Extracting River Features from Remotely Sensed Data: An Evaluation of Thematic Correctness

by

Josef Franz Hecher

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Carinthia University of Applied Sciences
School of Geoinformation and Environmental Technologies

Supervisors

Internal Supervisor: Dr. Gernot Paulus

School of Geoinformation and Environmental Technologies, Carinthia University of Applied Sciences, Villach, Austria

External Supervisor: Dr. Inci Guneralp & Dr. Anthony Filippi

Department of Geography, Texas A&M University, College Station, Texas, United States of America

College Station, July 2012

Science Pledge

By my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used in my thesis and I have always indicated their origin.

Villach, 30.8.2012

Place, Date

Signature

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Zusammenfassung

Diese Arbeit beschäftigt sich mit der GIS-gestützten Analyse von dynamischen Prozessen mäandrierender Flüsse. Durch die Anwendung von Fernerkundungs- sowie GIS Software werden Flusselemente von Mäandern mittels zwei verschiedener Klassifizierungsalgorithmen extrahiert. Das Ziel dabei ist einerseits den optimalen Klassifizierungsprozess von Flusselementen zu bestimmen und andererseits die Separabilität von Flusselementen durch automatische Klassifikationsmethoden zu evaluieren.

Bedingt durch Erosion und Sedimentation kann sich der Verlauf eines mäandrierenden Flusses innerhalb weniger Dekaden merklich verändern. Die Veränderungen können dabei anhand von diversen Flusselementen wie zum Beispiel Altwasser, Sandbänke, verlassene Flussläufe, etc., die durch Erosions- und Sedimentationsprozesse entstanden sind, nachvollzogen werden. Für die Untersuchung von Flusslandschaften spielen diese Elemente also eine zentrale Rolle. In der Praxis erfolgt die Lokalisierung der Flusselemente entweder als Feldarbeit vor Ort oder mittels GIS basierter Analyse von Luftbildaufnahmen. Unter der Hypothese, dass es möglich ist Flusselemente aufgrund ihrer spektralen und räumlichen Charakteristika automatisch zu klassifizieren, beschränkt sich diese Arbeit auf den Teil der GIS gestützten Analyse von Flusselementen. Der zentrale Punkt im ersten Teil der Arbeit ist die Konzipierung spektral- und objektorientierter Analyseverfahren die in Kombination mit Satellitenbildern, hochauflösenden Luftbildaufnahmen, digitalen Geländehöhenmodellen, etc. zur Klassifikation der relevanten Flusselemente führen. Durch visuelle Interpretation sowie der Anwendung von Accuracy Assessment Methoden werden die Ergebnisse der Analysen evaluiert um somit die optimale Klassifikationsmethode zu identifizieren. Die zweite Fragestellung der sich die Arbeit widmet ist wie genau (im Sinne von thematisch korrekt) diverse Flusselemente mittels automatischer Klassifizierungsalgorithmen unterschieden werden können. Die Basis für die Beantwortung der Fragestellung bilden die Ergebnisse aus dem ersten Teil der Arbeit. Es werden abermals mithilfe von Accuracy Assessment Methoden diverse Indices und Koeffizienten berechnet um eine Aussage über die thematische Korrektheit der Klassifizierungsmethoden zu treffen.

Die Analysen wurden mit den Softwareprodukten Feature Analyst mit ArcGIS (ESRI) als Plattform sowie mit ENVIs (EXELIS) Support Vector Machine durchgeführt. Als Projektgebiet der Arbeit dient der untere Flusslauf des Brazos Rivers in Texas, USA. Der Brazos River zählt zu den längsten Flüssen der USA und weist zahlreiche Meander Schlingen sowie andere Formen von Erosions- und Sedimentationsprozessen auf.

Abstract

The purpose of this study project is to apply two classification methods to extract different morphological river features from Landsat 5 TM images. In addition, the separability of the various river features is tested to evaluate the thematic correctness of the classified data. River features of meandering rivers evolve through dynamic avulsion, erosion and deposition processes. Although many studies focused on the analysis of these river environments, diverse methods of GIS and remote sensing based river feature classification methods have not been evaluated and assessed yet. In the literature several techniques to monitor spatio-temporal changes such as lateral river channel migration are already mentioned but the tendency there is to identify the changes by examining time spans rather than a point in time. Besides that the semiautomatic river feature methods described in related studies mainly focus on the identification of a river channel itself and do not consider additional features such as oxbows, scars, relic channels, etc. that in fact are significant characters in riverine environments. Therefore, this thesis evaluates the application of a supervised classification using ENVI's *Support Vector Machine* and an object based classification using the ArcGIS extension *Feature Analyst* to extract river features from Landsat 5 TM images including ancillary data files. Furthermore, the results of the classification methods are evaluated with regard to thematic correctness and separability of the various classified river features using Accuracy Assessing methods. Finally the long time changes in the riverine environments are traced by interpreting the distribution of the classified river features. Accordingly, the approach of this work contributes to ongoing researches concerning semiautomatic or automatic river feature extraction.

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List of Abbreviations

ANN	*Artificial Neural Network*
AOI	*Area Of Interest*
BW	*Black-and-White*
CIR	*Color Infrared*
CUAS	*Carinthia University of Applied Sciences*
DEM	*Digital Elevation Model*
DOQQ	*Digital Orthophoto Quarter Quadrangle*
DSM	*Digital Surface Model*
DTM	*Digital Terrain Model*
ENVI	*Environment for Visual Images*
ESRI	*Environmental Systems Research Institute*
Evf	*Envi Vector File*
GIS	*Geographical Information System*
GPS	*Global Positioning System*
IfSAR	*Interferometric synthetic aperture radar*
Km^2	*Square Kilometers*
LIDAR	*Light Detection and Ranging*
M	*Meter*
MrSID	*Multi-resolution Seamless Image Database*
NAIP	*National Agricultural* Imagery *Program*
NAD	*North American Datum*
NASA	*National Aeronautics and Space Administration*
NDVI	*Normalized Difference Vegetation Index*
NED	*National Elevation Dataset*
SPOT	*Système Pour l'Observation de la Terre (System for Earth Observation)*
SVM	*Support Vector Machine*
TAMU	*Texas Agricultural and Mechanical University*
TIN	*Triangulated Irregular Network*
TIFF	*Tagged Image File Format*
TM	*Thematic Mapper*
TNRIS	*Texas Natural Resources Information System*
USGS	*United States Geological Survey*
UTM	*Universal Transverse Mercator*
VLS	*Visual Learning Systems*
µm	*Micrometer*

1. Introduction

This chapter describes the main content of the thesis. First the motivation of the thesis is explained, followed by a description of the objectives of the work. The Hypothesis is stated in the third subchapter. The three last subchapters encompass the method of solution, expected results, and an overview of the structure of the paper.

1.1 Motivation

Rivers and Streams are among the most powerful, important and remarkable forces on earth that form its appearance causing erosion and sediment deposition. For example the Mississippi River carries almost a billion tons of soil and rock per year to the Gulf of Mexico (Lutgens & Tarbuck, 1995), enlarging Louisiana's area by about 35% within the last 6000 years, due to sediment deposition. The avulsion processes associated with these forces play a crucial role in the occurring spatio-temporal river dynamics (Edwards & Smith 2001). Although avulsion processes in meandering rivers are nothing new and had always occurred, we are still not able to predict precisely the conditions leading to the avulsion of a meandering river (Slingerland & Smith, 1998). In fact, understanding the ways in which river channels have migrated through time is critical to tackling many geomorphologic and river management problems (Yang et al., 2002).Sooner or later avulsion processes are causing channel migrations changing the course and the appearance of a river. In historically terms rivers in the southeast of Texas have been strongly influenced by avulsions (Blum & Aslan, 2006). An example that depicts the power of rivers is the flood of the Yellow River in China in 1931. Almost four million people were killed. A flood in 1993 on the Mississippi River caused $15 billion in property damages (Lutgens & Tarbuck, 1995). However, these are only a few examples of how avulsion processes affect the shape of a landscape and manmade structures. Therefore in numerous study projects methods had been developed to extract river features and provide the attained data for ongoing analysis of riverine environments. Manual digitization and classification using aerial photographs or satellite images are common ways to extract river features (Passalacqua et al., 2012). More recent approaches focus on the (semi) automatic extraction of objects in remotely sensed data (e.g., Grazzini et al., 2010; Sun et al., 2012). In order to find out how effective automatic extraction processes actually are, two feature extraction methods will be applied and evaluated.

1.2 Objectives of the work

The main purpose of the study is to test different classification methods concerning meander river features and evaluating their separability. Therefore, first it is necessary to understand the avulsion processes taking place at the Brazos River in Texas, USA and determine locations affected by avulsion processes along the river. Subsequently, representative places of avulsion have to be digitized and assigned to the respective river feature class according to the specialist literature. Furthermore, the river features in the study area have to be digitized manually. The main objectives are to perform automatic feature extraction methods using the Support Vector Machine (SVM) and Feature Analyst (FA) and to evaluate the results with regard to the thematic correctness.

1.3 Hypothesis

With the application of GI- and remote sensing software and techniques in combination with remotely sensed data it is possible to classify different river features due to their spectral and spatial characteristics.

1.4 Method of solution

In order to understand the avulsion process of a meandering river and to gain information about spatio-temporal trends, it is crucial to analyze not only the river channel itself but also and especially its environment. Therefore several GIS, remote sensing as well as image processing techniques will be applied to identify and to map river features in a predefined study area.

The first step is to find and prepare adequate remotely sensed data (Landsat 5 TM) for the analysis processes. Then the appearance of the selected images is enhanced by applying spatial convolution filters, vegetation index transformations as well as image reduction in order to detect and sharpen the edges of features in the image (e.g., river channels, lakes, oxbows, etc.) and to alleviate human visual as well as subsequent machine analysis (Pratt, 2001). Consequently the river environment itself is examined by the visual localization of the river features within the study area using the Landsat 5 TM images and DOQQs. The existing river features can be regarded as witnesses of avulsion processes and are presented in the literature (e.g., Allen, 1965; Jagers, 2003). However, a part of the visually identified features are then digitized and serve as training areas that are afterwards representative for the respective river feature class. Simultaneously, during this process the spectral statistics for each pixel found within the training areas are collected (Jensen, 2004). Subsequently thematic information is extracted from the remotely sensed images by applying two different classification methods. Afterwards, the results of the three classification methods will be compared to each other.

The first method uses a supervised classification algorithm. It utilizes the spectral information of the primarily digitized training areas to assign the pixel of a raster to the corresponding river feature class. The second method applied is object oriented image segmentation and classification. Compared to the first method the main difference is that object oriented image segmentation and classification algorithms regard training areas not only as class samples of pixel signature values but also as image objects that incorporate certain shapes. In other words, image objects are individual areas with spectral and spatial homogeneity (Benz, 2001). Both methods include the processing of ancillary data as an attempt to enhance the quality of classification outputs (e.g., Hutchinson, 1982; McIver & Friedl, 2002). As long as the information supports the image classification process, any type of spatial or even non spatial data is considered as ancillary data including maps representing elevation, slope, soils, hydrology, political boundaries, etc. (Jensen, 2004). In addition, all the river feature classes located in the study area are digitized manually utilizing the DOQQs that have a higher spatial resolution as the Landsat 5 TM data.

The next step comprises the performance of a visual evaluation of the classification results. The best results of the derived images form the basis for the subsequent Accuracy Assessment (Congalton & Green, 1999). Consequently, first it is possible to compare the classification methods based on facts and figures and, second, to evaluate the separability of the feature classes.

Finally, by interpreting the distribution of the classified river features, spatio-temporal avulsion trends as well as long time changes of the Brazos River channel are traced.

1.5 Expected results

The expected results of the research project are:

- Conceptual Model that encompasses two different automatic river feature extraction methods
- Mapping the location, occurrence, and spatio-temporal evolution of channel avulsions;
- Comparison between the different river feature extraction methods;
- Evaluation of river feature separability using automated classification algorithms.

1.6 Structure of the paper

The following chapter of this thesis covers the theoretical background of the work including project related specifications of riverine environments as well as relevant GIS and remote sensing methods and parameters. Chapter three describes the methodology of the work encompassing a problem definition as well as descriptions of the study area and input data. Besides that the applied methods and the workflow are specified using conceptual models. The results and interpretation of the thesis can be found in chapter four, followed by a discussion in chapter five. Chapter six recapitulates the thesis and gives a future outlook of the work. The three final chapters comprise the references to cited papers as well as used figures and tables.

2. Theoretical Background

2.1 River Environments

In this chapter the complexity of meander river environments are described. Additionally, the occurring river features are explained.

2.1.1 Meander

Meanders are sequences of river bends that are perpetually changing their shape. Most of the meandering processes occur during spring and summer flooding. During a flooding the amount of water in the channel increases as well as its velocity, so that the river is powerful enough to change the landscape. At that time also river discharges, sediment loads, and bed scour are consequently larger (Edwards & Smith, 2001). When the river transports the sediment downstream, the rate of sediment depends on available amount of sediment in the river, as well as on the river's discharge (Knighton, 1998). As the water flows around the bend in vortex flow the formation of a meander is caused by the resulting secondary flow. The helical flow transports the eroded sediment from the outside of a bend (concave bank) towards the inside of a bend (convex bank) across the floor (Hickin, 2003). Put more simply, water on the concave bank is flowing faster than on the inside (Callander, 1987). Geologically speaking, these areas are considered as areas of high-energy. This is because the deepest part of meanders is on the outer side of a river bend and the shallow areas are located on the inner side. Thus, the faster and more powerful water on the outside of the river bend starts to erode the material from the river bank. The sediments then are transported downstream and deposited on a curves inner side or point bar further downstream (Figure 1). Consequently, river curves gradually become more and more extreme which in turn causes an acceleration of the erosion process, forming a positive feedback loop. The consequences of these processes are meander loops consisting of two river bends that minimize the piece of land separating them. In other words the two river bands are approaching each other step by step (Figure2). The river bends will then reach a point where for example the next large flooding will have enough power to completely erode the land separating them and straighten the river's main flow (Figure 3).

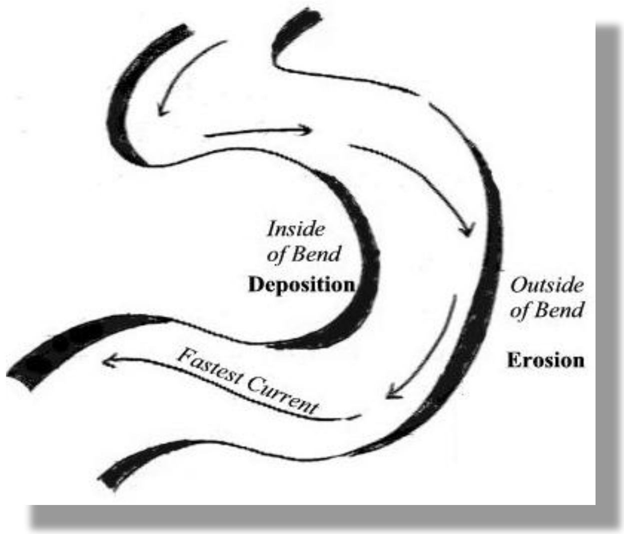

Figure 1: Erosion on the Concave Bank caused by High Energetic Water (Groundspeak Inc., 2012)

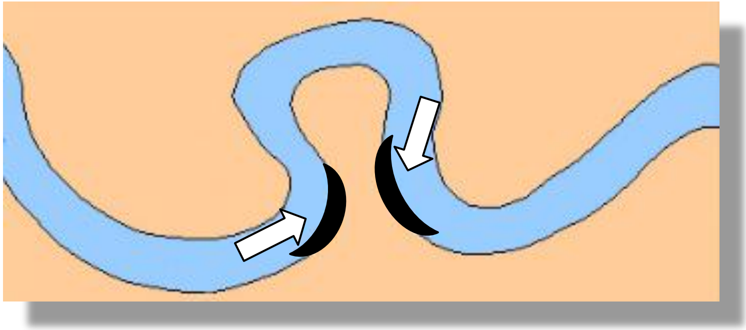

Figure 2: Gradual Erosion of two Neighboring River Bends in a Meander Loop (Dunvlanree, 2010)

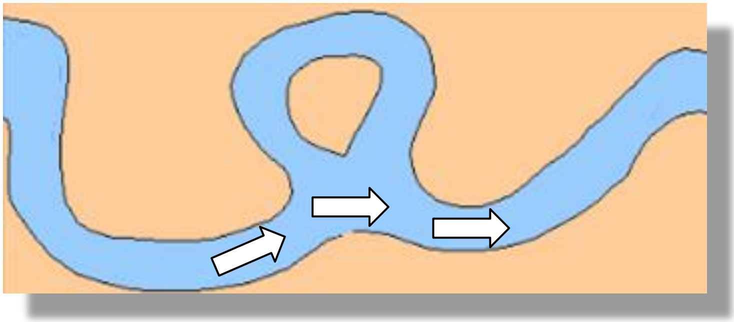

Figure 3: Straightened Meander Loop (Dunvlanree, 2010)

However, Meanders are not able to straighten themselves completely. Even small barriers in a straight part of a river channel that are able to withstand the stream current can trigger avulsion processes. The water flowing around the barrier is flowing slower than the rest of the water. In other words, it has less energy. The more energetic water on the opposite side to the barrier is then able to erode a riverbank depending on its soil composition. Then the eroded material is again swept downstream and very probably deposited on the inside of a river bend.
Figure 4 shows an example of an extreme meander loop formed by erosion and deposition that will possibly be cut off (Hickin, 2003).

Figure 4: Meander Loop of the Brazos River, College Station, Texas (Google Earth 2012)

To sum up, due to their dynamic nature, river channels and meanders perpetually change their appearance over long periods. The most obvious change is manifested in lateral migration of the channel. Secondly, avulsion processes also change the depth as well as the soil composition of the river. The meander formation encompasses erosion as well as deposition processes that transport soil and rocks downstream. These processes are also associated with the development of different types of river features.

2.1.2 River Features

Besides River channels and Meanders there exist a number of further river features that evolve from river avulsion processes. The ones that are relevant for this work are described in the following paragraphs.

Oxbow Lakes or Horseshoe are U-shaped water bodies that are the result of meandering rivers. Oxbow Lakes evolve from eroded river bends. When the two neighboring river bends approach and finally join each other a meander cut-off is formed. Hence, a cut-off is a channel that either emerges across the neck of a meander loop (neck cut-off) or across a point bar (chute cut-off) (Lagasse et al., 2004). These processes can either be caused by lateral erosion or in consequence of a flood. Then the remaining meander loop is separated from the new straightened river course by sediment deposition and finally an oxbow lake has been formed (Hickin, 2003). The result of this process is shown in figure 5 where the tree line around the oxbow clearly marks the former river course. The emphasized part of the channel shows the actual neck cut-off location.

Figure 5: Oxbow Lake at the Brazos River (Google Earth, 2012)

Scars are oxbow lakes that have been filled in with sediment. The sediment deposition is either caused by heterolithic/active filling (dominated by sand and representing a mix of suspended- and bed load) or by passive filling (dominated by lacustrine mud, suspended load and overbank fines) through ephemeral water streams between the scar and other water bodies (Martin, 2000) (Craig & Hollbrook 2000) (Holbrook & Alexandrowicz, 2011). Figure 6 shows multiple Scars beside the Rio Negro, Argentina. However, most of the scars are swampy depressions and can be considered as wetland as they serve as natural storages after floods or rainfall.

Figure 6: Scars at the Rio Negro, Argentina (Google Earth, 2012)

A Sandbar (Point bar) is a meander river feature that is characterized by the deposition of sediment. These depositional features are located on the inside of meander river bends, thus the convex bank (Figure 7). They slightly exceed the river water level in its elevation with a gentle slope. Hence, point bars are very likely to be overtaken by floods in periods of heavy rainfall. As mentioned before, the sediment is transported to the point bar by the helical flow from the concave bank to the convex bank. The sediment in this case is the product of river erosion on concave banks upstream (Hickin, 2003).

Figure 7: Sandbars on the Brazos River, Texas (Google Earth, 2012)

Relic Channels are former river channels that have been abandoned because of lateral river channel migration (Lagasse et al., 2004). Similar to scars they are depressions in the landscape that may include water. Though, the vast part of their former capacity is filled with sediment. Figure 8 shows an example of a Relic Channel in the Brazos Valley, TX.

Figure 8: Part of a Relic Channel, Brazos River (Google Earth, 2012)

Other river features that will not be described in detail in this work are, inter alia, side bar, cut bank, scroll bar, delta, secondary channel, etc. A larger number of classes would aggravate to obtain proper classification results. Besides that, some features such as scroll bar, secondary channel and delta, either occur very rarely or cannot be found at all in the project area. In addition, Feature Analyst and the Support Vector Machine would not be able to distinguish between certain features without help from other (post)processing tools or methods.

2.2 Remote Sensing

Remote sensing is specified as a procedure to acquire information of objects on the earth's surface using sensors in aircrafts or satellites. In contrast to in situ methods, remote sensing measures objects from far distances. Consequently, the user has to rely on the functionality and the results of optical, acoustical or microwave sensors that gather spectral and spatial information (Schowengerdt & Robert, 2007). The great advantage of remote sensing is the possibility to create information in form of (raster) images that cover broad areas on the earth's surface in relatively short amount of time. In addition isolated, dangerous or inaccessible areas can be reached by the sensors. However, users of remotely sensed information must be aware that there are numerous sources of error within the creation and processing phases of this data. The following chapters give an insight into a few remote sensing methods and techniques that are relevant for this work.

2.2.1 Image Enhancement

As images derived from remote sensing methods undergo human visual or machine analysis, their appearance is a decisive factor for the results of subsequent processing steps. Therefore, image enhancement deals with algorithms that are applied to remotely sensed images in order to improve their appearance. In this chapter two image enhancement operations are described including spatial convolution filters and vegetation transformations.

Spatial frequency is an important parameter concerning remotely sensed data. It is defined as number of changes in brightness value per unit distance for any particular part of an image (Minakshi, 2005). Areas with few changes in brightness are considered as low frequency areas. Areas with significant changes in brightness values are seen as high frequency areas. Two dimensional spatial convolution filters change these spatial frequency characteristics of images by applying convolution masks to the raster pixels (Pratt, 2001). Convolution masks are moving raster cells (Kernels) of a certain dimension that overlay the raster grid of remotely sensed images (Figure 9). To each cell of the convolution mask a certain value is assigned, depending on the user´s intention, to mathematically evaluate the value of the currently centered pixel. Figure 10 is an example for the application of a high pass filter convolution mask that sharpens or accentuates the edges of spatial features within an image (Jensen, 2004). The (Pixel) Band values (*BV*) in the source image and the corresponding pixel values in the (3x3) convolution mask (*C*) used in the formula to calculate the filtered value *F*.

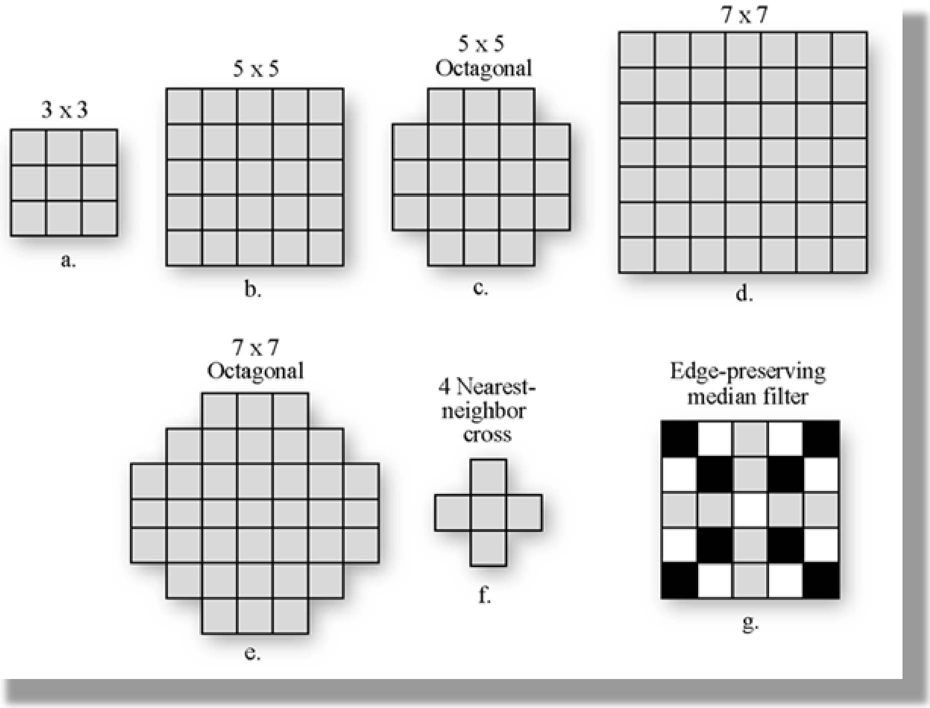

Figure 9: Convolution Masks of various sizes and shapes. (Jensen, 2004)

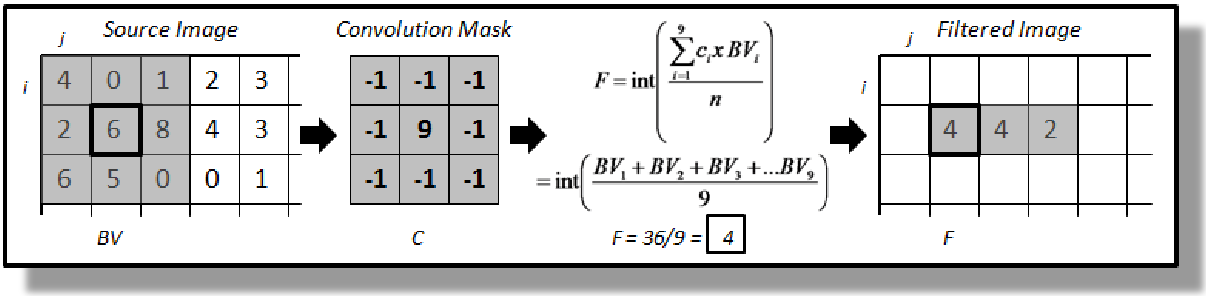

Figure 10: Applying Convolution Mask to source image

2.2.2 Vegetation Indices

Vegetation Indices are designed to point out a particular property of vegetation. They are calculated by using the characteristic reflectance properties of the vegetation. There exist multiple Vegetation Indices and each one is designed to focus on a particular vegetation property (ENVI Online Help, 2005). For example, one of the most generic Vegetation Indices is the Normalized Difference Vegetation Index (NDVI), developed by Rouse et al. (1974). The NDVI is based on the fact that the solar radiation reflection of live green plants is relatively low in the photosynthetically active radiation (PAR) spectral region but therefore relatively high in the near-infrared spectral region (Equation 1) (Gates, 1980). The reflection coefficient is thereby directly associated with the vitality of the vegetation – the more vital the vegetation is, the higher is the reflectance coefficient in the Near Infrared Band. Consequently, the NDVI allows to differentiate between vegetated areas and other land cover types. Figure 11 shows an extract of the NDVI transformation applied to the Landsat 5 TM scene covering the project study area. Most of the dark areas in this case represent water bodies, bright values represent vegetation.

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}$$

Equation 1: NDVI calculation.

Figure11: NDVI image of Study Area

The last image enhancement operation that is described in this work is the Tasseled Cap or Kauth-Thomas Index Transformation (Kauth & Thomas 1976). The Tasseled Cap transforms the input into greenness (measure of vegetation), brightness (measure of soil) and wetness (interrelationship of soil and canopy moisture) content images (Jensen 2004). In Figure 12 is a Tasseled Cap image where moisture is represented by blue, vegetation by green and soil by red pixels.

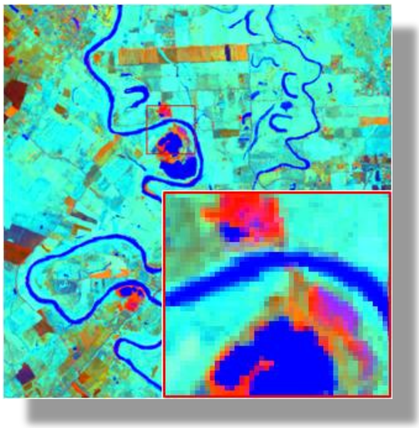

Figure 12: Tasseled Cap image of the Study Area

2.2.3 Classification methods

One of the most often used information extraction method concerning remote sensing is Land-cover/Land use (e.g., urban, vegetation, agriculture, water bodies) classification using statistical pattern recognition in combination with remotely sensed multispectral data (Narumalani et al., 2002). The key objective here is to perform an automatic categorization algorithm that classifies raster cells based on their spectral characteristics. In this chapter two supervised classification methods are mentioned.

In contrast to unsupervised classifications, in supervised classifications the location and the identity of segments of land-cover types are known a priori through field observation, interpretation of aerial photography, map analysis, etc (Hodgson et al., 2003). These digitized segments are called training areas and represent homogeneous instances of the related land cover types. The training areas are used to train the classification algorithm on the selected image. Afterwards, the automatic classification algorithm classifies the pixels of the image into the predefined classes (Figure 13).

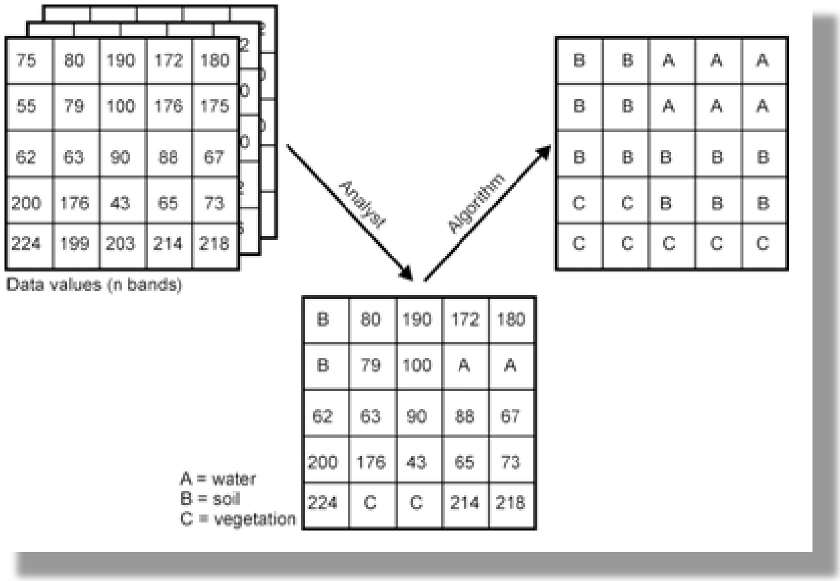

Figure 13: Supervised Classification scheme (Reudenbach, 2003)

The Support Vector Machine (SVM) is a pixel based classification tool that focuses on the spectral signatures of pixels. The inputs of a support vector machine are called feature vectors that represent the training objects. By using a kernel functions SVM maps the objects into a high- or infinite dimensional feature space. Then the main task of SVM is to calculate hyperplanes in the space that separate the training objects into classes. The data objects that are closest to the hyperplane form the critical basis of a training set (Figure 14). In ENVI's SVM an optional probability threshold parameter enables to mark pixels with probability values outside of the limits as unclassified (Pakhale & Gupta, 2010).

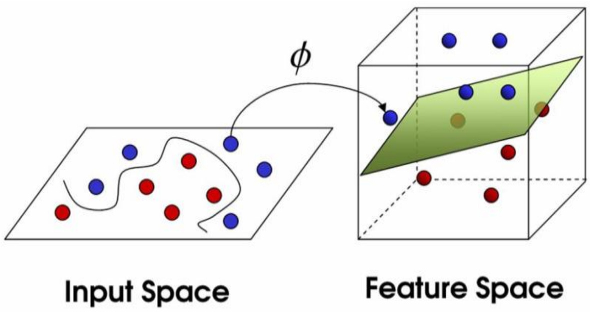

Figure 14: Principle of Support Vector Machines (imtech, 2006)

Feature Analyst (FA) as an object-oriented classification method does not only focus on the pixels' spectral signature, but also on the spatial information such as texture or form. The Feature Analyst™ was developed by Visual Learning Systems (VLS) and can be integrated as an extension to existing software platforms such as ArcGIS™ or ERDAS IMAGINE™. In the first phase object-oriented classification programs identify image objects that are characterized by spatial and spectral homogeneity (Benz, 2001). The objects, or image segments, are then classified by conventional methods such as nearest neighbor, minimum distance, maximum likelihood, etc.

2.3 Accuracy Assessment

As mentioned before, remotely sensed data contain error because they are always to a certain extent abstract and generalized representations of the earth's surface. In every step of handling the data errors may occur which accumulate through subsequent processing (Figure 15).

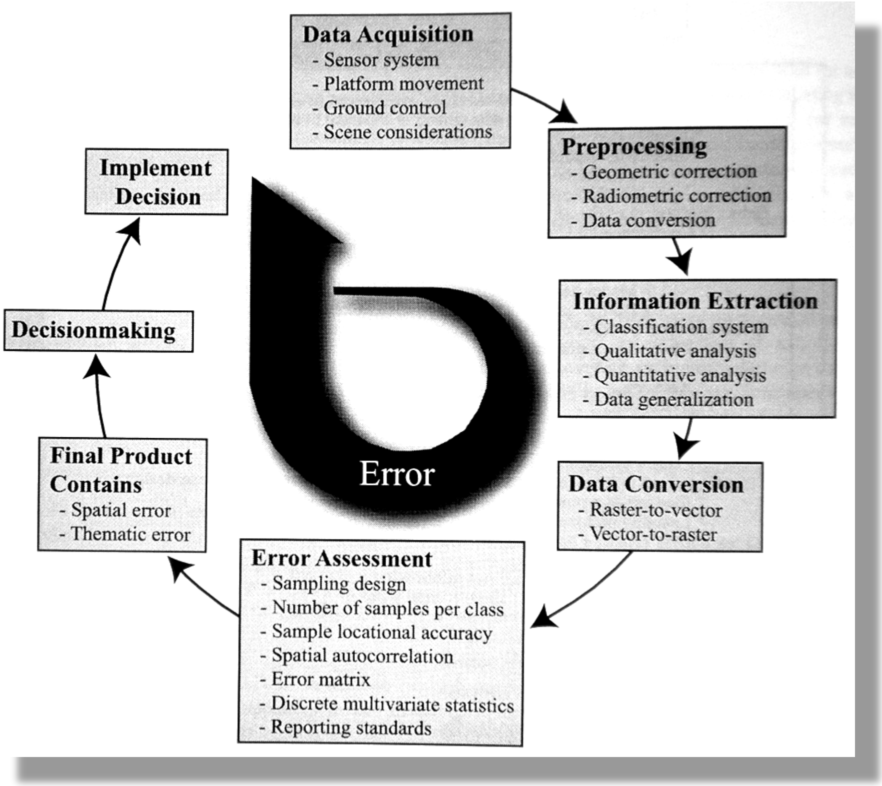

Figure 15: Sources of Error in remotely sensed information (Jensen, 2004)

Due to the fact that thematic information derived from remotely sensed data in some cases form the basis of important decisions, the results in the form of (digital) maps need to be accurate. Therefore Accuracy Assessment is an instrument to measure the location or thematic accuracy/quality and to identify sources of error and help to correct them. Finally Accuracy Assessment allows the comparison of performed techniques, algorithms, etc. to test which is best (Congalton & Green, 1999). Figure 16 summarizes the general steps that are used to assess the accuracy of remote sensing-derived thematic information.

State the nature of the thematic accuracy assessment problem.

- State what the accuracy assessment is expected to accomplish.
- Identify classes of interest.
- Specify the sampling frame within the sampling design:
  - *Area* frame (geographic region of interest)
  - *List* frame (consisting of points or areal sampling units)

Select method(s) of thematic accuracy assessment.

- Confidence-building assessment:
  - Qualitative
- Statistical measurement:
  - Model-based inference (concerned with image processing methods)
  - Design-based statistical inference of thematic information

Compute total number of observations required in the sample.

- Observations per class

Select sampling design (scheme).

- Random.
- Systematic.
- Stratified random.
- ....

Obtain ground reference data at observation locations using a response design .

- Evaluation protocol.
- Labeling protocol.

Error matrix creation and analysis.

- Creation:
  - Ground reference test information (columns)
  - Remote sensing classifications (rows)
- Univariate statistical analysis
  - Producer's accuracy
  - User's accuracy
  - Overall accuracy
- Multivariate statistical analysis
  - Kappa coefficient of agreement
  - Fuzzy

Accept or reject previously stated hypothesis.

Distribute results if accuracy is acceptable.

- Accuracy Assessment report.
- Digital Products.
- Analog (hard-copy) products.
- Image and map lineage report.

Figure 16: Workflow for assessing the thematic accuracy of remotely sensed data. (Jensen 2004)

A key component of thematic accuracy assessment is the Error Matrix. Error matrices compare the classified, remote sensing derived information to ground reference test information to identify commission errors and omission errors. Table 1 shows the structure of an Error Matrix consisting of k classes. The columns include the classes of the ground reference data and the rows are assigned to the classified data.

The intersection of the rows and columns summarize the number of sample units (i.e., pixels, clusters of pixels, or polygons) assigned to a particular category (class) relative to the actual category as verified in the field. Total number of samples examined is N (Jensen 2004).

In the diagonal of the matrix the correctly classified samples are recorded. The remaining cells in the inner part of the matrix are either errors of commission (a sample unit is assigned to a class although it does not belong to it) or errors of omission (a sample unit is excluded from the class where it belongs to). The Error Matrix is the basis for performing subsequent calculations that provide further information about the thematic accuracy.

Table 1: Error Matrix with k classes (Congalton & Green, 1999)

	Ground Reference Data (j columns)					
Classified Data (i rows)	**Class**	*1*	*2*	*3*	*k*	**Σ Row (n_{i+})**
	1	$\boxed{X_{1,1}}$	$X_{1,2}$	$X_{1,3}$	$X_{1,k}$	x_{1+}
	2	$X_{2,1}$	$\boxed{X_{2,2}}$	$X_{2,3}$	$X_{2,k}$	x_{2+}
	3	$X_{3,1}$	$X_{3,2}$	$\boxed{X_{3,3}}$	$X_{3,k}$	x_{3+}
	k	$X_{k,1}$	$X_{k,2}$	$X_{k,3}$	$\boxed{X_{k,k}}$	x_{k+}
	Σ Column (n_{+j})	**X_{+1}**	**X_{+2}**	**X_{+3}**	**X_{+k}**	$\boxed{N}$

2.4 Landsat 5

The satellite Landsat 5 Thematic Mapper (TM) was launched on March 1, 1984. As the fifth satellite of the Landsat program its satellite photos cover the continental earth´s surface as well as coastal regions. The major aim of the Landsat program is to detect changes on the earth's surface. For example, Landsat images are used to observe, detect and analyze changes in urban growth, agriculture, forestry, etc. Landsat 5 is equipped with a thematic mapper sensor, using optical cameras and featuring 7 bands (Table 2 & 3) (NASA, 2012).

Table 2: Landsat 5 TM Bands (NASA, 2012)

Band Number	Wave Length	Resolution
1	0.45-0.52 µm	30m
2	0.52-0.60 µm	30m
3	0.63-0.69 µm	30m
4	0.76-0.90 µm	30m
5	1.55-1.75 µm	30m
6	10.4-12.5 µm	120m
7	2.08-2.35 µm	30m

Table 3: Landsat 5 TM technical specifications (NASA, 2012)

Sensor type	Opto-mechanical
Spatial Resolution	30m (120m-thermal)
Spectral Range	0,45-12,5µ
Number of Bands	7
Temporal Resolution	16 days
Image size	185km X 172 km
Swath	185 km
Programmable	yes
Orbit	Polar, sun-synchronous
Altitude	705km

2.5 Digital Orthophoto Quarter Quadrangle

A Digital Orthophoto Quarter-Quadrangle (DOQQ) is digital remotely sensed raster image having a spatial resolution of 1 meter. A DOQQ consists of several merged images after displacements caused by are removed by terrain relief, camera lens distortion, camera tip and tilt, etc. have been removed through rectification processes. The DOQQ covers one quarter of an U.S Geological Survey (USGS) 7.5 minute Quadrangle. Typical DOQQs are either black-and-white (BW) or Color Infrared (CIR) images (Watermeier, 2002).

2.6 Digital Elevation Model

A Digital Elevation Model (DEM) is a surface model representing height information. As a generic term it describes raster as well as vector format data that are commonly created using either remote sensing, field surveying or through Interferometric synthetic aperture radar (IfSAR) sensors. For example, the Light detection and ranging (Lidar) system as a state of the art technique for capturing high resolution elevation data uses a laser combined with a high precision Global Positioning System (GPS) to collect three dimensional data of the earth's surface.

When represented in a raster format each cell of the DEM grid contains a height value. In vector format the DEM appears as a Triangulated Irregular Network (TIN), consisting of vertices and edges. The vertices hold x- , y- and z-values that in turn are most commonly used for a Delauney Triangulation (Weibel and Heller 1991) to build up the network. The third way of representing DEMs utilizes the stream tube concept (Onstad & Brakensiek, 1968). In this method landscapes are divided into small polygons that are based on contour lines and combined with height information (Wilson J. and Gallant J., 2000).

In general, DEM is seen as a generic term that encompasses digital terrain models (DTM) as well as digital surface models (DSM). The DTM outlines the earth's surface excluding objects such as buildings and plants. In contrast to the DTM, the DSM includes all of these objects.

2.7 Related Work

Several research studies were focused on the automated extraction of river features from remotely sensed data.

Dillabaugh et al. (2002) developed a process for semi-automated extraction of rivers from SPOT (Système Pour l'Observation de la Terre) images. The algorithm is based on a cost surface. Then the extracted river features have been refined additionally by using higher resolution (KFA1000, panchromatic, 5 m) images. More recent studies were based on High resolution Lidar data to extract river channel networks directly from a DEM using wavelet filtering (Lasheremes et al., 2007). With the computation of Gradients, Curvatures, and Slope-Direction Change at different scales utilizing wavelets channelized portion of a valley in a hilly study area have been identified. Passalacqua et al. (2012) also used Lidar data to extract geomorphic features in flat and engineered landscapes. Based on a curvature analysis natural river channels have been distinguished from manmade river structures. Essentially, these approaches have in common that their extraction algorithms identify river features with diverse spectral and spatial signatures such as sandbars and oxbows at the same time. They mainly focused on the extraction of active channel networks rather than passive and relic features.

In addition, researchers compared pixel-based to object-oriented image classification methods: Pakhale and Gupta (2010) generated land use maps of an Indian district using three different classification approaches: SVM, ANN (Artificial Neural Network) and eCognition. Pixel-based classification was performed by SVM and ANN, eCognition was used for the object-oriented classification. The results showed that eCognition delivered more accurate output than the pixel based methods. Weih R. and Riggan N. (2009) came to the same conclusion after they had compared the Feature Analyst software to a traditional pixel-based approach. Ten different land cover/land use class types were classified in Graland County, Arkansas. The research results indicated that the Overall Accuracy of the object-based classification was fifteen percent higher compared to the pixel-based classification.

3. Methodology

In this chapter the methodology of the thesis is discussed. Occurring problems during the implementation workflow and challenging aspects of the work are mentioned in the first chapter. Then the study area itself, including facts and figures, is described to get a better understanding for the whole spectrum of the project. The third chapter compromises the data used for the study as well as associated preparing processes. Next the method of solution is specified by using conceptual models. Finally the last chapter summarizes the most important facts of this section.

3.1 Problem Definition

A crucial point in the study is data quality as well as data continuity. Accuracy and actuality of the data determine the final significance of the results as error can accumulate through the several processing steps. Therefore, first the Metadata of the different data sources has to be examined thoroughly to guarantee the processing of adequate input from the beginning.

One of the major challenges is the extraction of relatively small river features that are represented by 30x30m pixels. Additionally, some river feature classes have a similar spectral signature (e.g. Oxbow and river water), what makes it difficult to distinguish between them. Therefore, first it is crucial to assure that a high positional accuracy is given and that training areas are selected advisedly.

Due to the fact that during the workflow data derived from different sources is being used, it is essential to focus on their temporal continuity. In other words, it has to be made sure that all different images or layers like DOQQ, DEM, Landsat, Filtered pictures, etc. had been generated in the same month, or at least in the same year. This is even more important when the possibility is considered that not only the river course or its features may differ from older images but also vegetation, building, weather, or other external factors that cause diverging and falsified results.

3.2 Study Area

The study area in this work is the lower Brazos River in Texas, USA. The section of the lower Brazos River begins nearby the Bryan-College Station metropolitan area and ends at its River Delta in Freeport, Texas. Parts of the study area overlay the Houston-Sugar Land-Baytown metropolitan area, which is the fifth largest in the United States (United States Census Bureau, 2011). The counties encompassed by the study area are: Brazoria, Fort Bend, Austin, Waller, Washington, Burleson and Brazos. The climate in the study area is subtropical with hot summers and mild winters (Table 4).

The Brazos River is the largest River in Texas, encompassing a drainage area about 118.000km². Starting from his headwaters in New Mexico, the river flows into the Gulf of Mexican after more than 1,900km (Phillips J., 2006) (Figure 17).

Table 4: Average temperature and precipitation rates

	College Station	***Freeport***
Annual average high temperature	26.11 °C	25.27°C
Annual average low temperature	14.44 °C	16,66°C
Average annual precipitation	812.8 mm	1,285.24 mm

Figure 17: The Brazos River Basin (The Brazos River Authority, 2010)

3.3 Data

For the study of the avulsion process, four Input datasets are used. In the following paragraphs these input files including metadata extracts as well as an overview of them are described. Additionally the applied preprocessing methods to these files are mentioned.
As shown in Table 5 the datasets that are applied to the study area consist of Landsat 5 data, a DEM, and Ortho photos.

Table 5: Description of Datasets used for the analysis process

Dataset	**Format**	**Type**	**Spatial Resolution**	**Creation Date**	**Source**
Landsat 5 TM	(Geo)TIFF	Raster	30x30m	2010	USGS
DEM	(Geo)TIFF	Raster	30x30m	2009	USGS
DOQQ	MrSID	Raster	1x1m CIR	2010	TNRIS

Two Landsat 5 scenes are needed for the analysis to cover the entire study area. The first scene covers the inland region, the second the coastal region of the study area (Figure 18). The satellite images are provided from the United States Geological Survey. The scenes have been projected to Universal Transverse Mercator (UTM) Zone 14 (inland scene) and Zone 15 (coastal scene), North American Datum of 1983 (NAD 83). As mentioned in Chapter 2.4, Landsat 5 TM generates images with a spatial resolution of 30 meters for 6 out of 7 Bands. However, the sixth band (thermal Band) has to be removed because of its differing resolution in order to avoid problems in subsequent analysis steps of the work. The Inland scene had to be re-rectified due to insufficient position accuracy.

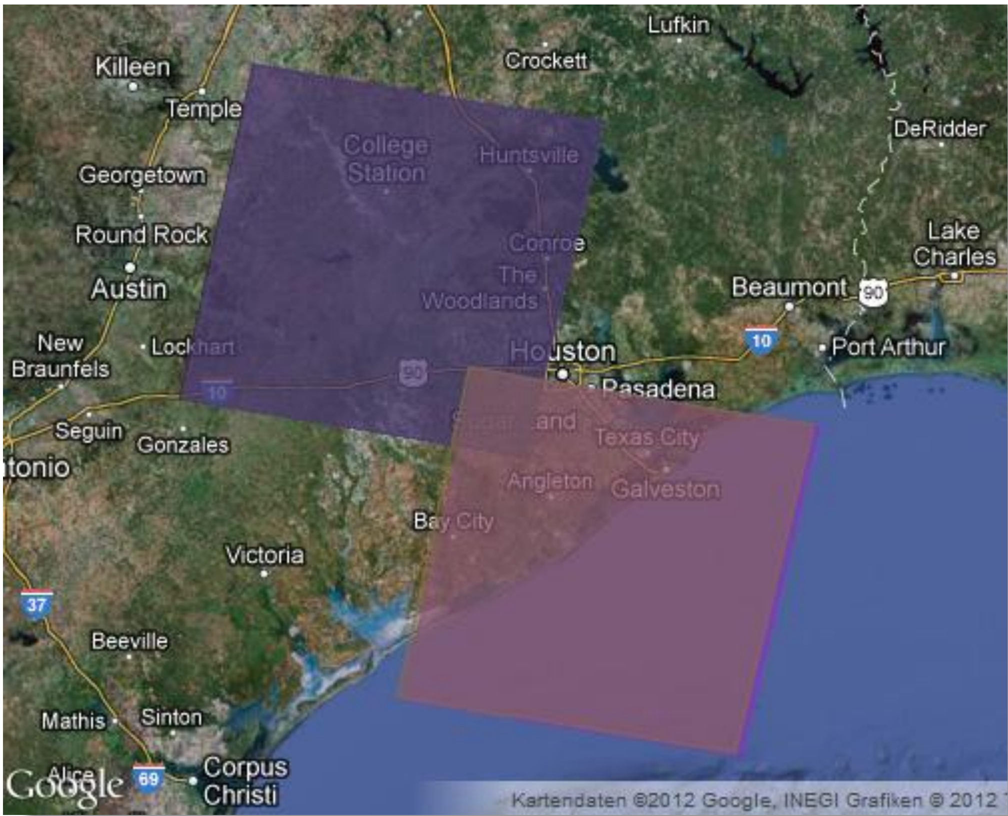

Figure 18: Footprints of two Landsat 5 images covering the study area (Google Earth, 2012)

The second dataset in table 5 is a DEM in GeoTIFF format that was generated in 2009. The DEM is a cut-out of the National Elevation Dataset (NED) produced and distributed by the USGS. The DEM as well is transformed to NAD83 UTM Zone 14 and Zone 15. The height information is provided in units of meters by pixels of 1x1 arc-second which approximately corresponds to 30x30 meters. Therefore, in order to have a complete overlay between the DEM and the Landsat 5 TM images, the DEM is re-sampled to a pixel size of 30x30 meters.

The DOQQ images are Color Infrared (CIR) and have been generated by the National Agriculture Imagery Program (NAIP) in 2010. The format used is Multi-resolution Seamless Image Database (MrSID). The reference Datum of the Data is the North American Datum 1983 (NAD 83) and the applied coordinate systems are either UTM Zone 14 or UTM Zone 15. Seven DOQQ datasets are used covering the entire study area.

3.4 Conceptual Model

In this chapter the main steps of the method of solution are presented, including a conceptual workflow model. The model delineates the way of classifying river features as well as assessing the resulting images with the help of GIS methods tools and methods.
Figure 19 shows the thematic structure of the workflow that has been followed during the entire Implementation process of the project. The workflow can be divided into four process phases:

(1) Data Preparation: Before performing the first analysis with the selected data it has to be preprocessed to minimize process times and optimize its properties and condition for further processing.

(2) Digitizing Process: Afterwards data has to be digitized that represent the different river features. The generated shapefiles are crucial for the next process steps.

(3) Classification Process: In this phase the two automatic supervised as well as the manual classification processes of the river feature classes take place.

(4) Accuracy Assessment: Finally the results are evaluated visually and by statistical methods.

Given the fact that two Landsat 5 TM scenes are required to cover the entire study area, the coastal and inland regions are treated as separate study areas in the implementation process.

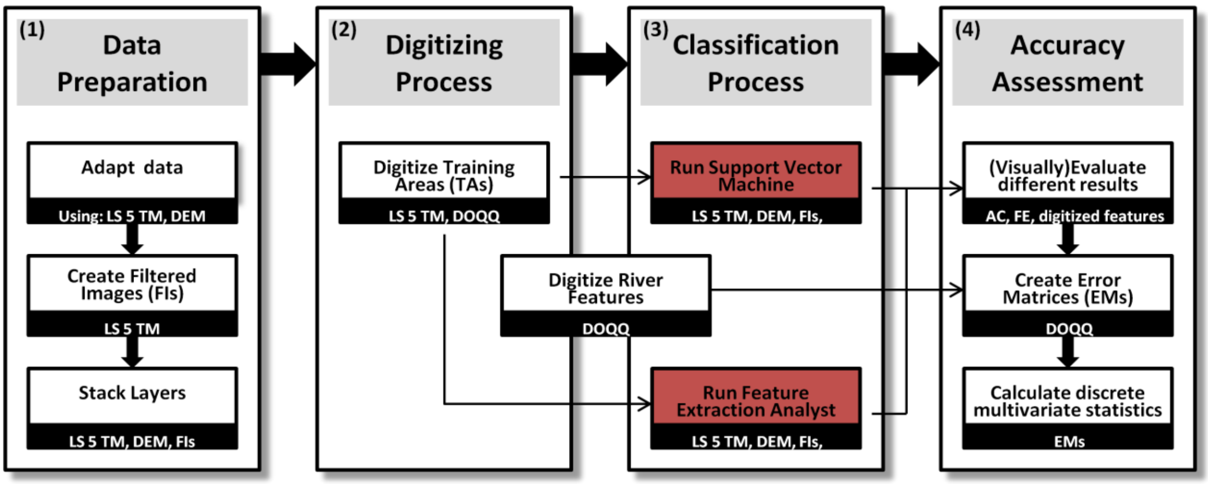

Figure 19: Conceptual analysis workflow for classification and assessment of river features

3.4.1 Data Preparation

In figure 20 the processing steps of the first phase are shown. Under the use of GIS and remote sensing techniques the raw Landsat 5 TM and DEM scenes are prepared for further processing by synchronizing the data, deriving new information through image enhancement methods and combining the raster data files with each other.

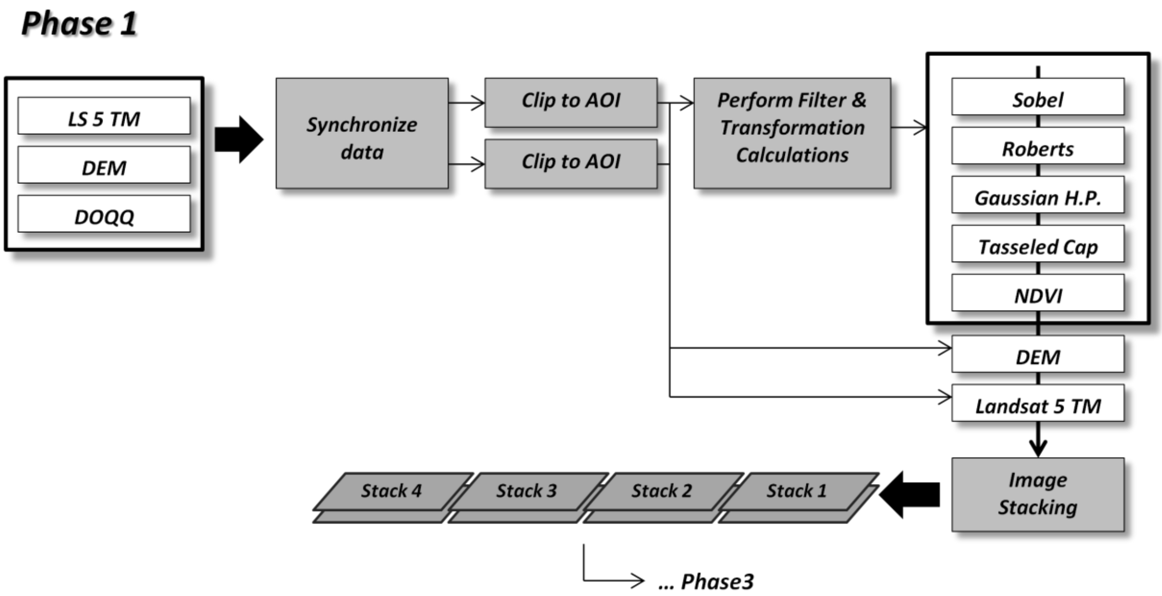

Figure 19: Processing steps of first phase

First of all, it has to be made sure that the data properties and quality of all the input files meet the demands of the project. This can be accomplished by a visual inspection of the data and by checking the Metadata information of the file. In case of insufficient data (quality), either new data sources have to be found, or the existent data has to be enhanced by deploying for example rectification, resampling, projection, etc. tools. Furthermore, all of the input datasets have to synchronized, in terms of geographical reference systems, cell size, etc.

Landsat 5 TM images cover an area of 31.820 km² (185km X 172 km) on the earth’s surface (chapter **Error! Reference source not found.**) and can cause long-lasting process times due to their large file sizes. When working with remotely sensed data, it is therefore essential to reduce the file size by clipping the area of interest (AOI) and deleting those regions that are not part of the predefined project area. Consequently, not only process times are improved, but also the personal handling with the visualized data, as the user’s focus is not disturbed by redundant data. Besides that, the sixth Landsat band is removed due its deviating spatial resolution that may cause problems in subsequent analysis.

By applying Filter and Transformation methods to the adapted Landsat 5 scene, new information can be derived from the image. The image filter operators Sobel, Roberts and Gaussian High Pass are performing edge detection methods to enhance and sharpen the river features’ edges. In addition, the data transformations Tasseled Cap and Normalized Difference Vegetation Index are utilized for vegetation mapping as well as for vegetation index calculation. In the final step of the first phase the newly derived data layers are stacked with the Landsat image as ancillary data files deploying four different combinations (Figure 21). The purpose here is to test if different stacking combinations lead to different classification results. A fundamental principle thereby is the identical alignment of the grid cells of all stacked data layers. As already mentioned, the basic prerequisites therefore (inter alia) are coinciding cell sizes, projections, coordinate systems and data extent.

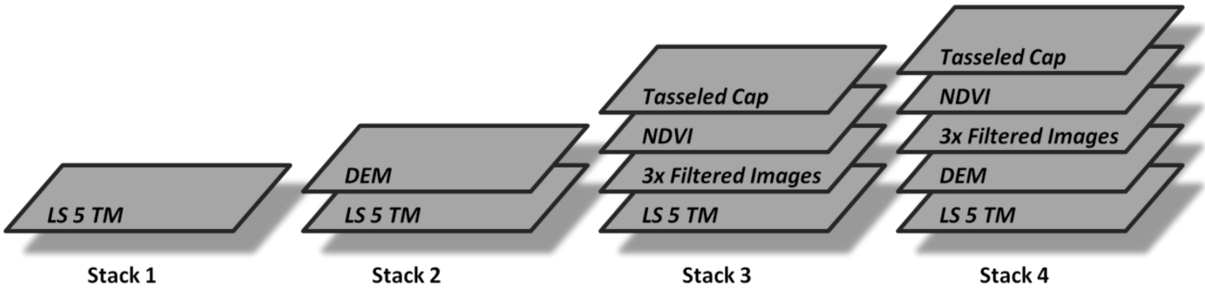

Figure 20: Data files stacked in four different band combinations

3.4.2 Digitizing Process

The second phase encompasses the digitization of training areas (TA) as well as the entire river features itself. According to the literature the features will be divided into five separate classes: River Channel, Oxbow, Scar, Relic Channel and Sandbar (Figure 22). Due to the fact that relic river channels are defined as features that can be both dry as well as watery and moistly, the feature are separated into two subclasses. Otherwise there would be a high spectral variability within a feature class what can possibly lead to misclassifications. Therefore, during the digitizing and classification phase the feature relic channel is split into subclasses relic dry channel and relic watery channel. In the last phase, concerning the Accuracy Assessment the two classes are merged and will be regarded as one single class again.

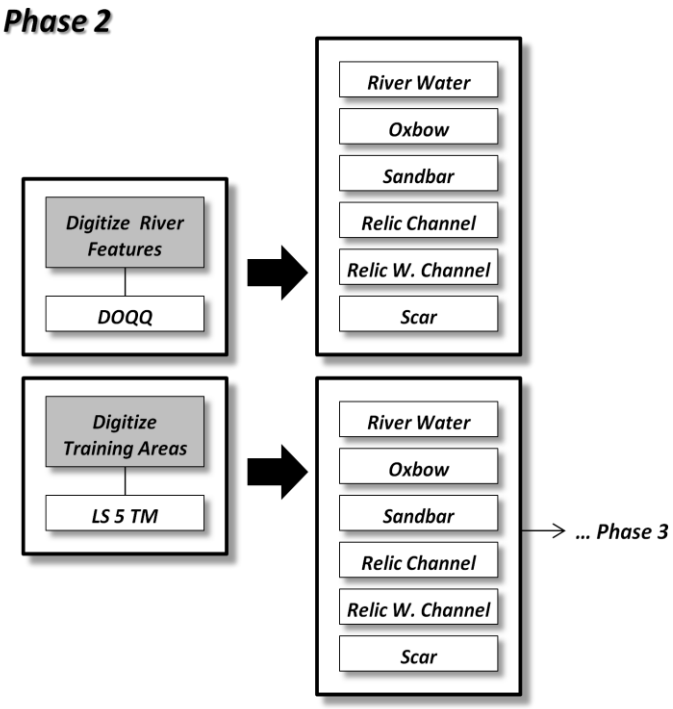

Figure 21: Digitizing River Features and Training areas

In the first step training areas for all river feature classes are sampled in the form of polygons. The resulting polygon shapefiles are needed for the subsequently performed automatic classification processes. Thereby only river features that belong to the Brazos River or have certainly been formed by the Brazos River, serve as training areas. Consequently, spectral variability within feature classes is avoided and posterior performed Accuracy Assessment will also only focus on Brazos River features. However, the training areas represent each of the predefined river feature classes. The adequate areas are identified with the aid of DOQQs as well as Google Earth images. Figure 23 shows that long river water polygons are digitized as samples that follow the shape of the river. Consequently in this case not only the river water's unique spectral signature is captured, but also its spatial signature in the sense that this feature appears as long line feature in nature. This digitization method will help to improve the results of the feature extraction tool. Furthermore, Figure 24 illustrates that the Landsat image is displayed in a 4-3-2 Red Green Blue band combination. With this combination land water boundaries appear clearly and alleviate the visual interpretation for the digitization. Besides that the high resolution DOQQs serve as verification images (Figure 24).

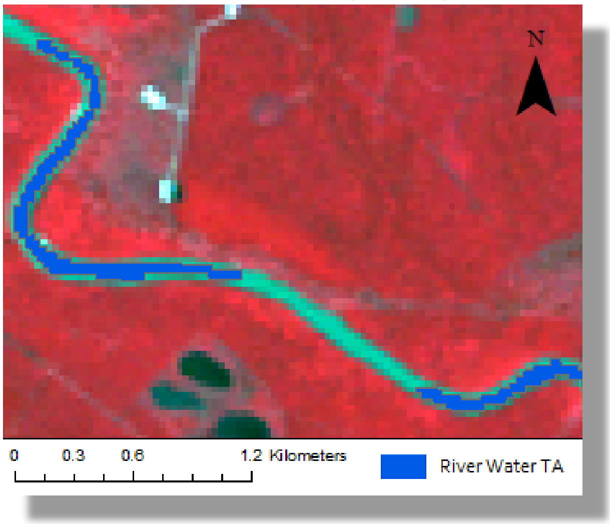

Figure 22: Digitized River Water training area

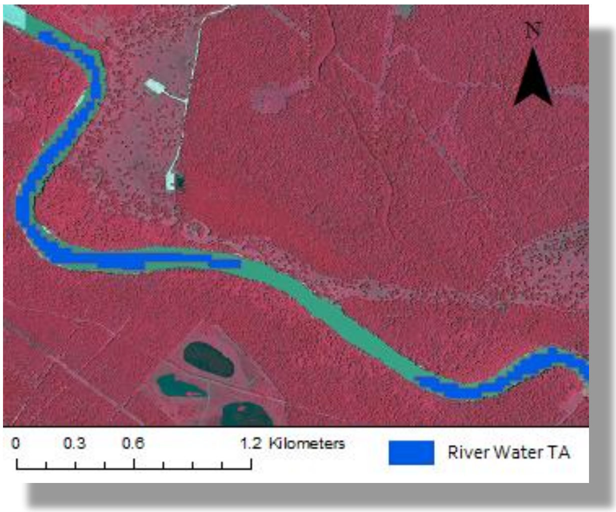

Figure 23: DOQQ serving as a verification image

Nevertheless, during the digitization process it may be still very critical to differentiate between certain river features. In this case using the DEM, other band combinations, Google Earth, etc. can help to avoid misinterpretations of training areas.
The second digitization step simultaneously can be considered as a classification process because it comprises the manual digitization of all river features within the study area using DOQQs. Even though this process is time intensive, the manually digitized polygons are necessary for subsequent analysis. In this case manual digitization is supposed to deliver relatively accurate results in vector format without applying any intermediate steps. The higher accuracy is primarily attained because of the higher spatial resolution

of the DOQQs compared to the Landsat scene (30x30m). Additionally with this method it is possible to directly ignore non relevant objects due to the competences of human comprehension. However, it has to be considered that manual digitization procedures are not barred from (human) error.

3.4.3 Classification Process

In this phase two supervised classifications algorithms are executed that automatically assign the river features to their river feature classes. Therefore, the digitized/sampled training areas as well as the four different stacked data files of the two previous phases are utilized as input data files (Figure 25).

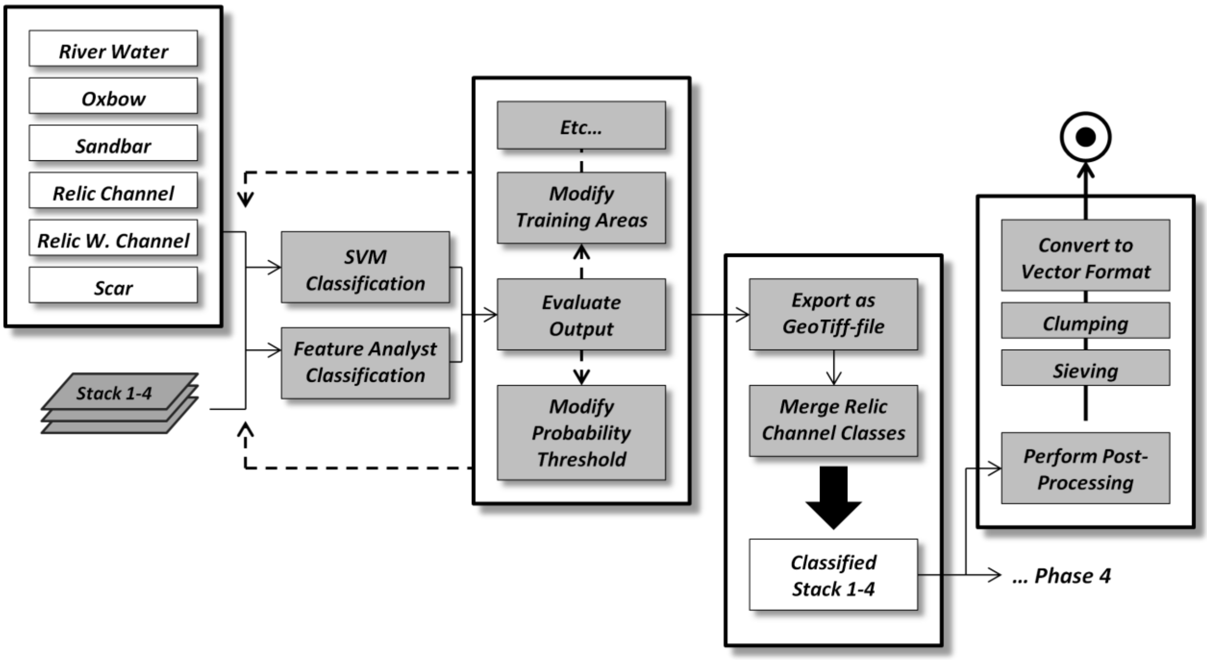

Figure 24: Classifying the River Features

The two classification processes are run with ENVI's Support Vector Machine (SVM) and Feature Analyst using ESRI's ArcMap10 as platform. Both classification processes perform their analysis on the same input data files: the four stacked raster files and the manually digitized Training areas pertaining to the Landsat 5 image. In the SVM first the training areas shapefiles are exported as ENVI Vector Files (.evf) and defined as a Region of Interest for one of the selected stacked input files. The Radial Basis Function is chosen as kernel type and the Classification Probability Threshold is set to a value between 90% and 98%.

In contrast to SVM, Feature Analyst (FA) considers both spectral and spatial context when performing a classification. The Object specific attributes are calculated automatically and are used for enhanced feature extraction. Hence, this method benefits from the digitization of training areas that follow the shape of the river features. The settings used for the FA classification have been selected automatically by FA's artificial intelligence algorithm. As Input Representation the Bull's Eye 2 pattern at a width of 17 pixels has been chosen (Figure 26). In the FA classification workflow hierarchical learning has not been performed because it can be regarded as a post classification process that would derogate a fair comparison between SVM and FA results (Blaschke et al., 2008).

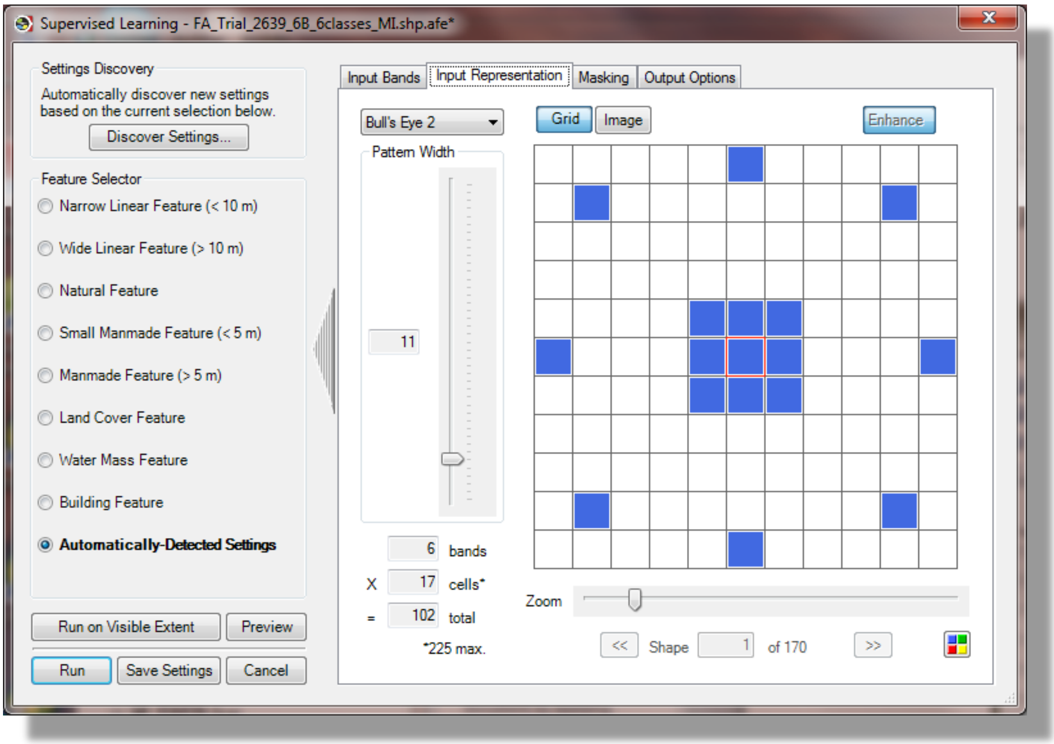

Figure 25: Feature Analyst settings; using Bull's Eye 2 pattern

When the classification processes are completed, the output files are evaluated visually. Depending on the sampled training areas, selected options, such as probability threshold, or the input files themselves, the generated images can be varying significantly. Hence several output files are created and evaluated before the best are exported as GeoTiff files. In the next step the two classes relic channel and relic water channel are merged since they have only been separated prior to the classification process due to their spectral heterogeneity. Since the main aim is to compare the direct output of the classification processes to evaluate the separability of the river feature classes, the "raw" classified raster images will form the basis for the Accuracy Assessment in the final phase. However, to perform a visual comparison between the manually digitized and the semi automatic classified images, the appearance of classified river features has to be enhanced. Therefore, the river features of the GeoTiff file are edited utilizing post processing tools such as sieving and clumping to delete isolated and aggregate clustered pixels. Finally, the edited features are converted into simplified polygons to resemble the actual shapes of the real river features.

3.4.4 Accuracy Assessment

The final phase involves the evaluation and interpretation of the different classification output files to identify the best result and to analyze the separability of the river features involved (Figure 27).

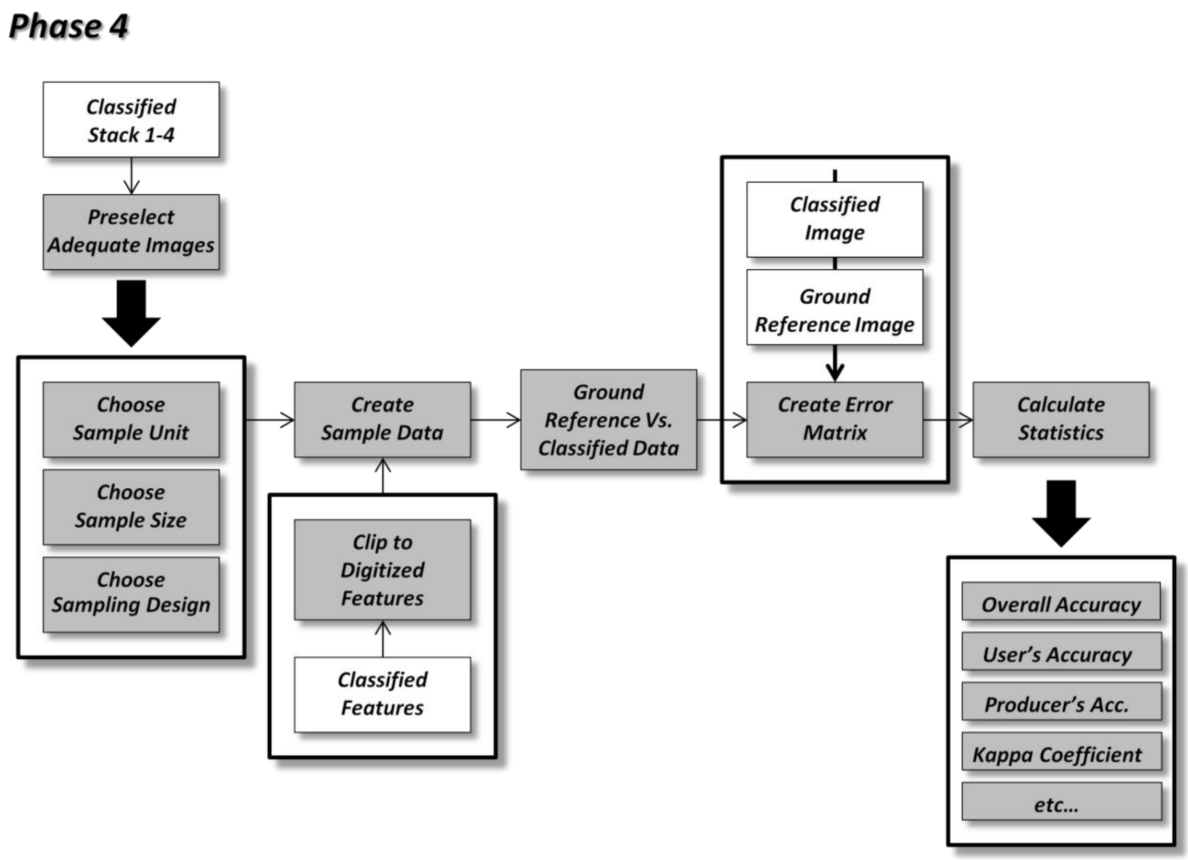

Figure 26: Accuracy Assessment steps

In the first step all automatically classified images are evaluated visually to identify the best results in terms of completeness, logical consistency and appearance in general as part of pre-selection. The selected raster images form the basis of further accuracy assessment methods to evaluate their thematic accuracy and the separability of the five river feature classes.

For the creation of the error matrix at least 50 samples for each class are generated using a stratified random sampling scheme (Congalton & Green 1999). The sampling unit for the Accuracy Assessment is single pixel as the preexisting pixel size is 30x30 meters, which is relatively broad. Due to the fact that the training area sampling was only focused on Brazos River features, also the Accuracy Assessment is applied to the regions close to the Brazos River. Consequently, classified pixel areas that are not within the zone of influence of the Brazos River can be ignored and are disregarded. This is realized by clipping the classified pixels to the extent of the manually digitized river features.

In the next step error matrices are generated by comparing the pixel values of the classified raster files to the DOQQs. For further evaluation of the error matrices the overall Accuracy (Equation 2), User's and Producer's Accuracy (Equation 3 & 4), as well as the Kappa Coefficient (Coefficient of Agreement) (Equation 5) are calculated. Producer's Accuracy is the percentage of reference points that have been captured during the classification process. User's Accuracy points out the agreement between remotely sensed and reference data. By contrast, Overall Accuracy and Kappa coefficient values describe the entire accuracy of a classified image. As a result the thematic correctness of the classified images can be compared between each other.

$$\text{Overall Accuracy} = \frac{\sum_{i=1}^{k} n_{ii}}{N}$$

Equation 2: Overall Accuracy

$$User's\ Accuracy\,\mathrm{i} = \frac{n_{ii}}{n_{i+}}$$

Equation 3: User's Accuracy

$$Producer's\ Accuracy\,\mathrm{j} = \frac{n_{jj}}{n_{+j}}$$

Equation 4: Producer's Accuracy

$$\hat{K} = \frac{n\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i+}n_{+i}}{n^2 - \sum_{i=1}^{k} n_{i+}n_{+i}}$$

Equation 5: Kappa coefficient

3.5 Summary

In the first subchapter challenging aspects of the thesis were mentioned that had to be dealt with. Chapter 3.2 comprises a summary of the study area's main characteristics, including a map visualizing the extent of the entire Brazos River basin. Next all the required input data files for the river feature extraction process were described. In the final subchapter the conceptual model of the work was presented. It separates the Implementation in four phases and provides descriptions of the applied processing steps.

4. Results and Interpretation

In this chapter the results of the study are presented accompanied by an interpretation of them. First the results of the three digitization methods are shown, followed by a comparison of them. The second part deals with the separability of the various river feature classes.

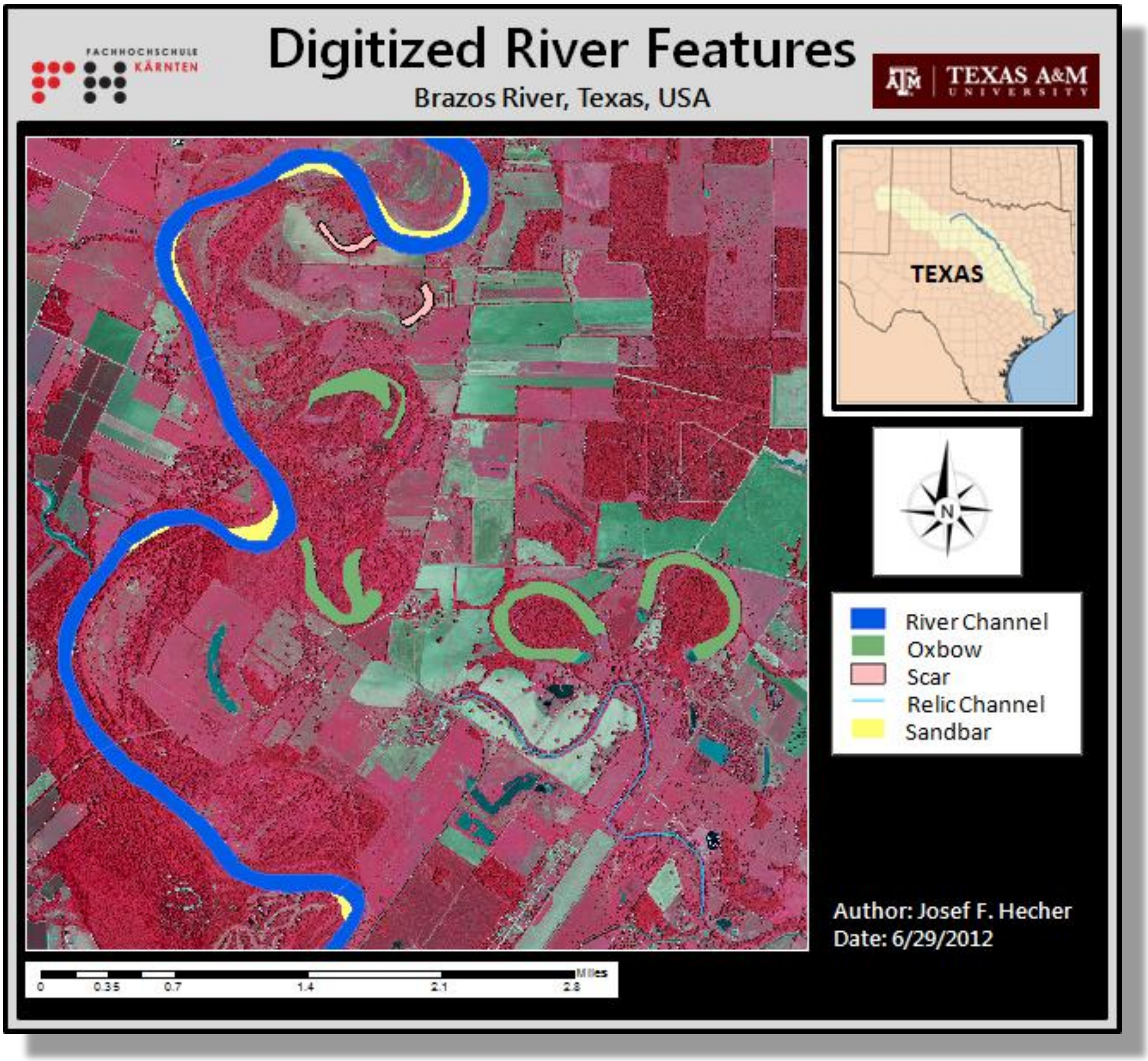

Figure 27: Manually digitized river Features

Figure 28 shows a map with the result of the manually digitized river features using DOQQs. Due to the high resolution of the DOQQ (1x1 meter) it was possible to create polygons that smoothly follow the shape of the various river features. In the map all five river feature classes can be found: River Channel, Oxbow, Scar, Relic Channel and Sandbar. Interpreting the allocation of these river features indicates that the river in this section has been moving westward through the past. A clearer example for lateral channel migration is visualized in figure 29. In this section the river migrated several kilometers across its floodplain due to erosion and deposition processes. Unfortunately, with the given results it is not possible to determine in what time interval the migration actually took place.

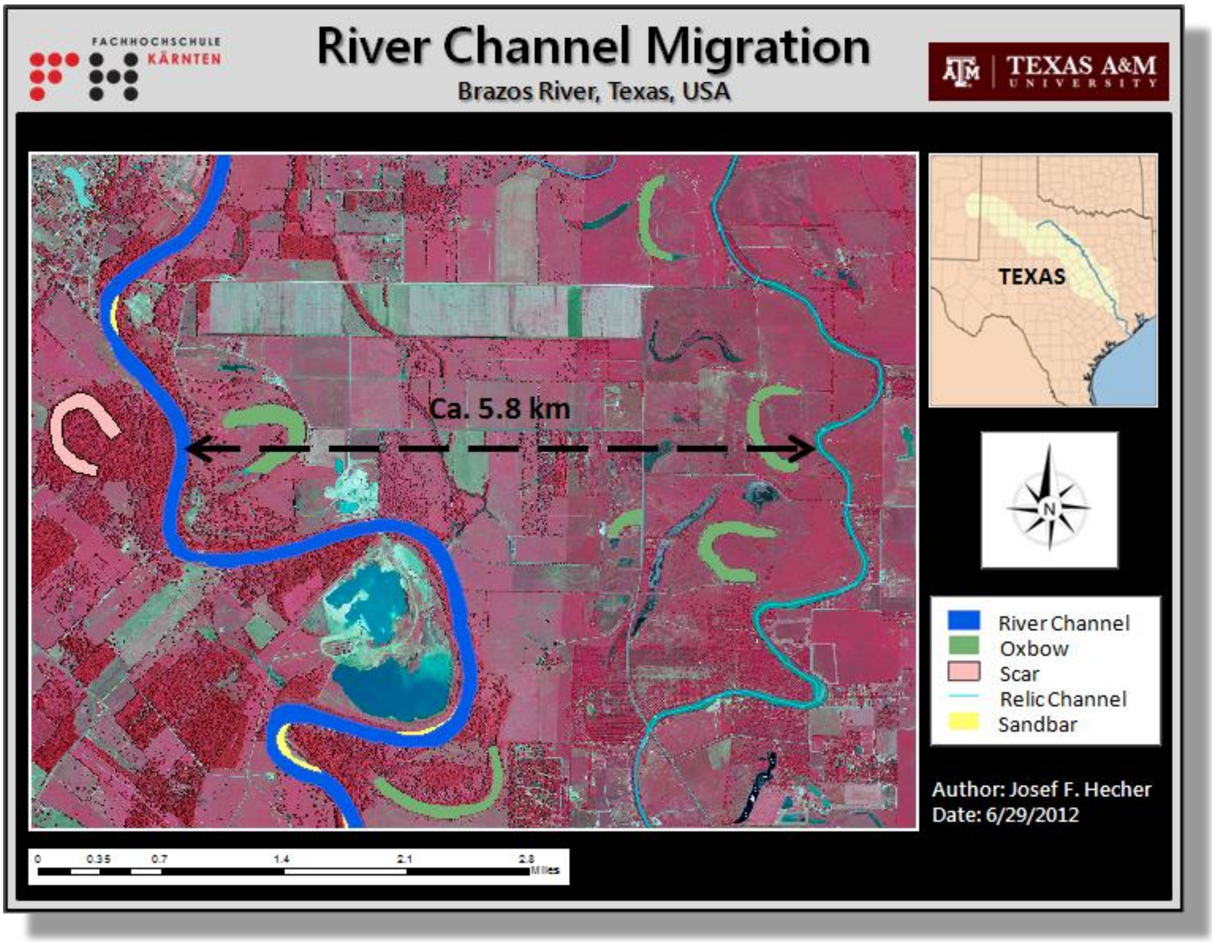

Figure 28: Example of lateral channel migration

Figure 30 covers the same area as figure 29 and shows the post processed result of the supervised classification method using SVM. The extracted river feature pixels have been converted to polygons. Before that, classified pixels have been edited using sieving and clumping. At the first glance it is obvious that SVM does not have any problems to classify the river water. Oxbow lakes are also classified, although it is not clear if some lakes have been misclassified. It can be seen clearly that some sandbar features have been misclassified. Relic Channel features are vastly confused with Oxbow features.

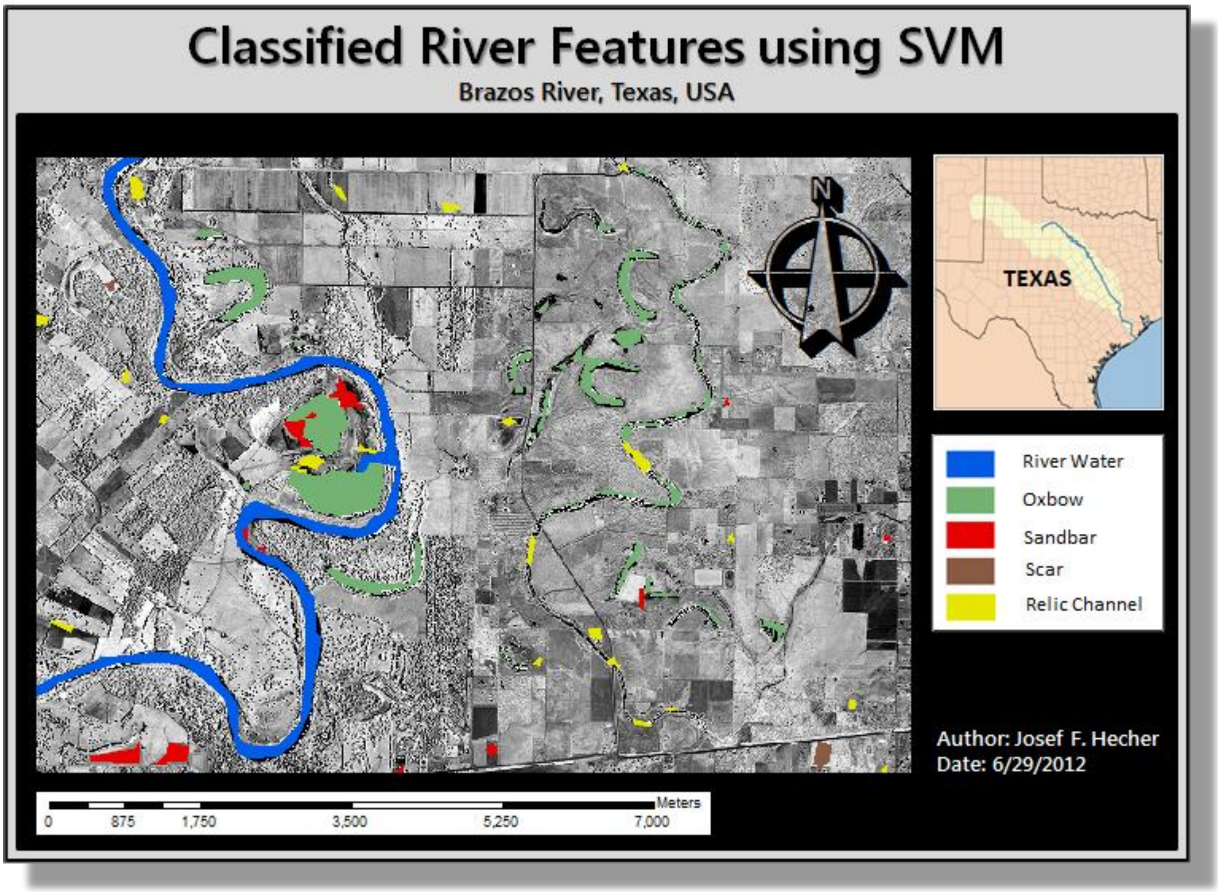

Figure 29: Post processed SVM Classification Output

Table 6 shows the Error Matrix of a SVM classification based on a six bands Landsat 5 image (6B). The river feature classes affected by a higher confusion are Scar and Relic Channel.

Table 6: Error Matrix of SVM classified 6 bands Landsat inland scene

Inland Scene (26 39)		Reference						
6Band SVM		River Water	Sandbar	Oxbow	Scar	relic channel		
Classified	River Water	58	1	1	0	0		60
	Sandbar	5	52	0	0	3		60
	Oxbow	2	0	48	2	8		60
	Scar	8	7	0	22	2		39
	relic channel	17	2	13	5	13		50
								0
		90	62	62	29	26		269

Table 7 lists the calculated accuracy values using the error matrix in table 6. Relic Channel class has the lowest User's and Producer's Accuracy values followed by Scar. The Overall Accuracy is 71.75 % and the Coefficient of Agreement is 64.19 %.

Table 7: Accuracy values of six bands Landsat 5 SVM classification

Overall-Accuracy	71,75%		193	269		
Producer's Accuracy	64,44%	River Water		35,56%	omission error	
	83,87%	Sandbar		16,13%	omission error	
	77,42%	Oxbow		22,58%	omission error	
	75,86%	Scar		24,14%	omission error	
	50,00%	Relic Channel		50,00%	omission error	
User's Accuracy	96,67%	River Water		3,33%	commision error	
	86,67%	Sandbar		13,33%	commision error	
	80,00%	Oxbow		20,00%	commision error	
	56,41%	Scar		43,59%	commision error	
	26,00%	Relic Channel		74,00%	commision error	
Coefficient of Agreement	64,19%		193	269	15271	72361

Table 8 is a generated Error Matrix including the five river feature classes. The input file for the classification process was a stacked inland Landsat 5 scene consisting of six Landsat Bands, a DEM, Sobel filter Bands, NDVI, and Tasseled Cap bands (6DSNT). In this classification process SVM did not classify any Scar pixels. Consequently, in this case the feature class Scar has been ignored in the Accuracy Assessment procedure.

Table 8: Error Matrix of SVM classified coastal scene including ancillary data

Inland Scene (26 39)		Reference						
6DSNT		River Water	Sandbar	Oxbow	Scar	relic channel		
Classified	River Water	56	4	0	0	0		60
	Sandbar	5	41	1	1	2		50
	Oxbow	0	0	45	3	7		55
	Scar	NA	NA	NA	NA	NA		NA
	relic channel	28	3	12	2	10		55
		89	48	58	NA	19		220

Table 9 lists the calculated Accuracy values using the Error Matrix in table 8. The class Relic Channel shows a low Producer's and User's Accuracy values. The Overall Accuracy is 69.09 %. The calculated Coefficient of Agreement is 58.93 %.
The interpretation of the Error Matrix indicates that SVM has problems to distinguish between River Water, Oxbow and Relic Channel in the class Relic Channel using the 6DSNT layer stacking combination.

Table 9: Calculated Accuracy values for SVM classification including ancillary data

Overall-Accuracy	69,09%		152	220		
Producer's Accuracy	62,92%	River Water		37,08%	omission error	
	85,42%	Sandbar		14,58%	omission error	
	77,59%	Oxbow		22,41%	omission error	
	NA	Scar		NA	omission error	
	52,63%	Relic Channel		47,37%	omission error	
User's Accuracy	93,33%	River Water		6,67%	commision error	
	82,00%	Sandbar		18,00%	commision error	
	81,82%	Oxbow		18,18%	commision error	
	NA	Scar		NA	commision error	
	18,18%	Relic Channel		81,82%	commision error	
Coefficient of Agreement	58,93%		152	220	11975	48400

The next figure (Figure 31) is a classified image using Feature Analyst. The classified features have been clipped to the digitized features to execute the evaluation of the thematic correctness. In this area, mainly the class Relic Channel is confused with other classes, such as River Water and Oxbow.

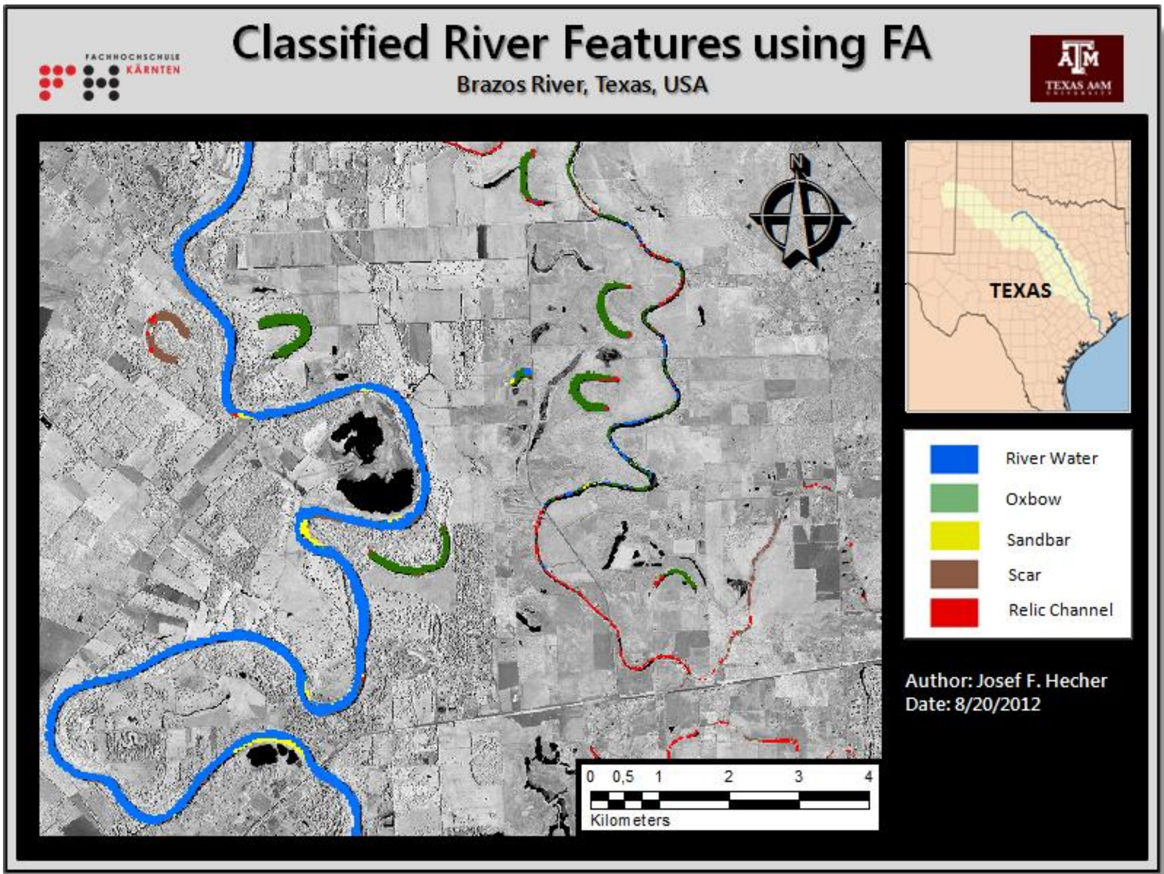

Figure 30: Feature Analyst Classification result

Table 10 is the generated Error Matrix of the Feature Analyst result. The input file consisted of the six Landsat 5 Bands and covers the inland project area. Most noticeable are the misclassifications concerning the class Scar. Feature Analyst confuses Scar with River Water and Relic Channel. This is also illustrated in table 11 that shows a low accuracy value for the class Scar. The Overall Accuracy of the classified image is 74.14 % and the calculated Coefficient of Agreement is 67.56 %.

Table 10: Error Matrix of classified Inland Scene using Feature Analyst

Inland Scene (2639) 6Band Feature Analyst		Reference						
		River Water	Sandbar	Oxbow	Scar	Relic channel		
Classified	River Water	58	1	0	0	1		60
	Sandbar	12	34	1	1	2		50
	Oxbow	2	0	47	3	8		60
	Scar	14	0	4	26	16		60
	Relic channel	5	0	2	3	50		60
		91	35	54	33	77		290

Table 11: Calculated Accuracy values for Feature Analyst Classification

Overall-Accuracy	74,14%		215	290		
Producer's Accuracy	63,74%	River Water		36,26%	omission error	
	97,14%	Sandbar		2,86%	omission error	
	87,04%	Oxbow		12,96%	omission error	
	78,79%	Scar		21,21%	omission error	
	64,94%	Relic Channel		35,06%	omission error	
User's Accuracy	96,67%	River Water		3,33%	commision error	
	68,00%	Sandbar		32,00%	commision error	
	78,33%	Oxbow		21,67%	commision error	
	43,33%	Scar		56,67%	commision error	
	83,33%	Relic Channel		16,67%	commision error	
Coefficient of Agreement	67,56%		215	290	17050	84100

Table 12 is a comparison of the accuracy values reached in the three different image classifications illustrated above. The three input files for the classification were a six bands Landsat image using SVM and FA, and stacked image including a DEM, Sobel Filter NDVI and Tasseled Cap bands using the SVM classification. The two SVM classifications show a similar thematic accuracy. It is noteworthy that the classified six bands image has higher total accuracy values (Overall Accuracy and Coefficient of Agreement) than the results of the input image containing ancillary data.
Concerning the single classes SVM especially has problems to correctly classify Scar and Relic Channel while Feature Analyst only has problems with Scar. In general, Feature Analyst delivers better results than the Support Vector Machine.

Table 12: Comparison of Accuracy values

		SVM 6B	SVM 6DSNT	FA 6B
Overall-Accuracy		71,75%	69,09%	74,14%
Producer's Accuracy	River Water	64,44%	62,92%	63,74%
	Sandbar	83,87%	85,42%	97,14%
	Oxbow	77,42%	77,59%	87,04%
	Scar	75,86%		78,89%
	Relic Channel	50,00%	52,63%	64,94%
User's Accuracy	River Water	96,67%	93,33%	96,67%
	Sandbar	86,67%	82,00%	68,00%
	Oxbow	80,00%	81,82%	78,33%
	Scar	56,41%		43,33%
	Relic Channel	26,00%	18,18%	83,33%
Coefficient of Agreement		64,19%	58,93%	67,56%

5. Discussion

In this chapter the results of the study are discussed. First, the expected results listed in chapter 1.5 are compared to the actual results of the research work. Secondly, the Hypothesis stated in chapter 1.3 is evaluated.

A conceptual model of the work that includes the all the necessary process steps in order to perform river feature classifications and evaluate their results is presented in chapter 3.4. The mapping of places of channel avulsion happened as part of the digitization of the training areas of the respective river feature classes. A comparison between the different river feature extraction methods as well as the separability analysis is part of chapter 4.

The hypothesis says that with the application of GI- and remote sensing software and techniques in combination with remotely sensed data it is possible to classify different river features due to their spectral and spatial characteristics. This hypothesis has been investigated by applying two different classification methods to two Landsat 5 TM images that cover the lower Brazos river floodplain. The outcome of the study confirms that GI-software and methods are able to identify and classify different river features. Without the performance of any post-processing methods the classified images reached Overall-Accuracies of up to 74%. The results show that SVM has problems to classify the river feature classes Scar and Relic Channel while FA has problems with classifying the Scar class. A possible explanation for the problems is that a 30m spatial resolution is not sufficient enough to classify relatively narrow features such as Relic Channels However, the spatial resolution of 30 meter was sufficient enough to test the separability of the river features but for a more detailed mapping of the river features high resolution DEM and satellite images are necessary. Beside the reduction of processing times another advantage of the lower spatial resolution is that a relatively comprehensive study area can be covered by very few images. As a consequence it is more likely to find images that have been taken within a short period of time what in fact enhances the consistency of the entire study.

6. Summary

In the final chapter of the thesis comprises a brief summary of the methodology and process steps. In addition, questions and approaches for further research activities in the ambits of riverine feature analysis are given.

6.1 Conclusion

The purpose of this research was to test the separability of several river features by using automatic classification methods. For the performance of the advanced pixel based method ENVI's SVM has been used. The object based classification was run with the Feature Analyst. Both methods require the digitization of representative Training areas of the respective river features. The training areas have been digitized on two Landsat 5 scenes that covered the study area, the lower Brazos River basin, TX. Simultaneously, high resolution DOQQs served as verification images. To the Landsat scenes several image enhancement operations have been applied to generate raster files with additional information content. The enhanced as well as the original Landsat scenes were then combined with the DEM and served in different combinations as input files for the classification methods. Thereafter, the classified output images have been evaluated and compared visually. The best output files formed the basis for subsequent Accuracy Assessment methods to determine their thematic correctness and the separability of the examined river features.

The results show that SVM has problems to distinguish between several river feature classes. Especially Scar and Relic Channel features are confused with other classes such as Oxbow or River Water. Possible reasons therefore are similarities in the spectral signature of the classes as well as the coarse spatial resolution of the input images. However, SVM successfully distinguished between river water, sandbar and oxbow features. Surprisingly the adding of multiple ancillary data layers did not cause a dramatic change in the thematic correctness of the SVM result. In comparison, Feature Analyst only had problems with the classification of the Scar features. In general, the result of the FA classification showed better accuracy values than those of SVM. For more accurate results in both classification methods high resolution data as well as the performance of additional post-processing methods would be necessary.

6.2 Further Perspectives

Future research in this field should be based on high resolution data and Feature Analyst Software. Consequently the spectral characteristics of narrow features such as small Relic Channels that have wooded banks can be captured much more easier and enhance the thematic correctness of the classified image. In addition, algorithms based on logical connectives should be implemented that help to classify features which certainly belong to a river. Sandbars for example only occur in river bends and are very close to water level. In other words, polygons representing Sandbars have to share a border with River Water polygons. If they do not share a border, the sandbar feature for example could have been misclassified due to spectral similarities with a common land cover type. With the usage of a shape based object recognition algorithm the confusion between usual lakes and u-shaped oxbow lakes formed by river erosion could be minimized (Isaka & Sakurai-Amano, 1995). With these algorithms it would be possible to ignore or delete features that have been misclassified and preserve those that in fact are actual river features.

Another aspect that has to be considered in future research is the classification of all known river features. As already mentioned before, only a part of the existing river features have been analyzed in this work.

7. References

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8. List if Figures

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