Spatial and Topological Analysis of Urban Land Cover Structure in New Orleans Using Multispectral Aerial Image and Lidar Data

Shuxian Liu

Follow this and additional works at: https://digitalcommons.lsu.edu/gradschool_theses

Part of the Physical and Environmental Geography Commons, Remote Sensing Commons, and the Spatial Science Commons

Recommended Citation

This Thesis is brought to you for free and open access by the Graduate School at LSU Digital Commons. It has been accepted for inclusion in LSU Master's Theses by an authorized graduate school editor of LSU Digital Commons. For more information, please contact gradetd@lsu.edu.
SPATIAL AND TOPOLOGICAL ANALYSIS OF URBAN LAND COVER STRUCTURE IN NEW ORLEANS USING MULTISPECTRAL AERIAL IMAGE AND LIDAR DATA

A Thesis
Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science

in

The Department of Geography and Anthropology

by
Shuxian Liu
B.S., Sun Yat-Sen University, June 2014
May 2020
ACKNOWLEDGEMENTS

At the time of finishing this thesis, I would like to thank many people for providing academic advice and various assistance to support my graduate study and thesis research project at Louisiana State University.

I owe special thanks to my advisor, Dr. Lei Wang, for his guidance, stimulating suggestions and thoughtful comments. His advice and support at all points along the way have helped me to clarify critical concepts, to master important technical skills, and to focus on the key research problems. I would like also to note my gratitude to Dr. Fahui Wang and Dr. Keim, and their informative courses have offered me necessary analytical techniques and geospatial analysis methods to conduct this research. My thanks also go to Mr. Sai, who supervised my research assistant work at LSU Facility Service, and I learned a lot of practical GIS and remote sensing techniques and communication skills over there. I am deeply indebted to Dr. Lei Wang and Dr. Fahui Wang for recommending me for this research assistant position, which made it financially possible for me to complete my graduate study at LSU.

Finally, much gratitude goes to my mother, Xinmei Zhao, and my father, Hongsheng Liu, for their love, constant emotional support and encouragement.
# TABLE OF CONTENTS

ACKNOWLEDGEMENTS .............................................................................................................. ii

ABSTRACT ................................................................................................................................. vii

CHAPTER 1. INTRODUCTION ................................................................................................. 1
  1.1 Research Background ...................................................................................................... 1
  1.2 Previous Methods for Urban Land Use and Land Cover Classifications ..................... 3
  1.3 Research Gaps and Problems ......................................................................................... 5
  1.4 Research Objectives ....................................................................................................... 7
  1.5 Structure of This Thesis ................................................................................................. 8

CHAPTER 2. RESEARCH METHODS ..................................................................................... 10
  2.1 Research Methods ......................................................................................................... 10
  2.2 Case Study Area - New Orleans ................................................................................... 13
  2.3 Data Sets Used in This Study ....................................................................................... 16

CHAPTER 3. URBAN LAND COVER CLASSIFICATION ..................................................... 22
  3.1 Data Preprocessing ....................................................................................................... 22
  3.2 Coarse Land Cover Classification Using Multispectral Aerial Image in the First Stage... 25
  3.3 Solar Shadow Simulation based on LiDAR and Separation of Water from Shadows ..... 27
  3.4 Rule-based Detailed Classification of Urban Land Cover in the Second Stage .......... 31
  3.5 Accuracy Assessment of Urban Land Cover Classification ......................................... 35

CHAPTER 4. ANALYSIS OF URBAN LAND COVER STRUCTURE AND
INERENCE OF URBAN LAND USE TYPES ........................................................................... 39
  4.1 Quantitative Analysis of Land Cover Structure in Different Urban Districts ................ 39
  4.2 Characteristics of Land Cover Structure for Different Land Use Types ..................... 40
  4.3 The Graph-theoretic Data Model for Land Cover Objects ............................................ 43
  4.4 Derivation of Thematic, Structural and Topological Attributes of Land Cover Objects .. 44
  4.5 Computational Inference of Land Use Types with Random Forest Method ............... 45
  4.6 Evaluation of the Importance of Thematic, Structural and Topological Attributes ...... 46
  4.7 Validation and Accuracy Assessment of Urban Land Use Inference .......................... 49

CHAPTER 5. CONCLUSIONS .................................................................................................. 50

REFERENCES ......................................................................................................................... 53

VITA ............................................................................................................................................ 55
LIST OF TABLES

Table 1. Classification of Building Types according to Building Height ........................................ 34
Table 2. Accuracy Assessment of Land Cover Classification from Two-stage Rule-based Method ................................................................. 34
Table 3. Accuracy Assessment for Per-pixel ISODATA Method on 5-band stacked Aerial Image ................................................................. 34
Table 4. Accuracy Assessment for Per-pixel ISODATA Method on Image and LiDAR Combined Data ............................................................................ 34
Table 5. Land Cover Structure for Different Urban Districts ........................................................................ 35
Table 6. Building Type Structure for Different Urban Districts ........................................................................ 36
Table 7. Land Cover Structure for Different Urban Land Use ........................................................................ 43
Table 8. Building Type Structure for Different Urban Land Use ........................................................................ 43
Table 9. Definition of 27 Variables in RANG Data Model ........................................................................ 45
Table 10. Accuracy Assessment for Urban Land Type Inference and Classification .......................... 49
LIST OF FIGURES

Figure 1. Data Flow and Processing Procedure ................................................................. 11
Figure 2. Geographic Location of New Orleans, Louisiana .................................................... 14
Figure 3. Case Study Area: New Orleans, Louisiana, USA .................................................... 15
Figure 4. Surface Topography of New Orleans. Blue Areas are below Sea Level ................. 16
Figure 5. Multispectral Aerial image. a) Natural Color Composition of Blue, Green and Red
     Bands; b) False Color Composition of Green, Red and NIR Bands .............................. 18
Figure 6. Airborne LiDAR Data in CBD Area of New Orleans. a) LiDAR Point Clouds; b)
     Digital Surface Model at 1 m resolution ....................................................................... 19
Figure 7. Zoning Districts and Land Use Codes in New Orleans ............................................. 20
Figure 8. Normalized Difference Vegetation Index Derived from Red and NIR bands of Aerial
     Image ............................................................................................................................ 23
Figure 9. Hill-shaded Relief Map of LiDAR Digital Surface Model (DSM) around CBD of New
     Orleans .......................................................................................................................... 24
Figure 10. Broad Land Cover Classification Result based on the Blue, Green, Red and NIR of
         Aerial Image and NDVI Data Layer with ISODATA Unsupervised Method .................. 26
Figure 11. The Solar Illumination Geometry and Shadows. a) Illustration of Sun Elevation
         Angle and Azimuth Angle; b) Shadow Length and Solar Elevation Angle ..................... 28
Figure 12. Comparison of Solar Shadows in Aerial Image with the Simulated Shadows from
         LiDAR DSM. a) Aerial Image; b) Hill-shaded Relief Image with Simulated Shadows from
         LiDAR DSM .................................................................................................................. 29
Figure 13. Separation of Water Bodies from Solar Shadows .................................................. 30
Figure 14. Inference of Land Cover Type for Solar Shadows according to Geographic Proximity
         Analysis. a) Land Cover Holes Caused by Shadows; b) after Shadows are Assigned Nearest
         Land Cover .................................................................................................................... 31
Figure 15. Morphologic Operations on Artificial Objects. a) before Morphologic Operations; b)
         after Morphologic Operations c) before Morphologic Operations; d) after Morphological
         Operations .................................................................................................................... 32
Figure 16. Final Detailed Land Cover Classification Result from the Two-stage Rule-based Method ............................................................................................................................................. 34

Figure 17. Randomly Sampled Points for Accuracy Assessment of the Urban Land Cover Classification ........................................................................................................................................................................ 36

Figure 18. Typical urban Land Use Types. a) Single-family Residential; b) Two-family Residential; c) Multi-family Residential, d) CBD; e) Commercial; f) Institutional; g) Parks and Open Space ........................................................................................................................................................................ 41

Figure 19. a) Spatial Distribution of Block Samples for Different Types of Urban Land Uses b) Spatial Distribution of Training Block Samples ........................................................................................................................................................................ 42

Figure 20. Box Plots of Three Selected Variables ........................................................................................................................................................................................................... 47

Figure 21. The Ordered List of Variable Importance Calculated by Mean Decrease Gini. .......... 48
ABSTRACT

Urban land use and land cover (LULC) mapping has been one of the major applications in remote sensing of the urban environment. Land cover refers to the biophysical materials at the surface of the earth (i.e., grass, trees, soils, concrete, water), while land use indicates the socio-economic function of the land (i.e., residential, industrial, commercial land uses). This study addresses the technical issue of how to computationally infer urban land use types based on the urban land cover structures from remote sensing data. In this research, a multispectral aerial image and high-resolution LiDAR topographic data have been integrated to investigate the urban land cover and land use in New Orleans, Louisiana. First, the LiDAR data are used to solve the problems associated with solar shadows of trees and buildings, building lean and occlusions in the multispectral aerial image. A two-stage rule-based classification approach has been developed, and the urban land cover of New Orleans has been classified into six categories: water, grass, trees, imperious ground, elevated bridges, and buildings with an overall classification accuracy of 94.2%, significantly higher than that of traditional per-pixel based classification method. The buildings are further classified into regular low-rising, multi-story, mid-rise, high-rise, and skyscrapers in terms of the height. Second, the land cover composition and structure in New Orleans have been quantitatively analyzed for the first time in terms of urban planning districts, and the information and knowledge about the characteristics of urban land cover components and structure for different types of land use functions have been discovered. Third, a graph-theoretic data model, known as relational attribute neighborhood graph (RANG), is adopted to comprehensively represent geometrical and thematic attributes, compositional and structural properties, spatial/topological relations between urban land cover patches (objects). Based on the evaluation of the importance of 26 spatial, thematic and topological variables in RANG, the random forest classification method
is utilized to computationally infer and classify the urban land use in New Orleans into 7 types at the urban block level: single-family residential, two-family residential, multi-family residential, commercial, CBD, institutional, parks and open space, with an overall accuracy of 91.7%.
CHAPTER 1. INTRODUCTION

1.1 Research Background

Information and knowledge about urban land use and land cover are important for urban planning and land resource managements. In the past decades, remote sensing technology has been widely used in urban land use and land cover (LULC) mapping applications in the world (Corbley 1996, Ridley et al. 1997). The terms “land cover” and “land use” have been often used in the literature interchangeably. However, their actual meanings are quite distinct in a strict sense. Land cover refers to the biophysical materials at the surface of the earth, such as, grass, trees, soils, asphalt, concrete, water, etc. In contrast, land use indicates the socio-economic function of the land, such as residential, industrial, commercial land uses, etc. It is a description of how people utilize the land (Barnsley and Barr 1997, Pauleit and Duhme 2000). Compared with natural scenes in rural areas, the urban landscape is much more complex and heterogeneous in terms of land cover composition and spatial arrangement. The urban landscape consists of diverse man-made and natural features, i.e., buildings, streets, bridges, parking lots, parks, lawns, trees, water ponds, etc. (Wu et al. 2018, Lowry and Lowry 2014). For example, many cities in Western European are often characterized by a complex spatial assemblage of tile roof and slate roof buildings, tarmac and concrete roads (Walde, Irene, et al, 2013). The same land cover can be used for different purposes and functions, and different land covers may be spatially arranged in a specific pattern to serve a common purpose and urban function.

Multispectral satellite remote sensing data with moderate spatial resolution (10-30 m), such as Landsat TM, SPOT, ASTER, have been utilized in exploratory investigations of the urban land cover classifications in the past decades (Foster 1980). The spectral measurements from
multispectral and hyperspectral remote sensing data closely relate to the biophysical properties of
land cover. Welch (1982) emphasized the importance of spatial resolution in addition to spectral
resolution for urban land cover and land use classification. Aerial photographs have long been
used effectively to support urban studies and urban planning activities (Jensen 1983, Garry 1992)
due to their high spatial resolution and wide availability. The emergence of high-resolution
multispectral satellite images (i.e. IKONOS, QuickBird and WorldView) and the increasing
availability of multispectral aerial images have made it possible to accurately map urban land
covers with a high fidelity. Previous studies show that multispectral satellite images with a spatial
resolution better than 5 m are able to disentangle various urban features in the dense old urban
cores (Foster 1983), and hence provide very detailed urban land cover information. Many studies
also demonstrated that the incorporation of the high-resolution LiDAR topographical
measurements can further improve the reliability, accuracy and detail level for urban land cover
classification (Barnsley and Barr 1996, Deloach 1998).

Urban land cover information can be directly derived from remote sensing data and is often
referred to as the first-order raw information. In contrast, urban land use information can be only
inferred by integrating the urban land cover information and other factors, which is referred to as
the second-order semantic information or higher-level thematic information (Barr and Barnsley
1997). Despite the progress and maturity in urban land cover classification, interpretation and
inference of urban land use types from remote sensing data are still a very difficult and challenging
task. Although the cities are spatial assemblages of diverse land cover parcels, different urban
function districts may have similar structure pattern, morphology and spatial properties. Many
scholars have observed that different types of urban land use have their unique characteristics in
This observation lays the theoretical foundation for the interpretation and inference of urban land use types from remotely sensed land cover structure.

1.2 Previous Methods for Urban Land Use and Land Cover Classifications

With the rapid development of remote sensing technology and the launches of various satellites, many land use and land cover classification algorithms and methods have been proposed and developed in the literature. Previous classification methods include visual interpretation of aerial photographs (Gill et al. 2008), traditional per-pixel based supervised and unsupervised classification methods, the kernel-based contextual classification methods (Herold et al. 2003, Stefanov and Netzband 2010), object-based methods (Baatz and Schäpe 2000, Benz et al. 2004, Hay and Castilla 2008, Blaschke 2010), and the graph-theoretic methods (Barnsley and Barr 1996, Barr and Barnsley 1997, Voltersen et al. 2014, Walde et al. 2014, Wu et al. 2018).

Some kernel-based contextual methods analyze class label frequency within a pre-defined moving window to determine the dominant land cover type associated with the central pixel (Wharton 1982). Other relative sophisticated kernel-based methods utilize texture or spatial metrics derived at different scales of spatial units, such as patch density, fractal dimension, complexity, entropy, and variance, to characterize the spatial-contextual arrangement of land covers within a regular window (Herold et al. 2003, Banzhaf and Hofer 2008, Ruiz Hernandez and Shi 2018). The kernel-based contextual classification algorithms account for not only the spectral properties of pixels but also its relationship to neighbor pixels. However, the performances of most kernel-based contextual classification methods are limited, due to the fixed size and shape of the moving window as the basic spatial unit for the derivation of texture and spatial metrics (Li et al. 2016).
Different from traditional per-pixel based classification methods that only utilize spectral information alone, object-based classification methods (Baatz and Schäpe 2000, Benz et al. 2004, Hay and Castilla 2008, Blaschke 2010) use image objects rather than individual pixels as basic spatial units in the classification. In object-based classification methods, an image is first segmented into discrete image objects (also known as patches, segments, parcels, regions), and each image object consists of adjacent pixels with similar properties (e.g. spatial and spectral). Then, both spectral and spatial information (e.g. size, shape, orientation) of image objects are used in the classification. With the advent and proliferation of high-resolution remote sensing imagery, the use of object-based classification method has largely increased in the recent decade.

The graph-theoretic methods have been proposed to incorporate structural properties and spatial relations between land cover objects to infer the urban structure and urban land use types in addition to the spectral and geometric properties of land cover objects (Voltersen et al. 2014; Waldel et al. 2014; Wu et al. 2018). The assumption is that each urban land use type exhibits distinct, consistent composition and spatial pattern of land cover objects and that urban land use function types can be inferred determined through analyzing the structural characteristics of and spatial relations between land cover objects (Barnsley and Barr 1996, Banzhaf and Höfer 2008, Schöpfer et al. 2008). Barr and Barnsley (1997) proposed a data model “eXtended Relational Attributed Graph” (XRAG) to represent and analyze the morphological, spatial, and relational properties of land cover objects for urban land use inference. Their seminal work has laid a solid foundation for the graph-theoretic based methods for inferring and classifying urban land cover structures and urban land use functions. An adjacent-event matrix derived from undirected graphs has been used to derive various attributes (variables) for modeling and describing the occurrence frequency and spatial arrangement of land cover objects (Barnsley and Barr, 1996; Kontoes et al.
Walde et al. (2014) proposed four sets of graph measures (variables) based on the neighborhood graphs for the purpose of inferring and classifying urban structure types and urban land use functions. Those include centrality measures, adjacency-event measures, connectivity measures, and additional measures, which quantitatively describe the spatial arrangement and structural relations between urban land cover features. Wu (2018) developed a new graph-theoretic data model known as Relational Attributed Neighborhood Graph (RANG). The RANG data model incorporates the graph measures (variables) of Walde et al. (2014) and significantly extended XRAG data model proposed by Barr and Barnsley (1997). Since the RANG data model includes geometric and compositional properties, hierarchical thematic relations and topological (spatial) relations between land cover objects, it is argued and demonstrated that the semantic information about urban structures and knowledge about urban land use function types may be computationally inferred and classified more effectively and accurately than previous methods (Wu et al. 2018, Wu 2018).

1.3 Research Gaps and Problems

Traditional per-pixel based classification methods with moderate resolution remote sensing image data are adequate for reliable and accurate urban land cover classification and urban land use interpretation. Some urban land covers may have similar spectral response which may lead to interpretive confusion. Many urban features (e.g. buildings, roads, parking lots) have a relatively small size and complex spatial pattern, and they cannot be resolved and extracted from coarse and moderate resolution images. High resolution remote sensing data with object-based classification has been increasingly used in the urban land cover and land use studies.

Although high-resolution multi-spectral remote sensing images provide adequate spatial details and spectral information for urban land cover recognition and classification, some technical
problems need to be addressed in the land cover classification. Due to trees, buildings and other elevated objects, fine resolution multispectral images suffer from solar shadows. The shadows appear as dark features, and sometimes they are difficult to be distinguished from water bodies. The true land cover types in the shadows are difficult to be determined based on the spectral information. In addition, high buildings are distorted from their true locations. The relief displacement makes tall buildings appear to lean over streets or other objects such as manholes, utility poles, and lower buildings. Building lean and occlusion problem is particularly serious in aerial images due to the inaccurate digital surface elevation model and incomplete orthorectification of aerial images (Zhou et al., 2005). A technique is required to address the solar shadow and building occlusion problem in the land cover classification of multispectral images.

Previous studies have demonstrated the integration of LiDAR topographic data with multispectral image data can enhance urban land cover classification. Previously, the height information from LiDAR data is often stacked as an additional data layer to spectral bands of the multispectral imagery and then used as input to per-pixel based or object-based classification algorithms. However, how to effectively fuse topographic and morphologic information from LiDAR into spectral information of multispectral imagery still needs further investigation and research.

Although many studies have been conducted and published for the city of New Orleans, the characteristics and structural properties of urban land cover in New Orleans are still largely unknown. Despite the availability of various high-resolution remote sensing data, no research has been reported to derive quantitative information about land cover components and their compositional and structural properties for different urban districts and different types of urban land use functions in New Orleans.
Simple object-based data models are not enough to numerically represent land cover structural properties and their topologic relations. XRAG, RANG and other graph-theoretic data model have been proposed to give a comprehensive description of geometric, morphologic, thematic properties and spatial relations between land cover objects and to support the computational interpretation and inference of urban land use types. Due to the intricacy and complexity of urban landscape, there is an uncertainty as to how natural and artificial land covers and features are spatially aggregated and arranged (Foster 1985). The relationship of urban land cover components with their urban land use functions is often indirect and complicated (Barr & Barnsley, 1997). So far, XRAG and RANG data models were only applied to a very small number of cities, and their effectiveness was only tested and examined for inferring and classifying a few of broadly and coarsely defined urban land use types. The graph-theoretic data model and associated structural and topological variables need to be evaluated for more and diverse cities for more finely defined urban land use types as to which variables are more important in the inference of land use types and what level of accuracy can be achieved in the more detailed classification of land use types.

1.4 Research Objectives

In recognition of the research gaps and problems, this research intends to tackle technical issues in the integration of multispectral aerial image and airborne LiDAR data for urban land cover classification and to evaluate the utility and effectiveness of RANG graph-theoretic data model in the computational inference of land use types in the case of New Orleans. Specific research objectives are to:

1) Develop a LiDAR based simulation technique to solve solar shadow problems in multispectral aerial image in urban land cover classification;
2) Develop a two-stage rule based classification method to integrate multispectral aerial image and airborne LIDAR data to overcome building lean and occlusion problems and to create a reliable and detailed land cover map; 

3) Derive quantitative information about land cover components and structure for different urban districts of New Orleans and analyze the characteristics of land cover composition and structure for different types of urban land use types in New Orleans; and 

4) Explore and evaluate the RANG graph-theoretic data model and its geometrical, thematic and topological variables about urban land cover objects in the computational inference of urban land use types, identify the most effective variables, and assess the land use type inference accuracy.

1.5 Structure of This Thesis

The present introductory chapter began with the explanations of two basic concepts “land cover” and “land use” and discussed the complexity of urban landscape and technical difficulties in the remote sensing of urban land cover and land use. Then, the previous remote sensing classification methods were reviewed with the general discussion of their rationales, characteristics, comparative advantages and disadvantages. Next, the research gaps and problems in remote sensing of urban land cover and land use are examined and identified. The specific research objectives for this research are designed and presented to overcome the problems and fill the research gaps in the previous studies.

After this introductory Chapter, the research methods will be overviewed, and the case study area and associate data sets used in this research will be described in Chapter 2. Subsequently, Chapter 3 focuses on the two-stage rule based classification of urban land cover in New Orleans. First, the data preprocessing techniques will be introduced to create NDVI and normalized digital surface model (nDSM). Then, the first-stage coarse land cover classification with four spectral
bands of the aerial image along with the derived NDVI data layer is presented. Afterwards, the LIDAR based solar shadow simulation method is presented to separate true solar shadows from water bodies. Through use of spatial proximity rule through ArcGIS nibble function, the urban land cover in shadows is determined. This is followed by the detailed description of the second-stage detailed land cover classification by integrating airborne LiDAR data. A set of rules are applied to segment LiDAR data to derive building and tree objects. The geometric properties of image objects are analyzed to develop rules for recognizing true buildings. Finally, a rigorous accuracy assessment is performed for the final urban land cover classification result. Chapter 4 starts with a section reporting the quantitative analysis of land cover components and structure for different urban districts in New Orleans. Then, the urban land use types in the case study area of New Orleans are defined, a set of training sample blocks are selected for these land use types, and the land cover structural properties for different types of land use blocks are examined and presented. The next section of this chapter present RANG graph-theoretic data model and the definition and derivations of associated variables. In the final section, the inference results for urban land use type from the random forest method are discussed, and the urban land use type inference and classification accuracy supported by the RANG data model and random forest method is evaluated for New Orleans. The final chapter, Chapter 5, summarizes the findings and contributions of this research and notes the limitations of this research.
CHAPTER 2. RESEARCH METHODS

2.1 Research Methods

This research aims to address the technical problems in the classification of urban land covers and the inference of urban land use types with remote sensing data. The city of New Orleans is used as the case study urban area. The primary data sets used in this study include a multispectral aerial image, airborne LiDAR data, and some ancillary GIS data layers. The key techniques and methods involved in this research include:

- initial coarse land cover classification in the first stage using the aerial image and NDVI data layer;
- LiDAR based solar shadow simulation and the separation of true shadows from water bodies;
- rule based classification method in the second stage for integrating multispectral aerial image and LiDAR data to achieve a fine scale urban land cover classification;
- the construction of RANG graph-theoretic data model and the derivation of geometrical, thematic and topological attributes/variables about urban land cover objects, and
- computational inference of urban land use types with the random forest method.

The data flow and processing procedure is illustrated in Figure 1. A NDVI data layer is derived from the red and NIR bands of 4-band aerial image using ERDAS Imagine software tool. Then, the NDVI data layer is stacked with 4 spectral bands of the aerial image as input to the coarse classification of the urban land covers. The ISODATA unsupervised classification is applied to the input spectral data consisting of four spectral bands of aerial image and NDVI data layer, and the urban land cover is coarsely classified into 3 broad classes: impervious surface,
vegetation, and dark features. Dark features include solar shadows of trees and buildings and water bodies, and they cannot be confidently separated using the spectral information alone at this stage.

The airborne LiDAR point clouds are interpolated into a Digital Surface Model (DSM), and a median filter is applied to reduce the data noise. By subtracting a bare-earth LiDAR DEM from the LiDAR DSM, a normalized digital surface model (nDSM) is created to represent the building and vegetation canopy height. The shadow lengths for several buildings are measured in the multispectral aerial image, and the heights of these buildings are obtained from nDSM. The building height and the shadow length are combined to estimate the elevation angle and azimuth angle of sun when the aerial image was acquired. Then, the shadows of trees and buildings are simulated using the LiDAR DSM. The sizable dark features that do not match the LiDAR simulated shadows are inferred to be water bodies, and those dark features that partially or completely match the LiDAR simulated shadows are inferred to be shadows. Then, adjacent shadow pixels are identified to form shadow objects using ArcGIS region group tool, and these

Figure 1. Data Flow and Processing Procedure
shadow objects are recoded to be either vegetation or impervious surface land cover according
their geographical proximity using the ArcGIS nibble tool. Through the above operations, the three
broad classes of vegetation, impervious surface and dark features in the initial urban land cover
classification are adjusted and updated. In this way, the shadow problem is solved in the first stage.
The updated urban land cover classes include vegetation, impervious surface and water.

In the second stage, the rule-based method is used to refine the initial broad land cover
classification by explicitly incorporating airborne LiDAR data. The elevated objects such as trees
and buildings in airborne LiDAR data do not have the building lean and occlusion problems, and
their geographic location and geometric footprint are not distorted in LIDAR data. Therefore, the
location and spatial extent of trees and artificial objects are determined mainly based on the LiDAR
nDSM. By using a set of heuristic rules and prior knowledge, the LiDAR nDSM is segmented into
ground, trees, and man-made objects. Through the overlay analysis, the broad classes in the first
stage classification are refined. The vegetation class is further separated into grass and tree, and
the impervious surface class is further separated into impervious ground and man-made objects. It
should be noted that artificial objects not only include buildings but also bridges, electricity poles
and lines, urban street furniture, etc. By using ArcGIS region group tool and zonal functions, the
size, thickness and shape compactness of artificial objects extracted from LiDAR nDSM are
computed. According to the heuristic rules about the size, thickness and compactness, the artificial
objects are separated into buildings, bridges, and non-building objects (electricity poles and lines,
street furniture, booths, etc.). Through above the operations in the second stage, the fine and
detailed urban land cover classification is achieved, including 6 land cover classes: grass, trees,
impervious ground, water, bridges and buildings. Buildings are further classified into 5 categories:
ordinary low-rise, multi-story, mid-rise, high-rise and skyscraper. The final detailed land cover
classes resulted from the two-stage rule based classification procedure provide a solid foundation for the subsequent analysis of land cover structure in New Orleans and the inference of urban land use types.

The graph-theoretic data model RANG developed by Wu (2018) has been adopted in this research to represent and model structural and spatial relations between urban land cover objects. Based on the adjacent-event matrix and undirected graph, a set of variables describing geometric, thematic, structural properties and spatial relations between urban land cover objects are derived, which are then used as the input variables for the computational inference of land use types with the random forest method. The importance of these input variables are evaluated, the accuracy of the random forest method is assessed for the inference of urban land use types, including single-family residential, two-family residential, multi-family residential, commercial, CBD, institutional, and parks and open space.

2.2 Case Study Area-New Orleans

The case study area for this research is the core part of the city of New Orleans, Louisiana. As shown in Figure 2, the case study area covers about 52 km², and it contains CBD (Central Business District), Vieux Carre (French Quarter), Mid-City, large portions of Central-city, Uptown, Marigny/Treme/Bywater, Lakeview, and Gentily districts. The center of the case study area is located at latitude of 29°58’12” N and longitude of 90°5’39” W, with a humid subtropical climate. Inside the case study area is a complex assemblage of diversified urban features, including residential buildings, commercial facilities, historical and cultural architectures, high-rise buildings, streets and roads, canals, parks, as well as industrial factories. The complex urban land cover structure and diversified land use types make it an ideal case study area for testing and evaluating techniques and methods for urban land cover and land use mapping and classification.
New Orleans is located along the Mississippi River in the southeastern region of the state of Louisiana, USA (Figure 2). It is the most populous city in Louisiana, with an estimated population of 391,006 in 2018. Serving as an important sea port, New Orleans is considered an economic and commercial hub for the broader Gulf Coast region of the United States. The historic heart of the city is the French Quarter (Vieux Carre), known for its French and Spanish Creole architecture and vibrant nightlife along Bourbon Street. The city is often described as the most unique in the United States, due to its distinct music, Creole cuisine, unique dialect, and its annual celebrations and festivals, most notably Mardi Gras. Founded in 1718 by French colonists, New Orleans has over 300 years of history. It has over 20 national register historic districts, 15 local historic districts, and many local and national landmark buildings. About 50% of the buildings were built before World War II, the earliest dating from the 18th century. The buildings and
architecture of New Orleans embody its history and multicultural heritage. Almost every architectural style can be found in New Orleans, including Creole cottages, baroque Cabildo, historic mansions, the balconies of the French Quarter, Egyptian Revival U.S. Customs building, and modernist skyscrapers.

Situated in the alluvial plain of the Mississippi River into the Gulf of Mexico, most parts of the city are below sea level. The north of New Orleans is Lake Pontchartrain, a brackish estuary. There are four main canals in this area, 17th Street Canal, London Avenue Canal, Orleans Avenue Canal, and Industry Canal. As shown in Figure 4, 63.2% of the case study area has a surface elevation below sea level. Its geographical location and low-lying flat terrain have historically made New Orleans very vulnerable to flooding. Although state and federal governments have installed drainage pumps and a complex system of levees and sea walls against storm surges of 5.4 to 6.0 meters, storm surges and flooding caused by major hurricanes frequently devastated the city. The major flooding disaster was caused by Hurricane Katrina on August 29, 2005. Hurricane

Figure 3. Case Study Area: New Orleans, Louisiana, USA
Katrina caused levees to fail, releasing tens of billions of gallons of water. This disaster led to sustained water damage to all urban structures and facilities, thousands of deaths, and displacement of longtime residents. A full 14 years after the hurricane’s landfall, much of New Orleans has been rebuilt and 90% of New Orleans’s pre-storm population is back, although the rebuilding of the city is still a work in progress. This study examines urban land cover and land use status in 2012, 7 years of reconstructions after Hurricane Katrina.

### 2.3 Data Sets Used in This Study

This study employed a 4-band aerial image, a high resolution airborne LiDAR data set, and three ArcGIS vector data files. The multispectral aerial image and airborne LiDAR data are used as the primary input for the fine-scale urban land cover classification with the two-stage rule based method. The street block polygons in ArcGIS street-block shape file are used as basic spatial units for the urban land use interpretation and inference. The district polygons in the ArcGIS planning...
district shape file are used to statistically analyze urban land cover composition and structural characteristics in different urban districts. The planning zones in the ArcGIS zoning shape file are used to develop the training and validation data sets for urban land use types.

2.3.1 Multispectral Aerial Image

The multispectral aerial ortho-imagery used in this study was acquired on November 29, 2012 through the Louisiana Coastline Area Project. It has four spectral bands: blue, green, red, and NIR (Near Infrared). Its spatial resolution is 1 m. Figure 5a shows the natural color composite of its blue, green and red bands, and Figure 5b shows the false color composition of green, red and NIR bands.

Owing to the high spatial resolution, small urban features can be recognized on these two color image compositions. The spectral information provided by four bands is important for urban land cover classification. Nevertheless, due to the elevated trees and buildings in the urban area, the image contains a large quantity of solar shadows, which adversely affect the land cover interpretation and classification. Also, it should be pointed that the aerial image was not fully and completed orthorectified. High buildings appear to lean over streets and blocked adjacent lower buildings and urban infrastructure, and they are distorted by the relief displacement from their
true geographic locations. Both shadow and building lean/occlusion problems have to be addressed in the land cover classification.

Figure 5. Multispectral Aerial Image. a) Natural Color Composition of Blue, Green and Red Bands; b) False Color Composition of Green, Red and NIR bands.

2.3.2 Airborne LiDAR Data

The airborne Lidar data used in this study were collected in February 2012 through Hurricane and Storm Damage Risk Reduction System (HSDRRS) project. This LiDAR data set was intended to support USACE (United States Army Corps of Engineers) interior drainage modeling of floodwalls, structures, and levees. The data set was archived and provided in LAS format by the NOAA Coastal Service Center (https://coast.noaa.gov/dataviewer/#/lidar/search/). The case study area contains 359565353 laser points, and the average LiDAR sampling density is about 7 points per square meter. The elevation vertical reference system is NAVD88, and surface elevation measurements unit is foot. As shown in Figure 6a, the dense LiDAR point clouds provide
detailed description of urban morphology, and buildings and trees can be recognized. The LiDAR point clouds can be processed to create a high resolution Digital Surface Model (DSM) as shown in Figure 6b. In addition, a bare-earth Digital Elevation model (DEM) with 0.6096 meters spatial resolution (Figure 4) for the case study area was also obtained from the NOAA Coastal Service Center. The elevated natural and artificial features such as trees and buildings were removed from this bare-earth DEM.

2.3.3 Ancillary GIS Datasets

The ancillary vector GIS datasets used in this study were obtained from City of New Orleans Open Data Portal (https://portal-nolagis.opendata.arcgis.com/), which is the public platform for exploring and downloading open data of the city of NEW Orleans. These files are provided in ArcGIS shape file format, which contains the boundary polygons and associated attribute tables.
The “Squares” shape files contains street block boundaries, and the attribute table include square-ID, square name, square area, and other attributes for each block polygon. This shape file was derived from the City of New Orleans Enterprise GIS Database, which are not a survey-quality product. There are 3746 street-block polygons in the case study area. The street-block boundary polygons are used as basic spatial unit for the analysis and inference of land cover structure.

The “Planning Districts” shape file shows urban district boundaries used in-house by the City Planning Commission of New Orleans, which was created based on 1990 Census tract boundaries. The attribute table of this shape file contains Label, objectID, Name, area, and other
attributes. The “Planning Districts” shape file is used in the quantitative analysis of urban land cover composition and structure at urban district scale.

The “Zoning Districts” shape contains the zoning polygons (Figure 7). The zoning is the most important urban planning and management tool. The zoning codes permit or prohibit certain urban land uses in each zone. In addition, the sizes, bulk, and placement of buildings may be regulated. The type of zone determines whether planning permission for a given development is granted. Zoning regulates land use to promote smart growth and preserve the quality of life in communities. The attribute table of “Zoning Districts” shape file contains many attributes for each zone, including zone class, zone description, future land use, future land use description, etc. This data set has been used in this research to develop the training and validation data sets for calibrating and evaluating the random forest classifier for inferring and classifying urban street-blocks into different types of urban land uses.
CHAPTER 3. URBAN LAND COVER CLASSIFICATION

3.1 Data Preprocessing

3.1.1 Multispectral Aerial Image Preprocessing and NDVI derivation

The multispectral aerial image is projected to UTM Zone 15 with reference to the North American Datum of 1983 (NAD83). To highlight and strengthen the difference of vegetation cover with other land cover classes, a Normalized Difference Vegetation Index (NDVI) is calculated using the red and NIR bands of the aerial image using the following equation:

\[ NDVI = \frac{NIR - Red}{NIR + Red} \]  

The NDVI values given in Equation (1) ranges between -1.0 and 1.0 (Figure 8), and are then scaled to values between 0 and 255. The NDVI data layer is stacked with original four spectral bands of the aerial image to form 5-band stacked aerial mage for subsequent land cover classification.
3.1.2 LiDAR Noise Filtering and nDSM Generation

Nine LiDAR point cloud tiles from the NOAA Coastal Service Center are combined to cover the case study area. Both LiDAR point cloud data and the bare-earth DEM data are projected from Louisiana South State Plane Coordinate system to UTM Zone 15, to keep the consistency with the coordinate system of the multispectral aerial image. The elevation unit of LiDAR point clouds and bare-earth DEM has been changed from feet to meters, with the vertical reference system of NAVD88. By using a set of tie points, the geolocation co-registration error between the
multispectral aerial image and LiDAR data is estimated to 0.382 m RMSE, namely, the co-registration accuracy is better than 1 pixel (1 m).

The elevation range of original raw LiDAR point cloud for the case study area is from -150 feet to 700 feet. Those points with an elevation less than –20 feet are considered as outliers and filtered out for the subsequent analysis. Outlier points only account for 0.001% of the entire data set. After data outliers are removed, the linear TIN-based interpolation method implemented in ArcGIS is used to interpolate the first-return LiDAR points into a regular elevation grid with 1 m spatial spacing, which is known as Digital Surface Model (DSM) (Figure 9). Some random noise and errors can be observed in DSM. A median filter with a 3*3 window is applied to the DSM to reduce the data noise.

Figure 9. Hill-shaded Relief Map of LiDAR Digital Surface Model (DSM)

The elevation range of original raw LiDAR point cloud for the case study area is from -150 feet to 700 feet. Those points with an elevation less than –20 feet are considered as outliers and filtered out for the subsequent analysis. Outlier points only account for 0.001% of the entire data set. After data outliers are removed, the linear TIN-based interpolation method implemented in ArcGIS is used to interpolate the first-return LiDAR points into a regular elevation grid with 1 m spatial spacing, which is known as Digital Surface Model (DSM) (Figure 9). Some random noise and errors can be observed in DSM. A median filter with a 3*3 window is applied to the DSM to reduce the data noise.
The 2-feet resolution bare-earth DEM is resampled into 1 m spatial resolution to match the LiDAR DSM and aerial image. Then, a normalized digital surface model (nDSM) is created using the following equation:

\[ \text{nDSM} = \text{DSM} - \text{DEM} \quad (2) \]

nDSM contains the height measurements of trees, buildings and other urban objects above the ground, which provide the critical information to extract trees and buildings in the subsequent analysis.

3.2 Coarse Land Cover Classification Using Multispectral Aerial Image in the First Stage

The ISODATA (Iterative Self-Organizing Data Analysis Technique) unsupervised classification method in ERDAS Imagine software package is applied to the 5-band stacked aerial image to generate initial coarse land classification. Each pixel of the 5-band stacked aerial image is characterized by 5 spectral values of blue, green, red, NIR and NDVI bands. The ISODATA algorithm iteratively groups pixels with similar spectral characteristics into a specified number of clusters according to some statistically determined criteria.

The ISODATA algorithm first places cluster centers as seeds, which are evenly distributed in the data space, and pixels are assigned to these clusters based on the shortest distance to center method. Then, the cluster means are recalculated in the next iteration, and pixels are re-grouped using the shortest distance criteria to the new means. At each iteration, the standard deviation within each cluster and the distance between cluster centers are calculated. If the standard deviation is greater than the user-defined threshold, the cluster is split into two new clusters. If the distance between two clusters is less than a specified threshold, they are merged to one cluster. After the merging and splitting process, the means for new clusters are calculated, and every pixel in the
scene is once again assigned to one of the new clusters according to the shortest distance criteria. This iterative process continues until the number of pixels in each cluster changes between iterations is smaller than a specified change threshold or the maximum number of iterations is reached.

![Image of land cover classification result]

Figure 10. Broad land cover classification result based on the blue, green, red and NIR of aerial image and NDVI data layer with ISODATA unsupervised method.

With ISODATA unsupervised classification method, the pixels in the 5-band stacked aerial image are first grouped to 36 spectral clusters. Then, these natural spectral clusters are visually interpreted and recoded into three broad land cover classes: vegetation, impervious surface, and dark features (Figure 10). Among 36 spectral clusters, 16 clusters are combined and recoded as
vegetation, another 16 clusters are combined and recoded as impervious surface, and the remaining 4 clusters are recoded as dark features.

The vegetation class includes grass, shrubs, and trees. Impervious surface class includes building roofs, parking lots, pavements, streets, roads, etc. Small patches of bare soils can be found in the parks and golf courses. Since bare soils only constitute a tiny part of the case study area, and they are combined into the impervious surface. Dark features include water bodies and solar shadows, which cannot be unambiguously distinguished based on the multispectral aerial image and the derived NDVI. Because many land cover subclasses under vegetation class or impervious surface class have similar spectral properties, more detailed fine-scale land cover classification is not attempted with only spectral information of multispectral aerial image in the first stage.

3.3 Solar Shadow Simulation based on LiDAR and Separation of Water from Shadows

Due to the dense buildings and trees in the urban area, solar shadows have been abundant features on the high-resolution aerial image. Since surface materials and objects in the shadows do not receive direct solar illumination due to the blockage of trees or buildings, their spectral reflectances are minimal and hence appears as dark features. With the distorted spectral and radiometric properties, the true land cover type of the surface materials within shadows cannot be correctly determined and classified with the multispectral aerial image. Shadows and water bodies are spectrally similar, they cannot be unambiguously separated on the multispectral aerial image. Therefore, shadows and water bodies are grouped into a broad class labeled as “dark features” in the initial land cover classification. In this study, the morphology information from airborne LiDAR is used to solve the shadow and water separation problem. The basic idea is to use the LiDAR DSM to simulate and model solar shadows, and the modeled solar shadows are used to separate the dark features into shadows and water bodies. Then, shadow pixels are grouped into
shadow objects, and their true land cover type are inferred from their geographic proximity to surrounding land covers.

To simulate and model shadows, the position (elevation angle and azimuth angle) of the sun at the time of aerial image acquisition needs to be determined (Figure 11). Although the aerial image acquisition date (November 29, 2012) is given, the acquisition time on that day is unknown from the metadata. Therefore, the elevation angle and azimuth angle of the sun cannot be determined from the Astronomical Almanac algorithm. Instead, an empirical method is used to estimate the solar position by measuring the shadow length and direction of three tall buildings on the aerial image. The following equations have been used to estimate solar elevation angle and azimuth angle in my empirical method:

\[ l = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \]  \hspace{1cm} (3)

\[ \beta = \arctan\left(\frac{h}{l}\right) \]  \hspace{1cm} (4)

\[ \alpha = 270 - \arctan\left(\frac{y_2-y_1}{x_2-x_1}\right) \]  \hspace{1cm} (5)

Figure 11. The solar illumination geometry and shadows. a) Illustration of sun elevation angle and azimuth angle; b) shadow length and solar elevation angle.
Where \((x_1, y_1)\) are the geographic coordinates of the bottom point \(A\) of the selected building, \((x_2, y_2)\) are the geographic coordinates of the shadow point \(B\) of the selected building top, \(l\) is the solar shadow length, \(h\) is the building height above the ground, \(\alpha\) is solar azimuth angle, and \(\beta\) is the solar elevation angle. The building height \(h\) is determined from LiDAR nDSM. For three buildings, the solar elevation angle and azimuth angle are calculated using Equations (3), (4) and (5). The average solar elevation angle is 45.439° above the horizontal ground surface, and the average solar azimuth angle is 187.25° from the true North direction. Using the estimated solar elevation and azimuth angles and LiDAR DSM, the solar shadows are modeled and simulated, as shown in Figure 12.

![Figure 12. Comparison of solar shadows in aerial image with the simulated shadows from LiDAR DSM. a) Aerial image; b) Hill-shaded relief image with simulated shadows from LiDAR DSM.](image)

Then, the overlay analysis is performed between LiDAR simulated shadows and the dark features classified from 5-band stacked aerial image. As shown in Figure 13, those dark features that do not overlay with the LiDAR simulated shadows are recoded as water bodies. The remaining
dark features that partially or completely overlay with the LiDAR simulated shadows are recoded as true shadows.

![Figure 13. Separation of water bodies from solar shadows](image)

After the shadows are separated from water bodies in the dark features, the geographic proximity analysis is conducted to infer true land cover type in the shadows. First, the shadow pixels are grouped into shadow objects using ArcGIS Region Group function. Then, the ArcGIS nibble function is used to search the nearest land cover object for each shadow object. As shown in Figure 14, if the nearest land cover is impervious surface, the shadow object is inferred to be an impervious surface too. If its nearest land cover is vegetation, the shadow object is inferred to be vegetation. Namely, the shortest distance criteria is used to infer the true land cover type of shadows.
After separating water bodies from shadows and assigning shadows to their nearest land cover types, the land cover classes are changed from vegetation, impervious surface, and dark features to vegetation, impervious surface and water. The data holes caused by shadows are filled up.

3.4. Rule-based Detailed Classification of Urban Land Cover in the Second Stage

In the second stage, the airborne LiDAR data are explicitly incorporated to refine the initial broad land cover classification from multispectral aerial image. The rule based method is adopted in the integration of LiDAR topographic information to refine land cover classification. Based on the LiDAR nDSM and the initial land cover classification result, the following set of heuristic rules and prior knowledge are used to separate the vegetation class grass and trees, and the impervious surface class into impervious ground and artificial objects.

If initial_cover = “vegetation” and LiDAR_height<= 1 m, then land_cover = grass
If initial_cover = “vegetation” and LiDAR_height > 1 m, then land_cover = tree

If initial_cover = “impervious surface” and LiDAR_height < 3 m, then land_cover = impervious ground

If initial_cover = “impervious surface” and LiDAR_height > 3 m, then land_cover = artificial objects

As a threshold height of 1 m is used to separate grass and trees, the classified grass class may contain some shrubs. The threshold height of 3 m is used to identify artificial objects, cars.

Figure 15. Morphologic operations on artificial objects. a) before morphologic operations; b) after morphologic operations c) before morphologic operations; d) after morphological operations.
and other small features are classified into *impervious ground* class. It should be noted that *artificial objects* not only include buildings but also bridges, electricity poles and lines, urban street furniture, etc. It should be emphasized that the elevated objects such as trees and buildings in airborne LiDAR data do not suffer from the building lean and occlusion problems as in the aerial image. Therefore, the geographic location and geometric footprint of trees and artificial objects determined from LIDAR data represent the true location and spatial extent. The use of LiDAR derived tree and man-made objects virtually solve the building lean/occlusion problem.

The artificial objects are further processed and classified. First, the *majority*, *erode* and *expand* morphologic operations are applied to man-made objects to improve their shape and eliminate small noisy objects (Figure 15).

Then, ArcGIS region group tool and zonal functions are used to calculate the areal size, thickness and compactness of man-made objects. The object thickness is defined as the distance from the thickest point within each object from its boundary. Essentially, it is the radius (in cells) of the largest circle that can be drawn within each object without including any cells outside the object. The compactness quantifies the degree to which an object is compact (or circular), and its value ranges from 0 to 1, where 1 is a circle, the most compact shape. Based on the areal size, object thickness and compactness, the man-made objects are further classified into *buildings*, *bridges*, and *non-building objects* using the following rules:

- If `object_area > 220000`, then `land_cover = bridges`
- If `object_compactness < 0.03`, then `land_cover = non-building features`
- If `object_thickness < 2.5`, then `land_cover = non-building features`
- else if, `land_cover = buildings`
The non-building objects mainly include electricity poles and lines, street furniture etc., and they are combined into the impervious ground class.

Through above the operations in the second stage, the fine and detailed urban land cover classification is achieved, including 6 land cover classes: grass, trees, impervious ground, buildings, bridges, and water.

Table 1. Classification of building types according to building height

<table>
<thead>
<tr>
<th>Building type</th>
<th>Number of stories</th>
<th>Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ordinary low-rise</td>
<td>1-3</td>
<td>&lt; 13 m</td>
</tr>
<tr>
<td>Multi-story</td>
<td>4-6</td>
<td>13-26 m</td>
</tr>
<tr>
<td>Mid-rise</td>
<td>7-12</td>
<td>26-50 m</td>
</tr>
<tr>
<td>High-rise</td>
<td>&gt; 13</td>
<td>50-100 m</td>
</tr>
<tr>
<td>Skyscraper</td>
<td></td>
<td>&gt; 100 m</td>
</tr>
</tbody>
</table>

Figure 16. Final detailed land cover classification result from the two-stage rule-based method. Black lines are the planning district boundaries.
According to the literature, the story height of building varies from 3.9 m to 4.5 m, and average story height is about 4.3 m. According to building height information given in nDSM, buildings are further classified into 5 categories: ordinary low-rise, multi-story, mid-rise, high-rise and skyscraper, shown in Table 1.

Figure 16 shows the final detailed fine-scale land cover classification result from the two-stage rule-based classification procedure. This detailed land cover map provides a solid foundation for the subsequent analysis of land cover structure in New Orleans and the inference of urban land use types.

### 3.5 Accuracy Assessment of Urban Land Cover Classification

To make a rigorous evaluation of the urban land cover classification, 300 sampling points are generated randomly (Figure 17). The number of sampling points are controlled to be proportional to the area of each land cover class.

For these 300 randomly selected checking points, the true land cover types are visually interpreted. In comparison with the classified land cover types for these checking points, a

<table>
<thead>
<tr>
<th>Reference</th>
<th>Bridge</th>
<th>Building</th>
<th>Impervious</th>
<th>Grass</th>
<th>Tree</th>
<th>Water</th>
<th>Total</th>
<th>UA(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Classified</strong> Bridge</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>Building</td>
<td>0</td>
<td>65</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>65</td>
<td>100</td>
</tr>
<tr>
<td>Impervious</td>
<td>0</td>
<td>1</td>
<td>108</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>109</td>
<td>94.49</td>
</tr>
<tr>
<td>Grass</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>53</td>
<td>0</td>
<td>0</td>
<td>57</td>
<td>92.98</td>
</tr>
<tr>
<td>Tree</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>3</td>
<td>51</td>
<td>0</td>
<td>58</td>
<td>87.93</td>
</tr>
<tr>
<td>Water</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>10</td>
<td>69</td>
<td>108</td>
<td>56</td>
<td>51</td>
<td>10</td>
<td>300</td>
<td></td>
</tr>
<tr>
<td><strong>PA(%)</strong></td>
<td>100</td>
<td>92.31</td>
<td>95.37</td>
<td>94.64</td>
<td>100</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>OA=96.05%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Kappa=0.94</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
confusion matrix is created, and the producer accuracy, user’s accuracy, overall accuracy and Kappa coefficient are calculated as show in Table 2.

![Image](image.png)

Figure 17. Randomly sampled points for accuracy assessment of the urban land cover classification

As shown in Table 2, the producer accuracy of trees reaches 100%. Producer accuracy of impervious surface and grass are over 90%. User accuracy of building, impervious surface and grass is over 90%. Producer accuracy of building is relative low comparing with other classes. Some building pixels are mistakenly classified to impervious ground or tree. Some buildings share similar spectral properties and height information with trees. The proximity analysis of shadows may also cause the misclassification of the impervious surface near the buildings. User Accuracy
of trees is less than 90%. To separate tree and grass, 1m height threshold was used. This can separate most of the grass from the trees. However, when dealing with the shadow problems, shadows around the trees were classified to the closest land cover class. This operation can solve most of shadow problems but may mistakenly assign some tree pixels into grass class. The overall accuracy for my two-stage rule-based classification method is as high as 94.08%. Kappa coefficient reaches 92.2%.

The two-stage rule-based land classification from this study is compared with the traditional per-pixel based ISODATA method under two input scenarios using the same set of 300 randomly selected points. Table 3 shows the accuracy assessment for the land cover classification result from applying the per-pixel based ISODATA method to the 5-band stacked aerial image (blue, green, red, NIR, and NDVI). The overall classification accuracy is only 65.46% with a Kappa coefficient of 0.53. In the second scenario, the height data layer of LiDAR nDSM is included and stacked with the blue, green, red, NIR, and NDVI of the aerial image to form 6-layer

Table 3. Accuracy assessment for per-pixel ISODATA method on 5-band stacked aerial image

<table>
<thead>
<tr>
<th>Classified</th>
<th>Shadow</th>
<th>Building</th>
<th>Impervious</th>
<th>Grass</th>
<th>Tree</th>
<th>Water</th>
<th>Total</th>
<th>UA(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shadow</td>
<td>19</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>19</td>
<td>100</td>
</tr>
<tr>
<td>Building</td>
<td>0</td>
<td>30</td>
<td>22</td>
<td>2</td>
<td>5</td>
<td>0</td>
<td>59</td>
<td>50.85</td>
</tr>
<tr>
<td>Impervious</td>
<td>0</td>
<td>31</td>
<td>82</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>115</td>
<td>71.3</td>
</tr>
<tr>
<td>Grass</td>
<td>0</td>
<td>1</td>
<td>6</td>
<td>39</td>
<td>6</td>
<td>0</td>
<td>52</td>
<td>75</td>
</tr>
<tr>
<td>Tree</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>12</td>
<td>21</td>
<td>0</td>
<td>36</td>
<td>58.33</td>
</tr>
<tr>
<td>Water</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>28</td>
<td>28.57</td>
</tr>
<tr>
<td>Total</td>
<td>39</td>
<td>62</td>
<td>113</td>
<td>55</td>
<td>32</td>
<td>0</td>
<td>300</td>
<td></td>
</tr>
<tr>
<td>PA(%)</td>
<td>51.28</td>
<td>48.39</td>
<td>72.57</td>
<td>70.91</td>
<td>65.63</td>
<td>100</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

OA=65.46%  Kappa=0.53
Table 4. Accuracy assessment for per-pixel ISODATA method on image and LiDAR combined data

<table>
<thead>
<tr>
<th>Classified</th>
<th>Shadow</th>
<th>Building</th>
<th>Impervious</th>
<th>Grass</th>
<th>Tree</th>
<th>Water</th>
<th>Total</th>
<th>UA(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shadow</td>
<td>23</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>12</td>
<td>37</td>
<td>62.16</td>
</tr>
<tr>
<td>Building</td>
<td>1</td>
<td>49</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>68</td>
<td>72.56</td>
</tr>
<tr>
<td>Impervious</td>
<td>0</td>
<td>36</td>
<td>50</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>88</td>
<td>56.82</td>
</tr>
<tr>
<td>Grass</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>50</td>
<td>1</td>
<td>0</td>
<td>52</td>
<td>96.15</td>
</tr>
<tr>
<td>Tree</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>12</td>
<td>34</td>
<td>0</td>
<td>39</td>
<td>87.18</td>
</tr>
<tr>
<td>Water</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>6</td>
<td>83.33</td>
</tr>
<tr>
<td>Total</td>
<td>26</td>
<td>88</td>
<td>66</td>
<td>65</td>
<td>35</td>
<td>17</td>
<td>300</td>
<td></td>
</tr>
</tbody>
</table>
| PA(%)       | 88.46  | 55.68    | 75.76      | 73.92 | 97.14| 29.42 |       | OA=70.33%
|             |        |          |            |       |      |       |       | Kappa=0.59 |

input data for traditional per-pixel based ISODATA method. The corresponding land cover classification accuracy is shown in Table 4. The overall accuracy for the combined use of aerial image bands and LiDAR height in traditional per-pixel method is 70.33%, better than the classification result from the sole use of aerial image, but largely lower than the accuracy of my two-stage rule-based classification method. The rigorous accuracy assessment and comparisons clearly demonstrate the effectiveness and superiority of the two-stage rule-based classification method for integrating the spectral information from aerial image data and morphology information of airborne LiDAR to derive detailed urban land cover classification.
CHAPTER 4. ANALYSIS OF URBAN LAND COVER STRUCTURE AND INFERENCES OF URBAN LAND USE TYPES

4.1 Quantitative Analysis of Land Cover Structure in Different Urban Districts

As shown in Figure 16, the case study area includes several urban planning districts: CBD (Central Business District), Vieux Carre (French Quarter), Mid-City, Central-city, Uptown, Marigny/Treme/Bywater, Lakeview, and Gentily. These districts form the core of the city of New Orleans.

Despite the availability of various high-resolution remote sensing data for the city of New Orleans, little research has been conducted to analyze land cover compositional and structural properties for different urban districts. At present, the structural properties of urban land cover in New Orleans are still largely unknown. The detailed land cover classification result from my two-stage rule-based method enables the first quantitative analysis of the land cover composition and structure in New Orleans, using the planning districts.

Table 5 and Table 6 show the statistical analysis results for the land cover and building type composition and structure for different urban districts.

Table 5. Land cover structure for different urban districts

<table>
<thead>
<tr>
<th>Land Cover</th>
<th>CBD</th>
<th>Vieux Carre</th>
<th>Central City</th>
<th>Uptown</th>
<th>Mid-City</th>
<th>Marigny</th>
<th>Gentilly</th>
<th>Lakeview</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tree</td>
<td>6.37%</td>
<td>11.67%</td>
<td>15.69%</td>
<td>28.63%</td>
<td>16.13%</td>
<td>15.11%</td>
<td>16.13%</td>
<td>24.03%</td>
</tr>
<tr>
<td>Grass</td>
<td>4.11%</td>
<td>4.37%</td>
<td>20.16%</td>
<td>17.70%</td>
<td>18.28%</td>
<td>19.24%</td>
<td>18.29%</td>
<td>31.98%</td>
</tr>
<tr>
<td>Impervious</td>
<td>40.72%</td>
<td>29.73%</td>
<td>42.63%</td>
<td>30.19%</td>
<td>42.65%</td>
<td>44.26%</td>
<td>39.43%</td>
<td>30.25%</td>
</tr>
<tr>
<td>Building</td>
<td>44.09%</td>
<td>49.23%</td>
<td>24.12%</td>
<td>23.28%</td>
<td>22.54%</td>
<td>20.79%</td>
<td>16.05%</td>
<td>13.74%</td>
</tr>
</tbody>
</table>

Table 6. Building type structure for different urban districts

<table>
<thead>
<tr>
<th>Building Type</th>
<th>CBD</th>
<th>Vieux Carre</th>
<th>Central City</th>
<th>Uptown</th>
<th>Mid-City</th>
<th>Marigny</th>
<th>Gentilly</th>
<th>Lakeview</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Rise</td>
<td>40.13%</td>
<td>78.08%</td>
<td>90.08%</td>
<td>93.92%</td>
<td>93.62%</td>
<td>99.19%</td>
<td>96.23%</td>
<td>98.19%</td>
</tr>
<tr>
<td>Multi Story</td>
<td>37.86%</td>
<td>20.89%</td>
<td>8.56%</td>
<td>5.45%</td>
<td>5.34%</td>
<td>0.79%</td>
<td>3.77%</td>
<td>1.81%</td>
</tr>
<tr>
<td>Mid Rise</td>
<td>11.64%</td>
<td>0.82%</td>
<td>1.38%</td>
<td>0.63%</td>
<td>1.04%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>High Rise</td>
<td>8.15%</td>
<td>0.23%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Skyscraper</td>
<td>2.12%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>
The CBD and Vieux Carre (French Quarter) are two most intensively developed urban districts, almost half of their land are occupied by densely distributed buildings. In comparison, Vieux Carre (French Quarter) has a better tree coverage than the CBD. Central City, Uptown and Mid-town have similar land cover composition. These urban districts are the second most intensively developed, and about a quarter of their lands are occupied by buildings. In comparison, Marigny/Treme/Bywater, Lakeview, and Gentily are relatively less intensive, building density is lower, and the vegetation coverage is higher. The skyscrapers are concentrated in the CBD area. High-rise buildings are mainly distributed in the CBD and can be also found in Vieux Carre (French Quarter). In Central City, Uptown and Mid-City, there are significant portion of buildings are multi-story or mid-rise, besides ordinary low-rise buildings. Marigny/Treme/Bywater, Lakeview, and Gentily are dominated by ordinary low-rise buildings.

4.2 Characteristics of Land Cover Structure for Different Land Use Types

The information and knowledge about the characteristics of urban land cover component and structure for different types of land use functions in New Orleans need to be examined. The definitions and classification of urban land use types vary from city to city and from application to application. Based on the NEW Orleans Comprehensive Zoning Ordinance and the official citywide master plan A Plan for the 21st Century: New Orleans 2030, the following 8 land use types are used in this study: single-family residential, two-family residential, multi-family residential, commercial, CBD, industrial, institutional, parks and open space. Since the case study area only contains very small area of industrial land use, the industrial land use type is not included in the subsequent statistical analysis and the computational inference and classification.
Figure 18 shows typical samples for different types of urban land use. Apparently, each type of urban land use has unique characteristics in terms of land cover composition and structures.

Figure 18. Typical urban land use types. a) single-family residential; b) two-family residential; c) multi-family residential, d) CBD; e) commercial; f) institutional; g) parks and open space
The street-blocks in “Squares” shape file are used as the basic spatial unit for the land cover structure analysis and the land use type classification. There are 3764 street-blocks in the case study area. Among these street-blocks, 272 blocks are selected as training samples (Figure 19), and their true urban land use types are determined based on the zoning codes provided by “Zoning Districts” shape file and verified by visual inspection of aerial image.

Based on these training samples, the statistical analysis on the urban land cover composition and structure is conducted for different types of urban land uses in New Orleans. The analysis results are shown in Table 7 and Table 8.

Figure 19. a) Spatial distribution of block samples for different types of urban land uses b) Spatial distribution of training block samples
This study adopts the graph-theoretic data model RANG developed by Wu (2018) to represent and model structural and spatial relations between urban land cover objects. As shown in the above section, each urban land use type has a distinct configuration of various styles of buildings, impervious space, grass and trees at an aggregated neighborhood/block level. Therefore, this study intends to infer and classify the urban land use types through land cover composition and spatial configuration.

A graph consisting of nodes and edges is widely used as a proxy of the spatial arrangement of land cover objects. Graph theory is a research field in mathematics and is widely used in geoinformation. For a neighborhood graph, two land cover objects are defined as neighbors, if they share common edge. The graph was generated by regarding the centroid points of land cover

Table 7. Land cover structure for different urban land use

<table>
<thead>
<tr>
<th>Land Cover</th>
<th>CBD</th>
<th>Commercial</th>
<th>Institutional</th>
<th>Park</th>
<th>Single-Family</th>
<th>Two-Family</th>
<th>Multi-Family</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tree</td>
<td>3.33%</td>
<td>2.26%</td>
<td>21.23%</td>
<td>31.06%</td>
<td>16.18%</td>
<td>24.15%</td>
<td>10.77%</td>
</tr>
<tr>
<td>Grass</td>
<td>1.29%</td>
<td>5.26%</td>
<td>23.97%</td>
<td>45.96%</td>
<td>28.79%</td>
<td>17.19%</td>
<td>8.91%</td>
</tr>
<tr>
<td>Impervious</td>
<td>12.75%</td>
<td>42.15%</td>
<td>29.46%</td>
<td>16.88%</td>
<td>29.86%</td>
<td>19.78%</td>
<td>29.16%</td>
</tr>
<tr>
<td>Building</td>
<td>82.64%</td>
<td>50.33%</td>
<td>25.34%</td>
<td>1.41%</td>
<td>25.16%</td>
<td>38.88%</td>
<td>51.17%</td>
</tr>
</tbody>
</table>

Table 8. Building type structure for different urban land use

<table>
<thead>
<tr>
<th>Building Type</th>
<th>CBD</th>
<th>Commercial</th>
<th>Institutional</th>
<th>Park</th>
<th>Single-Family</th>
<th>Two-Family</th>
<th>Multi-Family</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Rise</td>
<td>32%</td>
<td>82.56%</td>
<td>64.60%</td>
<td>94%</td>
<td>99.24%</td>
<td>98.68%</td>
<td>91.91%</td>
</tr>
<tr>
<td>Multi Story</td>
<td>30.20%</td>
<td>17.38%</td>
<td>32.74%</td>
<td>5.53%</td>
<td>0.76%</td>
<td>1.32%</td>
<td>8.09%</td>
</tr>
<tr>
<td>Mid Rise</td>
<td>16.88%</td>
<td>0.04%</td>
<td>2.66%</td>
<td>0.07%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>High Rise</td>
<td>3.89%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0%</td>
</tr>
<tr>
<td>Skyscraper</td>
<td>3.89%</td>
<td>0%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

4.3 The Graph-theoretic Data Model for Land Cover Objects

This study adopts the graph-theoretic data model RANG developed by Wu (2018) to represent and model structural and spatial relations between urban land cover objects. As shown in the above section, each urban land use type has a distinct configuration of various styles of buildings, impervious space, grass and trees at an aggregated neighborhood/block level. Therefore, this study intends to infer and classify the urban land use types through land cover composition and spatial configuration.
objects as nodes and the adjacent neighboring relationship as edges. The graph-theoretic data model RANG has seven dimensions:

\[
RANG = \{N, E, NP, EP, L, I, P\}
\]  

(6)

Where \(N=\{v_1, v_2, \ldots, v_n\}\) is the set of nodes that represents the land cover objects, \(E=\{e_1, e_2, \ldots, e_m\}\) represents spatial relations between land cover objects, \(NP=\{m_1, m_2, \ldots, m_n, c_d, c_b\}\) is the properties of nodes, which include two kinds of properties: morphological properties and semantic properties. Morphological properties include planimetric attributes (e.g., area, perimeter) and shape attributes (e.g., compactness). Semantic properties are used to describe the dominant land cover parcels of each land use objects. \(EP=\left(\begin{array}{ccc}
p_{11} & \cdots & p_{1t} \\
\vdots & \ddots & \vdots \\
p_{t1} & \cdots & p_{tt}
\end{array}\right)\) is the properties of relations, which store the spatial properties of nodes, and the frequency of edges between every combination of land cover objects derived from adjacent event matrix. \(L=\{l_1, l_2, \ldots, l_v\}\) is the set of labels assigned to land use types, \(I=\{a_1, a_2, \ldots, a_x\}\) is the properties relating to land use types, \(P\) is the probability belongs to specific land use types in \(L\). RANG can be generated by constructing adjacent neighborhood graph.

4.4 Derivation of Thematic, Structural and Topological Attributes of Land Cover Objects

Based on the adjacent-event matrix and undirected graph, a set of variables describing geometric, thematic, structural properties and spatial relations between urban land cover objects are derived, which are used as the input variables for the subsequent computational inference of land use types with the random forest method.

As shown in Table 9, 27 variables are defined and derived. These variables belong to four categories: centrality measures, adjacency-event measures, connectivity measures, and additional
measures. Centrality measures determine the importance of nodes in the graph. There are two types of centrality measures: degree centrality and betweenness centrality. Degree centrality counts the number of edges linked to each node. Betweenness centrality record the number of times shortest paths through a node. Beta index is a connectivity measure and is defined by the number of edges over the number of nodes.

4.5 Computational Inference of Land Use Types with Random Forest Method

Random Forest is a popular non-parametric classification method proposed by Breiman(2001). It was broadly used in classification and regression problems. Random Forest model generates a bag of decision trees. Different training samples are randomly selected to grow each tree (Walde et al. 2014). The out-of-bag (OOB) samples are excluded from training dataset for prediction. The output of random forest is determined by the majority votes of prediction of
trees. The advantage of random forest over decision tree is that random forest select best variables as split criterion for each tree which solve the overfitting problem of decision tree and unbiased (Mahesh, 2005). Because of diversity of indicators, random forest is effective to classify urban land use to different types at the street-block level. Random forest tool implemented in R package is used to create random forest model. 27 variables derived from RANG model are used as the input variables for random forest model. Two control parameters are important: $mtry$ (the number of input variables randomly chosen at each split) and $ntree$ (the number of trees in the forest). Using the 272 training samples, the optimal control parameter value is determined to be 6 for $mtry$ and 1000 for $ntree$ using a grid searching calibration algorithm.

**4.6 Evaluation of the Importance of Thematic, Structural and Topological Attributes**

The importance of these input variables is evaluated through box-plots and Mean Decrease Gini. Figure 19 shows the statistical boxplots for three selected variables, which shows the separability of each variable for distinguishing different land use types. As shown in Figure 5(a) and (b), the variables of mean building height and maximum building height can be used effectively discriminate CBD from other urban land use types. The variable of tree area ratio can be used to separate CBD and commercial land uses from other land use types, but cannot be used to separate CBD from commercial land use.
Figure 20. Box plots of three selected variables
Figure 20 shows the order of the most crucial variables sorted by the Mean Decrease Gini. Apparently, the average height of building, largest building area, proportion of tree area, proportion of build area, and height of the highest building are the 5 most crucial variables for inferring and classifying the urban land use types. 13 variables listed between grass area ratio and LinkGrassBldRatio have a moderate impact on the classification result, while the remaining 9 variables after HighestDegreeC have a negligible contribution.

Figure 21. The ordered list of variable importance calculated by Mean Decrease Gini.
4.7 Validation and Accuracy Assessment of Urban Land Use Inference

The 272 training samples are separated into calibration samples and validation samples. With the random forest method, the sample street-blocks are computationally inferred and classified into 7 land use types: single-family residential, two-family residential, multi-family residential, commercial, CBD, institutional, and parks and open space.

<table>
<thead>
<tr>
<th>Classified</th>
<th>CBD</th>
<th>Commercial</th>
<th>Institutional</th>
<th>Multi-family</th>
<th>Two-family</th>
<th>Single Family</th>
<th>Park</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBD</td>
<td>15</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Commercial</td>
<td>0</td>
<td>12</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Institutional</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Multi-family</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Two-family</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>16</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Single-family</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>Park</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>7</td>
</tr>
</tbody>
</table>

OA=91.74%

By comparing the Random Forest predicted land use type results with the reference validation samples, a confusion matrix can be created, which can be used to calculate the producer’s accuracy (PA), user’s accuracy (UA), overall accuracy (OA), and Kappa coefficient. Experiments show that the overall accuracy for land use type classification with random forest is 91.46%, if the calibration/validation sample ratio is set to 70/30, and 91.74% if the calibration/validation sample ratio is set to 60/40. When the calibration/validation sample ratio is changed to 50/50, the overall classification accuracy is reduced to 85%. Table 10 shows the confusion matrix, when the calibration/validation sample ratio is set to 60/40. Although there are a certain level of confusions between CBD and commercial land uses, and between multi-family residential, two-family residential and commercial land uses, the overall accuracy is as high as 91.74%. Both omission and commission errors are small. Our preliminary analysis demonstrates that the urban land use types can be computationally inferred and classified with a relatively high confidence and accuracy, based on the urban land cover composition and structure.
CHAPTER 5. CONCLUSIONS

Urban land use and land cover (LULC) mapping has been one of the major applications in remote sensing of the urban environment. Land cover refers to the biophysical materials at the surface of the earth (i.e. grass, trees, soils, asphalt, concrete, water), while land use indicates the socio-economic function of the land (i.e., residential, industrial, commercial land uses). The emergence of high resolution multispectral airborne and satellite images has enabled the automated classification of urban land covers with a relatively high accuracy and reliability. However, interpretation and classification of urban land use types still face various challenges. This study addresses the technical issue of how to computationally infer and interpret urban land use types based on the urban land cover structures derived from remote sensing data.

This study developed a LiDAR based simulation technique to solve the solar shadow problem in multispectral aerial image in urban land cover classification. A two-stage rule based classification method has been proposed to exploit the comparative advantages of multispectral aerial image and airborne LiDAR for optimal fine-scale urban land cover classification. The urban land cover of New Orleans has been classified into six categories: water, grass, trees, imperious ground, elevated bridges, and buildings with an overall classification accuracy of 94.2%, which is significantly higher than that of traditional per-pixel based classification method. The buildings in New Orleans are further classified into regular low-rising, multi-story, mid-rise, high-rise, and skyscrapers in terms of building height. This is most reliable and detailed urban land cover classification for New Orleans.

The land cover composition and structure in New Orleans have been quantitatively analyzed for the first time in terms of urban planning districts. It found out that the CBD and Vieux Carre (French Quarter) are two most intensively developed urban districts, almost half of their land
are occupied by densely distributed buildings. Central City, Uptown and Mid-town are the second most intensively developed, and about a quarter of their lands are occupied by buildings. In comparison, Marigny/Treme/Bywater, Lakeview, and Gentily are relatively less intensive, building density is lower, and the vegetation coverage is higher. Skyscrapers are concentrated in the CBD area. High-rise buildings are mainly distributed in the CBD, and can be also found in Vieux Carre (French Quarter). A significant portion of buildings are multi-story or mid-rise in Central City, Uptown and Mid-City, besides ordinary low-rise buildings. Marigny/Treme/Bywater, Lakeview, and Gentily are dominated by ordinary low-rise buildings. The information and knowledge about the characteristics of urban land cover component and structure for different types of land use functions in New Orleans have been derived and discovered.

A graph-theoretic data model, known as relational attribute neighborhood graph (RANG), is adopted to comprehensively represent the geometrical and thematic attributes, compositional and structural properties, spatial/topological relations between urban land cover patches (objects). Among the 26 spatial, thematic and topological variables in RANG, the average height of buildings, largest building area, proportion of tree area, proportion of artificial area, and height of the highest building are important for inferring the urban land use types. By using the random forest classification method, the urban land use of New Orleans is computationally inferred and classified into 7 types at the urban block level: single-family residential, two-family residential, multi-family residential, commercial, CBD, institutional, parks and open space, with an overall accuracy of 91.7%.

The major limitation of this study is that the current analysis did not cover the entire city of New Orleans, although the study area covers diversity of functional area. The training sample for urban land use types are still not large enough. We also observed that 1 m spatial resolution of
LiDAR is still not adequate to resolve individual buildings in the dense residential areas. The finer sub-meter level of LiDAR data set is required to perform object based analysis of individual buildings in the densely populated urban areas. In addition, the performance of RANG data model and random forest method need more extensive validation and evaluation by applying to other cities in the future studies.
REFERENCES


VITA

Shuxian Liu, an international student from China, received her bachelor’s degree at Sun Yat-sen University in 2014. She determined to pursue her master degree in Department of Geography and Anthropology at Louisiana State University. Her research interests focus on GIS and remote sensing application in urban study. She plans to receive her master degree on May 2020.