THE USE OF REMOTE SENSING AND GEOGRAPHICAL INFORMATION SYSTEMS TO CREATE LAND USE AND LAND COVER MAPS AND TO DETERMINE THE CHANGES IN THE LAND USE AND LAND COVER OVER A TEN YEAR PERIOD

By

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THE USE OF REMOTE SENSING AND GEOGRAPHICAL INFORMATION SYSTEMS TO CREATE LAND USE AND LAND COVER MAPS AND TO DETERMINE THE CHANGES IN THE LAND USE AND LAND COVER OVER A TEN YEAR PERIOD

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Construction of land use and land cover (LULC) maps was accomplished through the use of remote sensing and GIS. Remote sensing and GIS were used to classify 1990 Landsat 5 and 2000 Landsat 7 Mississippi Gulf Coast imagery into six LULC classes: urban, barren, forested vegetation, non-forested vegetation, marsh, and water. An accuracy assessment was performed on the 2000 LULC map to determine the reliability of the map. Finally, GIS software was used to quantify and illustrate the various LULC conversions that took place over the ten year span of time. The paper concludes that remote sensing and GIS can be used to create LULC maps. It also notes that the maps generated can be used to delineate the changes that take place over time.
ACKNOWLEDGMENTS

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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>ii</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>iv</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>v</td>
</tr>
<tr>
<td>CHAPTER</td>
<td></td>
</tr>
<tr>
<td>I. INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>Overview</td>
<td>1</td>
</tr>
<tr>
<td>Objective of Study</td>
<td>3</td>
</tr>
<tr>
<td>Background</td>
<td>3</td>
</tr>
<tr>
<td>II. LITERATURE REVIEW</td>
<td>7</td>
</tr>
<tr>
<td>Overview of Remote Sensing</td>
<td>7</td>
</tr>
<tr>
<td>Multispectral Image Processing</td>
<td>13</td>
</tr>
<tr>
<td>Selection of a Land Use/Land Cover Classification System</td>
<td>15</td>
</tr>
<tr>
<td>III. METHODOLOGY</td>
<td>17</td>
</tr>
<tr>
<td>Data Preparation</td>
<td>17</td>
</tr>
<tr>
<td>Image Enhancement and Classification</td>
<td>19</td>
</tr>
<tr>
<td>Accuracy Assessment</td>
<td>25</td>
</tr>
<tr>
<td>Categorical Change Analysis</td>
<td>27</td>
</tr>
<tr>
<td>IV. RESULTS</td>
<td>28</td>
</tr>
<tr>
<td>Classification</td>
<td>28</td>
</tr>
<tr>
<td>Change Analysis</td>
<td>31</td>
</tr>
<tr>
<td>Accuracy Assessment</td>
<td>34</td>
</tr>
<tr>
<td>V. CONCLUSIONS AND RECOMMENDATIONS</td>
<td>37</td>
</tr>
<tr>
<td>Conclusions</td>
<td>37</td>
</tr>
<tr>
<td>Recommendations</td>
<td>39</td>
</tr>
<tr>
<td>REFERENCES CITED</td>
<td>41</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

<table>
<thead>
<tr>
<th>TABLE</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1: Population Data for the MS Gulf Coast</td>
<td>5</td>
</tr>
<tr>
<td>1.2: Population Changes from 1970 to 2000</td>
<td>5</td>
</tr>
<tr>
<td>2.1: Level 1 LULC Classification Classes and Description</td>
<td>16</td>
</tr>
<tr>
<td>4.1: LULC Class Totals</td>
<td>33</td>
</tr>
<tr>
<td>4.2: LULC Cover Transition Matrix (acreage)</td>
<td>33</td>
</tr>
<tr>
<td>4.3: Classification Error Matrix</td>
<td>34</td>
</tr>
<tr>
<td>4.4: Accuracy Assessment Report</td>
<td>35</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>FIGURE</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1: Mississippi Gulf Coast</td>
<td>4</td>
</tr>
<tr>
<td>3.1: MARIS Vector Road Coverage with Ground Control Points</td>
<td>18</td>
</tr>
<tr>
<td>3.2: Mississippi Coast Clipped Landsat Imagery</td>
<td>19</td>
</tr>
<tr>
<td>3.3: Example of MS Coast Analysis View (water bodies have been cropped)</td>
<td>22</td>
</tr>
<tr>
<td>3.4: Raster Graphic of MS Coast with Color Ramp after NDVI Analysis</td>
<td>23</td>
</tr>
<tr>
<td>3.5: Example of MS Coast Vegetated Analysis View</td>
<td>24</td>
</tr>
<tr>
<td>3.6: Example of MS Coast Non-Vegetated Analysis View</td>
<td>24</td>
</tr>
<tr>
<td>3.7: Illustration of Randomly Generated Accuracy Assessment Sites</td>
<td>26</td>
</tr>
<tr>
<td>4.1: 1990 Level 1 Land Use / Land Cover Map</td>
<td>29</td>
</tr>
<tr>
<td>4.2: 2000 Level 1 Land Use / Land Cover Map</td>
<td>30</td>
</tr>
<tr>
<td>4.3: LULC Class Percentages for 1990</td>
<td>32</td>
</tr>
<tr>
<td>4.4: LULC Class Percentages for 2000</td>
<td>32</td>
</tr>
</tbody>
</table>
CHAPTER I

INTRODUCTION

Overview

Land use maps illustrate the function of an area or parcel of land while land cover maps show the landscape of a particular region. A series of land use or land cover (LULC) maps that cover a span of several years, can illustrate the rate at which a community is growing, which areas are showing the quickest development, and where that development is heading. A series of LULC maps can also be used to show the depletion of natural resources, the transition of one land cover into another type of land cover, or which areas might need protection from further infringement.

One means by which LULC maps might be produced quickly and accurately is the use of remote sensing of data and geographical information systems (GIS) for data analysis and depiction. Remote sensing and GIS are two sciences that have risen quickly with the enormous advances that have been made in technology over the past few years. Remote sensing is the term used to describe the collection of information without actually coming into contact with the area or object of interest. For the purpose of this research, remote sensing dealt strictly with raster data collected by satellite and airborne photography. GIS is a tool used to manipulate, analyze, display, and store large amounts of data (Wilkie and Finn, 1996).
There are several advantages that can be found through the use of remote sensing as a tool for the collection of data in building a LULC map. These advantages stem from the spatial, temporal, and spectral capabilities of the various remote sensing platforms. According to Wilkie and Finn (1996), remote sensing increases our ability to view the world as a single entity as well as numerous sections of the whole. Large regions can be observed, or with the expanding capabilities, highly detailed images of an area can be viewed. The second benefit of remote sensing is the temporal advantage. The environment is constantly changing and in order to produce LULC maps that effectively display these changes, a technology is needed that can record the area or phenomenon in question over a series of years, months or days. Finally remote sensing provides a broad spectral viewing capability. This allows the user to observe the differences in landscape that might not be apparent from just the visible spectrum and the naked eye. The user can analyze the characteristics of a region by viewing it with different bands of the spectrum.

GIS allows the user the ability to view and manipulate multiple layers of electronic information. The user may take satellite raster graphics, photography, maps, tabular data, and any other information that is related geographically and integrate it all into one large database. This information can then be mathematically manipulated, sorted, analyzed for trends and relationships, and displayed in a manner that is readily understandable to the average viewer.
Objective of Study

It is the purpose of the author to determine the feasibility of using remote sensing and GIS to produce accurate LULC maps of the Mississippi Gulf Coast over a span of 10 years and perform a change analysis. The LULC map classification would follow a modification of a Level 1 Anderson classification scheme with the following classes: urban/built up, non-forested vegetation, forested vegetation, barren, marsh, and water (Anderson, 1976).

Background

The Mississippi Gulf Coast (Figure 1.1) is a dynamic environment that is home to several unique and sensitive environments. Many of these are protected by various state and federal regulatory agencies. Monitoring is an important aspect of the protection strategy for these areas. The potential to use remote sensing and GIS to produce LULC maps over a span of years had recently been recognized as a potential way to give interested parties the ability to monitor the changes within the environment of the Mississippi Gulf Coast.

The three coast counties, Hancock, Harrison, and Jackson counties, have experienced a significant amount of change in past thirty years. In that time, US Interstate Highway 10 (I-10) was completed in this region and the gaming industry has become a significant component of the community. The population has undergone extensive growth and tourism has increased. Hence, in a few decades the coast has changed from a collection of small fishing communities to a region with a mixture of residential, commercial, industrial, and tourist areas.
Figure 1.1: Mississippi Gulf Coast
The population of the three coastal counties has experienced growth well above the 28.3 percent overall average of Mississippi for the past thirty years. From 1970 to 2000 the population has expanded from 239,944 to 363,988 (Mississippi State Data Center, 2001). This represents a growth of over fifty percent.

Table 1.1: Population Data for the MS Gulf Coast

<table>
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<tr>
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<tbody>
<tr>
<td>Hancock</td>
<td>17,387</td>
<td>24,496</td>
<td>31,760</td>
<td>42,967</td>
</tr>
<tr>
<td>Harrison</td>
<td>134,582</td>
<td>157,665</td>
<td>165,365</td>
<td>189,601</td>
</tr>
<tr>
<td>Jackson</td>
<td>87,975</td>
<td>118,085</td>
<td>115,243</td>
<td>131,420</td>
</tr>
<tr>
<td>Total</td>
<td>241,914</td>
<td>302,156</td>
<td>314,358</td>
<td>365,988</td>
</tr>
</tbody>
</table>

Table 1.2: Population Changes from 1970 to 2000

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<tbody>
<tr>
<td>Hancock</td>
<td>40.9%</td>
<td>28.7%</td>
<td>35.3%</td>
<td>147.1%</td>
</tr>
<tr>
<td>Harrison</td>
<td>17.2%</td>
<td>4.9%</td>
<td>14.7%</td>
<td>40.9%</td>
</tr>
<tr>
<td>Jackson</td>
<td>34.1%</td>
<td>-2.3%</td>
<td>14%</td>
<td>49.4%</td>
</tr>
<tr>
<td>Total</td>
<td>29.4%</td>
<td>4%</td>
<td>16.4%</td>
<td>51.3%</td>
</tr>
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</table>

With the continued development of the coast, it is important that efficient and economical methods are developed and implemented that will recognize the natural resources and developing urban areas along the coast. This will allow for planning
that will protect the various land cover types as well as provide a means for community growth.
CHAPTER II
LITERATURE REVIEW

Overview of Remote Sensing

In the broadest sense, remote sensing is the collection of information without actually coming into contact with the area or object of interest (Wilkie and Finn, 1996). Remote sensing has been around for a number of years and encompasses several platforms. Hot air balloons were used in the Civil War as a means of gathering information about the opposing armies without exposing the observing party to significant danger. Later, cameras were taken up in planes for military intelligence purposes, map making, forest inventories, agricultural studies, civil engineering, soil mapping along with other tasks that were made more efficient by this new technology. Finally man made it into space and has placed a number of satellites whose main function is to observe the earth and relay data to the interested parties (Barrett and Curtis, 1999).

In 1961, the first photographs of space were taken from a Mercury satellite. Since this time the interest in remote sensing has expanded, and satellites have played a major role in this field. Several advantages are associated with satellites. Researchers have the ability to observe vast tracts of land, or, as technology has increased, they can now narrow the observed area down to just a few hundred meters.
The orbit of a satellite can be controlled in such a way as to regulate how often it views a certain location. One such orbit is the sun-synchronous orbit. This low level orbit is at such a height and speed that it allows the satellite to view the same area of the earth at the same time of the day every time it passes that location. Another useful orbit is the geosynchronous orbit. This is a high level orbit, about 36,000 km above the earth’s surface, that remains fixed in one spot in relation to the earth (Barrett and Curtis, 1999).

There are a variety of satellites that have been introduced over the years with the purpose of monitoring the environment. The United States introduced the Landsat satellites in 1972. The French first introduced a satellite, SPOT-1, an earth resources satellite, in 1986. India put out its first Indian Remote Sensing satellite (IRS-1A) in 1988. Japan launched the Marine Observation Satellite (MOS-1) in 1990. These satellites were the first of many to be launched (Barrett and Curtis, 1999).

According to Barrett and Curtis (1999), the most important of the satellite families is the Landsat family. The first Landsat satellite was launched in 1972. The first three Landsat Satellites carried Return Beam Vidicon (RBV) camera systems and a Multispectral Scanner (MSS). The RBV recorded panchromatic images within the wavelength of 0.48-0.83µm. The MSS system recorded four different spectral bands from 0.5 m to 1.1µm. They covered the entire planet in an 18-day cycle. Landsat satellites 4 and 5 improved over the first three by replacing the RBVs with the Thematic Mapper (TM), which records 7 separate spectral bands.
The newer Landsat satellites repeated their cycle every 16 days. The resolution of the TM is 30m compared to the 79m resolution of the MSS in the earlier satellites. Landsat 7, which was launched on April 15, 1999, has several more improvements. It measures radiation from eight different bands of the spectrum. Its panchromatic sensor has a 15-meter resolution. The visible, near infrared, and short-wave infrared sensors have a 30-meter resolution. The thermal infrared sensor has a 60-meter resolution.

There are several advantages that can be found through the use of remote sensing as a tool for the collection of data. These advantages stem from the spatial, temporal, and spectral capabilities of the various remote sensing platforms. According to Wilkie and Finn (1996), remote sensing increases our ability to view the world as a single entity as well as numerous sections of the whole. Large regions can be observed, or with the expanding capabilities, highly detailed images of an area can be viewed. Another benefit of remote sensing is the temporal advantage. The environment is constantly changing and in order to effectively monitor the changes, a technology is needed that can record the area or phenomenon in question within a matter of hours or days or over a period of several years or decades. As the seasons change, the features of the land change also. Plants and trees may be bare in the winter and allow observation of the ground, or a type of plant may be identified by the season in which it blooms.

Remote sensing provides the ability to observe and record imagery of an area repeatedly throughout a fixed time frame. Remote sensing also provides a broad
spectral viewing capability. This allows the user to observe the differences in landscape that might not be apparent from just the visible spectrum and the naked eye. The user can analyze the characteristics of a region by viewing it with different bands of the spectrum.

Today, the majority of remote sensing technologies gather data by measuring the electromagnetic radiation (EMR) reflected off the object or area of interest (Wilkie and Finn, 1996). Radiation is of utmost importance to remote sensing, as it is the only form of electromagnetic energy that can travel through a vacuum and a medium (Barrett and Curtis, 1999). Its frequency and wavelength can distinguish the various types of radiation. The majority of naturally produced radiation that makes it to the earth’s atmosphere and surface is generated by the sun. This radiation includes gamma rays, X-rays, ultra-violet, visible, infrared, microwaves, and radio waves. About 50 percent of this radiation produced by the sun is within the visible spectrum (Wilkie and Finn, 1996).

Not all of the radiation produced by the sun actually makes it to the earth’s surface. The majority of the radiation is filtered out by the earth’s atmosphere. Oxygen and ozone absorb almost all of the radiation with wavelengths less than 0.3 \( \mu \text{m} \), while ozone absorbs some of the radiation in the wavelengths of the 0.32-0.36 \( \mu \text{m} \) region, and the wavelengths of 0.6 \( \mu \text{m} \), 4.75 \( \mu \text{m} \), 9.6 \( \mu \text{m} \), and 14.1 \( \mu \text{m} \). Carbon dioxide absorbs most of the radiation around the wavelength of 15 \( \mu \text{m} \) and has a weak absorption band at 4 \( \mu \text{m} \) and 10 \( \mu \text{m} \). Water vapor absorbs most of the radiation at a wavelength around 6 \( \mu \text{m} \). It also has several weak adsorption bands below 0.7 \( \mu \text{m} \).
and several adsorption bands of varying intensity between 0.7 and 0.8 \( \mu \text{m} \) (Barrett and Curtis, 1999).

Once the radiation makes it to the earth’s surface, one of several things will happen. It is either absorbed by the surface and becomes heat, transmitted through the surface, reflected, scattered, or absorbed and reradiated as thermal radiation (Wilkie and Finn, 1996). Reflected radiation is extremely important to remote sensor users as most of the sensors for remote sensing are based on it. The reflected radiation is what is actually seen or measured by the sensors (Barrett and Curtis, 1999).

Panchromatic, multispectral, and hyperspectral are different types of sensors that measure the radiation that is reflected off of the earth’s surface. A panchromatic sensor records the amount of radiation, within a broad range of the spectrum that is being reflected by the area or object of interest. This broad range of the spectrum includes the visible spectrum and small section of the infrared spectrum. Multispectral sensors create several images of an area or object of interest. Each image is recorded by measuring the amount of radiation reflected, in different ranges or narrow bands of the spectrum, from the area or object. For example, the band 4 sensor of the Landsat 7 satellite measures the quantity of radiation reflected within the wavelengths of 0.76 \( \mu \text{m} \) and 0.90 \( \mu \text{m} \), the near infrared wavelengths. Hyperspectral sensors are similar to multispectral sensors except that several hundred images of the same area or object of interest may be recorded, and the bandwidths or
ranges of the spectrum of the reflected radiation that are measured for each image are much narrower.

Every compound has a distinctive spectral signature or pattern. This pattern is a measure of the radiation over a range of wavelengths an object reflects. A spectral signature or a spectral response pattern is the measured brightness value of an object that distinguishes it from other features in an image. The brightness of an object changes depending upon the type of the radiation that is being measured. Using the spectral signature of an object provides a distinctive characteristic that can be used to distinguish between various vegetation, soils, crop conditions, and land uses or classes.

Spectral resolution refers to the narrowness of the section of the spectrum that is being measured. As previously mentioned panchromatic sensors measure a broad range of the spectrum while multispectral sensors measure narrower bands and hyperspectral sensors measure even narrower bands of the spectrum. The narrower the band of the spectrum is, and the more sections of the spectrum that can be measured, the more detailed the spectral image will be. This increases the chances that an object can be identified and analyzed (Wilkie and Finn, 1996).

There are several factors that influence the spectral signature of an object. For minerals, water content and carbon dioxide levels are two factors that must be taken into account. When dealing with the spectral signature of plants, one must take into account a large number of factors. These include, but are not limited to, the time of year and day, moisture, plant maturity, nutrient levels, disease, atmospheric conditions, and site environmental conditions (Barrett and Curtis, 1999). A lot of
effort has gone into cataloging the various spectral signatures of various plants and minerals. However, with the number of factors that influence the spectral signature, there is still a lot of research that has to be done.

**Multispectral Image Processing**

Once the digital imagery has been gathered it must be processed. These processes consist of manipulation and interpretation of the digital imagery through the aid of a computer. Image rectification is performed to make image data conform to a map projection and correct it for distortions that may stem from variations in altitude, velocity of the sensor, the earth’s curvature, relief displacement, nonlinearities in the sweep of the sensor, and atmospheric refraction (Lillesand and Kiefer, 2000). Georeferencing is the process of assigning map coordinates to the image data and resampling the pixels so that the image conforms to the map projection (Pouncey et al, 1999). Image enhancement is used to emphasize features of special interest so that they may be extracted more readily (Barrett and Curtis, 1999). Classification is the process of assigning discrete pixels of a multispectral image to classes based upon their spectral characteristics (Wilkie and Finn, 1996).

There are a number of techniques used in image enhancement to improve the visual interpretability of an image. Contrast stretching, level slicing, spatial filtering, edge enhancement, multispectral band ratioing and differencing, and principal components are a few of them (Lillesand and Kiefer, 2000). Two methods of image enhancement, normalized difference vegetation index (NDVI) and tasseled cap transformation, are used in this author’s research. NDVI is used to highlight areas of
vegetation in a multispectral image. It is determined by taking the ratio of the
difference between the radiation measured by the infrared and red sensors over the
sum of the radiation measured by the infrared and red sensors:

\[
NDVI = \frac{(IR - R)}{(IR + R)}
\]

The tasseled cap transformation is a series of algorithms that can be used to
optimize viewing for vegetation studies (Pouncey et al., 1999). Civco et al. also used
the tasseled cap transformation to help extract water and wetland features in their
research (1999).

Multispectral image classification is the process where individual pixels
within the image are assigned to discrete land cover classes. Supervised classification
and unsupervised classification are the two methods of classification that are most
often used. In supervised classification, training sites containing areas of known land
cover classes are selected. Each of the pixels is then classified based upon which of
the training sites that it matches most closely. In unsupervised classification, the user
selects the number of classes that he or she wants the multispectral image divided
into. The image is then separated into the selected number of classes. Each class will
contain pixels with similar spectral characteristics (Lillesand and Kiefer, 2000). The
user then assigns each class to a land cover class based on information gathered from
the field, maps, aerial photography, and any other useful data.
Selection of a Land Use/Land Classification System

When creating a LULC map, a decision must be made on how to divide the various classes. In the past, various governmental agencies have used a variety of classification systems when developing LULC maps. Each group would create a classification system specific to field being studied, which, due to the lack of comparable classes, creates problems for those who would like to compare the LULC classes. The use of a standardized classification system would enable a variety of organizations to produce maps with comparable classes. These maps could then be used by diverse users, and temporal comparisons could be made to determine changes that are taking place in the LULC over time (Anderson et al., 1976).

For the purpose of this thesis, the classification system that will be used is a slightly modified version of the one developed by the U.S. Geological Survey (Anderson et al., 1976). This is a hierarchical system with level 1 being the broadest and level 4 being the most specific. Table 2.1 lists and describes the level 1 LULC classes that will be used to classify the Mississippi Gulf Coast.

According to Jensen and Cowen (1999), level one LULC maps can be generated with sensors that have a spatial resolution between 20 and 100 meters. The Landsat data that is being used to produce the LULC maps has a spatial resolution of 28.5 meters; therefore, the author decided to concentrate the majority of the effort into producing Level One LULC maps.
Table 2.1: Level 1 LULC Classification Classes and Description

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>Urban/Built-Up</td>
<td>Includes all residential, commercial, and industrial development.</td>
</tr>
<tr>
<td>Non-Forested Vegetation</td>
<td>Includes all vegetation features that are not typical of forest, including agricultural and pasture grasslands, recreational grasses, scrub or shrublike vegetation features.</td>
</tr>
<tr>
<td>Forested Vegetation</td>
<td>All forest vegetation types including evergreen, deciduous, and wetland forest vegetation types.</td>
</tr>
<tr>
<td>Marshes/Wetlands</td>
<td>Predominately wetland or marsh features associated with the coastal zone, rarely indicative of upland wetland features or forested wetland vegetation.</td>
</tr>
<tr>
<td>Barren</td>
<td>Barren or sparsely vegetated areas most often representative of bare earth or soil.</td>
</tr>
<tr>
<td>Water</td>
<td>All water bodies including freshwater lakes, rivers, and streams, as well as marine water environments.</td>
</tr>
</tbody>
</table>
CHAPTER III

METHODOLOGY

Data Preparation

ERDAS Imagine 8.4 and ESRI Arcview 3.2 were used for importing the data, converting it into a usable format, enhancing and classifying imagery, and organizing the final product.

To facilitate analysis and comparison between various image and vector data, the data sets were projected and georectified. Since the most common projection for a large portion of the data that is available for this project is the Mississippi Transverse Mercator (MSTM), it has been designated as the default projection for this project. Mississippi Automated Resource Information System (MARIS) vector road coverage (Figure 3.1) was chosen as the reference by which all other data would be georectified. The satellite images were compared to the MARIS road coverage in order to find the image the came closest to matching the reference data. The 15 February 2000 image met this criterion and was georectified to the MARIS road coverage using 22 ground control points (GCPs) and the cubic convolution resampling method. The Root Mean Square (RMS) error was less than 0.3 pixels. In order to make the rectification process easier and more accurate, the remaining images were georectified to the 15 February 2000 image using the same GCPs as in
the initial georectification. The Root Mean Square (RMS) error was less than 0.3 pixels for all georectified images.

![Figure 3.1: MARIS Vector Road Coverage with Ground Control Points](image)

In order to perform an accurate LULC classification analysis, the area shown in each Landsat image should be identical. To contain the LULC analysis to Hancock, Harrison, and Jackson Counties, the Landsat scenes were cropped in ESRI Arcview using MARIS’s county outline of the relevant counties as the mask. However, the Landsat images did not show the entire area of Hancock County, and the amount of area shown in Hancock County was inconsistent. The western edge in the Landsat image varied from date to date. To correct for this, the image with the smallest area was used as a mask by which all the other images were clipped. Figure 3.2 shows the two clipped images used for the LULC classification and analysis.


**Image Enhancement and Classification**

To aid in the use of supervised classification techniques a number of training sites were gathered. The initial plans for gathering training sites involved preselecting the sites using a Landsat image. The Landsat image was used to locate sites of homogeneous pixels or land cover. In order to save time, an effort was made
to locate training sites that were relatively close to each other. Groups of pixels were located within Hancock, Harrison, and Jackson counties. A map of the three counties with a MARIS road coverage was generated that showed the locations of all of the training sites. A table with the latitude and longitude, predicted land cover class, ID number, and a column for the description of the area was also created.

Attempting to locate the training sites produced several problems. The quad map used to locate the sites was lacking several of the roads needed to find some of the areas in question. In other cases, the training sites were on private property and inaccessible. After speaking with some people familiar with the area and knowledgeable in the problems associated with the locating training sites, it was decided that a new strategy needed to be developed in gathering training sites. The researchers gathering the training sites decided to stop and use sites along the traveled route with large sections of homogenous land cover as training sites. Personnel at Veridian and the Department of Marine Resources also recommended several sites which were recorded as well. The data collected for each site included field notes, position, and photos. Using the MARIS DOQQs and known land cover on the Landsat images, additional training sites were delineated. These were also added to list of training sites gathered from the coast.

Exploratory analysis showed that no single method of classification was able to categorize the various LULC types into the desired classifications to the researcher’s satisfaction. In order to provide an accurate LULC classification, a series of steps was implemented that helped in separating the classes. The Landsat images were first broken down into various analytical masks: water, marsh, urban
and barren, vegetated. These masks were then used to create analysis views from the
Landsat images that could be further classified into the final LULC classes. The steps
for LULC classification listed below were used to classify both the 1990 and 2000
LULC classes except where stated otherwise.

Several methods of classifying water bodies were tried. These include:
unsupervised classification of the leaf on and leaf off Landsat images; supervised
classification of the leaf on and leaf off Landsat images; and unsupervised
classification of the leaf on and leaf off tassel cap image. It was decided that running
an unsupervised classification with 20 classes on bands 1(brightness), 2(greenness),
and 3(wetness) of the tasseled cap image produced a thematic data layer that best
defined the water boundaries. The unsupervised classification image, a thematic
image, was recoded to include only the water classes. Once the water boundaries
were defined, the thematic image was used as a mask to separate the water from the
terrestrial classes. Two analysis views were created: (1) an image showing just the
water bodies in the Landsat image, and (2) an image showing everything but the
water bodies (Figure 3.3).

After having tried unsupervised classification on both the analysis view
without water and the tassel cap image without water and supervised classification on
the Landsat image without water, it was determined that supervised classification,
using the maximum likelihood parametric rule and all the non-water training sites,
was the best method for pulling marsh lands out of the Landsat image. Once the
marsh land boundaries were sufficiently defined, the thematic image was used to
mask the marshes out of the Landsat image. This produced a Landsat analysis mask without marshes and water.

Figure 3.3: Example of MS Coast Analysis View (water bodies have been cropped)

The NDVI algorithm \([\frac{(IR-R)}{(IR+R)}]\) within ERDAS Imagine was used on the Landsat analysis views without the marshes and water bodies to produce a raster image (Figure 3.4) that highlighted areas of vegetation. From the 2000 data, it was determined that pixel with NDVI values greater than 0.1 best represented vegetation. From the 1990 and 1991 data, it was determined that pixel with NDVI values greater than 0.2 best represented the vegetated pixels. While not a large variation, it should be noted that the spectral signature of vegetation may vary depending on a number of factors including the amount of rainfall in a season, plant maturity and plant health. The resulting variance in the spectral signature could easily explain the observed difference in the NDVI values associated with vegetated pixels. A model was then
built that separated the vegetated pixels from the non-vegetated pixels and then created vegetated analytical masks from the vegetated pixels. These were used to create vegetation analysis view (Figure 3.5) and non-vegetation analysis view (Figure 3.6).

Figure 3.4: Raster Graphic of MS Coast with Color Ramp after NDVI Analysis

The non-vegetation mask was used to create an analysis view that contained urban, beach, and clear cut areas. Unsupervised classification with 20 classes was run on this view to create a thematic image in which the urban, beach, and clear cut areas were separated.

The vegetation analytical mask was used to create an analysis view that contained forested vegetation, non-forested vegetation, and clear cut areas. Supervised classification, using the maximum likelihood parametric rule with the
vegetated training sites, was run on the vegetation analysis view to create a thematic image in which the forest, non-forest, and clear cut areas were separated.

Figure 3.5: Example of MS Coast Vegetated Analysis View

Figure 3.6: Example of MS Coast Non-Vegetated Analysis View
The final thematic images which delineate water boundaries, marshes, urban areas, beaches, forests, non-forest vegetation, and clear cut areas were mosaiced together using a program written with ERDAS Imagine’s Macro Model Builder to form a complete land cover map of the entire area of interest.

**Accuracy Assessment**

The generation of an acceptable accuracy assessment of the LULC classification requires that a number of random sites be chosen that represent the classes in the LULC map. These sites must then be visited and described so that they can be accurately classified. The classified sites are then compared with the LULC map to generate the overall accuracy.

One of the main problems with acquiring information about each of the individual assessment sites is gaining access to the site. The random generation of the sites will more often than not place the assessment sites in locations not assessable to the researcher without spending a substantial amount of time getting permission from the landowner, whether it be private, state, or federal.

In order to help facilitate the efficiency and timeliness in gathering the data at the individual assessment sites, a methodology was developed that randomly placed all the assessment sites within 90 meters of a road. The MARIS (2001) road coverages: primary, secondary, and county roads for Jackson, Harrison, and Hancock Counties were buffered for 90 meters on either side and used to create a cropped LULC map with only the buffered MARIS road coverage. This buffered LULC map was used by ERDAS Imagine to create randomly generated accuracy assessment
The number of accuracy assessment sites created for each LULC class, when compared to the total number of accuracy assessment sites, was proportional to the ratio of acreage of each LULC class to the acreage of the buffered LULC map. Figure 3.7 illustrates an example of a LULC map and the buffered MARIS road coverage with several of the accuracy assessment sites. The accuracy assessment sites were located, using a Garmin Etrex Vista handheld global positioning system with an accuracy of 2 to 5 meters, and then the LULC class at each location was documented.

Figure 3.7: Illustration of Randomly Generated Accuracy Assessment Sites

The classification accuracy was then determined by entering the predicted LULC classes and the actual LULC classes into an error matrix. From the error
matrix, the producer’s accuracy, user’s accuracy, and the overall accuracy of the LULC classification was computed.

**Categorical Change Analysis**

To quantify the changes that occurred between the LULC map of 1990 and 2000, especially in the urban areas, one needs to know where the changes occurred and what land covers were converted to another land cover type. Arcview 3.2 was used as the tool for quantifying the changes between the individual classes. With the level 1 classification, there were six classes and 36 possible combinations of change between the 1990 classes and the 2000 classes.
CHAPTER IV

RESULTS

This section describes and illustrates the results obtained from the classification, change analysis, and accuracy assessment performed on the spectral data obtained from Landsat 5 and 7. These experimental methods yielded information used for assessment. Because of the spatial nature of the project and the visual nature of the information being evaluated, much of the results are shown in graphical form.

Classification

Figures 4.1 and 4.2 illustrate the LULC maps created from the 1990 and 2000 leaf-on Landsat imagery using ERDAS Imagine. These figures represent the results of the classification with each color corresponding to one of the LULC classes. The classification was performed using a combination of supervised and unsupervised classification approaches. The two classification methodologies were performed on the original Landsat images or a raster image created by running the NDVI algorithm or the Tasseled Cap Transform on the Landsat imagery. Once the classification on each image was completed, all the classes were recoded into one of the six level 1 LULC classes: urban, non-forested vegetation, forested vegetation, coastal marshes, barren, and water.
Figure 4.2: 2000 Level 1 Land Use/Land Cover Map
Change Analysis

ERDAS Imagine and ESRI Arcview were used to quantify the acreage of the six LULC classes from the 1990 and 2000 classification maps. The software was also able to quantify the amount and type of change that occurred in each of the LULC classes over the ten year study period. These numbers were used to create the following figures and tables. Figures 4.3 and Figure 4.4 illustrate the amount of land, by percentage, contained in each of the LULC classes for their respective years. Table 4.1 quantifies the amount of land contained in each LULC class, the percentage of the study area encompassed by the LULC class, and the amount of growth of each of the LULC classes from 1990 to 2000. Table 4.2 shows and quantifies the transition of one LULC class into another LULC class from 1990 to 2000. For example, the table shows that 69,446 acres of land that had been classified as forested vegetation in 1990 was classified as barren in 2000, and 22,341 acres of land that had been classified as non-forested vegetation in 1990 was classified as urban or built up in 2000. This can be used to determine the extent of the changes taking place in the LULC over time.

Using Tables 4.1 and 4.2 together, significant changes in the LULC can be recognized and type of LULC conversion taking place can be identified. From 1990 to 2000 barren areas saw a relatively dramatic increase. The areas that contributed the most to this change were forested vegetation and non-forested vegetation. This may suggest logging and development. During the same time span, urban areas also increased in size. The majority of this change came from the development of forested vegetation and non-forested vegetation into an urban class. Marshes saw a decrease
in size. Some of the marshes converted to water, while some of it was converted to urban. Non-forested vegetation areas also saw a decrease in size. Most of it was converted to forested vegetation areas, while a smaller but significant portion was developed into urban areas. Finally forested vegetation areas saw a decrease in size. The largest portion was converted to non-forested vegetation, with another portion converted to barren, and a significant portion was developed into urban areas.

Figure 4.3: LULC Class Percentages for 1990

Figure 4.4: LULC Class Percentages for 2000
Table 4.1: LULC Class Totals

<table>
<thead>
<tr>
<th></th>
<th>1990 (acreage)</th>
<th>Percent of Study Area</th>
<th>2000 (acreage)</th>
<th>Percent of Study Area</th>
<th>Amount of Change</th>
<th>Percentage Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>65,474</td>
<td>4.22%</td>
<td>99,788</td>
<td>6.42%</td>
<td>34,314</td>
<td>52.41%</td>
</tr>
<tr>
<td>Non-Forrested Vegetation</td>
<td>214,967</td>
<td>13.84%</td>
<td>148,873</td>
<td>9.59%</td>
<td>-66,094</td>
<td>-30.75%</td>
</tr>
<tr>
<td>Forested Vegetation</td>
<td>673,815</td>
<td>43.38%</td>
<td>614,411</td>
<td>39.56%</td>
<td>-59,404</td>
<td>-8.82%</td>
</tr>
<tr>
<td>Water</td>
<td>503,145</td>
<td>32.39%</td>
<td>517,191</td>
<td>33.30%</td>
<td>14,046</td>
<td>2.79%</td>
</tr>
<tr>
<td>Marsh</td>
<td>69,946</td>
<td>4.50%</td>
<td>45,740</td>
<td>2.94%</td>
<td>-24,206</td>
<td>-34.61%</td>
</tr>
<tr>
<td>Barren</td>
<td>25,818</td>
<td>1.66%</td>
<td>127,162</td>
<td>8.19%</td>
<td>109,344</td>
<td>392.54%</td>
</tr>
</tbody>
</table>

Table 4.2: LULC Cover Transition Matrix (acreage)

<table>
<thead>
<tr>
<th></th>
<th>Urban</th>
<th>Non-Forrested Vegetation</th>
<th>Forested Vegetation</th>
<th>Water</th>
<th>Marsh</th>
<th>Barren</th>
<th>1990 Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>31,479</td>
<td>22,341</td>
<td>27,502</td>
<td>1,300</td>
<td>9,295</td>
<td>7,872</td>
<td>99,788</td>
</tr>
<tr>
<td>Non-Forrested Vegetation</td>
<td>9,145</td>
<td>79,450</td>
<td>53,660</td>
<td>108</td>
<td>1,049</td>
<td>5,461</td>
<td>148,873</td>
</tr>
<tr>
<td>Forested Vegetation</td>
<td>9,900</td>
<td>76,929</td>
<td>518,657</td>
<td>330</td>
<td>5,921</td>
<td>2,673</td>
<td>614,411</td>
</tr>
<tr>
<td>Water</td>
<td>891</td>
<td>325</td>
<td>2,238</td>
<td>500,418</td>
<td>12,908</td>
<td>411</td>
<td>517,191</td>
</tr>
<tr>
<td>Marsh</td>
<td>2,207</td>
<td>1,588</td>
<td>2,312</td>
<td>419</td>
<td>39,107</td>
<td>107</td>
<td>45,740</td>
</tr>
<tr>
<td>Barren</td>
<td>11,853</td>
<td>34,333</td>
<td>69,446</td>
<td>570</td>
<td>1,665</td>
<td>9,295</td>
<td>127,162</td>
</tr>
<tr>
<td>1990Totals</td>
<td>65,474</td>
<td>214,967</td>
<td>673,815</td>
<td>503,145</td>
<td>69,946</td>
<td>25,818</td>
<td></td>
</tr>
</tbody>
</table>
**Accuracy Assessment**

The accuracy assessment was done using only the 2000 LULC data. This was the focus of the study as it was determined that there was no viable, valid method for gathering ground truth data for the 1990 imagery. Table 4.3 shows the error matrix used to calculate the accuracy report. The columns represent the actual ground cover determined by ground truthing. The rows represent the computer classified LULC classes. In the first row, nineteen of the sixty-four sites visited were classified urban. Of the nineteen sites, fifteen were actually urban, one was actually non-forested vegetation, two were identified as forested vegetation, and one was found to be barren. In the first column, twenty of the sixty-four sites were found to be urban from ground truthing. Of the 20 urban sites, fifteen of the sites were classified urban, two of the sites were classified as non-forested vegetation, one site was classified forested vegetation, and two sites were classified as barren.

Table 4.3: Classification Error Matrix

<table>
<thead>
<tr>
<th>Classification Based on Computer Analysis</th>
<th>Classification Based on Ground Truthing</th>
<th>Urban</th>
<th>Non-Forested Vegetation</th>
<th>Forested Vegetation</th>
<th>Water</th>
<th>Marsh</th>
<th>Barren</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td></td>
<td>15</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>19</td>
</tr>
<tr>
<td>Non-Forested Vegetation</td>
<td></td>
<td>2</td>
<td>6</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>Forested Vegetation</td>
<td></td>
<td>1</td>
<td>0</td>
<td>21</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Marsh</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Barren</td>
<td></td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>20</td>
<td>8</td>
<td>29</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>64</td>
</tr>
</tbody>
</table>
Table 4.4 shows the producer’s accuracy, the user’s accuracy, and the overall accuracy. Producer’s accuracy, the percentage of known sites that are correctly classified, indicates how well known cover types are classified. For example, the producer’s accuracy for the urban LULC was found by dividing the total number of known urban sites (20) by the number of sites that were both classified as urban and known to be urban (15). This results in an urban producer’s accuracy of 75%. User’s accuracy, the percentage of classified pixels that match the actual LULC class, is a measure of how often a pixel classified into a given category represents the actual ground cover. In this case, the user’s accuracy for the urban LULC was found by dividing the total number of sites that were classified as being urban (19) by the number of sites that were both classified urban and known to be urban (15). This results in an urban user’s accuracy of 78.9%.

Table 4.4: Accuracy Assessment Report

<table>
<thead>
<tr>
<th>Classification</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>75.0%</td>
<td>78.9%</td>
</tr>
<tr>
<td>Non-Forested Vegetation</td>
<td>75.0%</td>
<td>42.9%</td>
</tr>
<tr>
<td>Forested Vegetation</td>
<td>72.4%</td>
<td>91.3%</td>
</tr>
<tr>
<td>Water</td>
<td>66.7%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Marsh</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Barren</td>
<td>66.7%</td>
<td>40.0%</td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td></td>
<td>73.4%</td>
</tr>
</tbody>
</table>

From Table 4.4 the overall accuracy of the 2000 LULC classification map is 73.4%. This may have been acceptable if it were not for the individual statistics for
the user’s and producer’s accuracies. The accuracies for the water, marsh, and barren LULC classes do not line up with the overall accuracy. In looking back at the number of sites visited during the ground truthing, it was noted that there were three or less sites selected for ground truthing for each of the three LULC classes in question. Three site visits per LULC class for ground truthing are not enough to produce reliable results. Also, the user’s accuracy for the non-forested vegetation LULC class is considerably less than that of the overall accuracy. This may be due to the significant difference in the number of sites selected for ground truthing that were classified as forested vegetation (29) verses non-forested vegetation (8). Upon looking at the classification error matrix (Table 4.3), one can see that six of the sites classified as forested vegetation were determined to be non-forested vegetation. The six misclassified sites cause a much bigger difference in the accuracy results of the non-forested vegetation as compared to accuracy results of the forested vegetation.
CHAPTER V
CONCLUSIONS AND RECOMMENDATIONS

Various federal, state, and local agencies as well as a number of resource agencies have the task of gathering LULC information for planning and resource management purposes. With the increasing speed of development and the escalating demands on limited resources on the Mississippi Gulf Coast and other locations, it is more important than ever to find a viable method for mapping the various land cover and land uses and document the changes in LULC taking place. The methodology should be a repeatable process that can be completed in a timely, cost effective, and accurate manner. The overall scope of this paper was to determine if it is feasible to use remote sensing and GIS to produce a Level 1 LULC maps and determine the changes that are taking place over a given span of time.

Conclusions

Based on the results from this project, several conclusions can be made concerning the methodology used to produce the LULC maps, to determine the LULC maps’ accuracy, and to examine the changes taking place over time.

(1) Creating the LULC map is relatively quick. Once the satellite information was obtained, the most time consuming portion of building the LULC map is gathering the data for the training sites.
(2) Creating a LULC map using the researcher’s methodology is a repeatable process. The methodology was used to create two LULC maps. The maps were created from two different data sets from the Landsat 5 and Landsat 7 satellites.

(3) The overall accuracy was questionable. Although the overall accuracy obtained from the 2000 LULC map was shown to be 73.4%, a reasonable accuracy, the associated producer’s and user’s accuracies were questionable. The number of ground truthing sites for each of the LULC classes should have been greater.

(4) Due to an increased road networks from residential, commercial and industrial development and vice versa, using a road buffered LULC map to create randomly generated ground truthing sites may create a bias towards urban areas. This is especially the case if the number of ground truthing sites selected for a LULC class is weighted towards the ratio of the LULC class to the road buffered LULC map.

(5) Creating maps and tables to show the changes that take place over time in the LULC classes is a relatively simple task with the proper software. The maps illustrate where the changes are taking place, and the tables explain the type of conversions that are occurring. Development, habitat infringement, and foresting impacts are all types of conversions that can be indicated by the maps and tables created.

(6) Creating LULC maps and determining the changes taking place in the LULC classes is a repeatable process that can be done in a timely manner. However,
the ground truthing done by the researcher was not sufficient to produce a
reliable accuracy. Therefore the LULC maps and the changes shown to be
taking place are suspect. This result can be attributed, at least in part, to
limitations imposed on the collection of data used for ground truthing.
Further, the number of ground truthing locations may have been insufficient to
allow surface characterization for the region examined.

(7) If the overall accuracy were reliable, then it is feasible to use Remote Sensing
and GIS as tools to create LULC maps.

**Recommendations**

Several improvements could be made to the methodology.

- Use winter imagery as well as that from the summer in classifying a region.

  A number of urban areas and wetland in the study were inundated with
  hardwoods and would be easier to detect during a leaf off period. In
  subsequent research, O’Hara et al. (2003) used both leaf on and leaf off’
  Landsat imagery to classify the LULC types. Not only were they able to
  reliably increase the overall Level 1 classification accuracy from 73.4% to just
  over 90%; they were able to get an overall Level 2 classification accuracy just
  over 85%.

- The selection and number of accuracy assessment sites should be strongly
  considered when ground truthing. The assessment made for this study did not
  have enough water, marsh, and barren assessment sites to show a true trend on
  which to base the accuracy. It has been suggested that a minimum of 50 sites
for each LULC class should be used when performing the accuracy assessment (Lillesand and Kiefer, 2000).

- The number of ground truthing sites for each classified LULC class should be approximately equal. If there is a significant difference in the number of pixels used for ground truthing from one LULC class to another, it can affect the user’s and producer’s accuracies. The user’s accuracy for non-forested vegetation was skewed because the number of non-forested vegetation classified sites used in ground truthing was much less than the number of forested vegetation classified sites. An equal number of ground truthing sites for each LULC class would also do away with any bias due to ground truthing from a road buffered LULC map.

- Individual pixels were used as the sample unit when the ground truthing sites were selected in this research. According to Lillesand and Kiefer (2000), the sample unit may be defined as individual pixels, a collection of pixels, or a polygon. The type of sample unit is dependant on the application. Currently, polygon sampling was listed as seeing the most use. For future research the type of sampling unit used in ground truthing should be chosen with due consideration.
References Cited

Land Cover Classification System for Use with Remote Sensor Data. United


Cover Mapping Using Multiple Image Types,” ASPRS Annual Conference
Proceedings: From Image to Information, pp. 687-698.

Infrastructure and Socio-Economic Attributes” Photogrammetric Engineering &

Interpretation. John Wiley & Sons, Inc. New York, N.Y.

Mississippi Automated Resource Information System (MARIS). (2001). Land
Use/Land Cover Maps: Hancock, Harrison, and Jackson Counties. Retrieved from
the World Wide Web: http://www.maris.state.ms.us/

Land Use and Land Cover Classification of Urbanized Areas within Sensitive
Coastal Environments” IEEE Transaction in Geosciences and Remote Sensing,

ERDAS Worldwide Headquarters. Atlanta, Georgia.

University of Mississippi, State Data Center of Mississippi (2001). Public law data
from the World Wide Web: http://www.olemiss.edu/depts/sdc/countygro.pdf/

Resources Monitoring. Columbia University Press. New York, NY

41