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Optimizing large area coverage from multiple satellite-sensors

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Rapid damage information collection and dissemination during the disaster emergency response phase is a very important remote sensing-based approach. For large disasters like hurricanes and earthquakes, 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.

Keywords: remote sensing; disaster; emergency response; spatial optimization

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 *in situ* 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 3 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

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Figure 1. Relatively large disaster impact area requires multiple satellite images to be fully covered.

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 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.

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 (Nirupama 2002). Imagery collected from high spatial resolution (e.g. 1 m or better) remote-sensing satellite sensors have been widely used in disasters such as earthquake,

Table 1. Example high spatial resolution satellite sensors revisit frequency.

Satellite sensor	Revisit frequency
GEOEYE – 1	2.1 days at 35º off-nadir, 2.8 days at 28º off-nadir, 8.3 days at 10º off-nadir
WORLDVIEW-2	1.1 days at 1 m GSD or less, 3.7 days at 20º off-nadir
QuickBird	1–3.5 days at 30º off-nadir (depending on latitude)
IKONOS	3 days at 40º latitude

flood, hurricane, volcano, terrorism and so on 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 coving 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. 1–3 days) from pointable sensors on board. Table 1 shows several examples of the revisit frequency of some high spatial resolution sensors.

Hodgson et al. (2010) modelled 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 1 day of a disaster event varies from 17% to 39% (depending on sensor-pointing capabilities). However, if based on three satellite sensors, the likelihood will increase to over 94%. 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) and so on. In this article, 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 modelled '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. Modelling 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 (Hodgson and Kar 2008; Hodgson et al. 2010, RSHGS) modelled 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 SDSS named RSHGS to predict satellite image collection opportunities of a specified hazard location. This model provides a generic approach for modelling 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 polygonal disaster impact area, we need some points to represent the multitude of satellite-pointing angles. With these points available, by combining the RSHGS model, 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 siting multiple facilities (and an almost infinite set of possible siting 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 crated 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

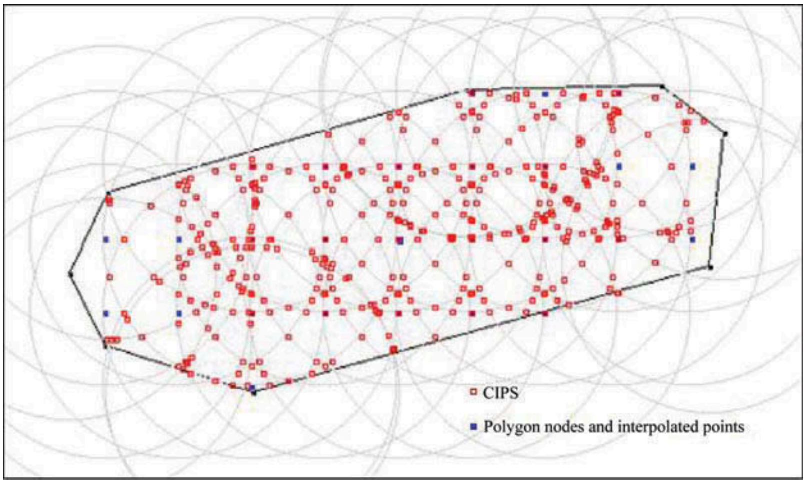


Figure 2. CIPS as potential satellite-pointing angles representative points.

point is not enough, and an infinite number of possible locations need to be considered to represent the space. In this study, we have the same continuous space representation problem. 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.

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 subareas based on the minimum swath width of the given high spatial resolution satellite sensors (Figure 2). CIPS shown in Figure 2 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).

4. Modelling 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. 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:

$$\text{Minimize} \sum_i \frac{\mathrm{CA_i}}{\mathrm{SA}} * (\mathrm{W_1}^*\mathrm{SR}_i + \mathrm{W_2}^*\mathrm{SpeR}_i + \mathrm{W_3}^*\mathrm{ND}_i + \mathrm{W_4}^*\mathrm{ONA}_i) \quad (1)$$

$$\text{Subject to} : \cup\mathrm{CA}_i = \mathrm{SA} \quad (2)$$

$$\mathrm{SR}_i < \text{specified value} \quad (3)$$

$$\mathrm{SpeR}_i = \text{specified values} \quad (4)$$

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

$$0 < W_{1,2,3,4} \leq 1 \quad (6)$$

where:

i = index of available collection opportunities
CA_i = polygon *area* covered by collection opportunity i
$\cup\mathrm{CA}_i$ = union of *area* covered by the collection opportunity combination
SA = polygon *area* of disaster impact area
SR_i = spatial resolution *rank* of collection opportunity *i*
SpeR_i = spectral resolution *rank* of collection opportunity *i*
ND_i = number of *days* collection opportunity *i* collected after a disaster event
ONA_i = off nadir angle *rank* of collection opportunity *i*
$W_{1,2,3,4}$ = 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 m). 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. As the values for spectral resolution are nominal and the scales for spatial, ranked spectral, collection delay, and off-nadir angle are on different scales, a ranking scheme is used to normalize each variable.

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 article, we developed a unique optimization model for the satellite image acquisition planning optimization problem.

The basic flow of our optimization model is outlined in Figure 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 Equations (3) and (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 4 illustrates the basic structure of the algorithm used in the spatial optimization model. The algorithm starts by generating a list of base solutions with each collection opportunity being a candidate solution. Each base solution is examined for the spatial coverage constraint defined in Equation (2) (meaning it covers the entire disaster impact area). A fitness calculation will be performed, and the base solution will be added to the acquisition plans list. Or this base 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 base solution (child base solution based on selected parent base solution). This new created child base solution will be added back to the base solution list to run next round loop.

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 2 summarizes the working assumption:

- Natural disaster (i.e. a hurricane) on 1 June 2013
- Satellite images collected within 3 days
- 1 m spatial resolution or better
- Panchromatic band (spectral coverage).

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 5 shows the result of 493 CIPS and 13 RCIPS.

Based on these 13 RCIPS, a total of 169 unique daytime satellite image collection opportunities can provide part of or full coverage of the disaster area. These 169 collection opportunities result in more than 500 combinations of satellite-sensor opportunity that

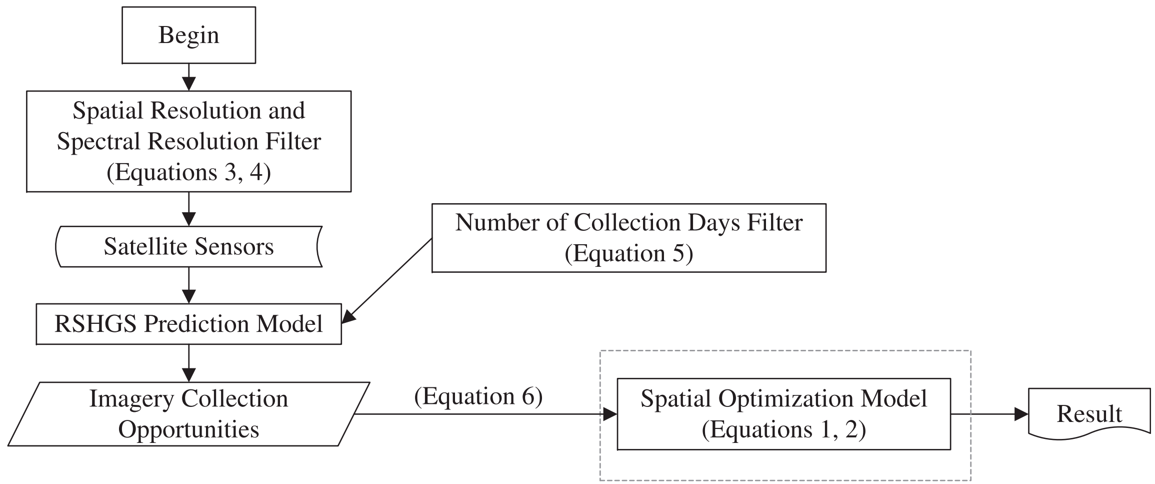


Figure 3. Basic flow of the optimization model.

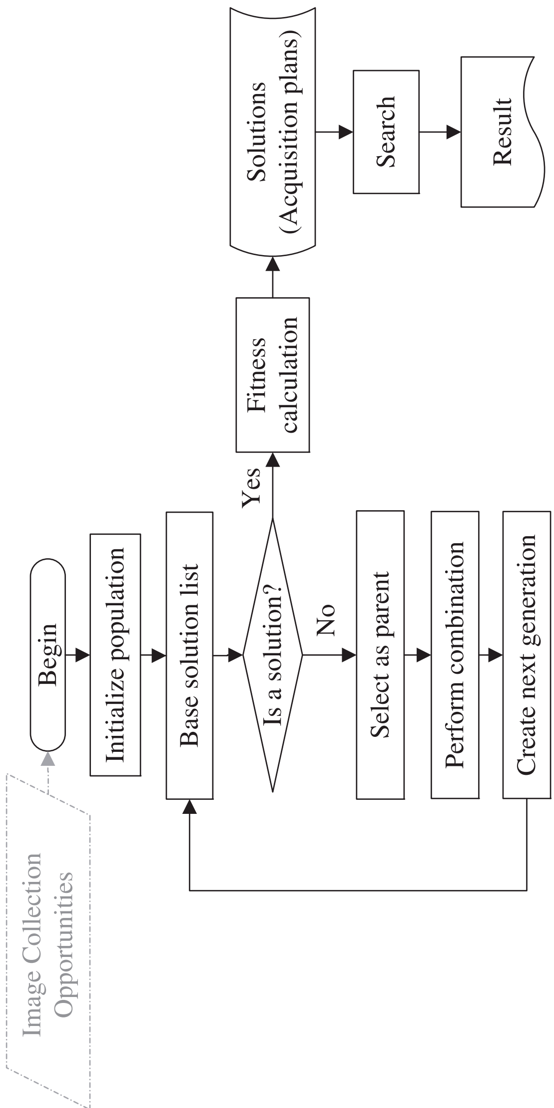


Figure 4. Algorithm structure for optimization model.

Table 2. Working assumptions of the application case.

Spatial resolution	Spectral coverage	Disaster event date	Number of collection days	Study area
1 m or finer	Panchromatic	1 June 2013	3 days	Mississippi coast

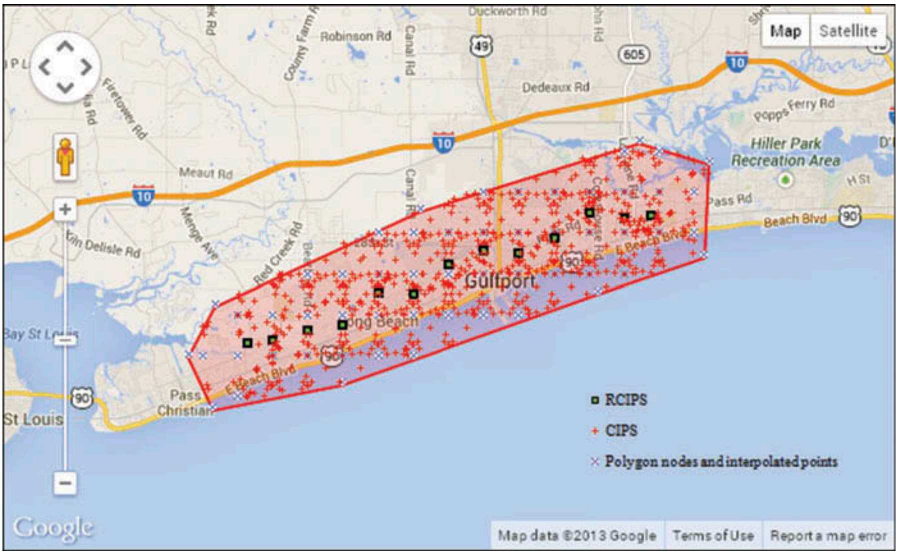


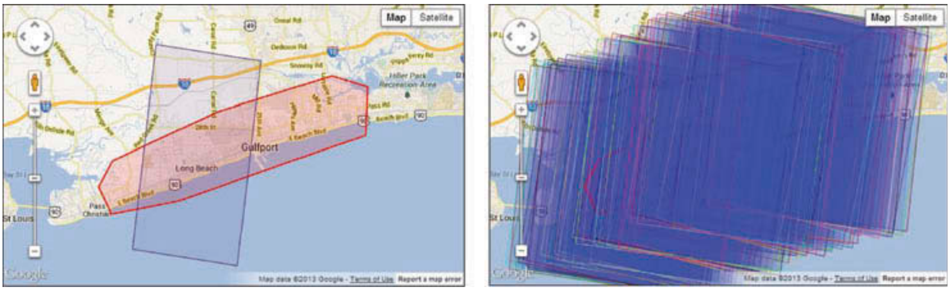
Figure 5. The multitude of satellite pointing angles for the study area represented by 493 CIPS and 13 RCIPS.

cover the entire disaster impact area. Table 3 shows an example satellite image collection opportunity derived from RSHGS prediction model, and its spatial coverage is shown in Figure 6(a). Figure 6(b) shows the spatial coverage detail of these 169 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. Two images from WORLDVIEW 1-Pan and GEOEYE 1, respectively, can fully cover the impact area as the first-best solution. The second-best solution is to use image swaths from GEOEYE 1 and WORLDVIEW 2-Pan. The third best solution is to use image

Table 3. Example satellite image collection opportunity.

Satellite name	Collection time	Sub-sat latitude	Sub-sat longitude	Satellite altitude	Off-nadir angle	Satellite azimuth	Satellite heading
CARTOSAT 2A PAN	1 June 2013 10:29:35 AM	29.6898	−86.1707	632.85	27.071	100.599	187.607



(a) (b)

Figure 6. (a) Spatial coverage of the example satellite image collection opportunity. (b) Spatial coverage detail of 169 daytime collection opportunities.

OID	Sensor Name	Spatial Resolution	Band Number	Local Time	Number of Hours	Off-Nadir Angle	Swath-km
	Solution #1:	score = 117.1487					
61	WORLDVIEW 1 Pan	0.55	1	1 June 2013 11:55:12 AM	11.92	26.484	17.6
147	GEOEYE 1 GeoEye- 1	0.41	5	1 June 2013 11:52:53 AM	11.88139	20.001	15.2
	Solution #2:	score = 117.9217					
56	GEOEYE 1 GeoEye- 1	0.41	5	1 June 2013 11:52:54 AM	11.88167	18.801	15.2
154	WORLDVIEW 2 Panchrom	0.46	1	1 June 2013 12:22:51 PM	12.38083	26.541	16.4
	Solution #3:	score = 118.368					
61	WORLDVIEW 1 Pan	0.55	1	1 June 2013 11:55:12 AM	11.92	26.484	17.6
167	WORLDVIEW 2 Panchrom	0.46	1	1 June 2013 12:22:51 PM	12.38083	26.657	16.4

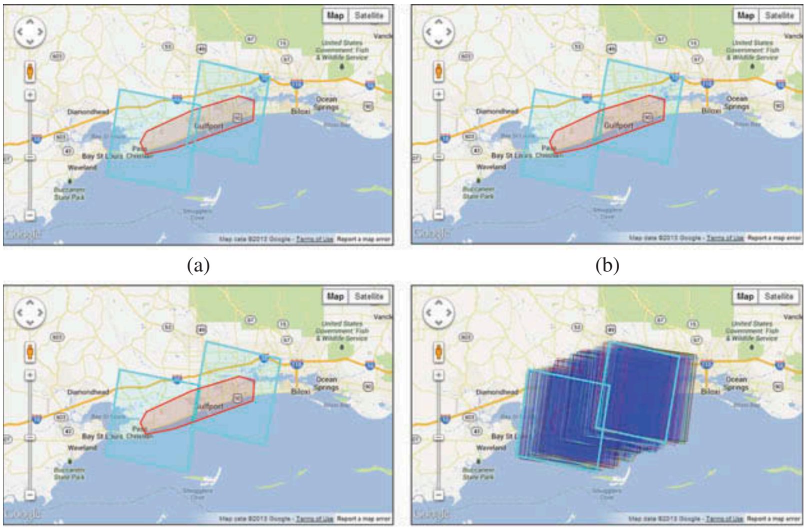
Figure 7. Best three image collection plans derived from the optimization model.

swaths from WORLDVIEW 1-Pan and WORLDVIEW 2-Pan. Figure 7 shows the details of these plans, and the swath coverage detail is shown in Figure 8. The solutions in Figure 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.

The proposed model and algorithm was applied to another scenario which has the same start date and collection window, but we set the spatial resolution to 0.5 m. Forty-eight available image collection opportunities are available from Satellites GEOEYE 1, WORLDVIEW 1 and WORLDVIEW 2. Figure 9 shows the details of the spatial coverage of these 48 collection opportunities and the first-best image acquisition plan.

7. Conclusions

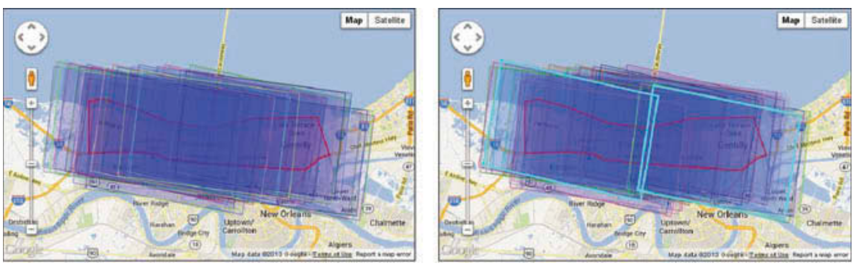
This research presents a spatial optimization algorithm for solving the satellite image acquisition planning problem during the disaster emergency response phase. The



(a) (b)

(c) (d)

Figure 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 169 available image collection opportunities.



(a) (b)

OID	Sensor Name	Spatial Resolution	Band Number	Local Time	Number of Hours	Off-Nadir Angle	Swath-km
	Solution #1:	score = 57.5848					
40	WORLDVIEW 2 Panchrom	0.46	1	1 June 2013 11:23:01 AM	11.38361	19.283	16.4
42	GEOEYE 1 GeoEye- 1	0.41	5	1 June 2013 10:53:02 AM	10.88389	12.542	15.2

(c)

Figure 9. Available image collection opportunities and the best plan: (a) shows the spatial coverage detail of 48 collection opportunities, (b) shows the spatial coverage of the best image collection plan and (c) shows the coverage detail of the best plan.

optimization model is solved under three non-spatial constraints: spatial resolution, spectral resolution and 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 modelling 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. Single season or single year remote-sensing image acquisition planning may be optimized not only to reduce costs but also to reduce variation in the desired spatial/spectral resolutions (or other constraints).

For the future work, feedback from federal emergency response partners will be integrated; more works are needed to address the model sensitivity and the polygon representation, for example, impact area is represented as multiple polygons.

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References

Arostegui, M. A., S. N. Kadipasaoglu, and B. M. Khumawala. 2006. "An Empirical Comparison of Tabu Search, Simulated Annealing, and Genetic Algorithms for Facilities Location Problems." *International Journal of Production Economics* 103 (2): 742–754. doi:10.1016/j.ijpe.2005.08.010.

Balas, E., and M. W. Padberg. 1972. "On the Set-Covering Problem." *Operations Research* 20 (6): 1152–1161. doi:10.1287/opre.20.6.1152.

Battiti, R., and A. A. Bertossi. 1999. "Greedy, Prohibition, and Reactive Heuristics for Graph Partitioning." *IEEE Transactions on Computers* 48 (4): 361–385. doi:10.1109/12.762522.

Birkin, M., G. Clarke, M. Clarke, and A. Wilson. 1996. *Intelligent GIS: Location Decisions and Strategic Planning*. Cambridge: Wiley.

Boston, K., and P. Bettinger. 1999. "An Analysis of Monte Carlo Integer Programming, Simulated Annealing, and Tabu Search Heuristics for Solving Spatial Harvest Scheduling Problems." *Forest Science* 45 (2): 292–301.

Boston, K., and P. Bettinger. 2002. "Combining Tabu Search and Genetic Algorithm Heuristic Techniques to Solve Spatial Harvest Scheduling Problems" *Forest Science* 48 (1): 35–46.

Caprara, A., P. Toth, and M. Fischetti. 2000. "Algorithms for the Set Covering Problem." *Annals of Operations Research* 98: 353–371. doi:10.1023/a:1019225027893.

Caro, F., T. Shirabe, M. Guignard, and A. Weintraub. 2004. "School Redistricting: Embedding GIS Tools with Integer Programming." *Journal of the Operational Research Society* 55 (8): 836–849. doi:10.1057/palgrave.jors.2601729.

Church, R. L. 1984. "The Planar Maximal Covering Location Problem." *Journal of Regional Science*, 24 (2): 185–201.

Church, R. L., and C. S. Revelle. 1976. "Theoretical and Computational Links Between P-Median, Location Set-Covering, and Maximal Covering Location Problem." *Geographical Analysis* 8 (4): 406–415.

Colesanti, C., and J. Wasowski. 2006. "Investigating Landslides with Space-Borne Synthetic Aperture Radar (SAR) Interferometry." *Engineering Geology* 88 (3–4): 173–199. doi:10.1016/j.enggeo.2006.09.013.

Cooper, L. 1963. "Location-Allocation Problems." *Operations Research* 11 (3): 331–343. doi:10.1287/opre.11.3.331.

Ducheyne, E. I., R. R. De Wulf, and B. De Baets. 2006. "A Spatial Approach to Forest-Management Optimization: Linking GIS and Multiple Objective Genetic Algorithms." *International Journal of Geographical Information Science* 20 (8): 917–928. doi:10.1080/13658810600711287.

Guo, D., and H. Jin. 2011. "IRedistrict: Geovisual Analytics for Redistricting Optimization." *Journal of Visual Languages and Computing* 22 (4): 279–289.

Hodgson, M. E., and B. A. Davis. 1998. "PE & RS Special Issue – Remote Sensing and GIS for Hazards – Foreword." *Photogrammetric Engineering and Remote Sensing* 64 (10): 976–976.
Hodgson, M. E., B. A. Davis, Y. Cheng, and J. Miller. 2010. "Modeling Remote Sensing Satellite Collection Opportunity Likelihood for Hurricane Disaster Response" *Cartography and Geographic Information Science* 37 (1): 7–15.
Hodgson, M. E., B. A. Davis, and J. Kotelenska. 2010. "Remote Sensing and GIS Data/Information in the Emergency Response/Recovery Phase." In *Geospatial Techniques in Urban Hazard and Disaster Analysis*, edited by P. S. Showalter and Y. Lu, 327–354. Dordrecht: Springer.
Hodgson, M. E., and B. Kar. 2008. "Modeling the Potential Swath Coverage of Nadir and Off-Nadir Pointable Remote Sensing Satellite-Sensor Systems." *Cartography and Geographic Information Science* 35 (3): 147–156.
Jensen, J. R., and M. E. Hodgson. 2006. "Remote Sensing of Natural and Man-Made Hazards and Disasters." In *Manual of Remote Sensing: Remote Sensing of Human Settlements*, edited by K. Ridd and J. D. Hipple, 401–429. Bethesda, MD: American Society for Photogrammetry and Remote Sensing.
Jha, M. N., J. Levy, and Y. Gao. 2008. "Advances in Remote Sensing for Oil Spill Disaster Management: State-of-the-Art Sensors Technology for Oil Spill Surveillance." *Sensors* 8 (1): 236–255.
Kirkpatrick, S., C. D. Gelatt, and M. P. Vecchi. 1983. "Optimization by Simulated Annealing." *Science* 220 (4598): 671–680. doi:10.1126/science.220.4598.671.
Lan, G. H., G. W. DePuy, and G. E. Whitehouse. 2007. "An Effective and Simple Heuristic for the Set Covering Problem." *European Journal of Operational Research* 176 (3): 1387–1403. doi:10.1016/j.ejor.2005.09.028.
Mehrez, A., and A. Stulman. 1982. "The Maximal Covering Location Problem with Facility Placement on the Entire Plane." *Journal of Regional Science* 22 (3): 361–365. doi:10.1111/j.1467-9787.1982.tb00759.x.
Miller, H. J. 1996. "GIS and Geometric Representation in Facility Location Problems." *International Journal of Geographical Information Systems* 10 (7): 791–816. doi: 10.1080/02693799608902110.
Morrill, R. L. 1981. *Political Redistricting and Geographic Theory*. Washington, DC: Association of American Geographers.
Murray, A. T., and D. Q. Tong 2007. "Coverage Optimization in Continuous Space Facility Siting." *International Journal of Geographical Information Science* 21 (7): 757–776. doi:10.1080/13658810601169857.
Nirupama and S. P. Simonovic. 2002. "Role of Remote Sensing in Disaster Management." In *Water Resource Research Report*. London: The University of Western Ontario. Accessed December 6, 2013. http://ir.lib.uwo.ca/wrrr/3
Ostir, K., T. Veljanovski, T. Podobnikar, and Z. Stancic. 2003. "Application of Satellite Remote Sensing in Natural Hazard Management: The Mount Mangart Landslide Case Study." *International Journal of Remote Sensing* 24 (20): 3983–4002. doi:10.1080/0143116031000103826.
Owen, S. H., and M. S. Daskin. 1998. "Strategic Facility Location: A Review." *European Journal of Operational Research* 111 (3): 423–447.
Pan, G., and D. L. Tang. 2010. "Damage Information Derived From Multi-Sensor Data of the Wenchuan Earthquake of May 2008." *International Journal of Remote Sensing* 31 (13): 3509–3519. doi:10.1080/01431161003730865.
ReSPT. *Remote Sensing Planning Tool*. Accessed December 5, 2013. prototype.respt.org
RSHGS. *Remote Sensing Hazard Guidance System*. Accessed June 1, 2013. http://ww2.rshgs.sc.edu/
Stramondo, S., C. Bignami, M. Chini, N. Pierdicca, and A. Tertulliani. 2006. "Satellite Radar and Optical Remote Sensing for Earthquake Damage Detection: Results From Different Case Studies." *International Journal of Remote Sensing* 27 (20): 4433–4447. doi:10.1080/01431160600675895.
Sunar, F., and C. Ozkan. 2001. "Forest Fire Analysis with Remote Sensing Data." *International Journal of Remote Sensing* 22 (12): 2265–2277.
Tong, D., and A. T. Murray. 2012. "Spatial Optimization in Geography." *Annals of the Association of American Geographers* 102 (6): 1290–1309.

Tong, D. Q., A. Murray, and N. C. Xiao. 2009. “Heuristics in Spatial Analysis: A Genetic Algorithm for Coverage Maximization.” *Annals of the Association of American Geographers* 99 (4): 698–711. doi:10.1080/00045600903120594.

Tralli, D. M., R. G. Blom, V. Zlotnicki, A. Donnellan, and D. L. Evans. 2005. “Satellite Remote Sensing of Earthquake, Volcano, Flood, Landslide and Coastal Inundation Hazards.” *ISPRS Journal of Photogrammetry & Remote Sensing* 59: 185–198.

Visser, S. J., and A. S. Dawood. 2004. “Real-Time Natural Disasters Detection and Monitoring From Smart Earth Observation Satellite.” *Journal of Aerospace Engineering* 17 (1): 10–19. doi:10.1061/(asce)0893-1321(2004)17:1(10).

Xiao, N. C. 2008. “A Unified Conceptual Framework for Geographical Optimization Using Evolutionary Algorithms.” *Annals of the Association of American Geographers* 98 (4): 795–817. doi:10.1080/00045600802232458.

Zhang, H. H., Y. N. Zeng, and L. Bian. 2010. “Simulating Multi-Objective Spatial Optimization Allocation of Land Use Based on the Integration of Multi-Agent System and Genetic Algorithm.” *International Journal of Environmental Research* 4 (4): 765–776.

Zhang, Y., and N. Kerle. 2008. “Satellite Remote Sensing for Near-Real Time Data Collection.” In *Geospatial Information Technology for Emergency Response*, Vol. 6, edited by S. Zlatanova and J. Li, London: Taylor & Francis.