:2028310803	183/64	A4	AMNH
ETM+	2001/02/25	15m Pan 30m Vis, NIR 60m TIR	7182063000105650	182/63	E1	GLCF
ETM+	2000/03/26	15m Pan 30m Vis, NIR 60m TIR	7182064000008650	182/64	E2	GLCF
ETM+	2002/04/24	15m Pan 30m Vis, NIR 60m TIR	7183064000209850	183/64	E3	GLCF
SRTM	2000	1m Vertical 90m Horiz	065-556	182/63	S1	GLCF
SRTM	2000	1m Vertical 90m Horiz	065-557	182/64	S2	GLCF
SRTM	2000/02	1m Vertical 90m Horiz	065-615	183/64	S3	GLCF

Abbreviations: VNIR = Very Near InfraRed; SWIR = Short Wave InfraRed; TIR = Thermal InfraRed; Pan = Panchromatic; NIR = Near InfraRed; Horiz = Horizontal

Table 5.2. Physical habitat variables classified in this study, along with the ASTER Bands used in the classification.

| Variables	ASTER Bands
Water depth	Infrared band (Band 3)
Presence of whitewater	Green and red bands (Bands 1 and 2)
Islands and shallows	Green, red, and infrared bands (Bands 1, 2, and 3)
Bank cover	Green, red, and infrared bands (Bands 1, 2, and 3)
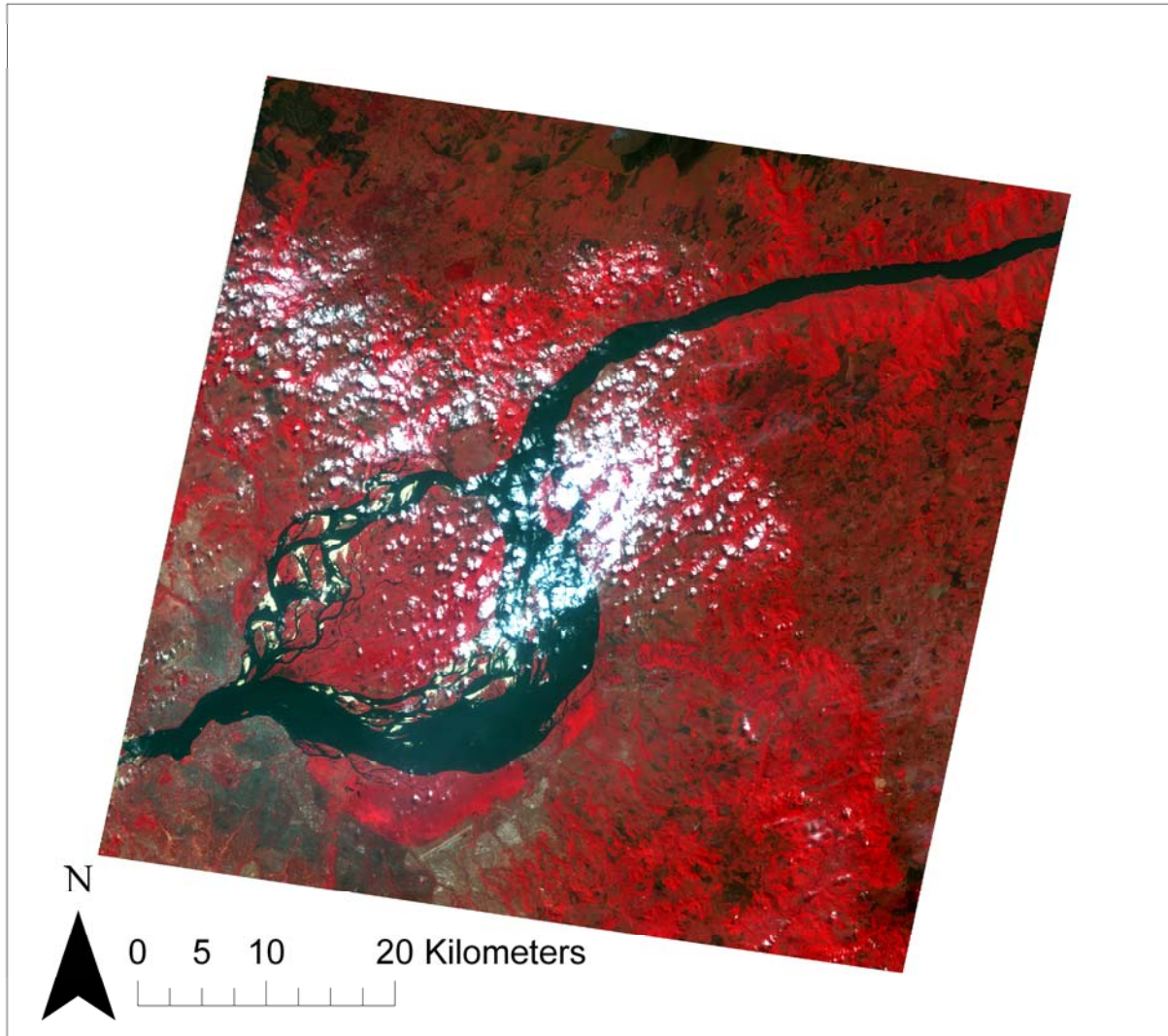
Figure 5.1. ASTER Tile A1, 3-2-1 Band combination. Although this images was originally intended for classification, it was not classified because of its differing land cover and geomorphology.
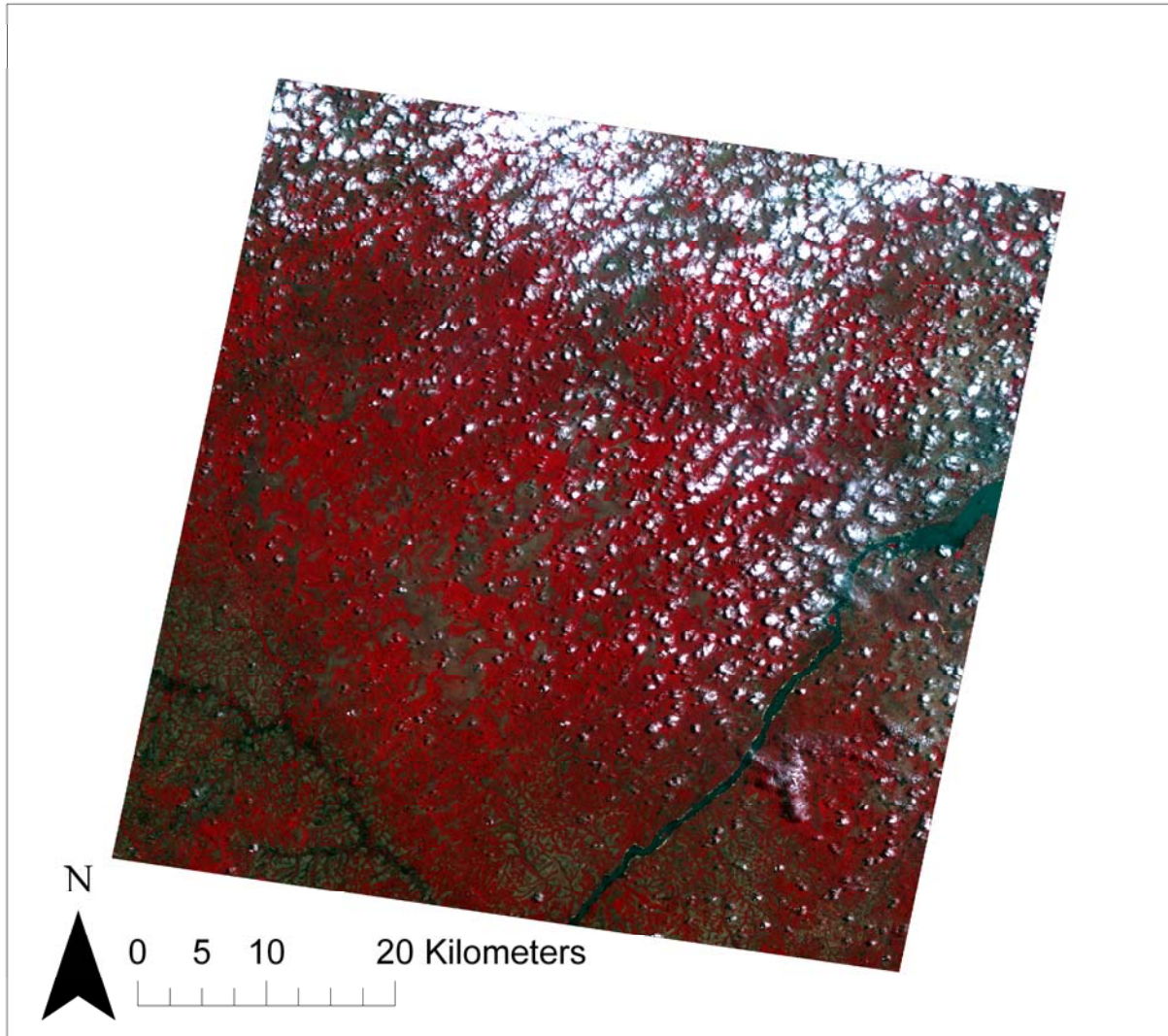
Figure 5.2. ASTER Tile A2, 3-2-1 Band combination. Sandstone is the dominant bedrock in this area.
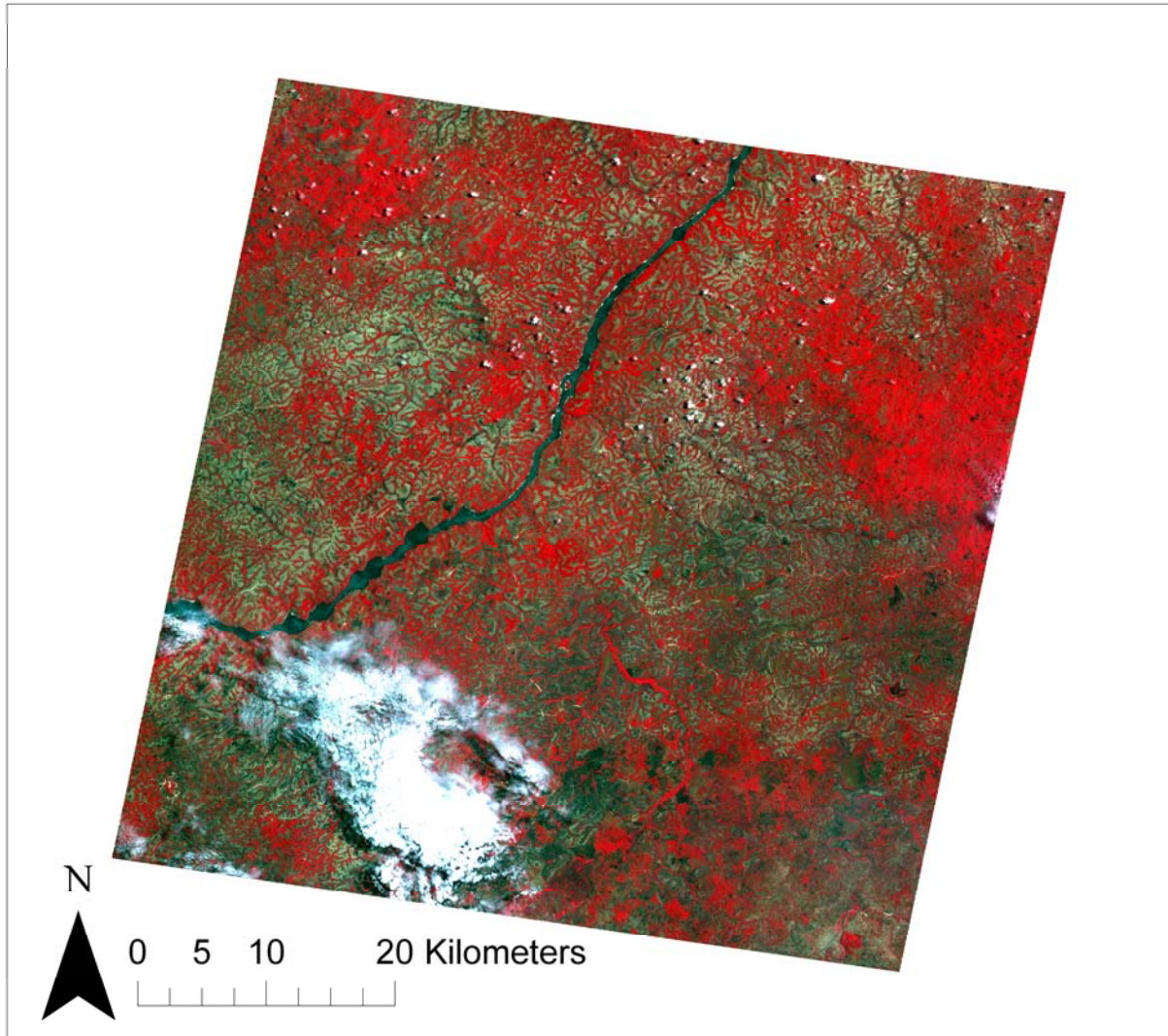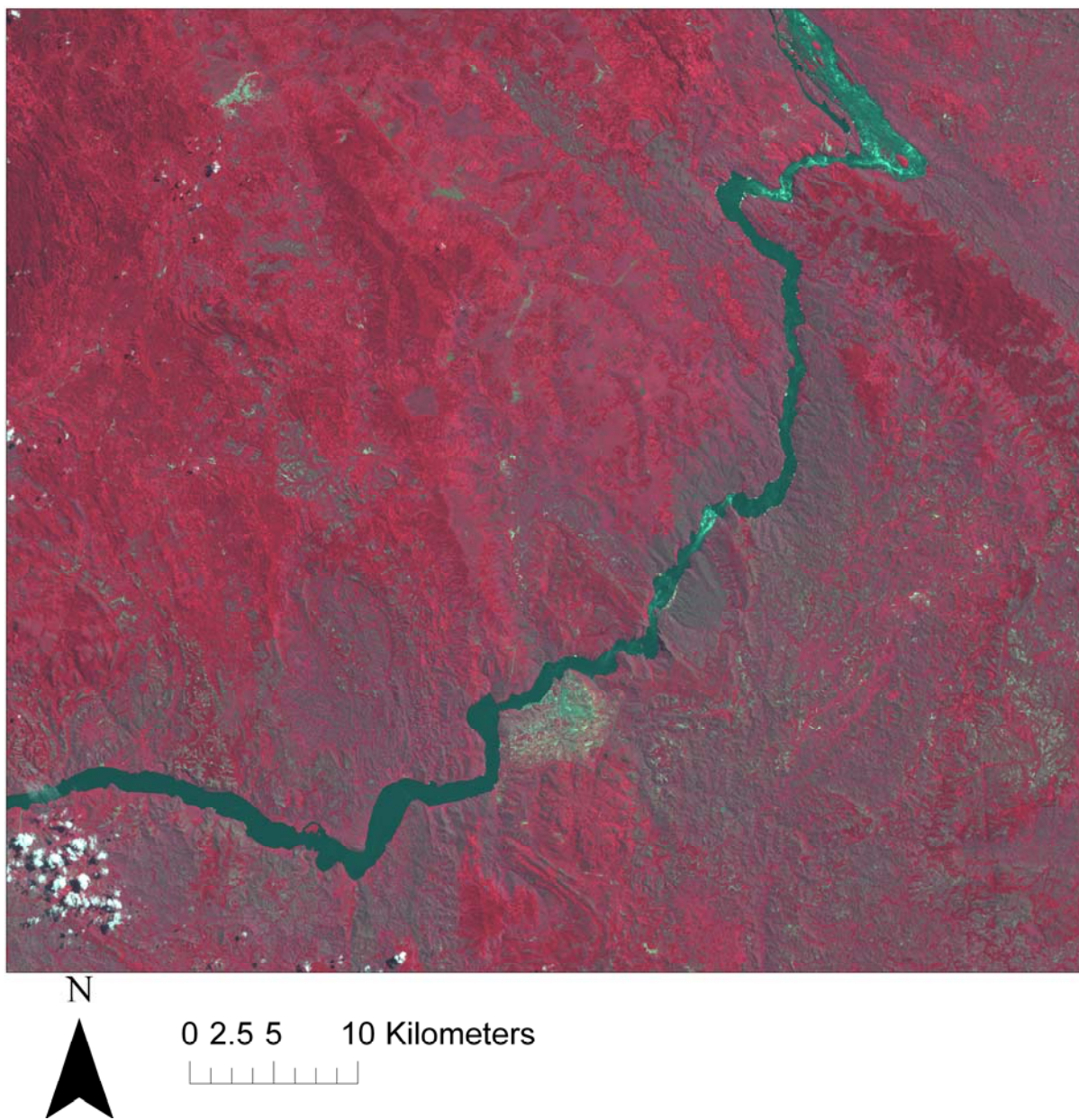
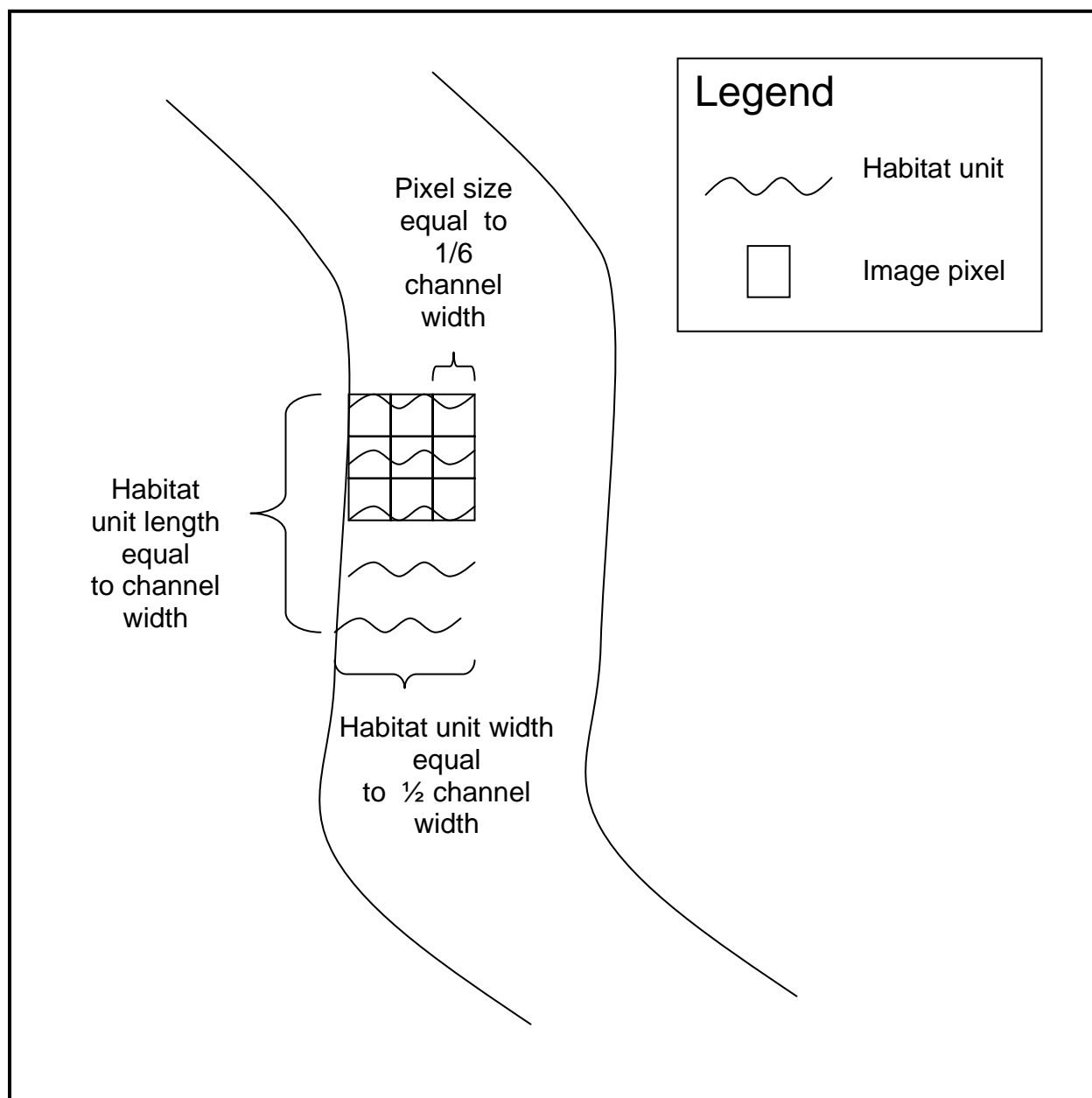**Figure 5.3.** ASTER Tile A3, 3-2-1 Band combination. Sandstone is the dominant bedrock in this area.
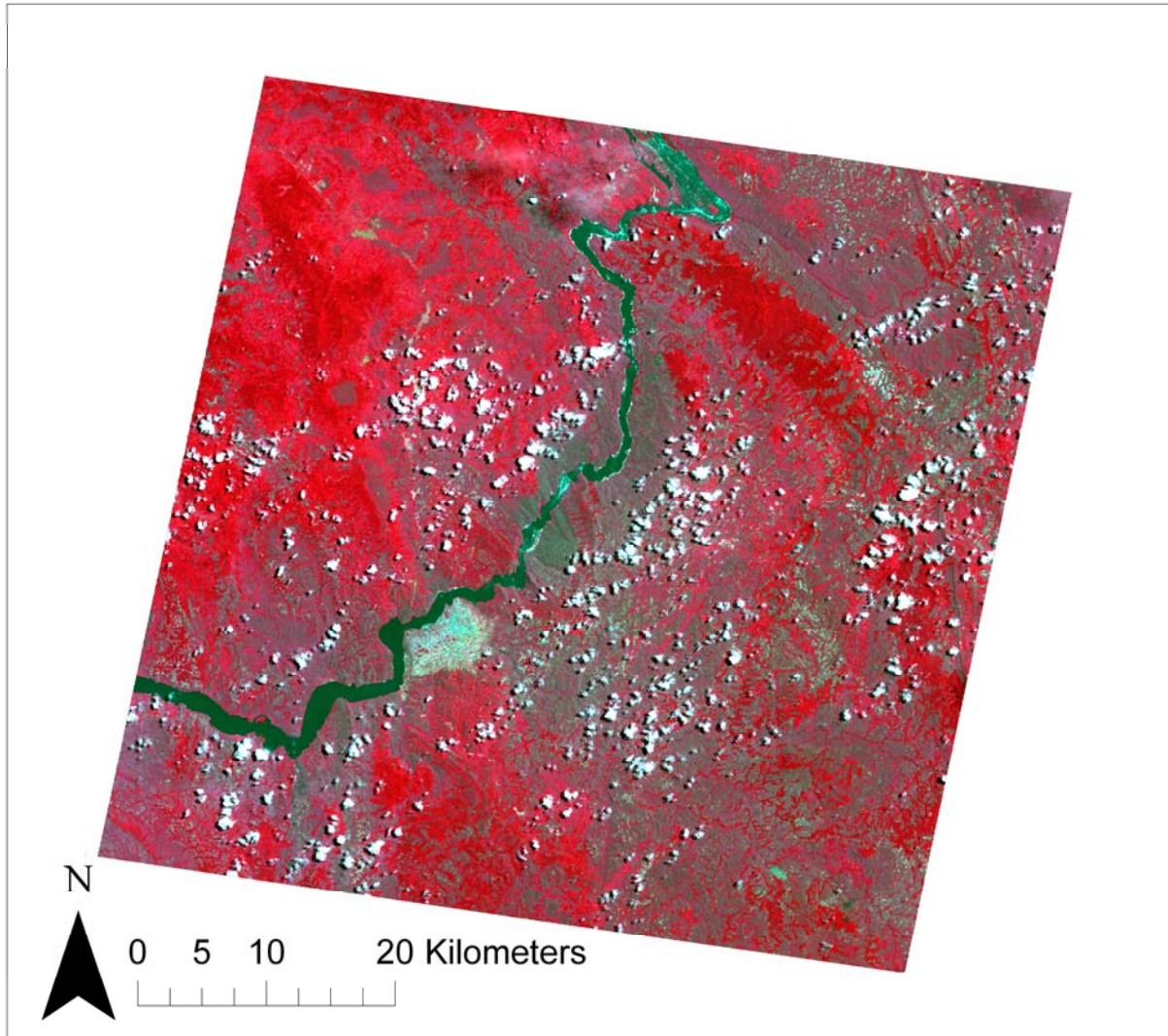
Figure 5.4. ASTER Tile A4, 3-2-1 Band combination. The bedrock in this area is dominated by a series of metamorphic rocks.
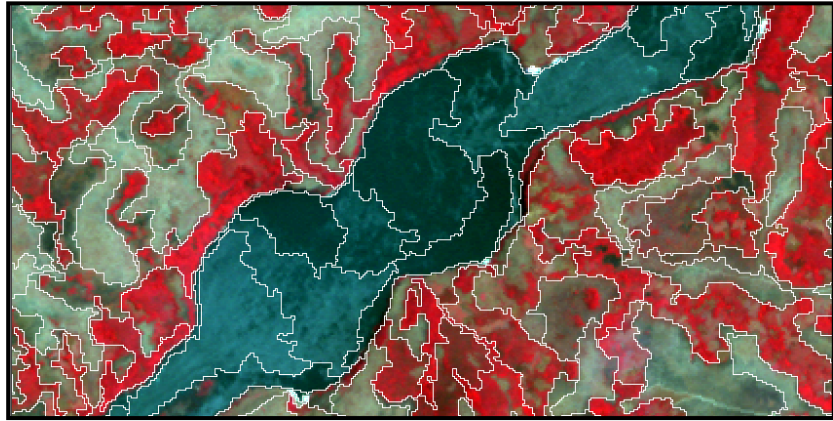
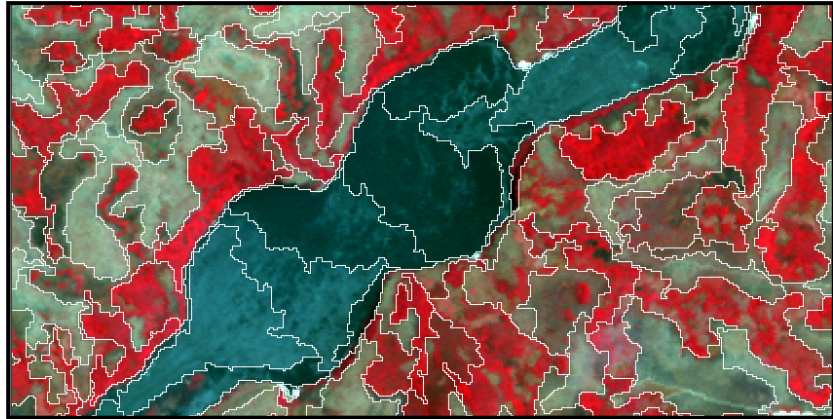**Figure 5.5.** Subset of Landsat ETM+ Tile E3, 4-3-2 Band combination.

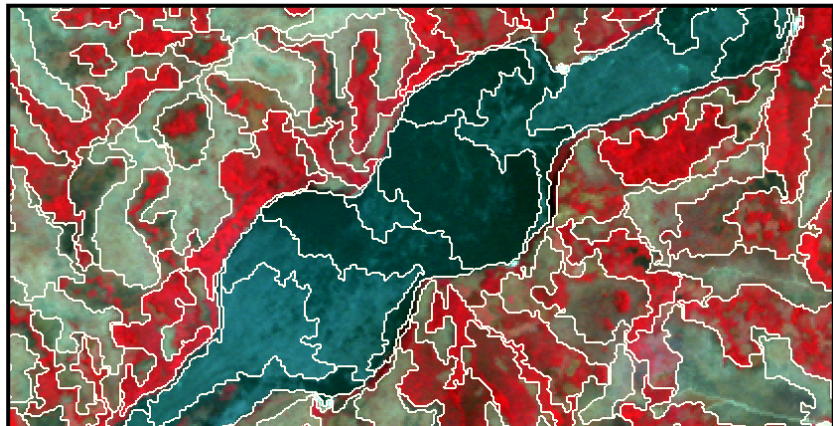**Figure 5.6.** Minimum necessary resolution for mapping channel habitat.

**Top-down
Scale Factor 35**

**Middle-out
Scale Factor 35**

**Bottom-up
Scale Factor 35**

Figure 5.7. Examples of image objects created by differing segmentation directions. Note the variations in object shape within the river channel.

```
Class Hierarchies and Membership Functions

1st Classification
•WATER = mean DN value of Aster Band 3 < 49
•NOT WATER = inverse of WATER


2nd Classification
•CHANNEL = mean DN value of Aster Band 3 < 49 AND area > 5000 px
•NOT CHANNEL = inverse of CHANNEL


3rd Classification
•RIVER = mean DN value of Aster Band 3 < 49
•NOT RIVER = inverse of RIVER
        •ISLANDS = area < 5000 pixels
        •NOT ISLANDS = inverse of ISLANDS


4th Classification
•LEVEL 1 = object level 1
        •RIVER (1) = mean DN value of Aster Band 3 < 49
                •WHITEWATER = mean brightness > 68-55
                •NOT WHITEWATER = inverse of  WHITEWATER
        •NOT RIVER (1) = inverse of RIVER
                •ISLANDS (1) = area < 5000 pixels
                        •EXPOSED SAND = Standard Nearest Neighbor classifier
                        •SHOALS = Standard Nearest Neighbor classifier
                        •VEGETATION = Standard Nearest Neighbor classifier
                •NOT ISLANDS (1) = inverse of ISLANDS


•LEVEL 2 = object level 2
        •RIVER (2) = mean DN value of Aster Band 3 < 49
        •NOT RIVER (2) = inverse of RIVER
                •ISLANDS (2) = area < 5000 pixels
                •NOT ISLANDS (2) = inverse of ISLANDS
```
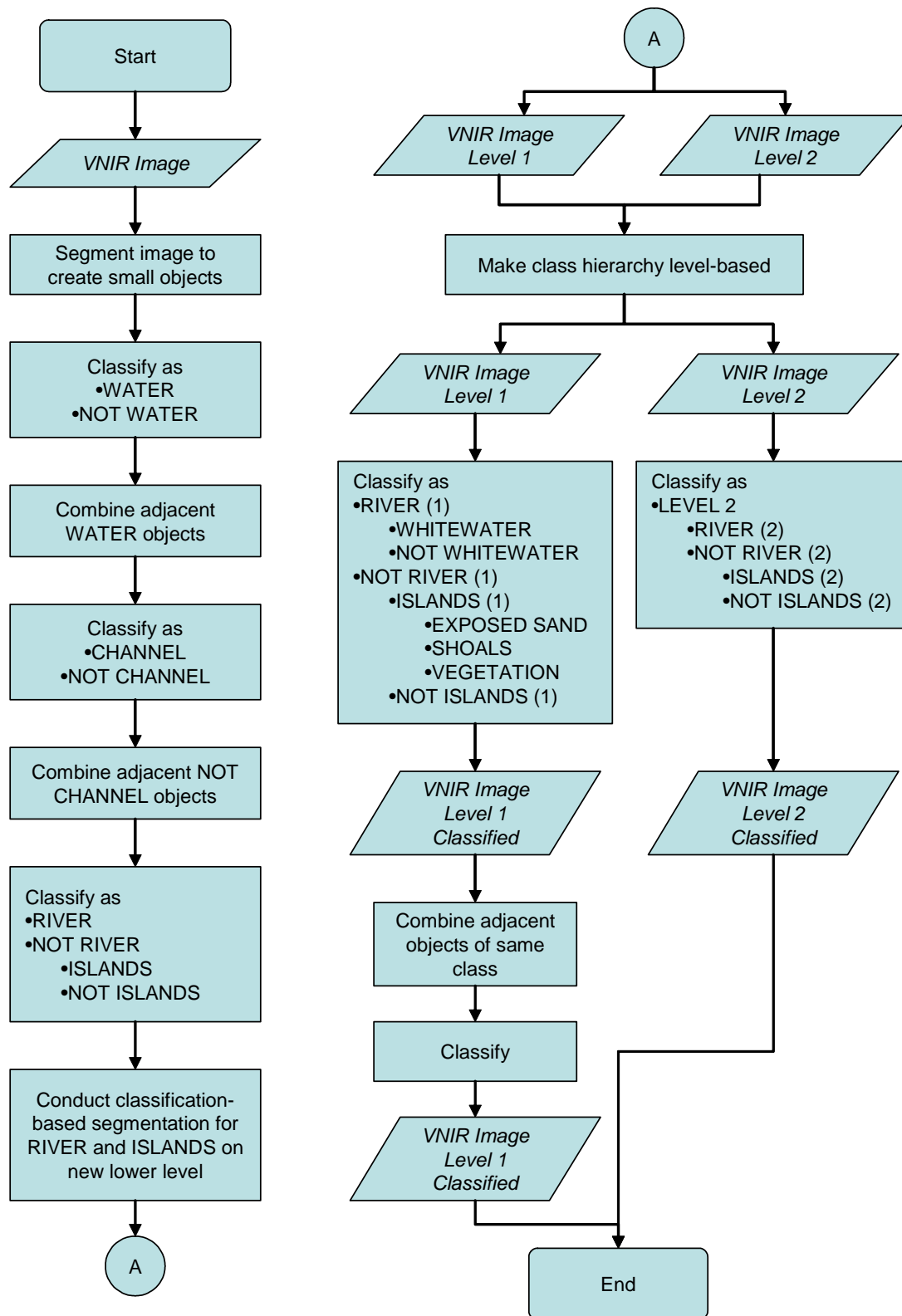
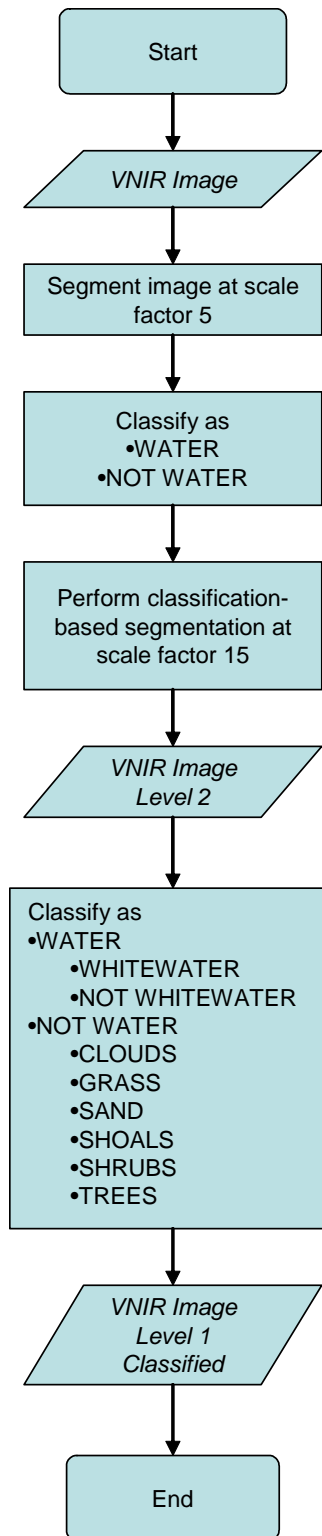**Figure 5.8.** Class hierarchies and membership functions for Stage 1 of object classification.

Figure 5.9. Workflow for Stage 1 of object classification.

Class Hierarchies and Membership Functions

•WATER = mean DN value of Aster Band 3 < 49
      •WHITEWATER = mean brightness > 68-55
      •NOT WHITEWATER = inverse of WHITEWATER

•NOT WATER = inverse of WATER
      •CLOUDS = nearest neighbor
      •GRASS = nearest neighbor
      •SAND = nearest neighbor AND ((borders WATER) OR (borders SHOALS))
      •SHOALS = nearest neighbor AND border to WATER
      •SHRUBS = nearest neighbor
      •TREES = nearest neighbor

Figure 5.10. Class hierarchies and membership functions for Stage 2 of object classification.

Start

VNIR Image

Segment image at scale factor 5

Classify as
•WATER
•NOT WATER

Perform classification-based segmentation at scale factor 15

VNIR Image Level 2

Classify as
•WATER
 •WHITEWATER
 •NOT WHITEWATER
•NOT WATER
 •CLOUDS
 •GRASS
 •SAND
 •SHOALS
 •SHRUBS
 •TREES

VNIR Image Level 1 Classified

End

Figure 5.11. Workflow for Stage 2 of object classification..

Class Hierarchies and Membership Functions

LEVEL 1 = object level 1
•NOT RIVER (1) = inverse of RIVER 1
    •URBAN = manually classified
    •GRASSES = nearest neighbor
        •BANK GRASSES = superobject is BANK (2)
        •ISLAND GRASSES = superobject is ISLAND (2)
        •LAND GRASSES = superobject is LAND (2)
    •SAND/CLOUDS = nearest neighbor
        •BANK SAND = superobject is BANK (2)
        •ISLAND SAND = superobject is ISLAND (2)
        •LAND CLOUDS = superobject is LAND (2)
    •SHRUBS = nearest neighbor
        •BANK SHRUBS = superobject is BANK (2)
        •ISLAND SHRUBS = superobject is ISLAND (2)
        •LAND SHRUBS = superobject is LAND (2)
    •SUBMERGED ROCKS OR SAND = nearest neighbor AND (superobject is BANK (2) OR ISLANDS (2))
        •BANK SUBMERGED ROCKS OR SAND = superobject is BANK (2)
        •ISLAND SUBMERGED ROCKS OR SAND = superobject is ISLANDS (2)
    •TREES = nearest neighbor
        •BANK TREES = superobject is BANK (2)
        •ISLAND TREES = superobject is ISLAND (2)
        •LAND TREES = superobject is LAND (2)
    •WATER = nearest neighbor
        •DEEP WATER = inverse of SHALLOW WATER
        •SHALLOW WATER = 0<ASTER 3<20
•RIVER (1) = superobject is RIVER 2
    •WHITEWATER = nearest neighbor ASTER 1 and 2
        •DEEP WHITEWATER = inverse of SHALLOW WHITEWATER
        •SHALLOW WHITEWATER = nearest neighbor ASTER 3
    •NOT WHITEWATER = nearest neighbor ASTER 1 and 2
        •DEEP NOT WHITEWATER = inverse of SHALLOW NOT WHITEWATER
   •SHALLOW NOT WHITEWATER = nearest neighbor ASTER 3

LEVEL 2 = object level 2
•RIVER (2) = superobject is RIVER (3)
    •ISLANDS (2) = relative border to RIVER (2) = 1
        •BANK (2) = borders RIVER (2)
        •LAND (2) = inverse of BANK (2)
    •NOT ISLANDS (2) = inverse of ISLANDS (2)
•NOT RIVER (2) = inverse of RIVER (2)

LEVEL 3 = object level 3
•RIVER (3) = mean DN value of Aster Band 3 < 49 AND area > 1.5 million square meters
    •ISLANDS (3) = relative border to RIVER (3) = 1
    •NOT ISLANDS (3) = inverse of ISLANDS (3)
•NOT RIVER (3) = inverse of RIVER

Figure 5.12. Class hierarchies and membership functions for Stage 3 of object classification.
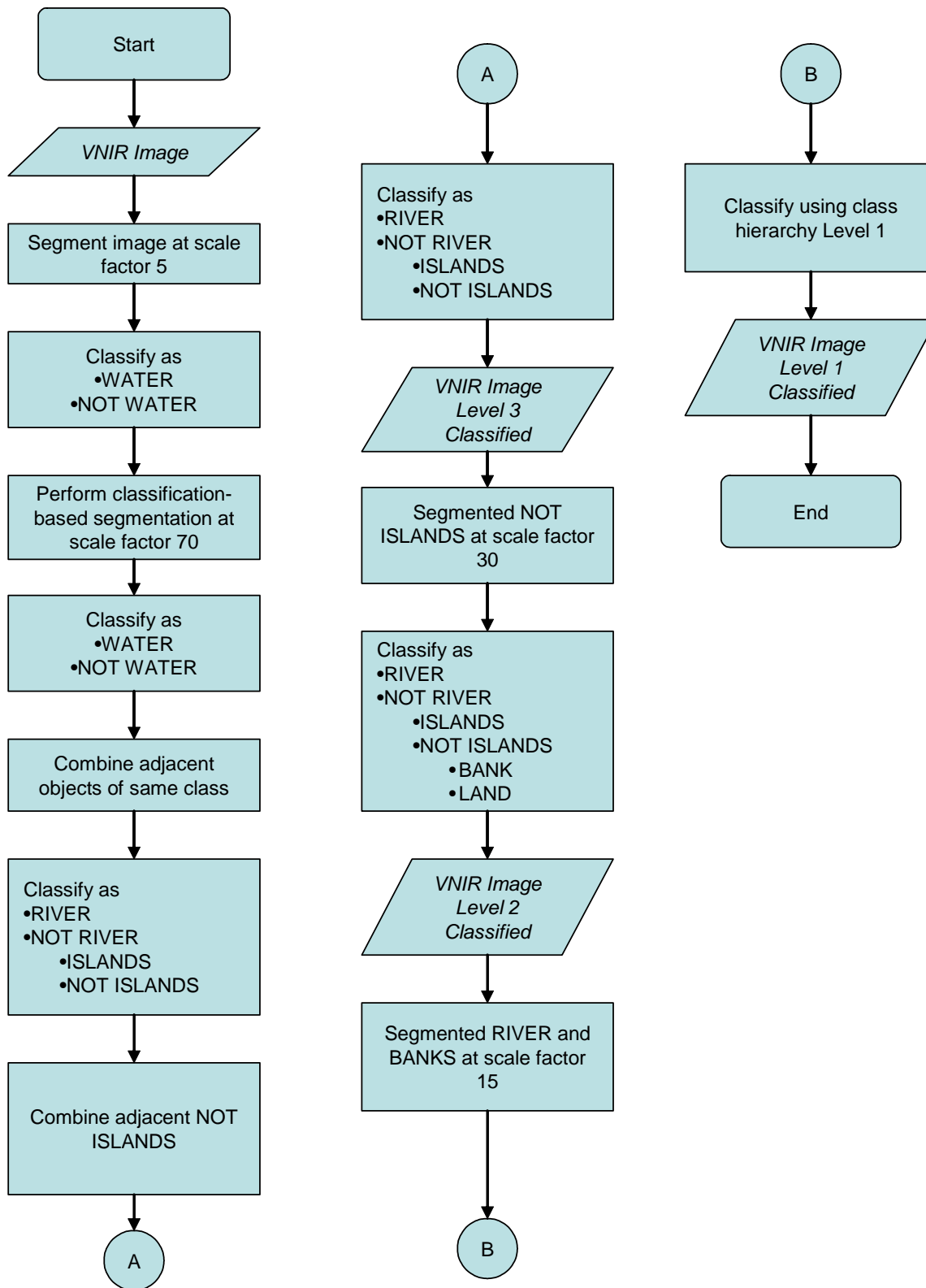
Figure 5.13. Workflow for Stage 3 of object classification..

CHAPTER 6 – RESULTS AND DISCUSSION

The final classified images for each stage in the object-oriented classification can be seen in Figures 6.1 though 6.15. Classification statistics can be found in Tables 6.1 through 6.6. The following sections provide discussions of these results.

6.1 Discussion of Classification Results

Stage 1 - Classifying Whitewater through Masking

Although the classification of whitewater is fairly simple compared to later, more advanced classifications which include water depth and land cover, several important problems related to habitat classification were solved during this stage. These problems included 1) how to distinguish the main river channel from other water bodies; 2) how to distinguish islands within the channel from other land bodies; 3) how to differentiate between sand, shoals, and vegetation on islands; and most importantly, 4) whether whitewater can be identified using the first three bands of ASTER. A visual comparison of the classified image to the original image suggests that the solutions arrived at in this stage produced excellent results. The classification of the main river channel follows the actual channel very closely. In a very few places, such as one possible backwater pool and some shallow areas near the bank (indicated in Figure 6.4), small portions of the channel were classified as part of the bank. In other places, however, the software identified small spectral differences that might have escaped a human observer's notice.

This verified that the spectral and contextual criteria employed in classifying the river channel were accurate.

The other problems were solved equally successfully. Islands were correctly separated from the mainland using contextual features, and each island was classified further using a crude system of classification (sand, shoals, and vegetation) and object samples. Similarly, areas with more whitewater turned out to be separable from areas with less whitewater by using object brightness, which in eCognition is defined as the "mean value of the spectral mean values of an image object" (*eCognition User Guide* 2004:110). This makes intuitive sense, as whitewater areas generally appear brighter to the naked eye than areas without whitewater. The majority of the *whitewater* and *not whitewater* objects seem to be appropriately classified, and appear to follow the continuous nature of whitewater itself – some areas are definitely whitewater, some are definitely not whitewater, and others are somewhere in between. In summary, most image objects appear to be appropriately classified based on a visual comparison to the original image.

The resulting *whitewater* and *not whitewater* areas (which can be thought of as analogous to rapids and glides-pools, respectively) compare well to the traditional minimum mapping unit (MMU) for channel habitat. In many cases, these units run the entire width of the river and are at least as long as the river is wide, although in some cases they are only a fraction of the river's width and length (see Figures 6.2 and 6.3). Far from being a problem, however, this could actually mean that the automated classification produces a more detailed map than a human observer would produce using traditional mapping guidelines. These MMU guidelines were developed for field mapping teams, and they were most likely created to prevent teams from creating time-consuming, overly-detailed products. Since automated mapping proceeds much more quickly than field mapping, field MMU guidelines should perhaps specify the coarse limit

for automated mapping accuracy, while the fine limit will be controlled by spatial resolution of the image data. In the case of ASTER and the Congo River, habitat units several times smaller than the traditional MMU can be classified. This level of detail can be especially useful on the Lower Congo because its large size and extensive whitewater make sampling difficult, while relatively small backwater and scour pools offer highly accessible sampling locations.

The stability of classification statistics were fairly strong overall. The best classification statistics, based on the highest membership value for each object, are given in Table 6.1. Most objects had fairly high membership values, with the turbulence and sand classes having mean values of 0.8 or higher, and vegetation and shoals having slightly lower values in the 0.5 to 0.7 range. The classification stability statistics, based on the difference between the highest and second-highest membership values, are given in Table 6.2. The classification stability is good overall, with mean values of at least 0.55 for all classes. A number of objects could almost equally well be classified as *whitewater* or *not whitewater*. This does not mean that these objects were poorly classified. Rather, the low membership values tell us that these objects are somewhere between *whitewater* and *not whitewater* – not as agitated as the strongest rapid or cascade, but not as calm as a pool or glide. Because the degree of whitewater present exists along a continuum, and the ends of the continuum were marked using exemplars, the fuzzy membership values may give us an idea of how close each object is to each of the two extremes. Objects with high membership values are close to the extremes, while lower membership values identify objects in the transition area between extremes. An alternative explanation for low membership values is that the objects in question contain several mixed pixels, with combinations of *whitewater* and *not whitewater* areas. In order to confine our classification to only objects with high membership values, we could raise the default membership value for the

classification, or alternatively, we could export our classification with its fuzzy membership values into a GIS and reclassify our objects based on their membership values. This ability to rank objects along a continuum using fuzzy membership values is therefore a potentially powerful tool.

Stage 2 - Classifying Whitewater and Land Cover

The second stage of procedural development was less methodologically complex than the first, but it too was essential in order to answer particular questions associated with automatically classifying habitat and land cover. These questions included 1) whether major land cover types could be classified; 2) whether whitewater and land cover could be quickly classified on the same object level, without the need for a time-consuming classification-based segmentation; and 3) whether class-related features could be used to improve the classification accuracy of some spectrally similar habitat and landcover types.

Again, the answers were primarily positive. The procedures for Stage 2 were less complex and time-consuming than the first stage, but provided more information in some respects. Comparison of the classified image to the original ASTER image shows that the classification represents the original image quite well overall, although some problems do exist (see Figure 6.5). For instance, opaque clouds are well-classified, but partially-translucent clouds result in the underlying landcover generally being classified as grassland. This confusion may be handled by classifying these areas manually when the number of misclassified objects is small, or by masking out those portions of the image dominated by clouds before classification. In addition, a number of objects outside the main channel were classified as water, but it is difficult to verify from the imagery whether these areas are indeed covered with water. Several cloud

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shadows were also classified as water. Once again, where the number of misclassified cloud shadows is small, they can be quickly reclassified manually. Large cloud banks should be masked out of the image prior to classification.

Many of the initial erroneous classifications were resolved by judiciously selecting class related features to distinguish spectrally similar objects. For example, sand and clouds are almost indistinguishable in some places, since both have a high reflectance in all bands. In this area, however, exposed sand is most likely to be associated with the river channel, so all sand objects were required to be adjacent to either water or shoals. This immediately corrected most of the confusion between clouds and sand. Similarly, grasslands and shoals are spectrally similar, but since shoals occur only in water, the class *shoals* was required to be adjacent to water, which corrected most erroneous classifications of shoals. In a very few places, however, grassland adjacent to a misclassified cloud shadow is labeled as a shoal. Again, the infrequency of this allows for the problem to be easily corrected by hand.

A comparison of the Stage 2 whitewater classification to the Stage 1 classification shows a close, but not perfect, correlation (compare Figures 6.1 and 6.5, Figures 6.2 and 6.6, and Figures 6.3 and 6.7). At a coarse scale, the *whitewater* and *not whitewater* objects occupy the same parts of the channel, although there are some differences, particularly near the large island. These differences are most likely due to the use of different scale factors and different segmentation procedures in each stage, and represent an improvement in the segmentation methodology.

The Stage 2 classification provides more information than the Stage 1 classification in some ways, but in other ways it loses information. The Stage 2 classification provides much more information about land cover, which can have an impact on channel habitat, particularly

close to the channel itself. The Stage 2 classification also captures and classifies much of a tributary to the Lower Congo in the southeast portion of the image, which is useful in itself. What is lost, however, is the ability to distinguish habitat units in the river from water bodies outside the main channel (such as the tributary), and the distinction between the mainland and the islands. In the advanced classifications to follow, these deficiencies are rectified by combining the procedures of the two earlier developmental stages.

The classification statistics for this stage were predictably more varied than the previous stage because of the greater number of classes. The best classification statistics are given in Table 6.3. A number of individual objects have low membership values, but this is understandable given the continuous nature of vegetation – some objects are most likely not pure examples of a single class, but possibly combinations of more than one class. The highest membership values (over 0.8) belong to the whitewater and forest classes, while shoals, shrublands, and sand share values between 0.7 and 0.8. The lowest values belong to clouds and grasslands. This is perhaps because the samples used for the class *clouds* are quite bright, and not all clouds are as bright as the samples. Note that the wispy, translucent clouds have fairly high membership values in some cases, but are incorrectly classified as grasslands. Once again, clouds distort the spectral information and there is little that can be done to correct the problem. The classification stability statistics are given in Table 6.4. Again, whitewater classes have the highest stability values. The others are fair, with values around 0.5, except for sand and shoals, which have values of approximately 0.12 and 0.25 respectively. Shoals and grasslands are spectrally very similar, as are clouds and sand, which may account for the low values. In both the best classification and stability statistics, the whitewater classes (those most connected to channel habitat) have the highest values.

Stage 3 - Advanced Classification

        As noted previously, this third stage of procedural development combined the advantages

of each of the prior approaches. Contextual information was used on multiple object levels to

determine whether objects were inside or outside the main channel and whether they were

located on a bank, on an island, or on the mainland. Land cover was also classified, including

water bodies. Depth and whitewater within the channel were also classified separately. This

resulted in the most complex procedures and classification hierarchy yet.

        A visual comparison shows that the classification conforms fairly well to the original

ASTER image (Figures 5.3 and 6.8). Land cover classifications generally appear to be accurate,

and a large percentage of the tributaries in the northwestern and southeastern portions of the

image are correctly classified as water (despite the fact that they are only two pixels wide in

some places). Objects within the channel appear to be correctly classified in terms of

whitewater, as with the previous classifications.

        Some issues remain with the classification, however. As before, areas beneath

translucent clouds are erroneously classified as grasslands, and cloud shadows are classified as

water. A few objects remain unclassified. Additionally, although the major tributaries in the

image are correctly classified, they are only classified as deep or shallow water, and not

according to the presence or absence of whitewater. The majority of both *whitewater* and *not*

whitewater objects were classified as deep, which makes sense given the depth and velocity of

the river. Far fewer objects were classified as shallow. In several cases, *shallow whitewater*

objects were classified in the middle of *deep not whitewater* areas. Many of the shallow areas

were located near banks and islands, which is to be expected, but the proximity of the shallow

areas to bank vegetation suggests that the high values in the infrared band might also be caused

by vegetative matter in the water or on the bank. Areas of submerged rocks or sand appear to be properly classified, however, as they can be clearly seen in the imagery. These shallow, submerged areas predictably exhibit a high reflectance in all bands, unlike the shallow areas identified by the infrared band alone.

The third stage classification of whitewater compares well to both Stage 1 and 2 classifications. Overall, *whitewater* and *not whitewater* areas are similarly classified between the different stages. Some small differences do exist, most likely because of changes in membership criteria and segmentation procedures between the stages.

The best classification statistics are given in Table 6.5. The highest value is associated with the class *deep not whitewater* at 0.91, and the lowest with *land clouds* at 0.61. Most values have values in the range of 0.7 to 0.9. Whitewater classes have relatively high values, varying between 0.78 and 0.91. The classification stability statistics are given in Table 6.6. *Island sand* has the highest value at 0.76, and *shallow water* has the lowest at 0.15. Within the whitewater categories, the values run from 0.42 for *deep not whitewater* to 0.34 for *shallow whitewater*.

Although fuzzy classification values in Stages 1 and 2 could be used to provide qualitative information about an object's similarity to an exemplar, this is not necessarily the case in this stage. In the earlier stages, membership functions were relatively uncomplicated, and constructed in such a way that fuzzy membership values provide information about an object's position along a continuum. Because of the addition of depth to the classification hierarchy, the fuzzy membership value now takes into account uncertainty over membership to both depth and whitewater categories. This problem could potentially be solved, however, by separating depth and whitewater into different object levels, or by removing depth as a class altogether.

Automated Classifications

The protocols developed for Tile A3 were next applied to Tiles A1, A2, and A4. Because each image is slightly different in terms of land cover, channel morphology, cloud cover, and lighting conditions, the protocols could not be applied directly without modifications. For example, different atmospheric and lighting conditions required that new samples be selected for each class which relies on nearest neighbor samples (such as trees, shrubs, grasses, etc). As noted in the discussion on membership functions and feature space, the water bodies in each image were generally identified using a DN of 49 or less in ASTER Band 3. This value produced results of differing quality for each image, and so this number was adjusted for each scene until a reasonably accurate result was achieved – meaning that the entire river channel was properly classified, while the number of isolated objects classified as water outside the channel was minimized. In Tile A4, the class *urban* was introduced using a nearest neighbor sample. Results were disappointing, however, since the spectral characteristics of the *urban* class bore similarities to several other classes. The class was therefore inactivated, and the urban area must be manually classified. Tile A4 also contains some land cover types which seem to differ from the other images, and it is difficult to determine whether the classification system adequately describes the land cover here. Tile A1 is quite different from all other images, with different land cover types (including large urban and rural areas and cropland) and channel characteristics. The channel here is much wider and more slow moving, and the whitewater categories developed in Tile A3 are not applicable. Although some tests were conducted in an attempt to refine the classification of Tile A1, time constraints prevented a satisfactory classification for this image.

The class that most influences habitat, whitewater, seems to be well represented in Tiles A2, A3, and A4. Even the relatively complex section of river in the northern portion of A4 seems to be fairly accurately classified. Problems still exist where clouds shadows or semi-transparent clouds obscure the river, but overall the results appear to be quite good.

The problems that occurred in the Stages 1 through 3 classifications predictably persisted in this stage. These problems included misclassification of translucent clouds; classification of cloud shadows as water; poor classification of shallow areas (other than *submerged rocks or sand*); and confusion of sand and clouds near the river channel. Higher amounts of cloud cover in images A2 and A4 made some of these problems more pronounced.

The total processing time required to execute the classification protocol was approximately 15 minutes per image. This time was increased, however, by the time needed to redefine membership functions and select new object samples. Including this requirement, the overall time needed to classify each image was about one hour once a full procedure and classification hierarchy was developed.

Landsat Classifications

Many of the situations encountered when executing the classification protocol on different ASTER images were similarly experienced when the procedure was applied to the Landsat image subset. As with the ASTER images, membership functions and samples had to be modified prior to classification. The lower resolution of the Landsat data also made image interpretation more difficult. Comparing the Landsat classification (Figure 17) to the ASTER A3 classification, one can see differences between the classifications in both the land cover and the river channel, although they correspond fairly well at a coarse level. In addition to having

different resolutions, the two images were taken at different dates, which further complicates comparison. Overall, the Landsat classification is less detailed than the ASTER classification, probably because of the spatial resolution difference, but still produces an acceptable result from the perspective of the minimum mapping unit guidelines.

Accuracy Assessment

Although a formal accuracy assessment could not be conducted because of a lack of ground truth data, the final habitat classifications were compared to the textual descriptions from Robert (1946) and to the 1:100,000 topographic maps. The descriptions from Robert are very broad, but in general they support the classifications, noting that the portions of the river comprised by Tiles A2, A3, and A4 are extremely turbulent, with over 50 rapids between them, making them completely unnavigable. This is reflected in the classifications in that large sections of the river in these areas were classified as *whitewater*. Comparisons to the topographic maps were overall quite favorable, with most chutes, rapids, islands, and rock formations being correctly identified. Table 6.7 describes the results of the comparison to the maps on an image-by-image basis. In a few cases, islands were identified, but were incorrectly classified as bank. This occurred when islands were bordered by submerged rocks or sand, which are not part of the membership function for islands. This should be easily remedied by altering the membership criteria for islands.

6.2 Guidelines for Object-Oriented Classification of Habitat

The results of this study suggest a number of lessons which can serve as guidelines for future object-oriented classifications of channel habitat. These guidelines can be divided into

three categories based on that portion of the classification process to which they apply: data set selection, image segmentation, and object classification.

Data Set Selection

This study supports the guidelines given in Chapter 2 which suggest that ASTER and Landsat ETM+ provide the necessary spatial resolution to map habitat in large rivers. Depending on the initial assumptions, ASTER can be used to map rivers as small as 30 to 90 meters in width, and Landsat ETM+ for rivers as narrow as 60 to 180 meters. Although the lower limits of the spatial resolution were not tested in this study, successful classification of several tributaries supports these conclusions. In the case of elevation data, however, SRTM and ASTER DEMs are not sufficient for mapping the river's surface because their accuracies tend to break down over water, and in most cases, the elevation data for the channel itself are spurious. On the other hand, ancillary data, such as photographs of the area, textual descriptions, existing topographic maps, and GIS layers proved to be quite useful in this study.

Image Segmentation

Object scale is an important factor in the image segmentation process, and object scale is governed by the MMU. In Chapter 2, general guidelines for MMUs were given based on literature for field measurements. These guidelines, which were most likely written to prevent field teams from spending excessive time mapping small changes in the channel, are probably unnecessarily restrictive for mapping using remotely sensed images. Satellite images with the proper spatial resolution relative to channel width, when used in conjunction with an automated classifier, can map at a much finer scale than that specified by these guidelines. This supports

the contention of Marcus et al. (2003) that automated classifications of remotely sensed images can produce habitat maps that are actually more accurate than field teams. With this in mind, it is probably best to consider the guidelines for MMU in Chapter 2 as guidelines for a minimum *acceptable* mapping unit.

Another important lesson related to image segmentation is that multiple object scales will often be required. For example, habitat units in the river may require objects of a different size than land cover objects on the channel banks or on islands. In general, the bank-water interface requires the smallest object scale, and for this reason, it is best to segment the image at the smallest scale first, and then combine image objects of similar classes to achieve the desired scale for each part of the image.

Object Classification

In the area of object classification, lessons learned apply primarily to the selection of feature space and the construction of classification hierarchies. For example, in terms of spectral features, whitewater seems to be best identified using the mean values of the green and red bands (ASTER Bands 1 and 2) and the mean object brightness. Water bodies are best identified using the mean value of the near infrared band (ASTER Band 3). Water depth does not appear to be well-represented using the infrared band, but shallow areas of submerged rocks and sand appear to be classifiable using the green, red, and infrared bands.. For other classes, such as land cover, a combination of the three bands provides the greatest spectral separability. Since the validity of these measures has not been tested using ground truth data, however, we cannot say definitively that these measures accurately reflect the features we are attempting to identify. Nevertheless, there are logical reasons why they should be used as a starting point.

A number of spatial features are also helpful in classifying habitat, particularly in separating spectrally similar classes. This is the case with sand and clouds, where sand is partially defined by its adjacency to water, and with shallows and grasslands, where shallows are similarly defined. In other cases, spatial features are critical to a class's definition, as when area is used to differentiate between the main river channel and smaller bodies of water in the image. Other examples include the use of the relative border function to identify islands, and adjacency to water to distinguish between banks and mainland. It is important to note, however, that these spatial features require multiple classification iterations because of their dependency on other classes for their definitions, and in some cases this can prolong the processing time. Distance between objects is a particularly troublesome feature, as the distance between each object in the image must be computed. A judicious use of spatial features is therefore advised, but a little forethought can prevent most problems.

Finally, properly structured class hierarchies are a critical part of the classification process. Although this is usually a straightforward process, it does require some thought about the nature of the objects to be classified. When using spatial features, it is important to note that multiple object levels may be required, and this multi-level aspect must be built into the class hierarchy (as in the advanced classifications).

6.3 Methodological Issues

The most obvious methodological issues in this study, the lack of adequate ground truth data, was recognized during the research proposal stage. The major drawback of this problem is that it is impossible to verify whether the final map of channel habitat is accurate. This issue has been mitigated in a two ways. First, ancillary data sets were used to offset the lack of ground

control data. Ground photos were used to guide the land cover classification, and topographic

maps and textual descriptions were used to check the results of the habitat classification in the

channel. Second, the methodology of this study focuses on how an object-oriented approach can

improve the process of habitat classification, rather than how it can improve the results. Even if

the feature spaces for the habitat classes is shown to be wrong, the process could still be used

with other, more appropriate data sets.

Another methodological issue is that of estimating water depth with the infrared band.

The Lower Congo is deep and turbulent, and both qualities tend to make depth estimation

difficult. The apparent misclassification of *shallow whitewater* areas in *deep not whitewater*

areas, along with the close proximity of most shallows to vegetated areas, indicates that the

infrared band alone is most likely a poor choice for depth assessment on large rivers.

In addition to the four physical variables mapped in this study, several other variables

were initially considered, but were not mapped for different reasons. These variables included

geography, topography, and water velocity. Geologic features, such as bedrock material, and

topographic features, represented by the SRTM DEM, were visually examined to determine

whether there was any correlation between these features and whitewater in the channel. This

visual analysis did not reveal any relationship between the spatial data sets and the physical

variables of geology, topography, and whitewater, and therefore these factors were not

incorporated into the object-oriented classification. There does seem to be some correlation,

however, between valid elevation data values in the DEM and whitewater in the channel. As

noted previously, much of the elevation data in the channel is spurious because of the inability of

radar interferometry to produce elevation values over water. Where there is significant

whitewater in the river, however, the DEM returns a valid elevation value, which may be due to

the altered surface characteristics caused by whitewater. If there is indeed such a relationship, the DEM might be used in future image segmentations and classifications to identify turbulent areas.

Water velocity was also considered as a potential variable for mapping. Although water velocity cannot be measured outright in a satellite image, some comparative statements about velocity can made where the river curves, since the inside of a bend is generally slower than the outside. Automation of the classification of curves proved to be a difficult topological problem, and manual classification of the curves as input for classification was not successful. For these reasons, water velocity was not used as a habitat mapping criteria.

Another methodological problem was the difficulty in accurately classifying urban areas. Because of time constraints and the fact that land cover classification was secondary to classification of channel features, this problem was not adequately solved. However, much of the current work with object-oriented classification is in the land cover area, and further research in the literature may provide a solution.

The final methodological problem was the inability to generate a habitat map of the entire Lower Congo River because of excessive cloud cover in the Landsat images. Numerous Landsat 7 images of this region exist, however, and though many are covered with clouds, an examination of the USGS image catalog suggests that it may be possible to classify the river by using portions of different images. Because these images are not free, this avenue cannot be pursued unless funding becomes available.

Table 6.1. Best classification statistics for Stage 1 (based on the highest membership value for each object).

Class	Objects	Mean	StdDev	Minimum	Maximum
not islands (1)	3	0.70	0.42	0.10	1.00
whitewater	168	0.84	0.15	0.50	1.00
not whitewater	182	0.84	0.15	0.50	1.00
vegetation	5	0.62	0.32	0.20	1.00
exposed sand	1	1.00	0.00	1.00	1.00
shoals	17	0.55	0.29	0.10	1.00

Table 6.2. Classification stability statistics for Stage 1 (based on the difference between the highest membership value and the second highest membership value for each object).

Class	Objects	Mean	StdDev	Minimum	Maximum
not islands (1)	3	0.67	0.47	0.00	1.00
whitewater	168	0.69	0.31	0.00	1.00
not whitewater	182	0.71	0.31	0.00	1.00
vegetation	5	0.62	0.32	0.20	1.00
exposed sand	1	1.00	0.00	1.00	1.00
shoals	17	0.55	0.29	0.10	1.00

Table 6.3. Best classification statistics for Stage 2.

Class	Objects	Mean	StdDev	Minimum	Maximum
whitewater	762	0.88	0.15	0.28	1.00
not whitewater	1827	0.88	0.15	0.11	1.00
shoals	720	0.72	0.15	0.29	1.00
forest	68108	0.86	0.13	0.11	1.00
grasslands	34675	0.68	0.21	0.10	1.00
shrublands	101647	0.80	0.18	0.10	1.00
sand	103	0.72	0.27	0.13	1.00
clouds	4897	0.60	0.30	0.10	1.00

Table 6.4. Classification stability statistics for Stage 2.

Class	Objects	Mean	StdDev	Minimum	Maximum
whitewater	762	0.77	0.30	0.00	1.00
not whitewater	1827	0.80	0.27	0.00	1.00
shoals	720	0.25	0.17	0.00	0.59
forest	68108	0.50	0.29	0.00	1.00
grasslands	34675	0.54	0.29	0.00	1.00
shrublands	101647	0.44	0.22	0.00	0.86
sand	103	0.12	0.08	0.00	0.24
clouds	4897	0.59	0.32	0.00	1.00

Table 6.5. Best classification statistics for Stage 3.

Class	Objects	Mean	StdDev	Minimum	Maximum
island grass	11	0.83	0.16	0.49	0.98
bank grass	295	0.74	0.24	0.15	0.99
land grass	8188	0.77	0.25	0.10	1.00
bank sand	127	0.67	0.29	0.14	1.00
island sand	7	0.76	0.30	0.26	1.00
land clouds	2319	0.61	0.31	0.10	1.00
bank shrubs	1014	0.82	0.16	0.28	1.00
island shrubs	22	0.81	0.12	0.50	0.99
land shrubs	28617	0.85	0.13	0.13	1.00
bank trees	600	0.74	0.19	0.11	1.00
island trees	8	0.78	0.19	0.47	0.99
land trees	19212	0.83	0.15	0.11	1.00
deep water	1157	0.84	0.17	0.11	1.00
deep not whitewater	541	0.90	0.10	0.45	1.00
shallow not whitewater	82	0.82	0.12	0.52	1.00
shallow whitewater	149	0.73	0.19	0.18	0.99
deep whitewater	581	0.84	0.18	0.10	1.00
shallow water	1334	0.71	0.11	0.13	0.85
bank submerged rocks or sand	196	0.79	0.21	0.16	0.99
island submerged rocks or sand	40	0.88	0.14	0.45	1.00

**Table 6.6.** Classification stability statistics for Stage 3.

Class	Objects	Mean	StdDev	Minimum	Maximum
island grass	11	0.16	0.09	0.02	0.28
bank grass	295	0.17	0.10	0.00	0.37
land grass	8188	0.33	0.20	0.00	0.75
bank sand	127	0.66	0.31	0.00	1.00
island sand	7	0.76	0.30	0.26	1.00
land clouds	2319	0.61	0.32	0.00	1.00
bank shrubs	1014	0.41	0.22	0.00	0.76
island shrubs	22	0.46	0.15	0.22	0.74
land shrubs	28617	0.45	0.24	0.00	0.96
bank trees	600	0.55	0.31	0.00	1.00
island trees	8	0.61	0.32	0.02	0.99
land trees	19212	0.70	0.29	0.00	1.00
deep water	1157	0.59	0.30	0.00	1.00
deep not whitewater	541	0.42	0.23	0.00	0.79
shallow not whitewater	82	0.36	0.23	0.00	0.75
shallow whitewater	149	0.34	0.24	0.00	0.75
deep whitewater	581	0.41	0.26	0.00	0.79
shallow water	1334	0.15	0.12	0.00	0.68
bank submerged rocks or sand	196	0.22	0.14	0.01	0.49
island submerged rocks or sand	40	0.25	0.12	0.01	0.44

Table 6.7. Comparison of classifications to topographic maps.

| Tile	Results of comparison
A2	All islands are identified, although in a few cases they are classified as banks because of an error in the membership function. No rapids or chutes are marked on the topographic map in this section.
A3	All chutes and islands are correctly identified.
A4	All major islands or rock formations are identified either as an island or as submerged rocks or sand. As with Tile A2, some are incorrectly classified as bank because of an error in the membership function. All chutes and rapids are properly classified as *whitewater*.
E3	Not all of the major islands and rocks are identified, although most are contained within a *whitewater* or submerged material classification.
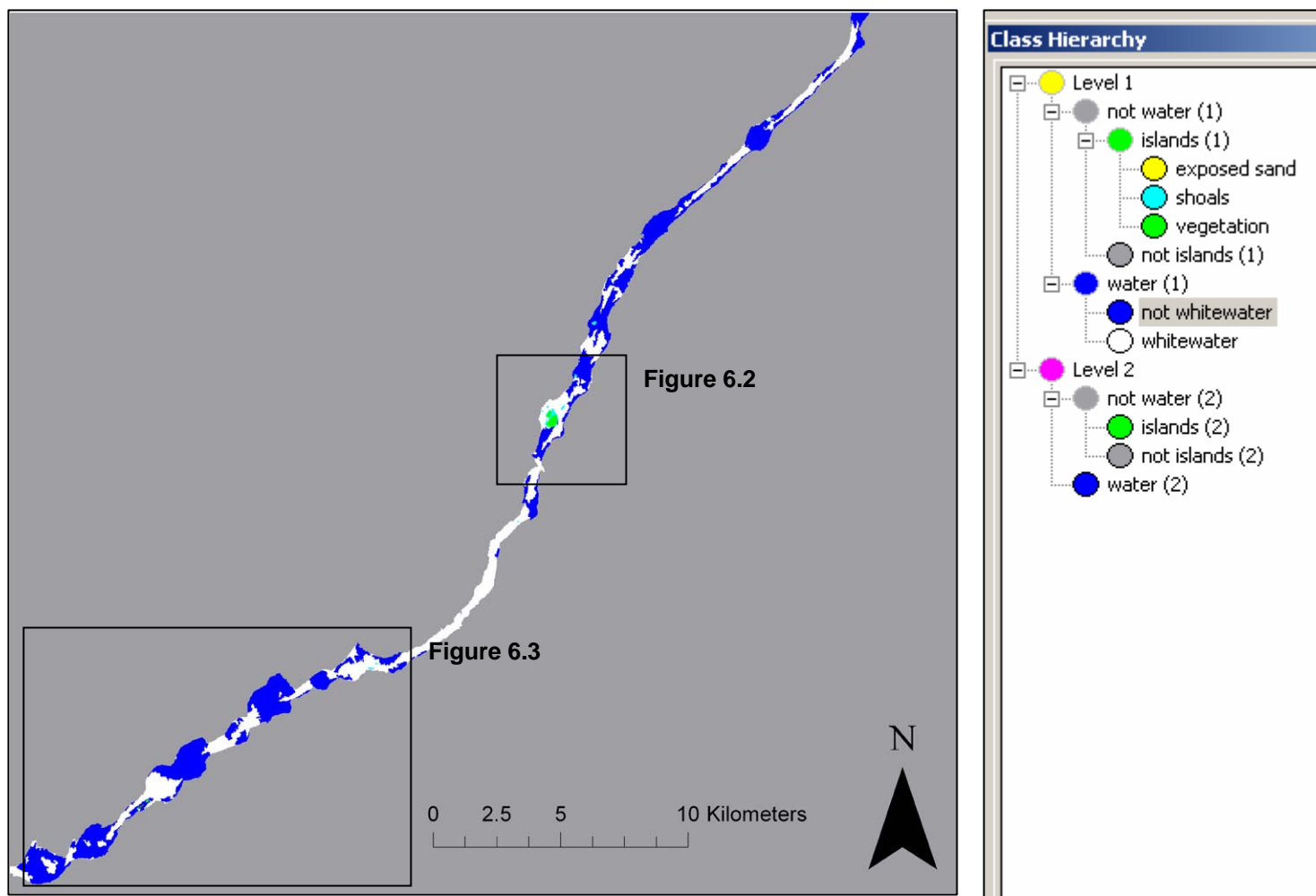
Figure 6.1. Classification results for Stage 1.
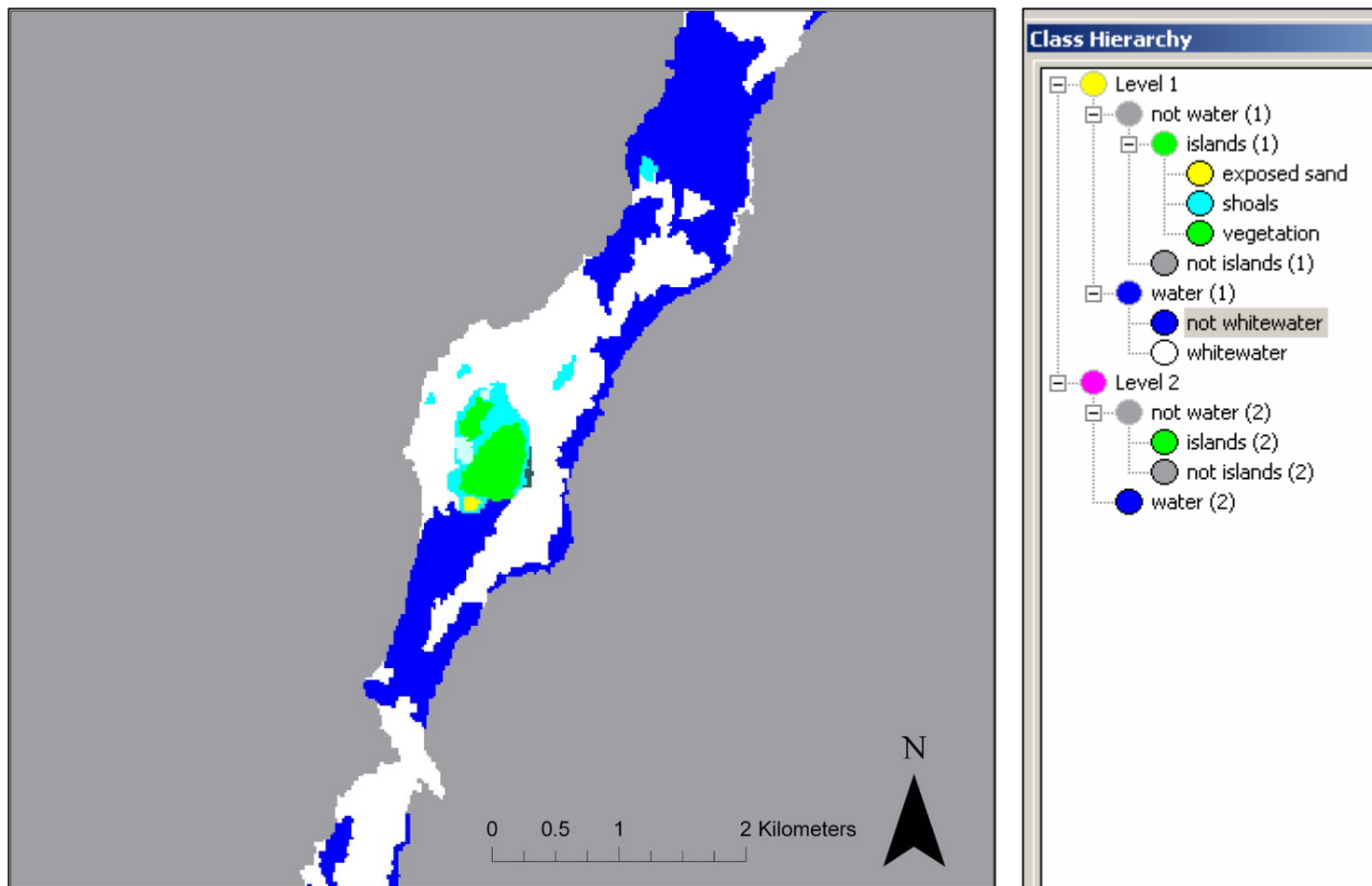
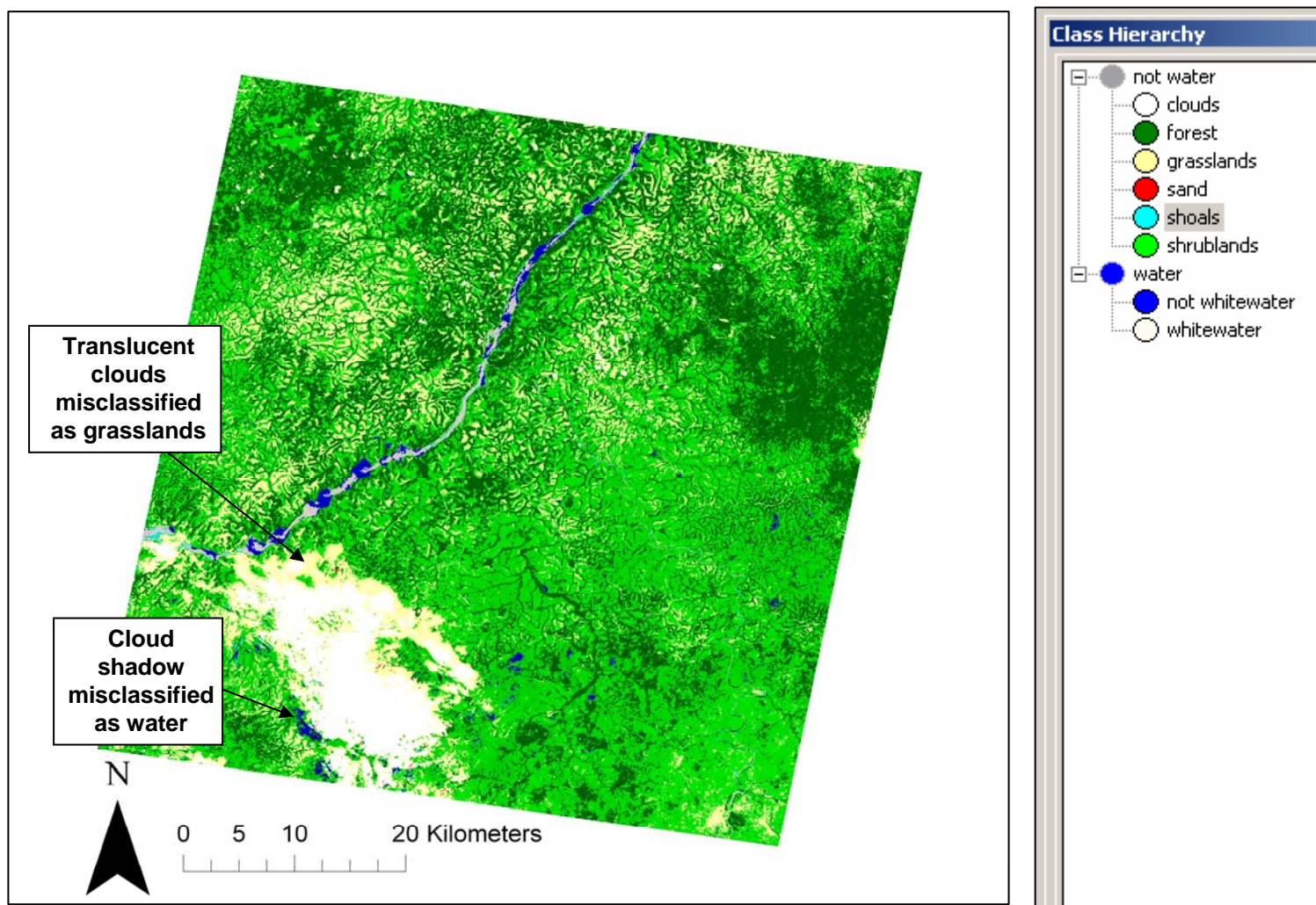**Figure 6.2.** Detail of classification results for Stage 1.
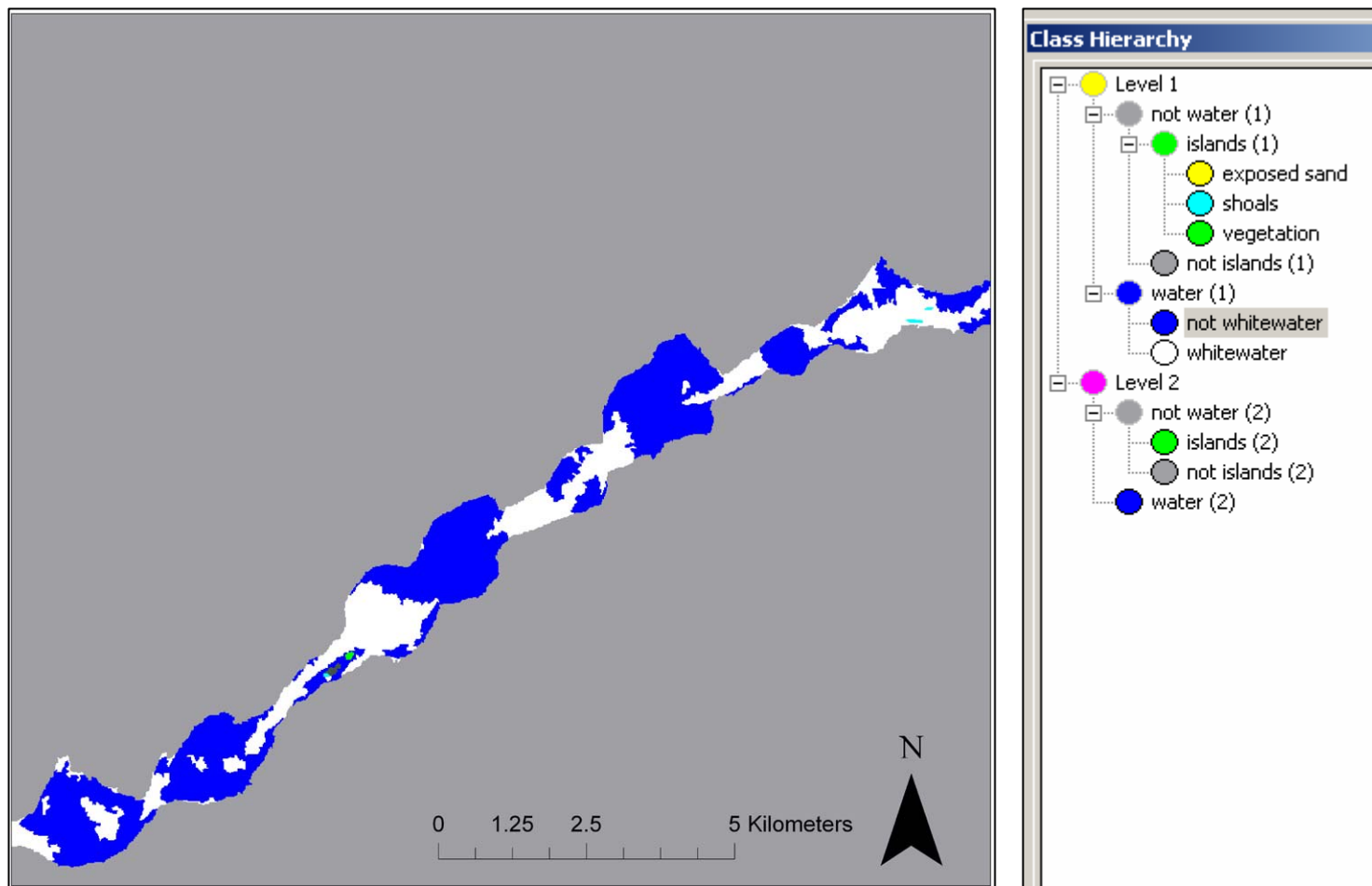
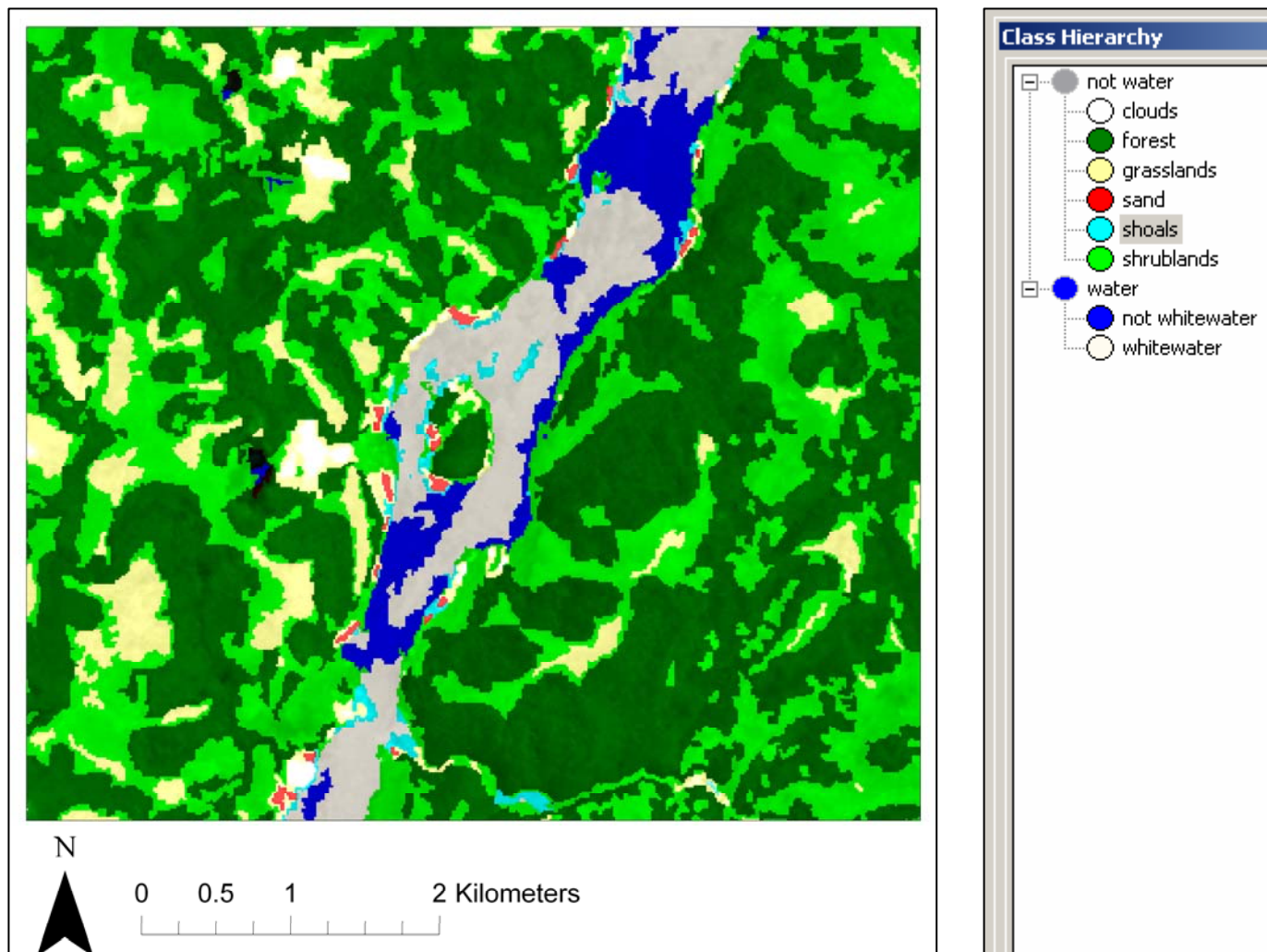**Figure 6.3.** Detail of classification results for Stage 1.
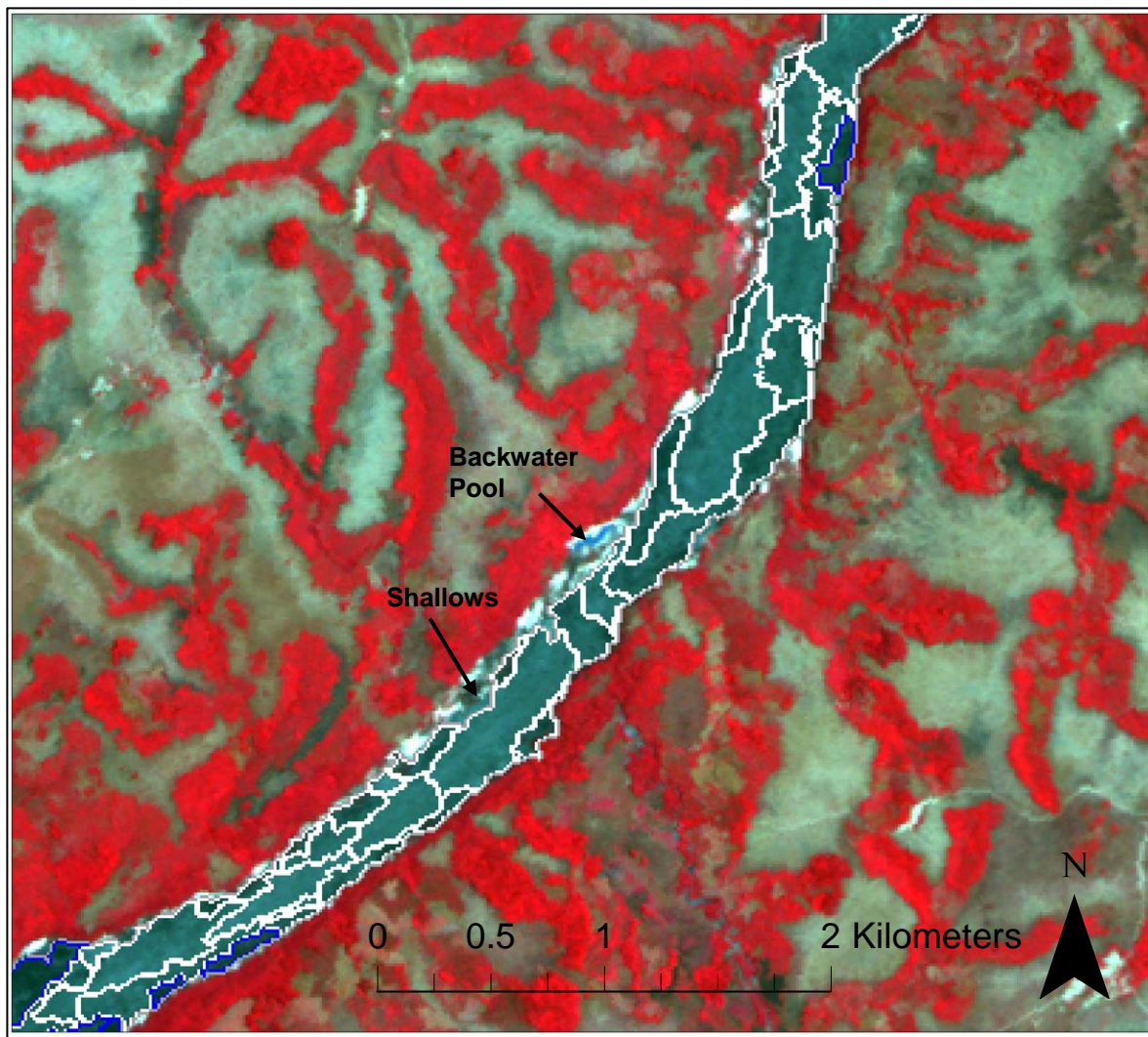
Figure 6.4. Examples of misclassified objects. Note the backwater pool and shallows that were incorrectly segmented and classified as part of the bank.
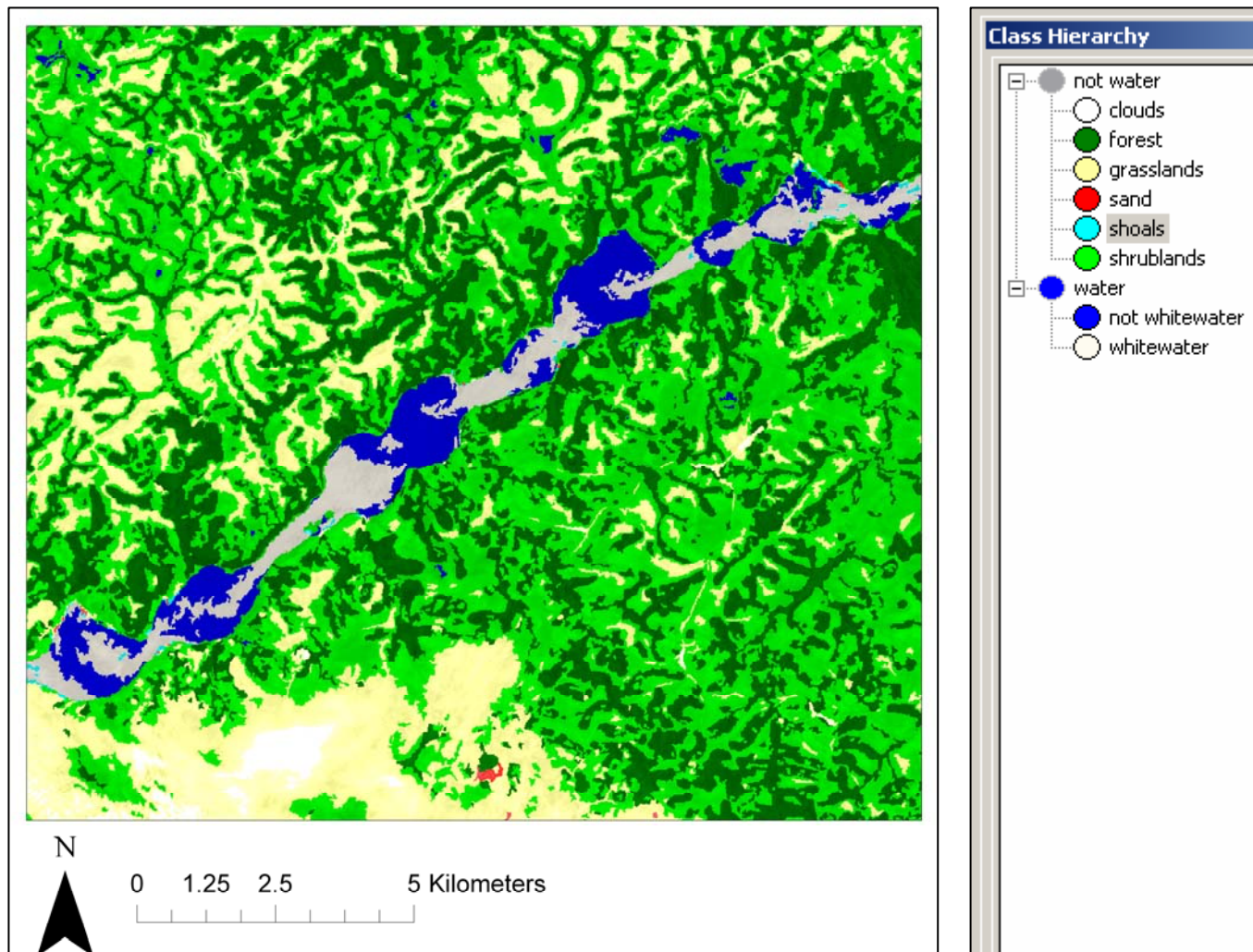
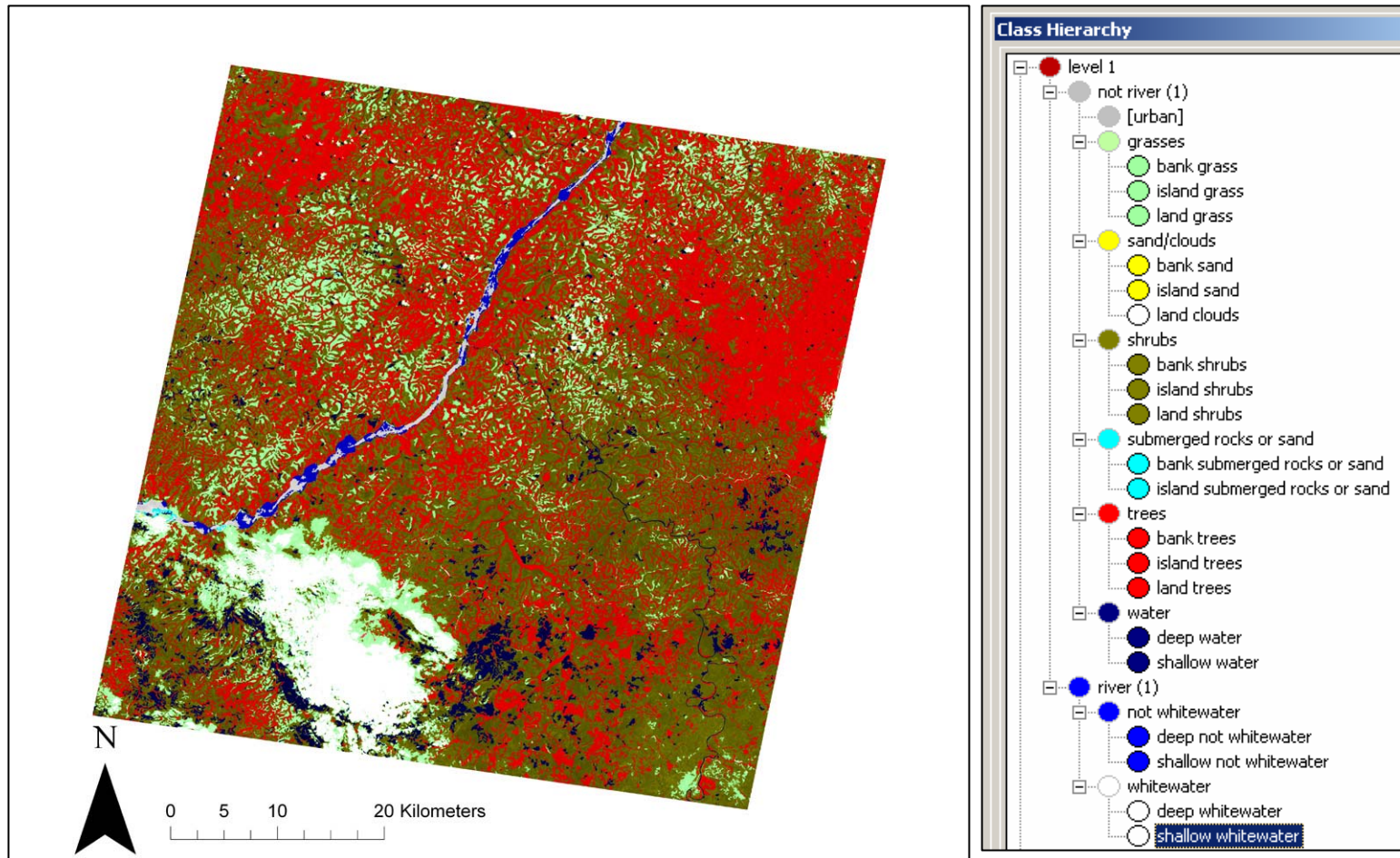**Figure 6.5.** Classification results for Stage 2.

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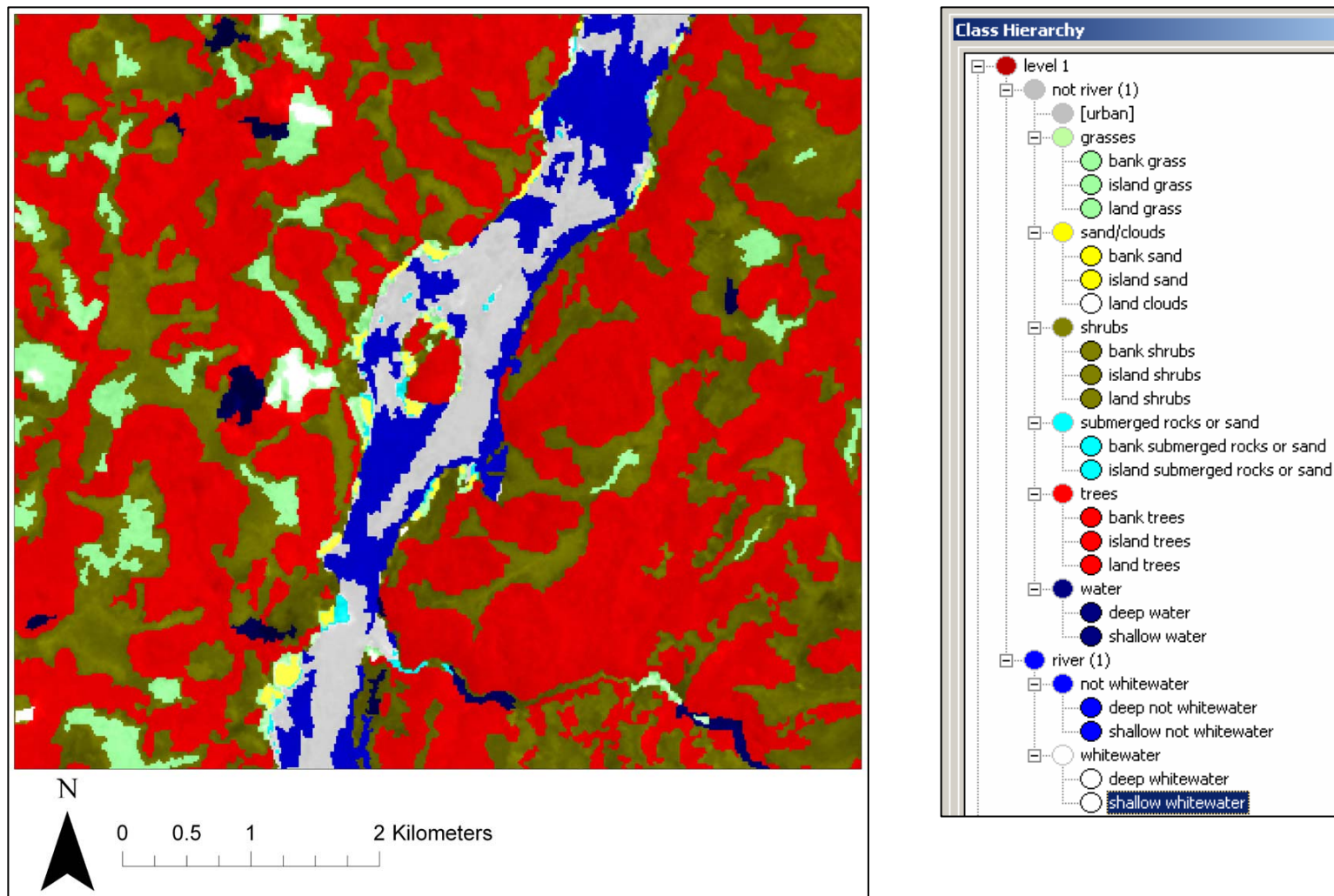**Figure 6.6.** Detail of classification results for Stage 2.

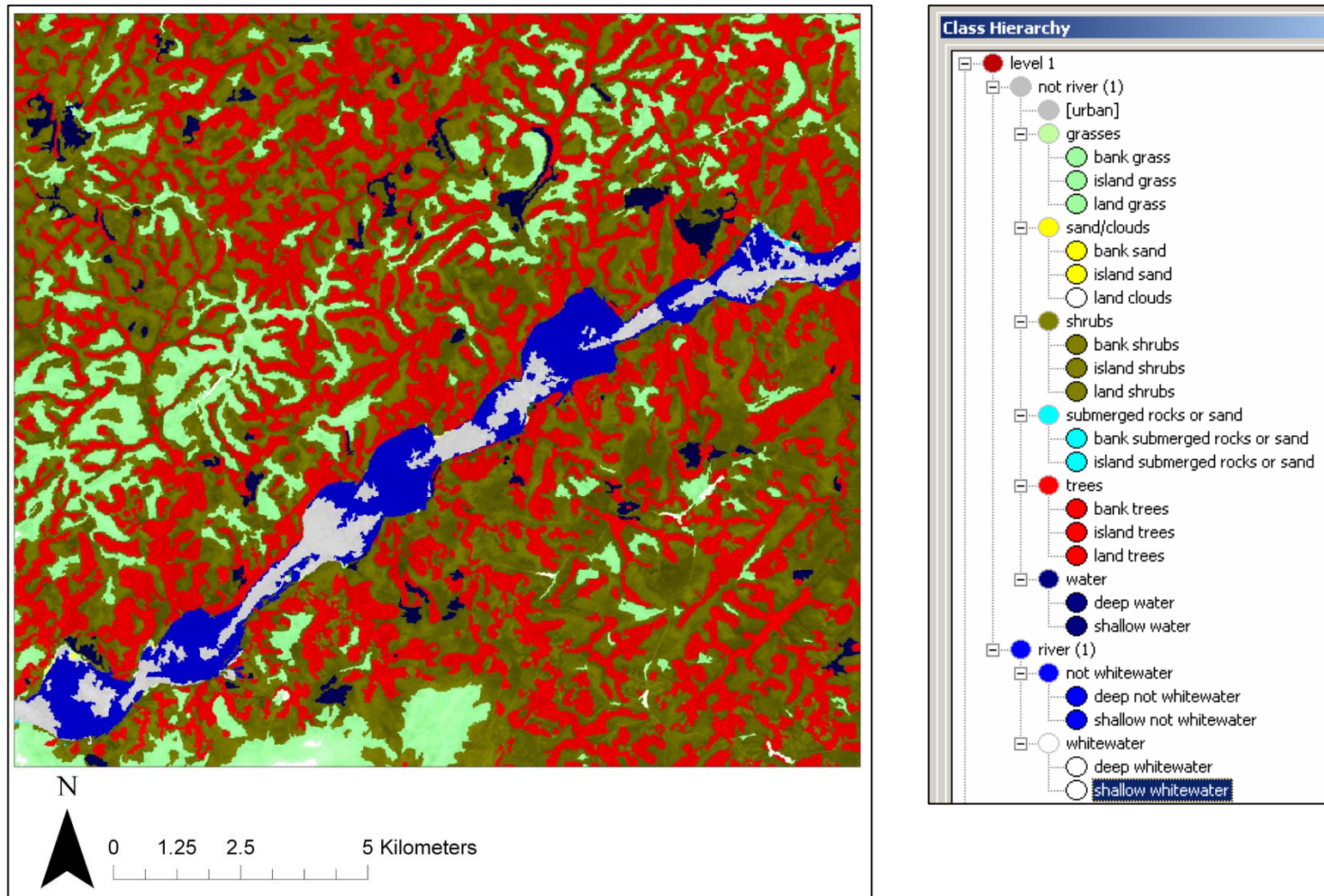**Figure 6.7.** Detail of classification results for Stage 2.

Class Hierarchy

- level 1
  - not river (1)
    - [urban]
    - grasses
      - bank grass
      - island grass
      - land grass
    - sand/clouds
      - bank sand
      - island sand
      - land clouds
    - shrubs
      - bank shrubs
      - island shrubs
      - land shrubs
    - submerged rocks or sand
      - bank submerged rocks or sand
      - island submerged rocks or sand
    - trees
      - bank trees
      - island trees
      - land trees
    - water
      - deep water
      - shallow water
  - river (1)
    - not whitewater
      - deep not whitewater
      - shallow not whitewater
    - whitewater
      - deep whitewater
      - shallow whitewater

N

0   5   10   20 Kilometers

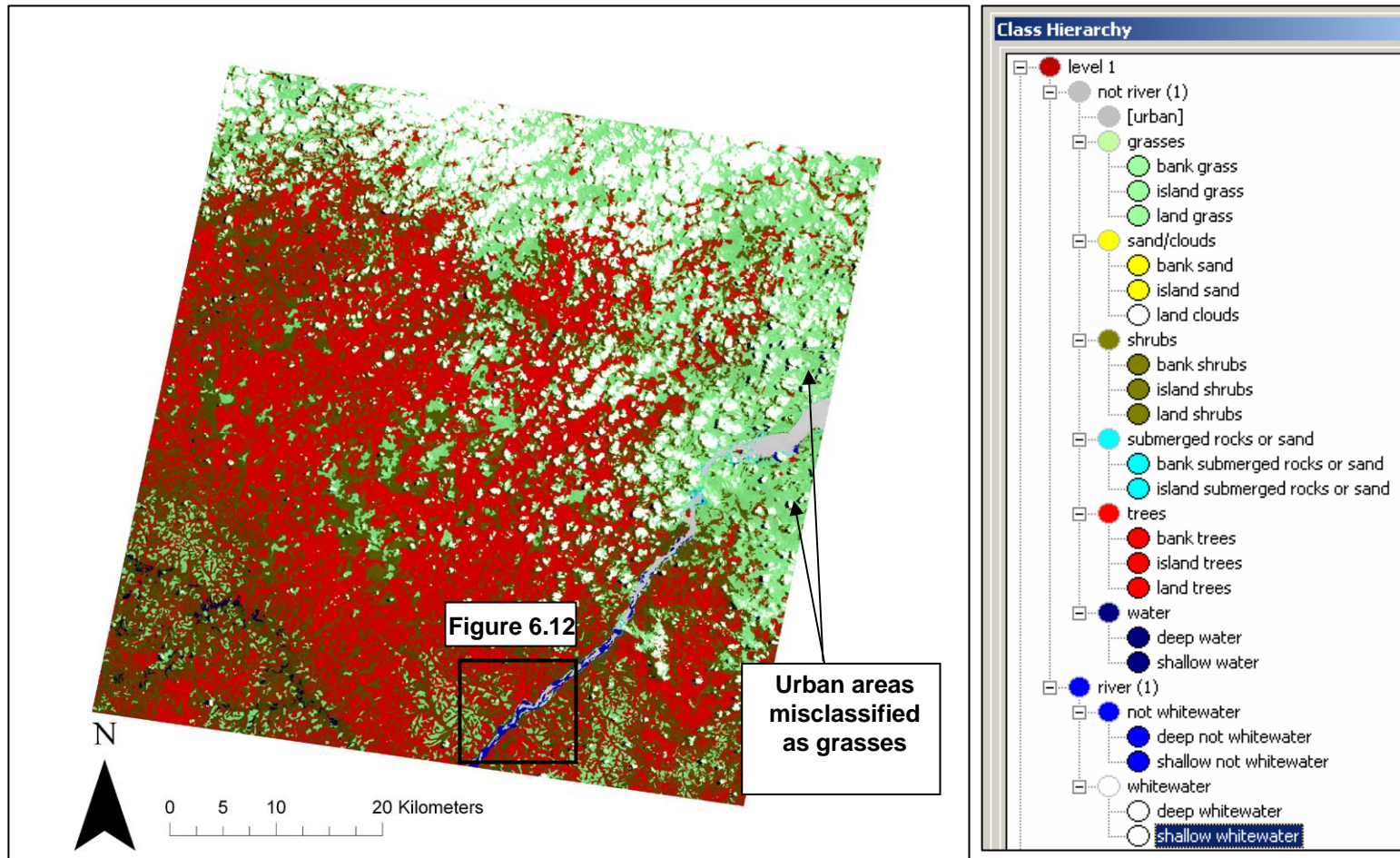**Figure 6.8.** Classification results for stage 3.

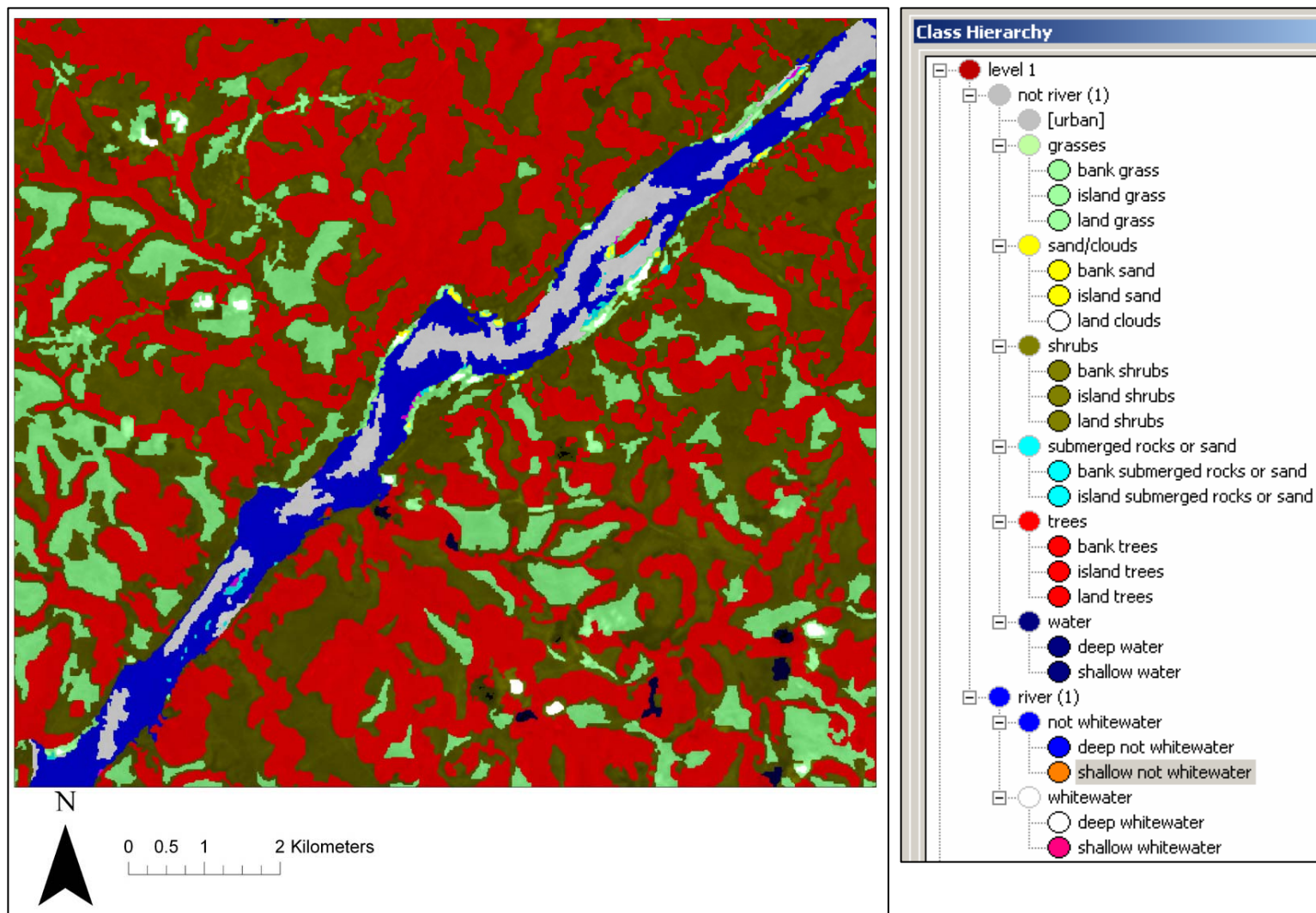**Figure 6.9.** Detail of classification results for Stage 3.

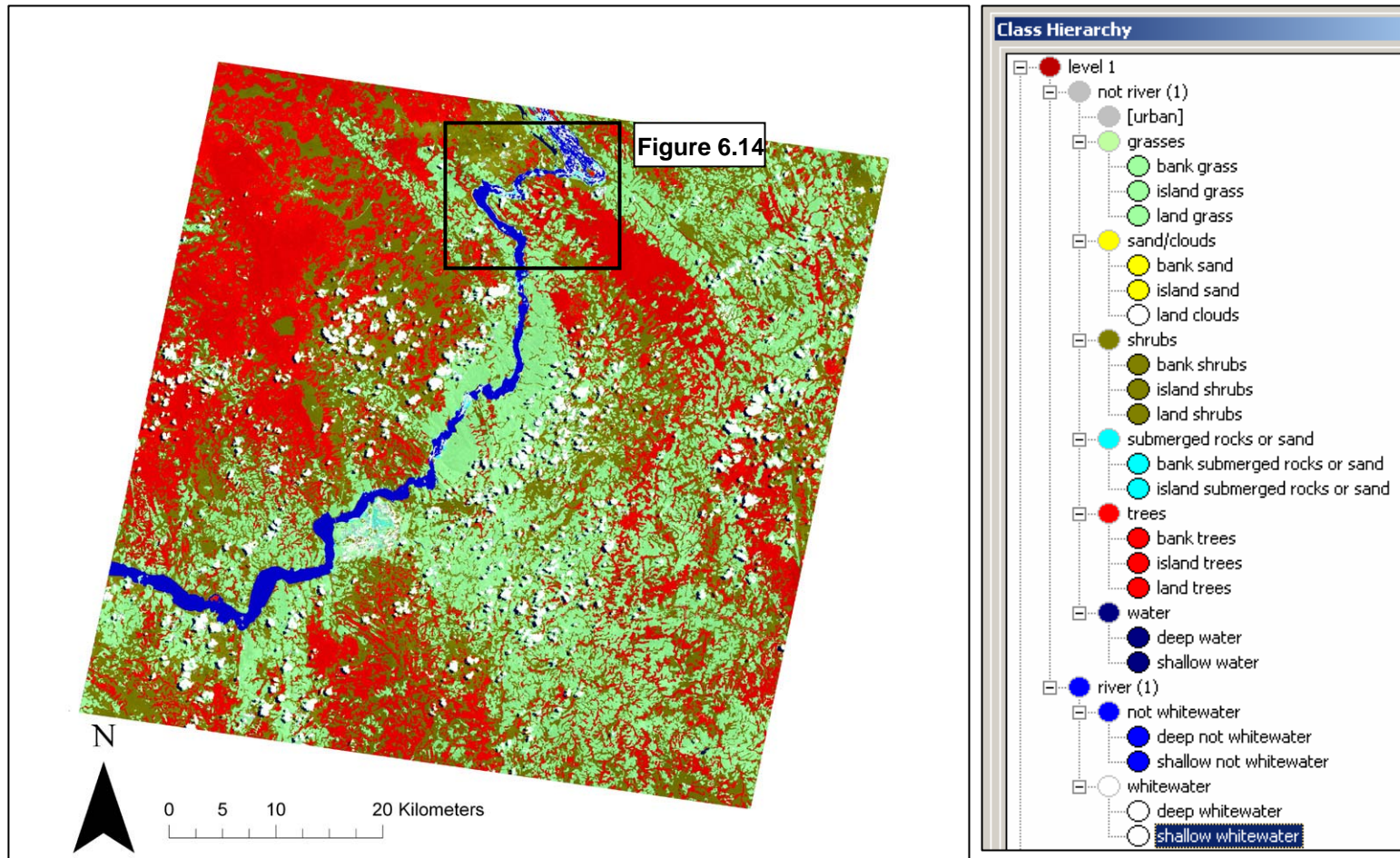**Figure 6.10.** Detail of classification results for Stage 3.

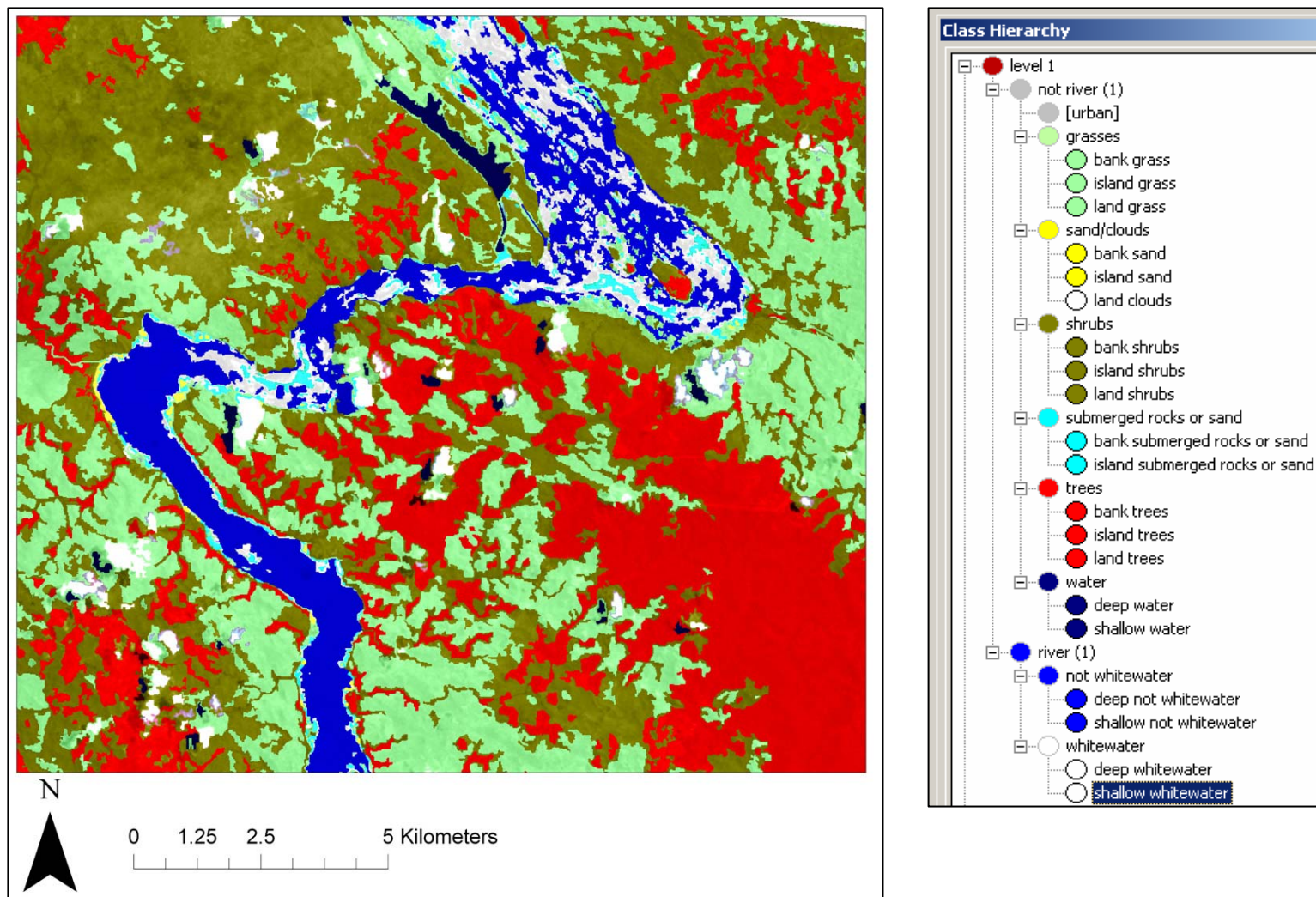**Figure 6.11.** Classification results for Tile A2.

Figure 6.12. Detail of classification results for Tile A2. Note the small shallow areas in pink.
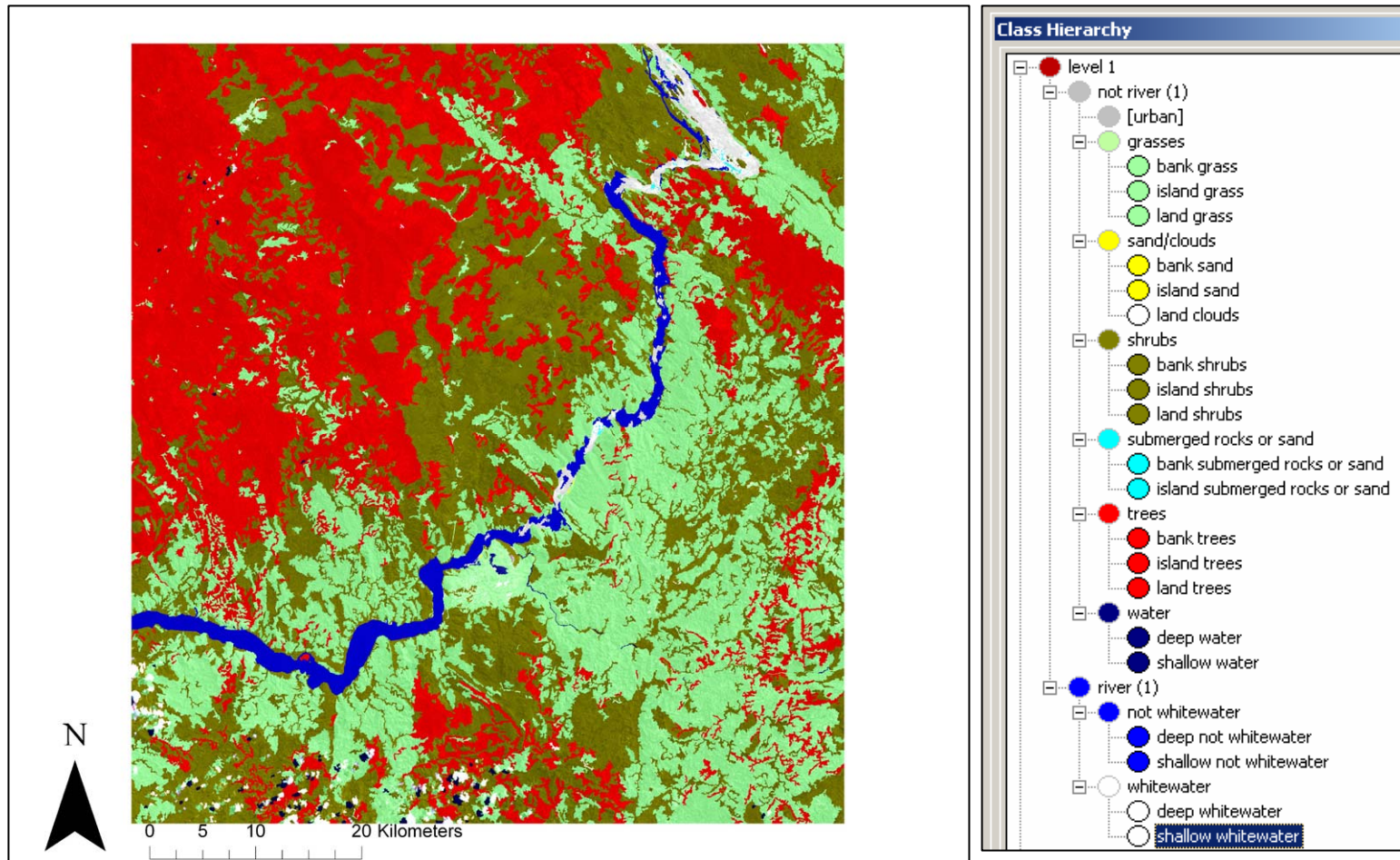
Figure 6.13. Classification results for Tile A4.

Figure 6.14. Detail of classification results for Tile A4.

Figure 6.15. Classification results for subset of Tile E3 (Landsat).

CHAPTER 7 – CONCLUSIONS

This investigation addressed the central research question of whether an object-oriented approach can be used with medium-resolution multispectral satellite images to map habitat units related to fish assemblages on a large river. At the completion of this study, a number of conclusions can be made regarding the strengths and limitations of an object-oriented classification technique to map depth, whitewater, and land cover on the Lower Congo River. These conclusions are enumerated below, and a summary of the answers to the specific research questions posed in Chapter 3 can be seen in Table 7.1.

First, we can say that spatial context in an object-oriented classification allows us to differentiate objects which cannot be distinguished by spectral information alone. In the context of this study, this allowed us to differentiate between classes which are similar or even identical spectrally by using spatial information as a discriminator. This can be seen at several points in the class hierarchies. For example, while all water bodies share the same spectral criteria, the river channel was defined using the class-related feature of area. Banks, islands, and mainland are all spectrally similar, and were differentiated from each other using class-related features. Banks and islands could be separated from the mainland by their adjacency to the river channel, while islands were identified by their relative border to water and the mainland was identified by its large area. Because of their high reflectance in all bands, sand and clouds are virtually identical spectrally in some cases, but the association of sand with water in the study area makes it possible to distinguish the two with much greater accuracy. A similar situation exists for

shallows and grasslands - both share similar spectral characteristics, but shallows occur only in water. Thus, an object-oriented approach allows us to make distinctions that would be impossible to make using a conventional pixel-based approach that cannot utilize spatial context. This can be especially useful when the spectral resolution of the imagery is low, as the ability to use spatial context may in some ways make up for the inability to separate classes spectrally.

The second conclusion is that habitat units are well-represented by objects and objects provide a more intuitive approach to habitat classification than pixels. Whereas pixel-based analysis allows the use of only one scale - the scale of the pixel - object-based classification allows us to identify meaningful objects in the river at multiple scales, such as small shallows or very large rapids. This use of polygons to represent objects at multiple scales in the image is similar to the way a human interpreter would classify an image, and it produces objects more intuitive to an observer than the "salt-and-pepper" results of pixel-based classifiers.

Third, fuzzy classification allows us to not only express a degree of certainty about an object's membership to a class, but it can also be used to qualitatively assess a habitat unit's position on a scale relative to two exemplars. In the case of whitewater, for example, a rapid is at one end of the scale while a pool is at the other. The closer an object's fuzzy membership value to 1 in *whitewater* or *not whitewater*, the closer it resembles a rapid or pool respectively. Values closer to 0.5 indicate a degree of whitewater somewhere in between.

Fourth, we can say that, based on both theory and practice, ASTER and Landsat ETM+ satellite imagery provide sufficient spatial resolution to map habitat units based on whitewater and bank cover in large rivers like the Congo, and possibly on rivers as small as 30 meters wide, in some cases. It does not seem likely, however, that large, turbulent rivers are easily classified

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in terms of depth using only the infrared bands on Landsat and ASTER, though shallow areas of submerged rocks and sand appear to be identifiable using the green, red, and infrared bands.

Finally, the procedures established here can be automated so that multiple images can be classified using the same procedure. Although some adjustment of the membership functions is required, the overall procedure is applicable as long as the general character of the river and land cover do not change significantly from image to image. While only 15 minutes of processing time was required for each image, the full procedure generally required an hour per image because of the need to adjust membership functions to accommodate differing light and atmospheric conditions. This time might be substantially reduced if atmospherically corrected images were used, or if all images were acquired at the same time.

This study was conceived as a bridge between the worlds of object-oriented landcover classification and more traditional pixel-based methods of fluvial habitat classification. Its results support current findings in both areas. The ability to utilize spatial context is thought to be one of the primary advantages of an object-oriented approach in landcover classification, and this study supports that assertion with respect to fluvial habitat. This study also reinforces the findings of Legleiter and Goodchild (2005), who found that fuzzy classifications may provide a more realistic way of mapping habitat than traditional binary methods. In addition, the results of this study suggest that fuzzy values may also be used as a qualitative measure of a characteristic such as degree of whitewater.

These conclusions translate into a number of advantages for the field researcher looking to use an object-oriented approach to classify fluvial habitat. While the first choice of many researchers might be existing topographic maps, object-oriented classification of satellite images may provide a better alternative. One reason is that such a classification provides a more

detailed map of habitat within the river than most maps provide. Using the topographic maps referred to in this study as an example, these maps merely provide elevation data and some general information about the locations of chutes, rapids, and falls. The classifications created in this study, in contrast, convey a detailed map of whitewater, submerged rocks and sand, and bank cover, all from a more recent source. This map of habitat variables may then be used be researchers attempting to identify specific habitats – for example, an area without whitewater near a bank with overhanging vegetation. In addition, the procedure can be run on images from different sensors and dates, so that changes in habitat with seasonal changes in flow or vegetation can be taken into account.

Others might argue that similar results may be achieved using a pixel-based classifier and a GIS in combination. This is really an unsatisfactory solution, however, as anyone who has tried to work with multiple image processing packages knows. The number of times a user would be required to move between the image processing and GIS packages would be numerous, and each transfer of information is time-consuming and problematic. An object-oriented classifier provides the best of both approaches in one interface.

The list below summarizes the major contributions of this study to the classification of channel habitat using remotely-sensed images.

- Demonstrated that medium-resolution multispectral imagery can be used to map habitat units on large rivers using an object-oriented classification procedure.
- Developed a classification system for channel habitat appropriate for medium-resolution multispectral satellite images.
- Developed an object-oriented methodology for classifying channel habitat that effectively utilizes spatial context.

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- Developed guidelines for future habitat classifications using an object-oriented approach.

- Produced a detailed map of habitat units along portions of the Lower Congo River.

Although a number of interesting conclusions can be made from this study about the potential of object-oriented classification for habitat mapping, the final habitat map could be verified using ground observations. This study would benefit greatly by conducting ground truth data collection and accuracy assessment. Because of the logistical problems associated with an accuracy assessment on the Congo River, this research would most likely be conducted on a smaller, more accessible river using higher-resolution imagery. Particularly important are the verification of the degree of whitewater and the presence of submerged rocks or sand.

A number of other areas for future research are suggested by this study's results. First, two important habitat units associated with connectivity, falls and cascades, were not mapped because of insufficient elevation data. Other techniques for mapping these features might be explored. Second, habitat units might be mapped over time, to understand how channel habitat changes with seasonal and annual variations in flow. This area might be particularly fruitful, as changes in flow are the major form of environmental variability in fluvial ecosystems (Jackson et al. 2001). Third, the limits of the imagery's spatial resolution might be pushed further by attempting to classify habitat in some of the Lower Congo's tributaries. The main channel itself easily meets the guidelines for spatial resolution, but several of the tributaries are at the lower end. This might be especially useful for sampling teams, as the tributaries may provide more accessible sampling locations and different fish assemblages. Fourth, the methodology should be applied to atmospherically-corrected image data to determine whether this reduces the required classification time for each image. Since the image data from ASTER and Landsat are acquired

at approximately the same time each day, atmospheric correction may remove some of the differences between the images. Fifth, an attempt can be made to distinguish between different types of whitewater. For example, whitewater in a rapids or cascade indicates a different channel condition than whitewater in a plunge pool. Spatial context might be further exploited to discriminate between these two types of whitewater. Finally, this approach should be applied to higher resolution data. Since much of the need for habitat mapping in the United States is on rivers and streams far smaller than the Congo, these methods might be successfully applied to scanned aerial photos or images from aircraft-mounted digital sensors.

As noted in Chapter 2, automated classifications are a supplement, not a replacement, for field observations. Nevertheless, the techniques described here can provide a number of advantages to researchers who need information about habitat on large rivers when field sampling is not feasible.

Table 7.1. Answers to research questions posed in Section 3.2.

Research Question	Conclusion
Can objects representing habitat units be extracted from medium-resolution multi-spectral imagery?	Yes. In order to meet minimum mapping requirements, the spatial resolution of the image data should be between 1/2 and 1/6 of the channel width.
Assuming that multiple object scales will be used for analysis, what scales should be used for segmentation?	A very small scale should be used initially to delineate between the river channel and bank. Once this is accomplished, object scales should be selected to match the features being extracted.
Once an image has been segmented, can its objects be classified as habitat units?	Yes, although the definition of "habitat unit" must be modified to accommodate the data.
How reliable is the resulting classification?	Good overall. Comparisons to existing topographic maps show that the classification is at least as accurate, if not more so, than the maps.
Can object-oriented methods developed with data at one resolution be applied to coarser-resolution data?	Yes. Predictably, however, the resulting classification is not as detailed.
Does an object-oriented approach provide procedural advantages over traditional approaches?	Yes. An object-oriented approach is particularly useful for distinguishing objects based on spatial relationships. See Section 7.1 for discussion.
What guidelines can be established for future habitat classifications using object-oriented methods?	See Discussion in Section 6.2.

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