Remote Sensing Satellite Image Acquisition Planning: Framework, Methods and Application

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REMOTE SENSING SATELLITE IMAGE ACQUISITION PLANNING:
FRAMEWORK, METHODS AND APPLICATION

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Additionally, I would like to acknowledge all of the faculty, staff, and my fellow graduate students of the USC Geography department.
Abstract

This dissertation explores the theories and methods of satellite remote sensing image acquisition planning within a spatial temporal context. For many time sensitive applications, such as disaster emergency response, timely acquisition of critical information is the key to intelligent and effective decision making. Remote sensing plays an important role in information collection for these time sensitive applications. Imagery collected from hundreds of remote sensing satellite sensors offer accurate, frequent and almost instantaneous data covering the Earth in a relatively short time. However, determining which satellite sensors can provide an appropriated kind of imageries during a restricted collection window for the analysis is problematic. Satellite image acquisition planning is developed to solve the problem. In this research, we explore the design and implementation of a spatial decision support system (SDSS) for satellite image acquisition planning. A SDSS framework is proposed, and several novel models and algorithms are developed to derive optimized satellite image acquisition solutions. Chapter 2 describes the components of the framework; Chapter 3 and Chapter 4 present several models including composite satellite image collection opportunities modeling, collection opportunities evaluation model, and a spatial optimization model. Based on the framework, models, and algorithm, Chapter 5 presents an application of satellite image acquisition planning for tidally influenced salt marshes for vegetation mapping. Collectively, this research provides a foundation for research and development towards the satellite image acquisition planning.
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CHAPTER 1 Introduction

1.1 Introduction

Remote sensing is defined as a technique of measuring information about an object without touching it (Jensen 2000). It is the only viable technology for synoptic monitoring of land surface, ocean, and atmospheric status at regional to global scales (Lippitt 2012). For its substantial advantages on data collection, remote sensing has been used in various applications for several decades and made significant contributions to our understanding of earth processes and human-environment interactions.

Imagery collected from hundreds of remote sensing satellite sensors offer accurate, frequent and almost instantaneous data covering the Earth in a relatively short time. Considerable GIScience research has been conducted for the application of remote sensing imagery in various disciplines. Most of the research focuses on how to extract useful information from such imagery. Little research has focused on where, when, and what is the appropriate satellite remote sensing solution. Rapid remote sensing imagery acquisition planning is very important, especially for some phenomena which address time-sensitive information requirements.

For example, hazard emergency response. For most natural hazards, the emergency response phase is very short, spanning only a few days after the event (Hodgson et al. 2010). State and local agencies involved in emergency response to natural disasters such as hurricanes have explicitly indicated they need imagery covering
the disaster area within *three days* of the event; and more desirably within *24 hours* of the event (Hodgson et al. 2010). Careful, but rapid planning of satellite image acquisition from targeted sources would greatly assist in the chaotic and somewhat communication hindered aftermath of disaster events as time-sensitive damage information derived from remote sensing images will become less important as time passes and in situ data become available (Hodgson, Davis, and Kotelenska 2010). However, this important step is often overlooked or ill-conceived and results in at least a few day delay of providing useful imagery/information to decision makers.

For satellite image acquisition planning, there are some challenges. First, there are numerous available satellite-sensor sources from multiple countries, agencies, or companies. Second, the pointable nature of high spatial resolution sensors increases the combination of choices. Third, satellite-orbit and swath coverage options for the diversity of satellite-sensors are not available. Therefore, given a location with an n-day collection window, there are tens of sensors that may provide hundreds of image collection opportunities for covering part of or the entire area. If remote sensing is to be effectively and reliably leveraged for a time sensitive phenomena, methods that permit satellite image acquisition planning and determine the best satellite remote sensing imagery solution will be required.

In the literature, there is little research focusing on the future satellite image collection opportunities modeling. Emery, Brown, and Nowak (1989) and Rosborough, Baldwin, and Emery (1994) developed modeling approaches for AVHRR satellite-sensors to provide automatic georeferencing of imagery. Hodgson and Kar (2008) developed a model to determine and map the potential swath coverage of pointable
remote sensing satellite sensor systems. Based on this model, they provided a generic approach for modeling future satellite sensor collection opportunities and Hodgson et al. (2010) demonstrated its use for the historic record of land-falling hurricanes in the United States.

This dissertation explores the design and implementation of a spatial decision support system (SDSS) for satellite image acquisition planning. Specifically, it seeks to: (1) design a SDSS framework for satellite image acquisition planning, which includes the databases, different GIS-based models, decision models, optimization models and some other components; (2) examine the methods and algorithms for the models proposed in the framework to derive optimized satellite image acquisition plans. Collectively, this research is intended to innovatively solve the satellite image acquisition planning problem for any time sensitive applications within a spatial-temporal context. These objectives are addressed in different chapters which are described in the following section.

1.2 Dissertation Structure

This dissertation is composed of six chapters. Chapter 1 is the introduction of this research. The proposed SDSS framework and different model components are described in Chapter 2. Chapter 3 defines the terms and models for satellite acquisition planning problem for a large area, it describes the algorithms, identifies the factors and presents a spatial optimization algorithm for solving the problem under spatial and non-spatial constraints.
Based on the models and results of Chapter 3, Chapter 4 extends the research and proposes a novel model to solve the satellite image acquisition planning and optimization problem for multiple large areas. Different application scenarios for hazard emergency response are examined. Chapter 5 applies the proposed framework and models to solve the image acquisition planning problem for salt-marsh vegetation mapping. This research integrated the research results in Chapter 3 and Chapter 4 with models for tidal prediction to model available image collection opportunities during relative low tides periods.

Chapter 6 provides a synthesis of the collective results of the dissertation and concludes with future research plans.
CHAPTER 2 The SDSS Framework

2.1 Overview

SDSS has experienced tremendous growth during the last few decades; however, there is still no universally accepted definition (Sugumaran and Degroote 2010). One definition is that SDSS are “explicitly designed to provide the user with a decision-making environment that enables the analysis of geographical information to be carried out in a flexible manner” (Densham 1991). Leipnik, Kemp, and Loaiciga (1993) defined SDSS as “integrated environments which utilize the databases that are both spatial and non-spatial models, decision support tools like expert systems, statistical packages, optimization packages, and enhanced graphic to offer the decision makers a new paradigm for analysis and problem solving”. Malczewski (1999) defined SDSS as an “interactive computer based system designed to support a user or group of users in achieving a higher effectiveness of decision making while solving a semi-structured spatial decision problem”.

SDSS research lies at the interface between Geographic Information Systems (GIS) and Decision Support Systems (DSS) (Armstrong and Densham 1990). Compared with GIS and DSS, SDSS is characterized by these two aspects: first, powerful mechanisms for the input and output of spatial data and graphical display capabilities; second, complex spatial relations and structures representation and specific analytical and modeling capabilities (Densham 1991).
Sprague (1980) proposed a three-level framework illustrated in Figure 2.1 for developing a SDSS which includes SDSS tools, SDSS generator and specific SDSS. Based on this framework, Armstrong and Densham (1990) described the architecture of the system and defined 5 software modules for a SDSS system as depicted in Figure 2.2. Each module provides a group of functionally related capabilities.

A database management system (DBMS) is defined as the core of the SDSS. It must be able to store and manipulate spatial and attribute data to support analytical modeling and spatial query. Model base management system (MBMS) is the modules library, the development of MBMS can be implemented within the DBMS or developed based on libraries of analytical subroutines, it can also only store some individual pieces of algorithms, and then implement specific modules by embedding them in SDSS, this make the implementation of new algorithms simplified. Graphical and tabular report generators are used to depicting the results from analytical models and statistical modules in cartographical or tabular mode.

The progression of SDSS can be divided into three phases. The first phase was the introductory phase in the late 1970s and 1980s. During this period, the development of SDSS was characterized by the definition of conceptual frameworks for SDSS, prototype SDSS development, desktop or workstation SDSS with single users and command line-driven user interfaces. The second phase was the maturing during the 1990s. During this period, advances in new technologies such as spatial models, intelligent components, and Web-based delivery platforms led to an increase in the development and application of SDSS and to the integration of them into SDSS architectures. Research and development concerning collaborative or public participatory SDSS was instigated with the
development of technologies to support multi-group decision making. The third phase was the growth of SDSS continued in the 2000s. The advancements in the development of Web-based spatial technologies as well as component- or service-based spatial technologies have increasingly been implemented into a variety of SDSS applications. Besides, server GIS technologies (e.g., ArcGIS Server) provide spatial analysis and processing services over the internet make the rapid development of Web-Based SDSS.

During the development of SDSS, there are some important contributions to fundamental concepts of SDSS. Early works from Marc Armstrong, Paul Densham and their colleagues contributed to the concept definition and codification of spatial decision support system as something beyond GIS. They defined the basic framework of a SDSS and provided some earliest examples of SDSS development (Armstrong and Densham 1990; Armstrong et al. 1991). Timothy Nyerges and Piotr Jankowski led the development of collaborative / participatory SDSS, they helped the development of the concepts behind effective collaborative SDSS, and they also demonstrated some application cases to help guide the continued development of effective collaborative systems (Jankowski et al. 1997; Jankowski, Andrienko, and Andrienko 2001; Jankowski and Nyerges 2001; Jankowski et al. 2006; Nyerges, Jankowski, and Drew 2002). Malczewski (1996, 1999, 2000, 2006) has been a leading researcher in the development of spatial multi-criteria evaluation systems which is a significant proportion of SDSS.

SDSS provides a powerful tool for decision makers to solve complex spatial problems; several specialized SDSS have been developed to assist decision-makers in many fields. Such as in urban planning, Matthews, Sibbald, and Craw (1999) implemented a SDSS for rural land use planning at the management unit level to explore
the land use options and the potential impacts of land use change. They followed the five modules architecture proposed by Armstrong, the developed SDSS includes a GIS, several land use modules, several impact assessment modules, a graphical user interface and some land use planning tools. In facility location, Ehler, Cowen, and Mackey (1995) developed a SDSS based on GIS to enable the site evaluation and selection. Arentze and Timmermans (2000) developed a SDSS integrated land-use and transportation planning for retail plan generation and impact assessment.


Remote sensing has usually been taken as a data source that provided limited input data for analytical models in SDSS. However, with the development of technologies and image processing techniques, remote sensing plays a more important role and has become an integral component of SDSS (Im 2006). One of the application fields of SDSS where remote sensing plays an important role is hazard management. As stated in previous section, remote sensing image data can provide real time or near time information over large area, hazard management professionals are becoming increasingly reliant on remote sensing data during different phases in a hazard management cycle. Salt
and Dunsmore (2000) developed a SDSS for post-emergency management of radioactively contaminated land to assist decision-makers in the evaluation and selection of remediation strategies for food production, in agricultural and semi-natural ecosystems at a regional scale. Bonazountas et al. (2007) implemented a SDSS for managing forest fires. The system they developed provided a series of software tools for the fire prevention, planning and the assessment of the propagation and combating. Teimouri et al. (2008) employed SDSS to assess damage estimation due to an earthquake, the SDSS integrated high resolution remote sensing images and other spatial data and was used to evaluate the building damage. Jensen et al. (2009) proposed a Remote Sensing and GIS assisted SDSS for hazardous waste site monitoring and management to assist strategic planning and emergency situations response. Hodgson and Kar (2008) and Hodgson et al. (2010) developed a web-based SDSS for DHS/FEMA and state emergency operations centers for predicting satellite image collection opportunities immediately after a disaster event. Indriasari et al. (2010) employed SDSS to solve complex maximal service area problem for optimal sitting of emergency facilities.

2.2 SDSS Framework

Following Sprague’s three-level framework for developing a SDSS, a framework was proposed to develop the SDSS for remote sensing satellite image acquisition planning. There are four components in the proposed framework (Figure 2.3).

Database is the core of the SDSS; there are different types of information need to be stored. The first type is satellite, sensor and band information, which will be used directly by the models to predict available satellite image collection opportunities. The second type is expert knowledge about spatial and spectral resolution requirements for
specific applications; this information is used in the decision support models. Some other information like spatial information of study area is also stored in the database. Details in the database design and structure are discussed in next section. GIS based models are the second component; these models including the satellite orbit models, sensors collection opportunities models are used to derive the available satellite image collection opportunities. The third component of the proposed framework is the SDSS which is used to evaluate the image collection opportunities. With the available satellite image collection opportunities derived from GIS-based models, an evaluation model will be used to evaluate the fitness of a collection opportunity quantitatively. The last component is the spatial optimization model. Based on the results of GIS based models and SDSS models, the best image acquisition plans will be derived under spatial and non-spatial constraints.

2.3 Databases

As illustrated in previous section, a DBMS is defined as the core of the SDSS. In this proposed research, a DBMS will be used to store these types of information:

(1) Satellite ephemeris information (orbital position and tracking) which will be used to predict available satellite image collection opportunities

(2) Satellites, sensors and bands information, which will be used for modeling the collection opportunities

(3) Expert knowledge on ideal/acceptable spatial resolution and band types

(4) Spatial information of study area
Figure 2.4 represents the basic relationships among satellite, sensor and band. In the database design, each satellite can carry multiple sensors and each sensor can have multiple bands (one-to-many relationships). So there is a 1: N relationship between satellite and sensor as well as sensor and band.

Although the virtual design of the satellite-sensor-band database was fairly straightforward, as illustrated in Figure 2.2, the implementation design was very complex. Numerous issues arose in the design phase that required a series of logically linked tables. For instance, a satellite or sensor could have multiple names (e.g., ERTS-1 became Landsat 1). This renaming could occur for several reasons but occurs most frequently when satellite-sensors are purchased from other companies. Similarly, the manufacturer of a satellite sensor may change the name of the satellite-senor over time (e.g., from IKONOS to GeoEye). Each satellite may contain multiple sensors. Each sensor may be owned by a separate country or company. Each sensor band may be operational or have problems. To resolve many of these temporal concerns, we created history tables that track each change made to the database in a transactional form. For the web interface and some of the web services some stored procedures that produce virtual views of combinations of the logically linked tables were created. Figure 2.5 describes the table structures in the database.

The satellite ephemeris (orbital position and track) is updated nightly from a NORAD database. This database of satellites-sensors-bands and ephemeris is growing and their orbits information is maintained and updated regularly.
2.4 GIS-based models

The models in the proposed framework are described in detail in the following chapters. Basically these models include satellite orbital models, image collection opportunities prediction models, image collection opportunity evaluation model, multi-criteria decision making models and spatial optimization models. These models work together to derive the satellite image acquisition solutions.
Figure 2.1 Sprague’s three-level framework for developing a SDSS
Figure 2.2 Armstrong and Densham’s architecture for a SDSS
Figure 2.3 Proposed SDSS framework for remote sensing image acquisition planning
Figure 2.4 1:N relationship between satellite, sensor, and band in the database
Figure 2.5 The primary tables used to support the satellite-sensor-band database
CHAPTER 3 Optimizing Large Area Coverage from Multiple Satellite Sensors

Abstract

Rapid damage information collection and dissemination during the disaster emergency response phase is a very important remote sensing-based approach. For large disasters like hurricane and earthquake, multiple satellite-sensor overpasses with varying pointing angles are required to fully cover the large impact area. This article presents an optimization model for satellite image acquisition planning utilizing geographic space, time, and collection scenario requirements. An online remote sensing planning tool prototype implementing the optimization model and algorithm is provided for disaster management agencies and emergency response decision makers to get ranked satellite image acquisition plans.

3.1 Introduction

The complete management cycle for hurricanes (e.g., hurricanes and floods) includes four states: the preparedness/warning stage as the disaster approaches, the response stage after the event, and subsequent recovery and mitigation stages. The emergency response phase is always very short, spanning only a few days after the event (e.g., 3 days) when the goal is to save lives and determine how large and how bad the disaster impact areas is. The speed of disaster information collection and dissemination is also very important for monitoring an ongoing disaster (e.g., flooding). A remote sensing approach to rapidly collect imagery over large areas immediately after the disaster event has substantial advantages over insitu observations for disaster emergency response. State and local agencies involved in emergency response to natural disasters such as hurricanes have explicitly indicated they need images covering the disaster area within three days of the event, and more desirably within 24 hours (Hodgson et al. 2010). If satellite-borne sensors are the source of imagery, the planning for image collections would need to be performed quickly as time-sensitive damage information derived from remote sensing images will become less important as time passes and in situ data becomes available (Hodgson, Davis, and Kotelenska 2010).

However, for such quick planning, there are some challenges. First, there are numerous available satellite-sensor sources from multiple countries, agencies, or companies. Second, the pointable nature of high spatial resolution sensors increases the combination of choices. Third, satellite-orbit and swath coverage options for the diversity of satellite-sensors are not available. Therefore, given a location with ‘n’ days (always post-event) of the disaster event, there are tens of sensors that may provide hundreds of
image collection opportunities for covering part of or the entire disaster area. For a relatively large disaster impact area, multiple satellite image collection opportunity combinations are required in a short time period (e.g., 3 days) to cover the entire impact area. For example, a Katrina-like impact area along the Mississippi coast could be covered with two satellite image collection opportunities from CARTOSAT 2B and GEOEYE 1 (Figure 3.1). With hundreds of image collection opportunities available, a challenging problem is to determine the best image collection opportunities combination which can cover the entire disaster area; more specifically, to determine which subset of satellite-sensor image collection opportunities and pointing angles are the “best” and which satellite-sensor should be tasked to cover what portion of the impact area.

In this research, a spatial optimization model is developed and implemented for satellite image acquisition planning to solve the covering problem under multiple constraints within a spatio-temporal context. We analytically designed a scenario test to demonstrate the proposed model and algorithm using an area similar in size to that impacted by Hurricane Katrina along the Mississippi coast. An online spatial decision support system (SDSS) named the remote sensing planning tool (ReSPT) was developed and implemented for disaster management agencies and emergency response decision makers.

3.2 Background

Few satellites and their sensors have been designed solely for the purpose of observing hazards (the exception being the Disaster Monitoring Constellation). While the variety of spectral bands provide adequate spectral coverage the spatial resolution may not be suitable for many objectives, such as mapping, building or transportation damage
remote sensing satellite sensors have been widely used in disasters such as earthquake, flood, hurricane, volcano, terrorism et al. for hazard mitigation and post-hazard events by government agencies and corporations. Considerable research has been conducted regarding the use of remote sensing for the warning, recovery or mitigation stages (Hodgson and Davis 1998; Sunar and Ozkan 2001; Ostir et al. 2003; Tralli et al. 2005; Jensen and Hodgson 2006; Colesanti and Wasowski 2006; Stramondo et al. 2006; Jha, Levy, and Gao 2008; Pan and Tang 2010). However, relatively little research has focused on the use of remote sensing during the hazard response stage.

For disaster emergency response, the use of high spatial resolution satellite sensors has been touted as the logical response for collecting images covering the disaster impact area (Visser and Dawood 2004; Zhang and Kerle 2008). Images collected from high spatial resolution satellite sensors offer accurate, frequent and almost instantaneous data covering the Earth in a relatively short time. Although the orbits of these satellites are fixed, the revisit frequency can be very short (e.g., one to three days) from pointable sensors onboard. Table 3.1 shows several examples of the revisit frequency of some high spatial resolution sensors.

Hodgson et al (2010) modeled the likelihood of collecting imagery over a hurricane disaster point location based on three high spatial resolution satellites. Their results indicate that if based on only one satellite sensor, the likelihood of collecting imagery within one day of a disaster event varies from 17 to 39 percent (depending on sensor pointing capabilities). However, if based on three satellite sensors, the likelihood will increase to over 94 percent. Rather than a single point representing the disaster area,
a polygonal impact area created a more complex problem. When multiple high spatial resolution satellite sensors are available, hundreds of image collection opportunities may be available for disaster management decision makers, a challenging problem is to determine the best combination of satellite-sensors and the appropriate pointing angle which can fully cover the disaster impact area.

Spatial optimization has long been an important research focus in geography subspecialties and contributes to many fields such as political geography, GIScience and transportation (Tong and Murray 2012). Different optimization models have been developed to solve unique optimization problems, such as the p-median problem (Church and Revelle 1976), set covering problem (Balas and Padberg 1972; Caprara, Toth, and Fischetti 2000; Lan, DePuy, and Whitehouse 2007), harvest scheduling problem (Boston and Bettinger 1999, 2002), location problem (Cooper 1963; Mehrez and Stulman 1982; Tong, Murray, and Xiao 2009; Tong and Murray 2012), and redistricting and partitioning problem (Morrill 1981; Xiao 2008; Guo and Jin 2011) et al.. In this paper, we focus on the application of spatial optimization methods used to assist in coordination and planning of image acquisition for a large disaster area during disaster emergency response.

A model is often used to identify or evaluate a solution to a spatial optimization problem (Birkin et al. 1996). Generally, there are three major components for a model constructed as an optimization problem: decision variables, a set of objective functions, and constraints (Tong, Murray, and Xiao 2009). Decision variables represent the remote sensing satellite image acquisition option, which is the image acquisition plan and subsequent tasking of satellite-sensors (i.e., directing a satellite-borne sensor to point,
collect, and store/transmit data) to collect over different portions of the impact area. The objective function explicitly establishes a goal to be achieved (e.g., minimize or maximize). Constraints are the limitations defined upon optimization parameters. The optimization model defined in this article follows the three-component structure solving the problem under several criteria and constraints. The results from the spatial optimization model are a list of ranked image collection combinations that cover the entire large impact area. The “best” remote sensing satellite image acquisition plans (e.g., top three) will be provided for disaster management decision makers which satisfy spatial resolution, spectral resolution and other logistical requirements. Subjective information is ultimately used to pick the satellite acquisition plan from the modeled “best” plans.

In the following section, more details about the optimization model are given. This is followed by a discussion of methods for solving the optimization problem. Application results over an example impact area along the coast of Mississippi are then presented. Finally, discussion and conclusions are provided.

3.3 Modeling the satellite image collection opportunities for a large area

To identify the “best” satellite image acquisition plan, the first task is to model which satellite-sensor combinations (e.g., some satellites carry multiple-sensors) can collect image covering part of or the entire disaster impact area “n” days after the disaster event. Hodgson and Kar (2008) and Hodgson et al. (2010) modeled the potential swath coverage of nadir and off-nadir pointable remote sensing satellite-sensor systems based on spherical trigonometry and a satellite orbital propagation model; they developed an online spatial decision support system named RSHGS to predict satellite image collection opportunities of a specified hazard location. This model provides a generic approach for
modeling future satellite-sensor collection opportunities for any pointable (or non-pointable) sensor. However, it is only applicable to a point disaster location but not an area. For a large disaster impact area (e.g., the State of South Carolina), we need some points to represent the multitude of satellite pointing angles. With these points available, by combining the RSHGS model, then we can model the satellite image collection opportunities for a large area.

The selection of the multitude of satellite pointing angles representing points is similar to the facility site selection in facility location problem (Owen and Daskin 1998). Similar to the objective of sitting multiple facilities (and an almost infinite set of possible sitting positions) to best serve potential demand, the pointable satellite-sensors can together represent a very large set of combinations of candidate sensors and their pointing angles over the disaster area. To minimize the combinatorial problem a set of key representative geographic locations representing the sensor-pointing angles is dynamically created for each disaster area.

The problem of representing geographic space in facility location models is a confounding issue (Murray and Tong 2007). Traditional methods use discrete points as the spatial, demand locations and service and central locations for areas depending on the geographic scale of analysis (Miller 1996). However, for continuous space facility siting problem which assumes that a facility can be placed anywhere in the plane, one central point is not enough and an infinite number of possible locations need to be considered to represent the space. The same continuous space problem in this study, for a polygonal impact area, any point in the polygon can be a satellite pointing angle representative point. However, there have been computational difficulties in addressing infinite points within
the polygon. Church (1984) and Mehrez and Stulman (1982) developed an approach for identifying a finite point set containing an optimal solution. They used the circle intersection point set (CIPS) to represent the continuous space and demonstrated that CIPS contain at least one optimal solution. Details and proofs please refer to the literatures.

In this research, we applied CIPS to derive the points representing the multitude of satellite pointing angles for a large area. The large disaster area is partitioned into sub areas dynamically based on the minimum swath width of the given high spatial resolution satellite sensors (Figure 3.2). CIPS shown in the figure as small squares are derived as potential satellite pointing angles representative points. However, the number of these points may be still rather large and some points are redundant. In this study, we eliminated CIPS that effectively represent the same swath-point areas. The reduced set of CIPS is referred to as Reduced CIPS (RCIPS). RCIPS will represent the multitude of satellite pointing angles projected on the large disaster impact area. Details about the utility of using RCIPS for an optimal solution can be found in Church (1984) and Murray and Tong (2007).

3.4 Modeling the best satellite image acquisition plan

Each collection opportunity has several attributes including spatial resolution, spectral resolution, swath width, off-nadir angle, time of collection and collection day that may be considered important for the application. Other factors like the cost of acquisition can also be added to the model if related data is available. Each of these attributes is weighted according to its relative importance defined by the decision-maker. Selecting the optimal combination of collection opportunities to cover the entire disaster
area becomes a complex optimization problem with multiple criteria and constraints. The mathematical specification of the optimization model is formulated as follows:

\[
\text{Minimize } \sum_{i} \frac{CA_i}{SA} \cdot (W_1 \cdot SR_i + W_2 \cdot SpeR_i + W_3 \cdot ND_i + W_4 \cdot ONA_i)
\]  (1)

Subject to:  
\[
\bigcup CA_i = SA
\]  (2)

\[
SR_i < \text{specified value}
\]  (3)

\[
SpeR_i = \text{specified values}
\]  (4)

\[
ND_i < \text{specified value (e.g., 3 days, 1 week)}
\]  (5)

\[
0 < W_{1,2,3,4} \leq 1
\]  (6)

Where:  
i = index of available collection opportunities

CA_i = polygon area covered by collection opportunity i

\[
\bigcup CA_i
\] = union of area covered by the collection opportunity combination

SA = polygon area of disaster impact area

SR_i = spatial resolution of collection opportunity i

SpeR_i = spectral resolution of collection opportunity i

ND_i = number of days collection opportunity i collected after a disaster event

ONA_i = off nadir angle of collection opportunity i

W_{1,2,3,4} = equalized weights for spatial resolution, spectral resolution, number of collection days and off nadir angle

In this model, the objective function (Equation 1) minimizes the weighted combination score of a satellite image acquisition plan constructed with several image collection opportunities. The constraint in Equation 2 specifies that the disaster impact area should be fully covered. The constraint in Equation 3 specifies that the spatial resolution of an image collection opportunity should be finer than a user specified value.
(e.g., 1 meter). Constraint in Equation 4 specifies that the spectral resolution of an image collection opportunity should contain specified values (e.g., red, green, blue). Constraint in Equation 5 specifies that the collection day of an image collection opportunity should be less than a specified value (e.g., within 3 days after a disaster event). Constraint in Equation 6 specifies that the weight value for each parameter ranges from 0 to 1. Decision maker can specify a value to represent the relative importance for each factor, a smaller value means more important. For example, 5 for ND\textsubscript{i} which means this factor is the most important, 15 for ONA\textsubscript{i}, 40 for SR\textsubscript{i} and SpeR\textsubscript{i} which they are equally important but less important than ND\textsubscript{i}. These weights (5, 15, 40, and 40) then will be equalized to values within 0 and 1 \( \frac{5}{5 + 15 + 40 + 40 = 100}, \frac{15}{100}, \frac{40}{100}, \frac{40}{100} \). As the values for spectral resolution are nominal and the scales for spatial, collection delay and off-nadir angle are on different scales, a normalization-scheme is used to normalize each variable. In this study, linear functions are used to normalize the values of these factors. For example, for factor ‘collection delay’, if the specified desired collection window is 3 days (72 hours), function (7) will be used:

\[
ND_i^{Normalized} = \frac{ND_i}{72} \tag{7}
\]

3.5 Solving the optimization problem

A variety of search methods have been widely applied to solve various computationally challenging spatial optimization problems, such as integer programming (Boston and Bettinger 1999; Caro et al. 2004), greedy search (Church 1984; Battiti and Bertossi 1999), genetic algorithms(Boston and Bettinger 2002; Ducheyne, De Wulf, and De Baets 2006; Tong, Murray, and Xiao 2009; Zhang, Zeng, and Bian 2010), tabu
search (Boston and Bettinger 2002; Guo and Jin 2011), and simulated annealing
(Kirkpatrick, Gelatt, and Vecchi 1983; Arostegui, Kadipasaoglu, and Khumawala 2006). These methods have proven to be effective for solving different optimization problems, such as genetic algorithms for combinatorial optimization problems. In this paper, we developed a unique optimization model for large area satellite image acquisition planning optimization problem. Based on the problem size, this algorithm is an exact method based on breadth first search.

The basic flow of our optimization model is outlined in Figure 3.3. The first step is to establish a filter to eliminate those sensors that do not meet specified spatial resolution range and spectral resolution types. This filter is used to ensure satellite image collection opportunities satisfy constraints defined in Equation 3 and Equation 4. All satellite-sensors combinations meeting the spatial and spectral resolution requirements become part of the initial solution set. The next step is to specify a time constraint in the number of collection days (e.g., ‘n’ days after a disaster event, defined in Equation 5. The RSHGS model will run using the initial set of satellite-sensors combinations and their near-future orbital tracks (restricted by the number of collection days constraint) to derive a list of satellite image collection opportunities. For each image collection opportunity, weights for the different parameters will be used (Equation 6).

The available satellite image collection opportunities meeting constraints are then used as input to the spatial optimization model. The best satellite image acquisition plans based on the objective function defined in Equation 1 and spatial constraints defined in Equation 2 are derived.
Figure 3.4 illustrates the basic structure of the algorithm used in the spatial optimization model. The algorithm starts by generating a list with each collection opportunity being a candidate solution. Each candidate is examined for the spatial coverage constraint defined in Equation 2. If it covers the entire area, this candidate solution will be added to the solution pool. If it does not meet the requirement, this candidate solution will be selected as the parent and a new image collection opportunity (this will create an image collection opportunity combination) will be added to create a new candidate solution (child base solution based on selected parent base solution). This new created candidate will be added back to the candidates list to run next round loop. With the solutions pool ready, for each solution, fitness calculation will then be performed, by running the optimization search, the final research will be derived.

3.6 Results

The optimization model was applied to solve the spatial optimization problem for satellite image acquisition planning during a hypothetical disaster emergency response phase. We selected a Katrina-like impact area along the Mississippi coast area as the study area. The following constraints were defined and Table 3.2 summarizes the working assumption:

- Natural disaster (i.e., a hurricane) on 1 June 2013
- Satellite images collected within 3 days
- 1 meter spatial resolution or better
- Panchromatic band (spectral resolution)
The CARTOSAT 2A –PAN, CARTOSAT 2AT-PAN, CARTOSAT 2B-PAN, GeoEye-GeoEye1, IKONOS-OSA, Quickbird 2 – BGIS2000, Worldview 1 – Pan and Worldview 2 - Pan satellite-sensor combinations meet the spatial and spectral resolution constraints. Eleven RCIPS are derived to represent the multitude of satellite pointing angles for the study area. Figure 3.5 shows the result of 493 CIPS and 11 RCIPS.

Based on these 11 RCIPS, a total of 143 unique daytime satellite image collection opportunities can provide part of or full coverage of the disaster area. Table 3.3 shows an example satellite image collection opportunity derived from RSHGS prediction model and its spatial coverage is shown in Figure 3.6a. Figure 3.6b shows the spatial coverage detail of these 143 daytime collection opportunities.

Using the optimization algorithm proposed in this research, the top three satellite image acquisition plans (i.e., combinations of satellite-sensor opportunities) are identified. Based on the exact method nature of the algorithm, these three acquisition plans are the guaranteed best solutions. The WORLDVIEW 2 Pan combination can provide two images to fully cover the impact area. The second best solution is to use image swaths from IKONOS OSA and WORLDVIEW 2 Pan. The third best solution is to use image swaths from CARTOSAT 2AT PAN and WORLDVIEW 2 Pan too, but the image from CARTOSAT 2A PAN is collected on 3 June. Figure 3.7 shows the details of these plans and the swath coverage detail is shown in Figure 3.8. The solutions in Figure 3.7 are based on equal weights for all factors in the optimization model. Factor weights may be changed. For example, if spatial resolution is the most important factor for the emergency response analysis, the weight priority can be given to spatial resolution to derive different results.
3.7 Conclusions

This research presents a spatial optimization algorithm for solving the satellite image acquisition planning problem during the disaster emergency response phase. The optimization model is solved under three non-spatial constraints: spatial resolution, spectral resolution, collection days from the event and one spatial constraint: full spatial coverage of the disaster area. By setting several filters with non-spatial constraints, the size of the empirical search space is reduced to efficiently derive the optimal solution.

Federal emergency response partners are evaluating the current implementation of the optimized modeling solution and providing feedback. With the provided online tool, disaster management agencies can quickly determine the appropriate mix of vendors, agencies, or satellite image service providers to enable a rapid data collection and analysis.

In addition, the proposed optimization method has the potential to be used for other non-disaster remote sensing problems. Planning for single season or single year remote sensing acquisitions may be optimized to not only reduce costs but variation in the desired spatial/spectral resolutions (or other constraints).
Table 3.1 Example high spatial resolution satellite sensors revisit frequency

<table>
<thead>
<tr>
<th>Satellite Sensor</th>
<th>Revisit Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>GeoEye – 1</td>
<td>2.1 days at 35° off-nadir, 2.8 days at 28° off-nadir, 8.3 days at 10° off-nadir</td>
</tr>
<tr>
<td>WorldView-2</td>
<td>1.1 days at 1 meter GSD or less, 3.7 days at 20° off-nadir</td>
</tr>
<tr>
<td>QuickBird</td>
<td>1-3.5 days at 30° off-nadir (depending on latitude)</td>
</tr>
<tr>
<td>IKONOS</td>
<td>3 days at 40° latitude</td>
</tr>
</tbody>
</table>
Table 3.2 Working assumptions of the application case

<table>
<thead>
<tr>
<th>Spatial resolution</th>
<th>Spectral coverage</th>
<th>Disaster event date</th>
<th>Number of collection days</th>
<th>Study area</th>
</tr>
</thead>
<tbody>
<tr>
<td>1m or finer</td>
<td>Panchromatic</td>
<td>1 June 2013</td>
<td>3 days</td>
<td>Mississippi coast</td>
</tr>
</tbody>
</table>
Table 3.3 Example satellite image collection opportunity

<table>
<thead>
<tr>
<th>Satellite Name</th>
<th>Collection Time</th>
<th>Sub-sat Latitude</th>
<th>Sub-sat Longitude</th>
<th>Satellite Altitude</th>
<th>Off-nadir Angle</th>
<th>Satellite Azimuth</th>
<th>Satellite Heading</th>
</tr>
</thead>
</table>
Figure 3.1 Relatively large disaster impact area requires multiple satellite images to be fully covered
Figure 3.2 CIPS (small squares) as potential satellite pointing angles representative points
Figure 3.3 Basic flow of the optimization model
Figure 3.4 Algorithm structure for optimization model
Figure 3.5 493 CIPS and 11 RCIPS representing the multitude of satellite pointing angles for the study area
Figure 3.6 (a) Spatial coverage of the example satellite image collection opportunity. (b) Spatial coverage detail of 143 daytime collection opportunities
<table>
<thead>
<tr>
<th>OID</th>
<th>Sensor Name</th>
<th>Spatial Resolution</th>
<th>Band Number</th>
<th>Local Time</th>
<th>Number of Hours</th>
<th>Off-Nadir Angle</th>
<th>Swath km</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1:</td>
<td>score = 115.7344</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>76</td>
<td>WORLDVIEW 2 Panchrom</td>
<td>0.46</td>
<td>1</td>
<td>5/1/2013 12:13:27 PM</td>
<td>12.22417</td>
<td>30.793</td>
<td>16.4</td>
</tr>
<tr>
<td>89</td>
<td>WORLDVIEW 2 Panchrom</td>
<td>0.46</td>
<td>1</td>
<td>5/1/2013 12:13:30 PM</td>
<td>12.225</td>
<td>31.745</td>
<td>16.4</td>
</tr>
<tr>
<td>#2:</td>
<td>score = 117.729</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>72</td>
<td>IKONOS OSA</td>
<td>0.82</td>
<td>5</td>
<td>5/1/2013 12:02:00 PM</td>
<td>12.03333</td>
<td>38.172</td>
<td>11.3</td>
</tr>
<tr>
<td>102</td>
<td>WORLDVIEW 2 Panchrom</td>
<td>0.46</td>
<td>1</td>
<td>5/1/2013 12:13:35 PM</td>
<td>12.22639</td>
<td>31.517</td>
<td>16.4</td>
</tr>
<tr>
<td>#3:</td>
<td>score = 118.412</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>128</td>
<td>WORLDVIEW 2 Panchrom</td>
<td>0.46</td>
<td>1</td>
<td>5/1/2013 12:13:29 PM</td>
<td>12.22472</td>
<td>30.964</td>
<td>16.4</td>
</tr>
</tbody>
</table>

Figure 3.7 Best three image collection plans derived from the optimization model
Figure 3.8 Top three image collection plans derived from the optimization model, (a), (b) and (c) represents #1, #2 and #3 solution in Figure 7 respectively. (d) shows the spatial coverage of the first solution over 143 available image collection opportunities.
CHAPTER 4 Satellite Image Acquisition Planning for Large Area Disaster 
Emergency Response\(^2\)

Abstract

Timely acquisition of critical disaster information is the key to intelligent and effective 
disaster emergency response decisions. Remotely sensed images provide an effective 
broad area means to collect critical information. Natural disasters, however, often have 
large impact areas – larger than a single satellite scene or swath width. Additionally, the 
impact ‘area’ may be discontinuous, particularly in flooding for tornado events. In this 
paper, a spatial optimization model is proposed to solve the large area satellite image 
acquisition planning problem in the context of disaster emergency response. In the model, 
a large area disaster impact area is represented as multiple polygons and image collection 
priorities for different polygons are addressed. The optimization problem is transferred to 
a set covering problem and solved by an exact algorithm. Application results demonstrate 
the effectiveness of the method and spatial decision support system implementing the 
model and algorithm was developed to derive ranked image acquisition plans.

4.1 Introduction

For emergency response, during the three days immediately following a disaster event, the most critical information is the accurate and timely intelligence about the extent, scope and impact of the event (FEMA 1999). Based on such information, disaster managers and decision makers then can make intelligent and effective response decisions. However, timely acquisition of such information is often prevented and hindered from conventional methods (e.g. ground surveys) because of the scope of the disaster (e.g. large areas) and transportation challenges (blocked roads and bridges). Instead, remote sensing systems provide an effective means (especially for large area disaster response) to timely collect critical information about the impact area in support of effective decision-making during the response phase.

Considerable research has been conducted about the application of remote sensing imagery during the mitigation, warning and recovery phases (Tralli et al. 2005; Ostir et al. 2003; Jensen and Hodgson 2006; Chen, Serpico, and Smith 2012), however, relatively little research has focused on the use of remote sensing during the hazard response stage, particularly on the acquisition challenge. For the application of remote sensing during the response phase, the first key issue is the coordination and planning of image acquisition (Hutton and Melihen 2006; Hodgson, Davis, and Kotelenska 2009). Hodgson and Kar (2008) modeled the potential swath coverage of nadir and off-nadir pointable remote sensing satellite-sensor systems, based on this model, which satellite-sensor can provide images covering a point disaster location can be predicted. However, the disaster impact area is always a polygon. Liu and Hodgson (2013) extended this work to a disaster area. They defined the disaster impact area as a polygon. Using a multi-criteria conceptual
model, they incorporated satellite image acquisition requirements (e.g., spatial resolution, spectral resolution, and fully spatial coverage) and created an optimum modeling solution. However, their model 1) requires the impact area to be a single polygon and 2) assumes all parts of the impact area to be equally important (i.e. it does not consider differences among portions of the impact area). For example, infrastructure and residential areas are more important than a forested area for emergency response.

In this research, we extend the satellite image acquisition modeling problem to a complex situation with multiple polygons and considering the differences among portions of the disaster impact area. A spatial optimization model for large area satellite image acquisition planning was developed and applied in disaster emergency response. In this model, different parts of the impact area are represented as different polygons with different weights. The acquisition planning optimization problem is transferred to a set covering problem with multiple constraints. An algorithm is developed and demonstrated using a hurricane disaster impact area along the coasts of Mississippi and Louisiana. An online SDSS was used to implement the model and an optimization algorithm was also developed for satellite image acquisition planning.

4.2 Background

Remote sensing has increasingly been used for researching hazards and some related practical applications. Intelligence revealed from remote sensing images can provide valuable information to hazard managers throughout the life cycle of the event. Over the past 40 years, considerable research has been conducted regarding the use of remote sensing for the warning, recovery or mitigation stages, however, relatively little research has focused on the use of remote sensing during the hazard response stage.
For the ability to collect imagery over large areas immediately after the hazard event, remote sensing approach has substantial advantages over other methods (e.g., insitu observations, field data collection) for emergency response. There are some successful applications of remote sensing for hazard emergency response. For example, Laben (2002) introduced the use of remote sensing data and GIS for emergency management at the Pacific Disaster Center. Huyck and Adams (2002, 2004) described the contribution of airborne and satellite imagery to emergency response efforts following the World Trade Center attack. San-Miguel-Ayanz et al. (2005) applied remote sensing systems to detect active fires for fire emergency management. Flanders, Mengel, and Terry (2006) introduced the application of remote sensing in oil spill detection and response. Hutton and Melihen (2006) discussed the use of remote sensing for emergency response and pointed out that preparation and planning is the only way to maximize the security and effectiveness of available information assets and the first step toward short emergency response phase. Hodgson, Davis, and Kotelenska (2009) summarized the use of remote sensing and GIS data/information in the emergency response and recovery stage of the hazard cycle. They described and discussed the social/institutional and logistical issues regarding the integration of geographical information technologies into the emergency response stage based on a nationwide survey about state-level hazard offices’ spatial data needs and use of geospatial technology. By introducing the evolutionary use of remote sensing data/information in three major hurricanes (i.e. Hurricane Andrew 1992, Hurricane Floyd 1999 and Hurricane Katrina 2005), they proposed five research aspects related to the use of remote sensing data/information in the response phase of the hazard cycle and take “Coordination and planning of image
acquisition” as the first key issue (Hodgson, Davis, and Kotelenska 2009). Since after a hazard event, hazard managers and emergency responders are always extremely busy and somewhat stressed; this makes the response phase not the best time to assess imagery data needs. To be most useful, image acquisition planning becomes very important before a hazard occurs, which means, to understand which satellite sensor can provide images to cover partial or entire potential hazard impact area.

Relatively little research has focused on the problem of collecting imagery from multiple satellites to quickly and completely cover the impact area. Ideally, a decision maker could use a generic tool/system to draw a point or polygon on the map and quickly determine which satellite sensors can provide images covering the point/polygon. Hodgson and Kar (2008) modeled the potential swath coverage of nadir and off-nadir pointable remote sensing satellite-sensor systems based on spherical trigonometry and a satellite orbital propagation model. Instead of searching archived images, this model innovatively provides a generic approach for modeling future satellite-sensor collection opportunities which can cover the hazard location. Based on this model, Liu and Hodgson (2013) studied the polygon-based satellite image acquisition planning and proposed the concept of spatial optimization for image acquisition planning innovatively. However, their research represented the hazard impact as a single polygon and did not address the difference within the impact area. For example, sparsely populated areas have less priority in data collection. In this research, we extend it to a more complex case which the hazard impact area is represented as multiple polygons. We examined the multi-polygons large area satellite image acquisition planning and optimization; different polygons can have different weights when make the image acquisition plan.
In the next section, the methodology is discussed in detail including the formation of optimization problem and the algorithm. This is followed by the application results with different scenarios. The article is concluded with a brief discussion.

4.3 Methodology

4.3.1. Satellite Image Requirements Identification

Weather forecast technology and models are becoming more and more advanced and accurate to monitor hazards, for example, when a hurricane forms, we can estimate the path of the hurricane, when it will land at what area, and what is the potential impact area along the hurricane path. With this kind of information, hazard management departments/agencies then can take effective ways to prepare for the response. For example, making evacuation plans, data acquisition plans. For satellite image preparation, the disaster-related remote sensing tasking and acquisition process begins with the identification of an information requirement that can only be satisfied through the application of remote sensing (FEMA 1999). The identification of satellite image requirements relies on the specification of spatial and spectral resolution. For different emergency response information need, there are different spatial and spectral resolution requirements. For example, to identify the river or flood extent, the satellite image should have NIR band with 2.0 meters or finer spatial resolution, for critical facilities or housing type, the best satellite image should from sensors with PAN band and 0.5m or finer spatial resolution. FEMA defined a set of Essential Elements of Information (EEI) for different types of hazards. These EEIs are categories assist in the acquisition of critical, geospatial information that allows government agencies to assess and respond to disasters (i.e. hurricanes and floods). They contain specific details essential to disaster response
such as weather forecasts, the existence of useful infrastructure and available support, each EEI has a set of observables and specific observables. For the inherent nature of natural hazards, these EEIs must often be collected from remotely sensed data. Hodgson and Jensen (2010) led a research to identify the satellite image requirements for different EEIs. Table 4.1 shows two example EEIs with the spatial/spectral resolution requirements.

In this study, we integrated the results of Hodgson and Jensen’s research. If the hazard management decision makers have clear image resolution requirements or know which satellite sensor they want to obtain from images, they can specify the spatial and spectral resolution or the satellite sensor directly to make the acquisition plan. A stakeholder could also select multiple EEIs. Figure 4.1 shows the detail of spatial/spectral resolution and EEI selection.

4.3.2. Problem formulation

Before proceeding, it is necessary to formally specify the satellite image acquisition planning problem of interest. As noted previously, the objective of this research was to optimize the satellite image acquisition planning for large areas which are represented as multiple polygons. A useful beginning point was to first detail identify the factors, the models and the constraints.

To optimize the satellite image acquisition plan for multiple large area polygons, the first thing is to identify the satellite image collection opportunities which can cover partial or full of the area. Hodgson et al. (2008) proposed a method for predicting future satellite image collection opportunities by specifying a point location. Their model will derive all of the collection opportunities from selected sensors. Based on this method, Liu
and Hodgson (2013) extended the research to fit polygon area. They used points to interpolate the polygon area and applied the concept of Circle Intersection Points Set (CIPS) and Reduced Circle Intersection Points Set (RCIPS) (Church 1984) to derive the available future satellite image collection opportunities. Based on their methods, we extend their research to multiple polygons. For multiple polygons, we still use points to interpolate each polygon and then derive RCIPS for future collection opportunities prediction. Details of deriving RCIPS are contained in this literature (Liu and Hodgson 2013). Figure 4.2 shows an example of RCIPS for multiple polygons.

With the future satellite image collection opportunities available, the next step is to build an estimation model. Each image collection opportunity has several attributes, like spatial/spectral resolution, ground swath width, overpass length, off-nadir angle, collection time, spatial coverage area. Weighted Linear Combination (WLC) model concept was used to integrate these factors for quantifying an image collection opportunity. Consider the notation:
\[ CO_i = (W_1 \cdot SR_i + W_2 \cdot SpeR_i + W_3 \cdot ND_i + W_4 \cdot ONA_i) \cdot (\sum_j \frac{CA_{i,j}}{SA_j} \cdot W_j) \]

\( i \) = index of collection opportunity
\( j \) = index of polygons

\( CO_i \) = Collection Opportunity i

\( SR_i \) = spatial resolution of collection opportunity i

\( SpeR_i \) = spectral resolution of collection opportunity i

\( ND_i \) = number of days collection opportunity i collected after a disaster event

\( ONA_i \) = off nadir angle of collection opportunity i

\( W_{1,2,3,4} \) = weights for spatial resolution, spectral resolution, number of collection days and off nadir angle

\( W_j \) = priority weight of polygon j

\( CA_{i,j} \) = area of polygon j covered by collection opportunity i

\( SA_j \) = area of polygon j

In this model, the scales for different factors are different. Normalization is applied to each variable. In this study, linear functions are used to normalize these factors. For example, the value of factor \( ND_i \) is the number of days (e.g., 1 – 7 days) when image collection opportunity i is collected after a hazard event, after normalization, its value will be 0 – 1 (e.g., \( \frac{ND_i}{7} \)). For the weights of different factors, we presented a conceptual model, which is the decision maker can specify the priority or use equal weights. \( CA_i \) represents the coverage area of image collection opportunity i.
A satellite image acquisition plan consists of one or multiple image collection opportunities, selecting the optimal combination of collection opportunities to cover the entire disaster area is a complex optimization problem with multiple criteria and constraints. For example, the combination of these collection opportunities needs to meet the spatial/spectral/time requirements. The mathematical specification of the optimization model is formulated as follows:

Minimize \( \sum_l CO_l \) \hspace{1cm} (1)

Subject to:

\( \bigcup_l CA_{l,j} = \text{impact areas} \) \hspace{1cm} (2)

\( SR_i < \text{specified value} \) \hspace{1cm} (3)

\( \text{SpeR}_i = \text{specified values} \) \hspace{1cm} (4)

\( \text{ND}_i < \text{specified value (e.g., 3 days, 1 week)} \) \hspace{1cm} (5)

\( 0 < W_{1,2,3,4} \leq 1, 0 < W_j \leq 1 \) \hspace{1cm} (6)

The objective, (1), is to minimize the total WLC score of a satellite image acquisition plan with multiple collection opportunities. This objective function is subject to five constraints. Equation 2 describes the spatial coverage constraints, which means the hazard impact area should be fully covered. Equation 3, 4 and 5 specifies the resolution requirements of the emergency response analysis, for example, the spatial resolution should be 1 meter or finer, the spectral bands of the satellite image should contain specified values (e.g., Pan, NIR), the collection day should be within 7 days after the hazard event. The constraint in Equation 6 specifies that the weight value for each parameter ranges, we specified their values range from 0 to 1 in this concept model.
4.3.3. Solving the problem

Spatial optimization is an important subspecialty in geography discipline and has contributed to many fields. Tong and Murray (2012) provide an overview of spatial optimization in geography with some illustrative examples; they analyze the properties, relationships and challenges behind spatial optimization problem. In this research, based on previous illustration, the hazard impact area (multiple polygons) is represented with interpolated set of points and each image collection opportunity is represented as a rectangle, as one collection opportunity can cover the entire or partial of the impact area, each rectangle can cover some interpolated points. Finding an optimized set of collection opportunities to cover the interpolated points with several constraints forms a weighted set covering problem.

The set covering problem (SCP) is defined as the problem of covering an m*n matrix by a subset of the columns with minimum cost, it is an important model for several applications such as crew scheduling. Much interest and research has been devoted to solving the set covering problem and a lot of algorithms have been proposed targeting different application cases, from micro size class (around 600 rows and 60,000 columns) to large size class (around 5,500 rows and 1,100,000 columns). Generally, these methods can be categorized into tow classes: heuristic and exact. We refer the reader to Caprara, Toth, and Fischetti (2000) for a complementary review of algorithms for the set covering problem.

In this study, considering the size of our SCP case (around 300 collection opportunities and 150 interpolated points), we applied an exact method to solve the problem. The most effective exact approaches to SCP are branch-and-bound algorithms.
Based on the idea of branch-and-bound, our method takes each image collection opportunity as a base solution and then searches the entire solution space based on breadth-first-search (BFS) to create new solutions. A fitness function was used to evaluate each base solution. Figure 4.3 describes the structure of the optimization algorithm.

4.4 Results

The proposed optimization model was implemented and applied to a web-based spatial decision support system (SDSS) for satellite image acquisition planning. In order to get the future satellite image collection opportunities, some constraints need to be specified. We defined two different application scenarios.

The first working assumption is defined to get the best satellite image acquisition plan by specifying spatial and spectral resolution directly. Images from satellite sensors with 1 meter or finer spatial resolution and Pan spectral band are desired, and they should be collected within 3 days. Based on these constraints, 8 satellite sensors including CartoSat, GeoEye, IKONOS and QuickBird 2 generate 156 potential image collection opportunities. Figure 4.4a shows the multi-polygons and the swath coverage of one sample image collection opportunity. Figure 4.4b shows the swath coverage of these 156 satellite image collection overpasses. Running the proposed optimization model, the best 3 acquisition plans have been derived. Figure 4.4c shows the swath coverage of the first best plan and the details of the best 3 plans are display in Figure 4.4d.

The second scenario is defined by specifying an EEI for emergency response analysis. “Housing Type” is selected to be the example and the potential satellite images should also be collected within 3 days. Three satellites (GeoEye, Worldview 1 and 2)
were selected to get the future image overpasses. Based on this setting, 56 assets are derived to run the optimization model. Figure 4.5a shows the swath coverage of one sample collection opportunity; from the figure we can see the length of the overpass is automatically adapted to cover the polygons along the path direction. Figure 4.5b shows all of these 72 assets. Based on the proposed optimization model, the best three satellite image acquisition plans are derived. Figure 4.5c shows the swath coverage of the first best solution and Figure 4.5d shows the details of the best plan.

4.5 Conclusion and Discussion

The application results demonstrate that the satellite image acquisition planning problem can be solved with the proposed optimization model effectively. When implementing the proposed model, polygons are represented with interpolated points, for the spatial coverage constraint defined in the model, fully covering a polygon means all of the interpolated points are covered by the collection opportunities combination. Figure 4.6 shows an example of polygon interpolation. In the figure, one sample collection opportunity is displayed on the map to indicate the spatial coverage.

In conclusion, this research presents a spatial optimization model for satellite image acquisition planning and optimization. In the model, an “area of interest” is represented with multiple polygons and different priority weights may be attached to different polygons. The model itself is subject to several constraints including spatial and non-spatial ones and is implemented with a SDSS. This SDSS provides a powerful tool for hazard managers and scientists interested in the process of acquiring and analyzing remote sensing imagery, by drawing the areas of interest on the map and set a few
constraints and weights for each constraint, available image acquisition plans can be derived and the best three solutions will be provided for reference.
Table 4.1 Example EEIs and their minimum spatial/spectral resolution requirements

<table>
<thead>
<tr>
<th>EEI Name</th>
<th>Spatial Resolution</th>
<th>Spectral Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Type</td>
<td>0.5</td>
<td>Pan</td>
</tr>
<tr>
<td>River or flood extent</td>
<td>2.0</td>
<td>NIR</td>
</tr>
<tr>
<td>Spatial / Spectral Resolution</td>
<td>EEI</td>
<td></td>
</tr>
<tr>
<td>------------------------------</td>
<td>------------------------------------------</td>
<td></td>
</tr>
<tr>
<td><strong>Spatial Resolution:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0 to 1.0 meters</td>
<td>Geographic location of a hurricane's eye</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Extent of ocean tides</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sea surface temperature</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Damage by observing water features</td>
<td></td>
</tr>
<tr>
<td><strong>Spectral Resolution:</strong></td>
<td>River or flood extent</td>
<td></td>
</tr>
<tr>
<td>☑ PAN</td>
<td>Storm surge extent</td>
<td></td>
</tr>
<tr>
<td>☑ Red</td>
<td>Vegetation functional health</td>
<td></td>
</tr>
<tr>
<td>☑ VIS</td>
<td>Business type</td>
<td></td>
</tr>
<tr>
<td>☑ MIR</td>
<td>Critical facilities</td>
<td></td>
</tr>
<tr>
<td>☑ Gamma</td>
<td>Electrical power facilities</td>
<td></td>
</tr>
<tr>
<td>☑ UV</td>
<td>Government facilities and systems</td>
<td></td>
</tr>
<tr>
<td>☑ X</td>
<td>Housing type</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.1 Satellite image requirements identification via Spatial/Spectral resolution specification or EEI selection
Figure 4.2 Multiple polygons are interpolated with points to derive RCIPS for future collection opportunities prediction
Figure 4.3 Basic structure of the proposed algorithm
Figure 4.4 Application results with specified spatial and spectral resolution requirements
Figure 4.5 Application results for “Housing Type” emergency analysis
Figure 4.6 Polygon representation with interpolated points
CHAPTER 5 Remote Sensing Image Acquisition Planning for Salt-Marsh Vegetation

Abstract

Salt marshes play a very important role in both environmental and economic aspects. Different stands of salt-tolerant vegetation provide innumerable ecologic, economic, and aesthetic benefits to coastal communities. Remote sensing has been used to map and monitor salt marsh vegetation for several decades. Various types of remote sensing imagery have been applied in different applications including hyperspectral, multispectral and high spatial resolution imagery.

Because of the influence of tides, salt marshes are regularly flooded by salt water during the tidal cycle. Coordinating image collection at optimum tidal periods (typically low tide) and phonological period of interest is challenging. Satellite overpasses for nadir-pointing instruments are predictable but pointable-sensors are flexible allowing for more ‘overpass’ opportunities but with various effects (e.g., coarser spatial resolution, changes in sun angle, etc.).

3 Shufan Liu, and Michael E. Hodgson. 2014. Remote Sensing Image Acquisition Planning for Salt-Marsh Vegetation. This manuscript will be submitted to Remote Sensing of Environment
No known research has been conducted on satellite image acquisition planning for tidally influenced regions. In this research, we developed and implemented a framework and model to address this problem. Models for tidal prediction, satellite overpasses, and imaging instrument pointing are integrated to predict available image collection opportunities. By weighting the desired criteria image collection opportunities can be weighted. An online spatial decision support system was developed to assist satellite image acquisition planning during relative low tides periods. Example applications for an area in South Carolina are demonstrated.

5.1 Introduction

Salt marshes are coastal wetlands and transition zones between land and open salt water which are drained and regularly flooded by salt water from tidal action. These areas are dominated by dense stands of salt-tolerant vegetation such as herbs, grasses, or low shrubs (Adam 1990). These vegetation play an important role in the ecological functions of salt marsh environments (Kokaly et al. 2003). They are highly productive and act as critical habitats for a wide variety of plants, fish, and other wildlife (Klemas 2001), they provide innumerable ecologic, economic, and aesthetic benefits to coastal communities. The intertidal habitats are key element in intertidal system dynamics (Belluco et al. 2006), they play a central role in mediating sea action on the coast and providing coastal protection, and they are essential to the stability of the salt marsh in trapping and binding sediments. Further, the biomass produced by this vegetation is often the largest contribution to the local incoming flux of soil. Salt-marsh vegetation is also a carbon sink. On the other hand, some invasive wetland plants, such as Spartina on the western coast of the United States, are also threatening coastal wetlands.
Salt-marsh vegetation is of a central research interest for several decades. For example, wetlands sustainable management, restoration, biomass production, vegetation mapping are common examples. More recently, coastal salt-marsh is also regarded as a climate change (through sea level rise) indicator. These monitoring always require up-to-date spatial information about the spatial distribution and characteristics of salt marshes. Remote sensing has played an important role for salt marsh research since 1960s (Hardisky, Gross, and Klemas 1986). Various types of remote sensing imagery including hyperspectral, multispectral and high spatial resolution have been utilized in mapping salt-marsh vegetation. For example, Howland (1980) applied multispectral aerial imagery for wetland vegetation mapping. Hardisky, Wolf, and Klemas (19830), Hardisky et al. (1984), and Hardisky and Klemas (1985) used remote sensing for salt marsh vegetation biomass estimation. Harvey and Hill (2001) used LANDSAT TM and SPOT satellite imagery for vegetation mapping. Schmidt and Skidmore (2003) discussed the spectral discrimination of vegetation types in a coastal wetland using hyperspectral imagery. Artigas and Yang (2005) used hyperspectral imagery combined with field collected seasonal reflectance spectra of marsh species to map the plant vigour gradient. Belluco et al. (2006) studied the application of multispectral and hyperspectral remote sensing for salt-marsh vegetation mapping, using data sets from ROSIS, CASI, MIVIS, IKONOS and QUICKBIRD. Gilmore et al. (2008) applied QUICKBIRD imagery to classify and map the common salt marsh plant community. Hestir et al. (2008) used hyperspectral remote sensing imagery for detecting and monitoring invasive weed species. Zuo et al. (2012) applied LANDSAT TM and CBERS-1 imagery to study the distribution of
spartina alterniflora. The NOAA Coastal Change Analysis Program (C-CAP) has focused on coastal wetland mapping, including salt-marsh, for almost thirty years.

Research in the remote sensing literature is generally focused on the methodology for mapping salt-marsh. Ozesmi and Bauer (2002) reviewed the classification techniques used to map and delineate different wetland types using various types of remotely sensed imagery. Silva et al. (2008) provided a review regarding the theoretical background and application of remote sensing techniques in aquatic plants in wetlands. Adam, Mutanga, and Rugege (2010) reviewed the application of multiple and hyperspectral remote sensing for identification and mapping of wetland vegetation. Klemas (2013) discussed the application of remote sensing for coastal wetland biomass. In these research effects, satellite images from different platforms provide detail information for quantitative, accurate and repeatable observations of the spatial temporal distributions of salt-marsh vegetation. Such observations can cover spatial scales ranging between tens of centimeters and some kilometers, and temporal scales from a single day to several years. Previous approaches to remote sensing of salt-marsh vegetation often focus on spectral characteristics of different species or image processing (i.e., classification) based analysis.

Because of the influence of daily tidal flow (and seasonal variability), coastal salt marshes can show distinct patterns of zonation (Rand 2000), which means low tidal flooding area and high tidal flooding area can be dominated by different types of species. Figure 5.1 shows an example of salt marsh during low tide and high tide. Most vegetation is exposed during the low tidal period, but during high tidal period, vegetation is largely inundated by tidal flooding. To better understand salt-marsh vegetation and get more accurate results about like vegetation spatial structure and patter, biomass estimation,
species diversity, salt marshes should not be flooded during image acquisition, thus, these acquisitions should be planned for periods of relatively low tides.

However, little research has been on the optimization or likelihood of acquiring satellite imagery during low tide period. To plan the satellite image acquisition during low tides for a specified salt marsh location, at least two questions need to be answered. First, when is the low tide period during future acquisition day(s)? Second, what kind of sensors on the satellites can provide images covering the salt marsh during the low tide period? Determining the co-occurrence of satellite imaging opportunities with low tidal periods is not a trivial problem, particularly with pointable satellite sensors. Tides are caused by the combined effects of the gravitational forces exerted by the Moon and the Sun and the rotation of the earth, they are vary geographically on timescales. Satellites are maintained on relatively fixed orbits (i.e. the orbit path is adjusted a few times each year), the repeat interval for different sensors vary on the order of several days.

Extensive research has been conducted concerning tidal analysis and prediction since 1867. Different methods and models have been developed, and various tidal prediction services are available. For example, the Center for Operational Oceanographic Products and Services (CO-OPS) provide comprehensive products about tides and currents. They estimate the water level based on harmonic constituents method and provide an online tide prediction website (NOAA). Figure 5.2 shows an example of the tide prediction results for the Charleston, SC monitor station.

Satellite image vendors have their own models to predict when their satellite sensors can collect imagery over an area. However, in general, these models are not
available for public access and they can only predict the company or agency’s satellite sensors. For some agencies/companies, and in particular for nadir-looking imaging sensors, the future collection opportunities are readily available, such as Landsat or Aqua/Terra satellites. In the literature, there are a few researches focusing on the satellite image acquisition planning. Emery (1989) and Rosborough et al (1994) developed modeling approaches for AVHRR satellite-sensors to provide automatic georeferencing of imagery. Hodgson and Kar (2008) developed a model to determine and map the potential swath coverage of pointable remote sensing satellite sensor systems. Based on this model, they provided a generic approach for modeling future satellite sensor collection opportunities and Hodgson et al. (2010) demonstrated its use for the historic record of land-falling hurricanes in the United States. Liu and Hodgson (2013) studied satellite image acquisition planning for large area which requires multiple collections from dissimilar satellite sensors. They proposed and developed a spatial optimization method to derive best image collection acquisition plans within a specified collection time window.

However, almost no research has been conducted concerning satellite image acquisition planning for tidal periods. The main goal of this article was to develop a general solution for multiple criteria (e.g. spectral and spatial requirements, tidal cycle thresholds, phonological cycle thresholds, etc.) satellite image planning. We demonstrate this general solution for tidal cycle modeling and satellite image collection opportunities. An online system was also developed for remote sensing satellite image acquisition planning for salt marsh.
In the next section, the data needs are described in detail. This is followed by the introduction of the methodology for satellite image acquisition planning during low tide periods. In section four, we demonstrate the implemented solution. The article is concluded with a brief discussion.

5.2 Tide Prediction Stations and Data Description

Salt marshes occur almost worldwide and in the U.S., salt marshes can be found on every coast. Approximately half of the nation’s salt marshes are located along the Gulf Coast (NOAA). For this research, we included the tide prediction information of the long-term monitoring stations along the Southeast and the Gulf coast of the U.S. (Figure 5.3).

For the satellites and their onboard sensors, we have constructed a database of imaging satellites with over 160 sensors. These sensors have various spatial resolutions with some sensors containing only one band while other sensors have more than 10 bands. Specific characteristics of each satellite, sensor, and band are contained in the database. Figure 5.4 presents the detail information of an example satellite sensor in our database. The satellite ephemeris (orbital position and track) is updated nightly from a NORAD database. This database of satellites-sensors-bands and ephemeris is growing and their orbits information is maintained and updated regularly.

5.3 Methodology

5.3.1. Tide prediction

Tides are from astronomical forces that are well-modeled from harmonic equations. With the exception of episodic events, intense high or low cells or strong
prevailing winds and heavy rainfall events influencing estuarine flow, a harmonic model is a relatively good prediction model. To achieve maximum accuracy in prediction, a partially empirical approach based upon actual observations of tides at a location over an extended period of time is necessary.

The NOAA CO-OPS program provides comprehensive services for tide observation and prediction. In this research, we used NOAA’s tide prediction service to retrieve the predicted tide results for these long-term stations. By specifying the date, datum, location and a few other parameters, detail tide prediction information for a specified location will be returned by a web service call. We then integrated this information into our satellite image acquisition planning model (described in next section). It should be noted that prediction of tidal heights at coastal locations between coastal tidal stations can generally be modeled through interpolation; however, prediction of tidal heights from coastal monitoring stations to locations within estuaries should consider the lag-time between coastal-to-estuarine locations (Ramsey, 1995). This issue is beyond the scope of this satellite-image collection modeling research presented here.

5.3.2. Satellite image acquisition planning

There are over fifty unclassified imaging satellites with relatively moderate (~1500-m) to high (< 0.5-m) spatial resolution orbiting around the Earth. Satellite image acquisition planning means to determine which satellites and their sensors are in a position to collect imagery over a specified location during a specified collection window. Additionally, adding other criteria to rank alternative acquisition plans is ideal. Hodgson and Kar (2008) demonstrated the use of a satellite-sensor prediction model to predict the potential swath coverage of remote sensing satellite sensors. They developed an online
spatial decision support system (RSHGS) to predict potential satellite image collection opportunities for a specified hazard location based on selected satellite sensors. Liu and Hodgson (2013) extended the research and developed a large area coverage optimization model from multiple satellite sensors. Generally, given a specified location and collection window, these models can determine which sensors, meeting spatial and spectral resolution criteria, can provide images to cover the location within the time period. The model by Liu and Hodgson (2013) can also rank alternative image collection opportunities using weights associated with key parameters. We have built our model based on this previous research. However, in this research we extended the satellite collection opportunity framework to include predictable physical processes in the environment. Our example of natural environmental criteria is the tidal cycle.

5.3.3. Modeling the best image collection opportunities

A single satellite image collection opportunity has several attributes including spatial resolution, spectral resolution, ground swath width, off-nadir angle, collection time and spatial coverage area (Liu and Hodgson 2013). These attributes are associated with the satellite orbit, sensor characteristics, and sensor attitude. Exogenous to the orbit and satellite is the dynamic environment of the earth. Largely well-behaved are the solar illumination, tidal cycle, vegetation phonological cycle, and stream-flow. Less well-behaved (and predictable over longer time-frames) are high/low cell, storm fronts, rainfall events, etc. The well-behaved environmental variables can typically be modeled and such variations predicted days, weeks, or even months ahead. Prediction of the less well-behaved variables beyond hours or days is problematic. To model the best image collection opportunities considering both orbit/sensor and natural environmental variables,
a model is needed to represent each variable component. The integration of the modeling components into a predict model could use strict thresholds (e.g. a pass/fail suitability model) or weighting of component values. For example, differences (e.g. in days) from an ideal date of the phonological cycle may be less important than differences (e.g. hours or tidal height in feet) in a collection time and the lowest tidal height. In this research, an example using sensor collection off-nadir angle and tidal height differences are used and weighted.

For salt marsh vegetation analysis, hyperspectral, multispectral and high spatial resolution images have often been used for mapping and monitoring salt marsh vegetation. In this research, we did not address the spatial/spectral requirements, but emphasis the image collection time. Therefore, collection time, and its relationship to the tidal cycle and vegetation phonological cycle, is one of the most important factors to determine if an image collection opportunity is a good fit. An image collected at lowest tide period is better than an image collected within other time periods. Another sensor factor is the off-nadir viewing angle, an image with smaller off nadir angle is generally regarded as a better choice than more oblique imagery. With these two factors, a weighted linear combination (WLC) model was used to integrate them together to derive a score (i.e., $CO_i$) which represents the fitness. Considering the following notation:

$$CO_i = W_1 * |CT_i - LT| + W_2 * ONa_i$$

\[ i = \text{index of collection opportunity} \]
\[ CO_i = \text{Collection Opportunity } i \]
\[ W_{1,2} = \text{weights for collection time and off nadir angle} \]
\[ CT_i = \text{Collection time of opportunity } i \]
\[ LT = \text{Lowest tide time of the image collection day} \]
\[ ONA_i = \text{off nadir angle of collection opportunity } i \]

In this example the unit of differences in collection time and low tide time (in minutes), and the unit of the angular difference (degrees) between a nadir and off-nadir collection opportunity are different. Other units might be used, such as tidal height differences (i.e. between low tide and tide at image collection time). One might also consider some type of standardization of the range in differences as a percentage of the difference in tidal heights or off-nadir angles. Non-linear model differences might also be more useful, as the differences near the low or high tide minima and maxima are less important than changes in time elsewhere (Figure 5.2). An example image collection opportunity with different attributes is shown in Table 5.1. For this image collection opportunity, collection time (CT) is 7/8/2014 10:54:29 AM, off nadir angle (ONA) is 36.585. Table 5.2 listed the predicted tides height, the lowest tide time (LT) is 7/8/2014 10:41:00 AM (i.e. 13 minutes difference). With this information, a score can be derived to represent the relative fitness of an image collection opportunity.

5.4 Results

The proposed model was implemented and applied in a web-based spatial decision support system to assist image planning for salt marsh vegetation. In this section, we present example results by using the developed spatial decision support system.
The working assumption is to obtain high spatial resolution images for salt marsh vegetation. Coastal salt marshes are spatially complex and temporally quite variable, high spatial resolution satellite images have been used more and more in various studies related to salt marsh vegetation. More accurate results are often expected with high spatial resolution images. In this working assumption, the desired candidate satellite sensors are GeoEye-1, IKONOS, QUICKBIRD, SPOT 5, WORLDVIEW-1, and WorldView-2. The coastal marsh near Charleston, SC is selected to be the study site. The target collection date, based on phonological considerations, is set to July 12, 2014. So in summary, the working assumption is we need images from one or more high spatial resolution satellite sensors to cover Charleston, SC area on or near in-time to July 12, 2014. Table 5.3 summarizes the environment variables.

By executing the implemented model, three available satellite image collection opportunities from GEOEYE-1, IKONOS and WORLDVIEW-2 were derived and ranked. Figure 5.5 shows the details of the results. The lowest tide daytime on 7/12/2014 is 1:24:00 PM. For this date three good image collections at nearly the same time (~7/12/2014 11:39:30 AM) are possible. However, the Worldview-2 satellite-sensor is the best opportunity as the off-nadir angle (6-deg) is so modest compared to the other two satellite-sensors on that day. Figure 5.6 shows the spatial coverage of the best image collection opportunity.

The collection date is open to any day and the ranked results will be derived based tides predictions and available satellite image collection opportunities. For example, with the same settings except collection date, for example, July 19th, 2014, the lowest tide daytime is 7/19/2014 7:30:00 AM, and there are 5 available image collection
opportunities from SPOT 5, QUICKBIRD, IKONOS, and GEOEYE. Image from SPOT 5 collected at 7/19/2014 10:12:54 is the best imagery based on the model. Figure 5.7 shows the basic interface of the online spatial decision support system.

5.5 Conclusion

In this research we have outline a framework for satellite image collection opportunities based on satellite orbit, sensor characteristics, and natural environmental factors. Assuming independence between variables, a weighted linear combination model is used as the integration approach. Application results demonstrate that the satellite image acquisition planning during relative low tide period problem can be solved with the proposed model effectively. The proposed model integrated tidal height prediction and image collection opportunity modeling, using a WLC model to integrate the individual variables and rank the collection opportunities. Remote sensing plays an important role for salt marsh vegetation analysis like monitoring, species identification, and mapping. Images from different satellite platform have been used in various applications. Since salt marsh vegetation is regularly flooded by the salt water brought in by the tides, to get better understanding of the distribution of vegetation and get more accurate results of vegetation mapping and other analysis, it is better to collect images during the relative low tide periods. This research provided a novel method from an integrative approach with model subcomponents, some from web services, to create an appropriate solution. The online spatial decision support system provides a useful tool for managers and scientists interested in remote sensing for salt marsh vegetation in the process of acquiring satellite imagery.
Limitations of the implemented system include reliance on a somewhat ‘coarse’
density of tidal station harmonics. The tidal cycle of estuarine stations often vary
somewhat in timing and magnitude with respect to the nearby coastal tidal station. An
improved tidal cycle model localized on specific estuarine areas would be improved the
precision of the tidal model component. Future research could include the uncertainty in
model predictions from natural environmental variables. More pragmatically, other
research could focus on the improvement of the spatial decision support system with
feedback from users or stakeholders.
Table 5.1 Example satellite image collection opportunity on 07/08/2014

<table>
<thead>
<tr>
<th>Satellite Name</th>
<th>Collection Time</th>
<th>Satellite location - Lat</th>
<th>Satellite location - Long</th>
<th>Off Nadir Angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>GEOEYE 1</td>
<td>7/8/2014 10:54:29 AM</td>
<td>31.8296</td>
<td>-75.2609</td>
<td>36.585</td>
</tr>
</tbody>
</table>
Table 5.2 Tide prediction results of 07/08/2014

<table>
<thead>
<tr>
<th>Date</th>
<th>Day</th>
<th>Time</th>
<th>Height</th>
</tr>
</thead>
<tbody>
<tr>
<td>07/08/2014</td>
<td>Tuesday</td>
<td>04:19 AM</td>
<td>4.82 H</td>
</tr>
<tr>
<td>07/08/2014</td>
<td>Tuesday</td>
<td>10:41 AM</td>
<td>-0.08 L</td>
</tr>
<tr>
<td>07/08/2014</td>
<td>Tuesday</td>
<td>5:15 PM</td>
<td>5.81 H</td>
</tr>
<tr>
<td>07/08/2014</td>
<td>Tuesday</td>
<td>11:40 PM</td>
<td>0.33 L</td>
</tr>
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</table>
Table 5.3 Working assumption variables

<table>
<thead>
<tr>
<th>Collection Time:</th>
<th>July 12, 2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location:</td>
<td>Charleston, SC</td>
</tr>
<tr>
<td>Satellite sensors:</td>
<td>GEOEYE-1, IKONOS, QUICKBIRD, SPOT 5, WORLDVIEW-1, WORLDVIEW-2</td>
</tr>
</tbody>
</table>
Figure 5.1 salt marsh with low tide and high tide (redrawn from wiki)
Figure 5.2 Tide prediction for Charleston, SC tide monitor station
Figure 5.3 Spatial distribution of tide monitoring and prediction stations along the Gulf Coast
Figure 5.4 Example satellite sensor band information in the database (ephemerides not shown)
**Results:** 3 assets available based on the selected filters. Lowest tide time: **7/12/2014 1:24:00 PM**

![Graph showing tide prediction](image)

<table>
<thead>
<tr>
<th>OppID</th>
<th>Satellite Name</th>
<th>Local Time</th>
<th>Sub-sat Longitude</th>
<th>Satellite Altitude</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>GEEOYE 1 GeoEye-1</td>
<td>7/12/2014 11:39:40 AM</td>
<td>-86.1192</td>
<td>679.37</td>
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<tr>
<td>1</td>
<td>IKONOS OSA</td>
<td>7/12/2014 11:26:37 AM</td>
<td>-83.4419</td>
<td>678.33</td>
</tr>
<tr>
<td>2</td>
<td>WORLDVIEW 2 Panchrom</td>
<td>7/12/2014 11:24:03 AM</td>
<td>-79.1383</td>
<td>763.17</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>OppID</th>
<th>Satellite Name</th>
<th>Satellite Azimuth</th>
<th>Satellite Heading</th>
<th>OffNadir Angle</th>
<th>TimeDiff</th>
</tr>
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<tr>
<td>0</td>
<td>GEEOYE 1 GeoEye-1</td>
<td>286.2</td>
<td>193.345</td>
<td>45.056</td>
<td>6260</td>
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<tr>
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<td>IKONOS OSA</td>
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<td>191.739</td>
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<td>2</td>
<td>WORLDVIEW 2 Panchrom</td>
<td>102.59</td>
<td>189.668</td>
<td>6.291</td>
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</table>

Figure 5.5 Detail information of tides prediction and available image collection opportunities
Figure 5.6 Spatial coverage of the best image collection opportunity from GEOEYE-1
Figure 5.7 Interface of the spatial decision support system developed for satellite image acquisition planning for salt marsh vegetation
CHAPTER 6 Conclusions

6.1 Summary of results

This dissertation seeks to advance the theories and methods of satellite remote sensing image acquisition planning within a spatial temporal context. We already have advanced technologies to collect, process, and deliver remote sensing data. However, even with hundreds of sensors orbiting around the Earth with capabilities to collect hundreds of images, operational image acquisition planning for time sensitive phenomena has been limited. This dissertation researched the theories, methods, models, and algorithms for developing an operational and effective satellite image acquisition planning SDSS.

Chapter 2 presents the proposed SDSS framework. Different components in the framework were described in detail.

Chapter 3 presented a spatial optimization model for solving the satellite image acquisition planning problem for a large area. The optimization model is solved under three non-spatial constraints: spatial resolution, spectral resolution, collection days from the event and one spatial constraint: full spatial coverage of the disaster area. By setting several filters with non-spatial constraints, the size of the empirical search space is reduced to efficiently derive the optimal solution.

Chapter 4 presented a spatial optimization model for solving multi large areas acquisition planning problem. In the model, an “area of interest” is represented with
multiple polygons with unique priority weights attached to each polygon. The model itself is subject to several constraints including spatial and non-spatial ones and is implemented with a SDSS. This SDSS provides a powerful tool for hazard managers and scientists interested in the process of acquiring and analyzing remote sensing imagery, by drawing the areas of interest on the map and setting a few constraints and weights for each constraint, available image acquisition plans can be derived and the best three solutions will be provided for reference.

Chapter 5 addressed the satellite image acquisition planning problem for tidally influenced regions. Based on the framework described in Chapter 2, models for tidal prediction, satellite overpasses, and imaging instrument pointing are integrated to predict available image collection opportunities during relative low tide periods. This research provided a novel method from an integrative approach with model subcomponents, some from web services, to create an appropriate solution. The online SDSS provides a useful tool for managers and scientists interested in remote sensing for salt marsh vegetation in the process of acquiring satellite imagery.

Collectively, this research provides a foundation for research and development towards the satellite image acquisition planning. Innovate models, algorithms, and a SDSS framework are developed for solving the problem. Rapid planning of satellite image acquisition from targeted sources would greatly assist in the information collection, extraction and delivery for time sensitive applications. An operational SDSS can and should be designed to maximize the effectiveness of satellite remote sensing imagery for time sensitive phenomena.
6.2 Future research

Satellite remote sensing image acquisition planning is conceptualized as a single SDSS with a defined objective of providing optimized image acquisition solutions to maximize the effectiveness of remote sensing applied for time sensitive applications. It would seem that the fields of Remote Sensing, GIS, Decisions Science, Spatial Databases, and Software Engineering could make significant contributions to the development of SDSS. Future research will be conducted from these aspects.

Spatial resolution and spectral resolution are the basic two criteria to determine if a remote sensing imagery can be used for a specific application. For example, for different natural disaster (e.g., flood, earthquake), the spatial and spectral resolution requirements are different. Expert knowledge of remote sensing imagery requirements for an application is important for rapid image acquisition planning. In this dissertation study, there is some expert knowledge about spatial/spectral resolution requirements for flood and hurricane already collected. Future research work will continue to build an expert knowledge database. With this database, the proposed SDSS framework then can be quickly leveraged for different time-sensitive phenomena applications.

Another research direction is the improvement of the models and algorithms. Existed models may be improved to get better time and space complexity. New models can be developed and added to build a model base which can be used for different scenarios.

Collaborative spatial decision making is another research direction. For a lot of time sensitive events, especially for hazard emergency response, remote sensing played a very important role and massive quantities of remote sensing data were collected during these
events by different stakeholders (e.g. government agencies or private companies). For example, the Hurricane Katrina of 2005, southern California wildfires in 2003 and 2007 were large events involving numerous stakeholders with different goals. However, the role of remote sensing data in informing the emergency response was limited by communications delays, a lack of coordinated processing or management, or a lack of clarity on the needs of response decision makers (Lippitt 2012). Collaborative decision making about image acquisition planning can assist greatly in this process. The identification of emergency response data requirements, the weights of different factors, and the collection priority for different areas and analysis, they all can be solved effectively via collaborative decision making. With these inputs, remote sensing image acquisition planning then can derive optimized image acquisition solutions efficiently.
References


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Appendix A - Permission to Reprint

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