SAC is a group of students committed to serving all of the student members of ASPRS. Our goal is to ensure that ASPRS is a Society that both benefits from student involvement and creates opportunities for those students.

SAC is led by a Council of seven students who meet monthly to discuss issues pertaining to ASPRS Student Members. What do they do?

- **Organize special sessions** of interest to students at ASPRS Annual and fall conferences. [http://www.asprs.org/Annual-Conferences/Program/](http://www.asprs.org/Annual-Conferences/Program/)

- **Create networking opportunities** during those conferences and bring together students looking for employment after graduation with potential employers in the industry.

- Inaugurate new programs within ASPRS.

- Design activities such as the GeoLeague Competition where students compete in teams using geospatial technology applications to solve a problem. [http://www.asprs.org/Students/GeoLeague-Challenge-2014.html](http://www.asprs.org/Students/GeoLeague-Challenge-2014.html).

**Promote student involvement in humanitarian projects** such as crowdsourcing the manual interpretation of imagery in Somalia to identify shelters that are being used as homes by refugees. [http://irevolution.net/tag/tomnod/](http://irevolution.net/tag/tomnod/).

All ASPRS Student Members are encouraged to become involved with SAC. Check out the SAC Social Networking sites and keep up with ongoing news.

**Student Newsletter**: [http://asprssignature.blogspot.com/](http://asprssignature.blogspot.com/)

**Facebook page**: [https://www.facebook.com/pages/ASPRS-Student-Advisory-Council/117943608233122](https://www.facebook.com/pages/ASPRS-Student-Advisory-Council/117943608233122)


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- Discounts on ASPRS Workshops
- Receipt of Region Newsletter
- Region specialty conferences, workshops, technical tours and social events
- Opportunity to participate in ISPRS activities
- Invitations to Technical Committee and Division meetings
- Local, regional, national and international networking opportunities
- Eligibility for over $18,000 in National and Region awards, scholarships and fellowships
- Opportunity to Access the ASPRS Membership Directory on the internet (search for other active individual members, sustaining members, and certified professionals)

VISIT HTTP://WWW.ASPRS.ORG/JOIN-NOW.HTML FOR MORE DETAILS!
HIGHLIGHT ARTICLE
5 Geospatial Technologies Lead the Living to the Dead
Nancy K. O’Hare, Brandon P. Adams, Marguerite Madden, and Thomas R. Jordan

PROFESSIONAL INSIGHT—AN INTERVIEW
11 UNM ASPRS Student Chapter

PEER-REVIEWED ARTICLES
25 Correction of Distortions in YG-12 High-Resolution Panchromatic Images
Yonghua Jiang, Guo Zhang, Deren Li, Xinming Tang, Wenchao Huang, and Litao Li
A method by which the positioning accuracy of YG-12 high-resolution panchromatic images using GCPs is significantly improved by eliminating inaccuracies caused by interior distortions and serious time-synchronization errors.

37 Optimal Land Cover Mapping and Change Analysis in Northeastern Oregon Using Landsat Imagery
Michael Campbell, Russell G. Congalton, Joel Hartter, and Mark Ducey
compare a number of well-established techniques with some new methods using a two-county area in northeastern Oregon as a case study.

49 Reliable Spatial Relationship Constrained Feature Point Matching of Oblique Aerial Images
Han Hu, Qing Zhu, Zhiqiang Du, Yeting Zhang, and Yulin Ding
A reliable feature point matching method for oblique aerial images using the spatial relationships of the point correspondences to remove outliers.

59 Sub-Pixel-Scale Land Cover Map Updating by Integrating Change Detection and Sub-Pixel Mapping
Xiaodong Li, Yun Du, and Feng Ling
A land cover map updating method that involves the use of a current coarse-resolution remotely sensed image and a previous fine-resolution land cover map to update fine-resolution land cover maps.

69 Mapping Wetlands and Phragmites Using Publically Available Remotely Sensed Images
Yichun Xie, Anbing Zhang, and William Welsh
Standard procedures for integrating NAIP (National Agriculture Imagery Program) and Landsat images with multiple processes of ground truthing, image classification and validation.
LETTER FROM THE EXECUTIVE DIRECTOR

REFITTING ASPRS

The Board of Directors has been laying the foundation to streamline the governance of ASPRS. Meanwhile, the staff have been working on four top priorities: 1) improving conferences; 2) fixing the business model and distribution of the journal; 3) modernizing the member database; and 4) getting better control of our many websites. On the conference front, perhaps you have already heard good news about UAS Mapping 2014 last October or the Pecora/ISPRS meeting in November. For the journal, we changed institutional pricing to be more in line with the market, and soon you will be able to access an improved and complete electronic version online. Although the member database may not sound exciting, when the modernization is complete we will be able to communicate with members more effectively, and they with each other. We will also roll out major website changes, adding capabilities like those showcased in uas.asprs.org.

Happy New Year – Happy New ASPRS!

To begin the New Year I invite you to take a journey with me. Some may say that ASPRS and its members have been on a journey for the past 80 years, but that the sailing has been rough, the ship has taken on water, and we’ve made little progress. Well, that’s about to change. ASPRS is setting off on a new journey. We are charting a new course. Let’s see if I can convince you to come on board.

Over the past nine months ASPRS has been hard at work refitting our ship and retraining our crew. The Board has begun repairs to the unwieldy governance structure, while Headquarters has begun making repairs in operations. For specifics, please see the sidebar. When these repairs are complete in the spring of 2014, our ship will be ready for sea once again. In anticipation, ASPRS seeks students, scientists, engineers, and business people to join the complement of women and men who choose to make this ship their professional home – who will call this ship “my ship”.

What’s in it for you, the world’s imaging and geospatial experts? Great rewards, including membership; continued on page 20
Geospatial Technologies Lead the Living to the Dead

By Nancy K. O’Hare, Brandon P. Adams, Marguerite Madden, and Thomas R. Jordan
INTRODUCTION

Increasingly, cultural institutions are turning to geospatial technologies to manage resources, enhance visitor experience, and provide “virtual tourism”, among other uses (Majó et al., 2004; Brown, 2006; Scott, 2006). For many local cultural or historical sites, such a turn has been difficult because these types of institutions often lack the funding and/or technical knowledge to leverage geospatial technologies. As part of our commitment to community service, members of the ASPRS Student Chapter at the University of Georgia (UGA) volunteered assistance to a local group, the Friends of Oconee Hill Cemetery (OHC).

The Friends of OHC was established in 1999 to encourage community attention and involvement in the restoration and preservation of OHC. Seeking funding to assure that the gravesites of all veterans receive regular maintenance, the Friends needed to determine how many veterans’ gravesites required care and where these gravesites were located. Such needs were the result of several factors. First, regular care of lots was originally the responsibility of the lot owner. Since 1915, lot care by the cemetery Sexton (caretaker) could be purchased separately. It was only since 1946 that perpetual lot care by the cemetery Sexton has been included in the lot purchase. The Sexton provides nominal care for all lots each winter, yet lacks the resources to do so on a regular basis during the long summer growing season. Second, each cemetery lot accommodates several internments. Maps of the lots exist, but not internments within a lot. Lastly, original records prior to 1896 were lost in a fire and could only be partially reconstructed through other sources including direct knowledge, tombstone inscriptions, and newspaper obituaries (Marshall, 1971; Marshall, 2009).

“We soon realized that other geospatial technologies could be used to assist in preserving the cemetery, easily locate specific gravesites by name, and help the public navigate to and appreciate the many areas of historical significance within the cemetery.”

The ASPRS Student Chapter at UGA was initially approached by the Friends of OHC to map veterans’ gravesites. We soon realized that other geospatial technologies could be used to assist in preserving the cemetery, easily locate specific gravesites by name, and help the public navigate to and appreciate the many areas of historical significance within the cemetery. This local collaboration also provided students with an opportunity for community outreach and an introduction to several open-source geospatial software tools.

OCONEE HILL CEMETERY BACKGROUND

Established in 1856, OHC is one of the oldest public cemeteries in Athens, Georgia, USA (Figure 1). The Old section of the cemetery follows the “rural” (also referred to as garden or Victorian) cemetery design first introduced in the USA in 1831 with the founding of Mount Auburn Cemetery in Massachusetts (French, 1974). As the various names suggest, this type of cemetery idealized park-like design with magnificent trees, impressive monuments, decorative ironwork, and statuaries (Figure 2). In 1900, the cemetery expanded. The design of the New section reflected changing aesthetics and the realities of maintaining garden type cemeteries. Monuments in the New section are more uniform and large trees less common. Together, both the Old and New sections of OHC reveal the changing nature of societal attitudes to burials.

Regardless of their dissimilar designs, both the Old and New sections of OHC are meaningful in terms of local and national history. OHC serves as the final resting place for Athenians from all walks of life, ranging from wealthy business owners to paupers. Some non-Athenians are also buried at OHC, including a group of Travelers (aka, Roaders or American gypsies). Nationally well-known or historically significant persons interred at OHC include Wilson Lumpkin, state and federal politician and supervisor of the forced march of Cherokee Indians on the Trail of Tears, prominent generals in the Confederate States Army including T.R.R. Cobb, Dr. Crawford Long who first adopted anesthesia for surgery, aviation pioneer Ben Epps, portrait miniature artist Lucy May Stanton, Dean Rusk who served as the US Secretary of State from 1961 to 1969, and musician Ricky Wilson of the iconic band the B52s.

Because OHC is both an historic and an active cemetery, it has the distinction of being the final resting place of veterans from every war or conflict in which the USA has participated. Veterans involved in the country’s early conflicts died before the cemetery’s founding in 1856; their remains are now interred at OHC after being moved from their initial burial locations. Until the mid-1800s, burials were commonly made on family land, land associated with churches, or in other public burial grounds, but none of these guaranteed that gravesites would remain undisturbed (Sloane, 1995). As public cemeteries opened, which promised gravesites would be undisturbed, existing burials on family/private land were frequently moved. The regular maintenance of the gravesites was the responsibility of the living family members; only in the mid twentieth century did the responsibility of regular maintenance, shift to the cemetery. However, in an historic cemetery, such as OHC, many lots are not in perpetual care, including those of veterans.
USING GEOSPATIAL TECHNOLOGIES

The following sections are organized by geospatial technology and include within each section both the methods and results.

PAPER RECORDS TO GIS

All existing cemetery maps and burial records were on paper. We used both sets of information to create a GIS database.

We first created a polygon feature layer of the individual lots in the Old section of the cemetery from the 8 ½” x 11” map in Marshall (2009), which was the only hard copy of this map available to us. This map was a composite of traditional land survey maps produced in 1894, 1906, and 1909. The maps lacked references to a geographic coordinate system, and to any features outside of the cemetery boundaries that could be used to place the map within a geographic coordinate system. This is simply a reflection of the era that produced the maps rather than any sort of inherent deficiencies in relative spatial locations. Placing the maps within a geographic coordinate system requires relating the local coordinates of at least four points on the map to the locations of the same points in a known geographic coordinate system. These points should be well-distributed, since rectification accuracy decreases outside of the spatial bounds of the ground control points (Welch and Jordan, 1996; McGlone, 2013). The known coordinates can come from ground collected GPS points or from newer orthorectified imagery of adequate spatial resolution and positional accuracy. We first attempted rectification using freely distributed 2009 National Agriculture Imagery Program (NAIP) true-color, growing season (leaf-on) imagery with 1-m spatial resolution. However, the spatial distribution of coincident identifiable features between the paper map and the NAIP imagery was limiting. The map of lots lacked accurate geographic references outside of the lot boundaries. In the NAIP imagery, the extensive tree canopy obscured many ground features. We then used a Trimble Geo6000 Xh GPS to collect ground control points within OHC, with a post-processed accuracy of ±1 to 2 m. The resultant root mean square error (RMSE) after georeferencing was ±3.6 m and this is the error associated with the spatial location accuracy of our GIS feature layer.

Figure 1. Location of Oconee Hill Cemetery in Athens, Georgia, USA.

Figure 2. Example of the monuments in the Old section of Oconee Hill Cemetery.
After rectification of the scanned cemetery map, boundaries of OHC lots were manually digitized. Automated vectorization was not suitable since the original maps had background lettering and numbering. Polygon features were attributed with lot number, family/owner’s name, and level of care (perpetual or none). We then created an associated data table, joined through the lot number, for each veteran’s burial, using Marshall (2009). This table included date of birth, date of death, military branch, military rank, conflict(s) served in, and whether the person was killed or disabled during military service. Marshall (2009) provided not only the tombstone inscription, but also supplementary information from the official Record of Internments for the cemetery, newspaper obituaries, and Charlotte Marshall’s extensive genealogical knowledge.

Of the 516 lots in the Old section of OHC, veterans’ gravesites occurred in 199 lots. The 199 lots contained gravesites of 316 veterans. These veterans served in the American Revolutionary War (2 veterans), War of 1812 (4), Mexican War (4), various conflicts related to Native American removal from the expanding USA territory (5), American Civil War (207), Spanish-American War (6), Philippines War (1), WW I (30), WW II (23) and Vietnam (2)\(^1\), plus veterans that served during times of peace (30). Of these 316 veterans, the gravesites of 93 veterans were interred in 76 lots that lacked perpetual care. Using this information, the Friends of OHC were able to secure a $25,000 donation to assure perpetual care for all veterans’ graves in the Old section of OHC.

**GEOPDF AND QR CODES FOR MAP DISTRIBUTION**

The perpetual care of lots by the cemetery Sexton does not include the costs for preserving the stone monuments which are suffering from 150+ years of weathering, soil erosion, vandalism, and damage from tree limbs falling from mature trees. One act of vandalism scarred more than 60 statues in one night (Banner-Herald, November 22, 1963). The Friends of OHC need a way to relate to visitors, promote local awareness to generate community support and respect of the historic nature of the cemetery, and to stimulate financial support.

Geographic data can be exported to portable document format (pdf) to create a GeoPDF which can be viewed using a free map application for mobile devices, such as Avenza reader (Wulrich, 2006; Pardue, 2008). If the mobile device is GPS enabled, the GeoPDF displays the user’s real time location on the map thereby providing an intuitive way to navigate. GeoPDFs could be used by OHC to guide a family to an ancestor’s gravesite or for self-guided tours highlighting, for example, historical figures or Victorian-era gravestone symbolism or veterans’ gravesites.

\(^1\) The New portion of the cemetery contains gravesites of veterans from Korea, both Iraq Wars, and the Afghanstan War. Our surveys in the New portion of the cemetery have not been completed. Therefore, this article focused on the completed surveys in the Old portion of OHC.

GeoPDFs for viewing only can be easily created through standard GIS software. For example, in ArcGIS, the map is simply exported to the GeoPDF format. Interactive GeoPDFs also can be created, but this currently requires TerraGo Tech’s proprietary stand-alone software or their plug-in for ArcGIS. An interactive GeoPDF allows the user to select layers to display and view supplemental information, such as photographs, videos, or hyperlinks. While a network connection to the server hosting the GeoPDF file is required for map distribution to the mobile device, once the GeoPDF is loaded, internet connectivity is not required.

For any GeoPDF to be useful for self-guided tours, real-time location accuracy is needed. We created a GeoPDF of an existing tour, designed by the Friends of OHC and currently distributed on paper, for Veteran’s Day. Typical cemetery lots are 6 m x 6 m. The base GIS layer created by rectifying a paper map had an RMSE of ±3.6 m after rectification. Additionally, there would be real-time GPS receiver error. The self-guided GeoPDF tour was tested in the field on an Apple iPad 4 using the free Avenza GeoPDF map viewer. Self-navigation by referencing the location of the iPad relative to the OHC GeoPDF placed the user in or on the edge of the desired cemetery lot 18 out of 19 times. Average error of the center of cemetery lot locations in real-time was ±4.3 m (n=19; range of 1.3 to 14.5 m). This level of accuracy is believed to be suitable for the general public to navigate to specific OHC lots to locate an ancestor’s gravesite or for the general public on self-guided thematic tours of the cemetery.

A way to distribute the GeoPDF tour of OHC also was necessary. This was accomplished by creating a quick response (QR) code to direct users to a web server for GeoPDF download (Figure 3). Both the software to generate and read QR codes is freely available. Users with mobile devices equipped with a camera can scan the QR code on handouts provided at the cemetery or on their website which automatically directs the user to a server at the UGA Geography-CGR website to view and download the GeoPDF featuring veterans’ gravesites. Users who are not physically within the map extent can view the map, but will not see their location on the map.

![Figure 3. Quick response (QR) code that links to a GeoPDF tour of veterans’ gravesites in the Old section of Oconee Hill Cemetery. To access, scan the QR code with a smart phone or tablet, open the link in a browser, then choose to open the map in a map app, such as Avenza PDF Maps (free). Once the map is opened in Avenza, it is available to the user even when an internet connection is not available. The user’s GPS location will be displayed as distance to the OHC map. The user’s GPS location will display as dot (typically blue) when physically within the OHC map extent.](image-url)
3D MODELS OF STATUES

The cemetery contains marble and granite statues and tombstones (collectively referred to as monuments) dating from the 1850s. All monuments are subject to weathering, and some have been vandalized or damaged by falling tree limbs or erosion. One act of vandalism scarred more than 70 monuments in one night (Banner-Herald, November 22, 1963). There is no photographic inventory of the monuments in OHC. If an inventory is done in the future, the value of the photographic record could be amplified by taking overlapping images so they could later be converted to three dimensional (3D) models using Structure from Motion (SfM).

Structure from Motion (SfM) algorithms create 3D models from a series of overlapping two dimensional (2D) images (Szeliski and Kang, 1994). While initially used for computer vision, SfM has been widely adapted for a variety of applications, including cultural and historic preservation (Westoby et al., 2012). While images input to SfM software have typically been acquired from handheld cameras, 3D models recently have been created from images acquired from unmanned aerial vehicles (Mancini et al., 2013; Mathews and Jensen, 2013; Zarco-Tejada et al., 2014). Although SfM can be used for multiple purposes (Stefanik et al., 2011; Westoby, Brasington, Glasser, Hambrey and Reynolds, 2012; Mathews and Jensen, 2013), our use was for the creation of 3D models of individual statues. More rigorous application would be capturing actual measurements and textural variation. We only evaluated the ability to capture measurements from a single statue.

We used AutoDesk 123D Catch (www.123dapp.com/catch) online SfM software, since one of our objectives was to use freely available software to introduce a local non-profit comprised of volunteers as well as UGA students to developing geospatial technologies. A high-resolution model was created from a series of 33 photographs (Figure 4). The software allows creation of a single scale measurement between two 3D points. We defined the scale of the model using a single measurement of the width of the letter “M” within the name, “Norma” on the model (90 cm). We measured 12 other features on the 3D model that were relatively distinct and compared these to the actual measurements from the statue (Table 1). All of the features lacked significant tonal differences, and many of the edges were either rounded, rough-hewn, or chipped, complicating placement of the marker at the same point from different viewpoints. The 3D model and actual measurements had an average difference of 3.3%. An animation of the final model can be viewed at http://maestro.crms.uga.edu/QRdocs/norma.avi.

Table 1. Comparison of 3D model measurements to actual measurements, in cm.

<table>
<thead>
<tr>
<th>Feature</th>
<th>3D model</th>
<th>Actual</th>
<th>Difference</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Width “N”</td>
<td>61.8</td>
<td>60</td>
<td>1.8</td>
<td>3.0%</td>
</tr>
<tr>
<td>Width “O”</td>
<td>59.8</td>
<td>60</td>
<td>0.2</td>
<td>0.3%</td>
</tr>
<tr>
<td>Width “R”</td>
<td>63.5</td>
<td>60</td>
<td>3.5</td>
<td>5.8%</td>
</tr>
<tr>
<td>Width “A”</td>
<td>88.5</td>
<td>90</td>
<td>1.5</td>
<td>2.5%</td>
</tr>
<tr>
<td>Height “N”</td>
<td>104.9</td>
<td>104</td>
<td>0.9</td>
<td>0.9%</td>
</tr>
<tr>
<td>Height “O”</td>
<td>108.4</td>
<td>104</td>
<td>4.4</td>
<td>4.2%</td>
</tr>
<tr>
<td>Height “R”</td>
<td>107.2</td>
<td>104</td>
<td>3.2</td>
<td>3.0%</td>
</tr>
<tr>
<td>Height “M”</td>
<td>107.4</td>
<td>104</td>
<td>3.4</td>
<td>3.3%</td>
</tr>
<tr>
<td>Height of scroll</td>
<td>542.0</td>
<td>545</td>
<td>3.0</td>
<td>0.5%</td>
</tr>
<tr>
<td>Width of base</td>
<td>1664.4</td>
<td>1570</td>
<td>94.4</td>
<td>6.0%</td>
</tr>
<tr>
<td>Height 1st step</td>
<td>121.7</td>
<td>130</td>
<td>8.3</td>
<td>6.3%</td>
</tr>
<tr>
<td>Height 2nd step</td>
<td>125.2</td>
<td>130</td>
<td>4.8</td>
<td>4.0%</td>
</tr>
</tbody>
</table>

Figure 4. Digital photograph of monument (left) and three dimensional model (right) created from 33 images using free online version of AutoDesk 123D catch (www.123dapp.com/catch).
**Summary**

This project connected the living to the dead in ways that enriched visitor experience and preservation of an historic cemetery. The enumeration and documentation of the physical locations of veteran’s gravesites in the Old section of OHC secured a $25,000 donation to guarantee their regular care and maintenance. UGA undergraduate and graduate students were introduced to a local cemetery with historic connections, statuarry art, and how to apply geospatial technologies. One group of UGA students used SfM to create 3D models of OHC monuments that are accessible online (https://www.youtube.com/watch?v=G4PMA5Y1ZDA).

Proprietary software would undoubtedly enhance the visual quality of our final projects, but open software may be preferred for initial access to geospatial technologies. For example, educational institutions and non-profits organizations are more likely to first explore new geo-spatial technologies with freely distributed, open-source geospatial methods, software and image/map data before committing financial resources to purchase and learn proprietary software.

In our opinion, many local groups are in need of assistance with basic geospatial skills. Technical skills required in this project (i.e., rectification, digitizing, developing attribute tables, simple queries, taking photographs) would be considered novice-level skills for professional GIS or remote sensing specialists. Sometimes, however, that is all that is needed to benefit the communities in which we live.

**Acknowledgements**

The Friends of Oconee Hill Cemetery approached us with the seed of this project; we are especially grateful to Helen Mills, Helen Constatino and Jane Begnaud. Brian Adler, Sexton of Oconee Hill Cemetery, kindly provided access to paper maps and shared his knowledge of the Cemetery. Larry Nackerud and Lauren Ricciardelli, School of Social Work at the University of Georgia, took over other aspects of the project not included here with enthusiasm and a grand ability to provide “volunteers”. UGA seminar class GEOG8550 in spring 2014 generated the 3D models displayed on the YouTube channel; this class was taught by Dr. Marguerite Madden and Dr. Deepak Mishra. Dr. Andrea Presotto provided thoughtful comments from a different perspective.

**Literature Cited**

Banner-Herald, November 22, 1963. Athens, GA


Cover photo courtesy of Kenn W. Kiser, morgueFile.com.
Introducing ASPRS’ newest student chapter at the University of New Mexico.

Christopher D. Lippitt, Faculty Advisor, UNM ASPRS Student Chapter, Vice President, Rio Grande Chapter; and Su Zhang, Chapter President, UNM ASPRS Student Chapter discuss the importance of student chapters to the industry.

Why did you decide to develop a student chapter at UNM?

Chris — We started as a venue to facilitate cooperation and self-determination amongst our GIScience students. Workshops, trainings, visits to facilities, hosting speakers, all of the activities of the student chapter allow a greater number of students to be exposed to greater number of opportunities and to determine the course of their own education, network, and career. We’ve already hosted a workshop focused on the use of R for spatial analysis and data handling thanks to Steve Sesnie and Sarah Lehnen of the US Fish and Wildlife Service here in Albuquerque.

We’ve got plans to establish a Volunteer Hazard Mapping Corp (VHMC) through the chapter, modeled after the VHMC at San Diego State University. I for one can’t wait to see what they do with the chapter next.

How is having a student chapter beneficial to the students?

Chris — In one word: exposure - to opportunities, to industry, to professional networks, to the culture of their intended industry, to scholarships. The chapter has the potential to allow a group of students to strategically augment their skillsets and professional network beyond those available in their formal program of study.

Su — From the standpoint of a student, the chapter works as a nexus for us to know other professionals, other faculty members, and other students. In a traditional academic environment, the only way for a student to know others who have the same interest through faculty members or classmates. Like Chris said, the student chapter will provide massive exposure benefits to any students who are interested in geospatial technologies.

How was the process of setting up the student chapter with ASPRS?

Su — It was a wonderful experience setting up the student chapter with ASPRS. The officers from the ASPRS Rocky Mountain Region helped us a lot with the whole process. They walked us through each step of the process and even helped us navigate the bumps that popped up along the way. They were always ready to answer questions we had and they took care of any issues right away. We want to specially thank Harold Cline, Michaela Buenemann, Jeff Young, and Sokhan Hing for their enormous help.

What are the goals of the chapter?

Su — The chapter has identified a number of goals, including: (1) advancing scientific knowledge in the disciplines of photogrammetry and remote sensing; (2) working with governmental and private organizations in promoting programs related to photogrammetry and remote sensing to the general public; (3) expediting the exchange of knowledge and ideas among the members of ASPRS and with those of other national and international organizations with similar or related interests; (4) serving the members as a central source of information related to photogrammetry and remote sensing.

A UNM ASPRS organized workshop focused on the use of R for spatial analysis and data handling. Steve Sesnie and Sarah Lehnen of the US Fish and Wildlife Service instructed the day long workshop.
How can ASPRS better assist their student chapters?

Chris — I like the idea of making funds available to support hosting local/regional events such as speakers or workshops - anything to facilitate interaction between the student chapters and the regional membership.

Su — I support the idea of allocating more “resources” to support the growth the student chapters. For example, an officer could be designated to interact with student chapters to listen to the special needs of a specific chapter. In addition, ASPRS could help student chapters interact with the industry by exposing members to more opportunities. It would also great if we could get free state-of-art technology training routinely to prepare the students to be ready for various challenges.

Will the student chapter plan any activities to expose local elementary and high school students to the industry?

Su — We are planning to do a series of events on the next GIS Day to expose local elementary and high school students to the industry. We are also planning to organize a field trip to Blue Skies Aerial Survey firm to provide a unique geospatial exposure to local students. Students will be able to experience the procedures used when acquiring aerial photography and the post-processing that leads to the final products. We hope such activities will arouse interests in local elementary and high school students for learning geospatial knowledge.

What do you feel should be the student chapters role in the Society?

Chris — I believe student chapters can act as the “boots on the ground” in between meetings. What I mean by that is they can organize events that are open to the regional membership, which serves both the chapter’s members and the regions. More practically, student chapter members are literally the future of the society, and obviously warrant the larger societies’ support. Supporting them in their role as regional facilitators of events serves everyone’s interests.

What is the future of ASPRS in your opinion?

Chris — ASPRS plays a critical role in the remote sensing and the GIS community; its established track record at the intersection of industry, academia, and government, independent from any particular corporate entity, and explicit relationship with the international society make it unique and, I believe, well positioned to foster and represent the larger geospatial community.

Su — The 21st Century is a century of “Digital Earth”. Significant progress towards Digital Earth has been achieved over the last couple of decades. Geospatial technologies are the fundamental elements of Digital Earth and I think ASPRS will play a significant role in promoting Photogrammetry, Remote Sensing, and GIS knowledge to the general public to prepare them to be ready for the Digital Earth Century. In addition, ASPRS plays a critical role in collaborating with other international geospatial groups across the world representing the U.S. geospatial community.
“Little is clearly understood about the prehistory of the Marshall Islands. Researchers agree on little more than that successive waves of migratory people from Southeast Asia spread across the Western Pacific about 3,000 years ago and that some of them landed on and remained on these islands. The Spanish explorer de Saavedra landed there in 1529. They were named for English explorer John Marshall, who visited them in 1799. The Marshall Islands were claimed by Spain in 1874. Germany established a protectorate in 1885 and set up trading stations on the islands of Jaluit and Ebon to carry out the flourishing copra (dried coconut meat) trade. Marshallese iroij (high chiefs) continued to rule under indirect colonial German administration. At the beginning of World War I, Japan assumed control of the Marshall Islands. Their headquarters remained at the German center of administration, Jaluit. U.S. Marines and Army troops took control from the Japanese in early 1944, following intense fighting on Kwajalein and Enewetak atolls. In 1947, the United States, as the occupying power, entered into an agreement with the UN Security Council to administer Micronesia, including the Marshall Islands, as the Trust Territory of the Pacific Islands. On May 1, 1979, in recognition of the evolving political status of the Marshall Islands, the United States recognized the constitution of the Marshall Islands and the establishment of the Government of the Republic of the Marshall Islands. The constitution incorporates both American and British constitutional concepts” (Background Notes, U.S. Dept. of State, 2014).

“U.S. nuclear testing took place between 1946 and 1958 on the islands of Bikini and Eniwetok. The people of Bikini were removed to another island, and a total of 23 U.S. atomic and hydrogen bomb tests were conducted. Despite cleanup attempts, the islands remain uninhabited today because of nuclear contamination. The U.S. paid the islands $183.7 million in damages in 1983, and in 1999, the U.S. approved a one-time $3.8-million payment to the relocated people of Bikini atoll. Kwajalein atoll is the site of an American military base and has been used for missile defense testing since the 1960s” (InfoPlease, 2014).

The Marshall Islands terrain is low coral limestone and sand islands. The lowest point is the Pacific Ocean (0 m), the highest point is an unnamed location on Likiep (10 m). About the same size as Washington, D.C., the coastline is 370.4 km long. (World Factbook, 2014)

Dr. Helmut Schmid was one of the original German V-2 Rocket Scientists from Peenemünde that were brought to the U.S. at the end of WWII. While most of the Germans were taken to White Sands Missile Proving Grounds, Dr. Schmid was moved to Aberdeen Proving Grounds in Maryland. His protégé was Dr. Duane C. Brown, the Father of American Computational Analytical Photogrammetry. While at Aberdeen, Dr. Schmid designed the WILD Heerbrugg BC-4 ballistic camera for tracking the flights of guided missiles at night. (I personally own one that I converted for terrestrial photogrammetry. Every Spring semester I have it taken out for my students to see how the “old timers” used to do things. Personally, I haven’t been
able to pick the thing up for the last 30 years. – Ed.) Some of the BC-4 camera systems were transferred to the U.S. Coast & Geodetic Survey for the BC-4 Photogrammetric Geodesy program of the 1960s and early 1970s and were directed by Dr. Schmid. (I once was introduced to Dr. Schmid. He was not impressed with a U.S. Army Captain; I got a grunt for an acknowledgement. – Ed.) The remainder of the BC-4 camera systems were transferred to the Kwajalein atoll for missile defense testing, their original purpose.

Thanks to Mr. Ed Carlson of NOAA, “There are at least 2 existing Marshall Island horizontal datums; the islands of Kwajalein, Eniwetok, and Roi-Namur defined by the U.S. Air Force in 1959 referenced to the International ellipsoid (a = 6,378,388 m, 1/γ = 297 – Ed.), and densified by the U.S. Coast & Geodetic Survey (USC&GS), now NGS, during 1960-63, and the island of Majuro defined by the U.S. Geological Survey (USGS) referenced to the Clarke 1866 ellipsoid (a = 6,378,206.4 m, b = 6,356,583.8 m – Ed.). Differences in positions (latitude and longitude) between these datums and a geocentric (1952), at Astropoint, Φ = 11° 15´ 07.2” N, Λ = 167° 28´ 27” E. Erappu Channel, code ERA, Φ = 10° 19´ 34.9” N, Λ = 169° 54´ 23.5” E. Jalous Astro, code ASK, as 61a, Φ = 15° 55´ 19.5” N, Λ = 169° 38´ 37.2” E, α = 18° 30´ 07.0” to 59 from south, International, H = 2.2 m. Jemo (1951), code ASD, at Λ (Astro), Φ = 10° 04´ 47.5” N, Λ = 169° 31´ 18.6” E, International, H = 9.0 ft. Kili, code KKM, at Kili Island. West Coast Observation Spot (1923), Φ = 5° 38´ 47”, Λ = 169° 07´ 00” E. Kwajalein Astro 1952, code ASJ, at Station 42, Ennylabegan I., Φ = 8° 47´ 19.2” ± 0.1” N, Λ = 167° 37´ 26.8” ± 0.2” E, α = 304° 33´ 39.0” ± 0.5” to 43 from north, International, height = 2.39 ft. Observed by 71st Engineer Survey Liaison Detachment with 60° astrolabe. Kwajalein Astro U.S. Navy 1944, code KWA, at Astro, Φ = 8° 44´ 06.3” N, Λ = 167° 44´ 28.6” E. Prismatic astrolabe used with chronograph checked by radio time signals. Approximately 300 stars computed. Observed by LT. E. V. Mohl, U.S.N.R., U.S.H.O., March 1944. Lae (1952), at 2. Astro Point, Φ = 8° 55´ 31.6” N, Λ = 166° 15´ 58.6” E, α = 64° 07´ 56.1” to 1 from south, International, H = 5.7 ft. Leuen Anchorage Observation Spot, code LET, Φ = 7° 45´ 32” N, Λ = 168° 13´ 23” E. Likiep, code LIK (?), at South Pass Reef. Φ = 9° 50´ 22” N, Λ = 169° 13´ 23” E. Likiep, code LIK (?), at 1 Astro Point, Φ = 9° 50´ 24.1” N, Λ = 169° 18´ 51.3” E, α = 126° 00´ 14.9” to 2 from south, International, H = 5.0 ft. Lotj Island, code LAD, at Observation Spot, Φ = 8° 55´ 18´ N, Λ = 166° 12´ 58” E. Majuro Astro, 1944, code MAJ, at Majuro Astro, 1944, Φ = 7° 04´ 25.7” N, Λ = 171° 19´ 18.0” E. U.S.S. Bowditch, prismatic astrolabe used with chronograph checked by radio time signals. Approximately 300 stars computed. Majuro, code ATR, at Astronomic Station No. 2, Φ = 7° 05´ 02.2” N, Λ = 171° 22´ 25.2” E, α = 83° 53´ 22.9” to a mark (1) from south, International, H = 9.3 ft. Maleolap (1952), at 1. Astropoint, Φ = 8° 54´ 15.5” N, Λ = 170° 50´ 41.1” E, α = 40° 04´ 27.4” to 2 from south, International, H = 7.9 ft. Mejit (1919), code MEC, at Astro Station B1, Φ = 10° 16´ 54” N, Λ = 170° 52´ 36” E. Melle Island, code MEB, Φ = 11° 21´ 38” N, Λ = 166° 59´ 13” E. Mili (1951), at 17a Astro Point, Φ = 6° 01´ 45.9” N, Λ = 171° 56´ 50.6” E, α = 134° 23´ 10.7” to 13 from south, International, H = 2.2 m. Namorik (1951), code ATQ, at 1a Astro Point, Φ = 5° 36´ 34.0” N, Λ = 168° 06´ 08.3” E, α = 348° 14´ 35.1” to 2 from south, International, H = 0.6 m. Namu (1951), at 1. Astro, Φ = 7° 45´ 47.6” N, Λ = 168° 13´ 14.2” E, α = 303° 01´ 41.7” to 2 from south, International, H = 4.5 ft. Pokaakkou, code POK, Φ = 14° 34´ 03” N, Λ = 168° 57’ continued
Dr. Abdullah: The topic of understanding the new standards, referred to as the “ASPRS Positional Accuracy Standards for Digital Geospatial Data”, is very important for all users of the new standards during this transition period. Therefore, I will dedicate more than one article to introduce the new standards, highlight its similarity with the legacy standards of the ASPRS 1990 and the National Map Accuracy Standards (NMAS), and provide examples on how to relate the new standards to the legacy standards. The new standards were approved by the ASPRS board during their meeting in Denver on November 17, 2014 and became the official new ASPRS map accuracy standards replacing the old standards of 1990.

As stated in the standards, the new standards are published to meet the dire needs of new era for the geospatial community. Such an era is characterized by rapid advancement in the field of geospatial data collection and data production. Among the main reasons that led to the development of the new standards are the following:

1. Legacy map accuracy standards, the ASPRS 1990 standards and the NMAS of 1947, are outdated. (over 30 years since the ASPRS1990 standards were published)
2. Many of the data acquisition and mapping technologies that legacy standards were based on are no longer used in today’s mapping process.
3. More recent advances in mapping technologies and methods enabled us to produce better quality and higher accuracy geospatial products and maps.
4. Legacy map accuracy standards were designed to deal with plotted or drawn maps as the only medium to represent geospatial data. Today’s digital mapping workflow requires different accuracy measures that are more suitable for the digital products.
5. Within the past two decades (during the transition period from hardcopy to softcopy mapping environments), most measures for relating image Ground Sampling Distance (GSD), map scale, and contours interval to the final product accuracy were based on film scanning practices which were established prior to the introduction of the first digital camera . Such practices and measures are no longer suitable for the products from digital sensors.
6. New mapping processes and methodologies have become much more sophisticated with advances in technology and advances in our knowledge of mapping processes and mathematical modeling. Such sophistication resulted in more accurate mapping products.
7. Mapping accuracy can no longer be associated with the camera geometry and flying altitude alone (focal length, xp, yp, B/H ratio, etc.). Accuracy of new mapping products is influenced by many other factors such as:
   • the quality of camera calibration parameters;
   • quality and size of a Charged Coupled Device (CCD) used in the digital camera CCD array;
   • quality of parallax determination or photo measurements;
   • quality of the GPS signal;
   • quality and density of ground controls;
   • quality of the aerial triangulation solution;
   • capability of the processing software to handle GPS drift and shift;
   • capability of the processing software to handle camera self-calibration,
   • quality of the digital terrain model used for the production of orthoimagery.

These factors can vary widely from project to project, depending on the sensor used and specific methodology. For these reasons, existing accuracy measures based on map scale, film scale, GSD, c-factor and scanning resolution no longer apply to current geospatial mapping practices.

8. Elevation products from modern active sensors such as LiDAR and IFSAR were not considered by the legacy mapping standards as it did not exist then. Therefore, new accuracy standards are needed to address elevation products derived from these technologies.

More information on the motivation behind publishing the new standards can be found in annex A of the new standards document (http://www.asprs.org/PAD-Division/Map-Accuracy-Standards-Working-Group.html)
The new standards bring new and improved approaches in dealing with current mapping products. It also provides a wealth of information and measures for the users to utilize that were never introduced by the legacy standards. Among such improvements are the following:

1. Providing unlimited number of horizontal and vertical accuracy classes that can accommodate products from any of the current or future mapping technologies.
2. Dealing with LiDAR and other modern technologies.
3. Utilizing positional accuracy thresholds for digital orthoimagery and digital elevation data that are independent of published GSD, map scale or contour interval.
4. Providing aerial triangulation accuracy measure.
5. Providing ground controls accuracy measure.
6. Providing orthoimagery seam lines accuracy measure.
7. Providing lidar relative swath-to-swath accuracy measure for LiDAR and IFSAR data.
8. Providing recommended minimum Nominal Pulse Density (NPD) for LiDAR data.
9. Providing horizontal accuracy measure for elevation data.
10. Providing definitions and guidelines for the delineation of low confidence areas for elevation data.
11. Providing guidelines on the required number and spatial distribution of QA/QC check points based on project area.
12. Providing methodology for reporting products accuracy.
13. Providing definitions of statistical terms that are related to accuracy computations and provide practical examples on its use.
14. Providing tutorial sections with practical examples on relating the new standards to the legacy standards.

In the following sections I will try to introduce the structure of the accuracy classes and the newly introduced sections of the new standards.

**Horizontal Accuracy Standards for Geospatial Data**

The new standards defines horizontal accuracy classes in terms of the value of errors presented in data represented by the Root Mean Square (RMSE). Such accuracy class definition do not limit the classes to a certain ranking or certain number of classes as the legacy standards did. This approach offers many advantages and flexibility for the users of the standards as it assigns an accuracy class for any product from any current or future technologies. Table 1 provides the horizontal accuracy classes for geospatial data.

Table 1 Horizontal Accuracy Standard for Geospatial Data

<table>
<thead>
<tr>
<th>Horizontal Accuracy Class</th>
<th>Absolute Accuracy</th>
<th>Relative Accuracy Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE&lt;sub&gt;ex&lt;/sub&gt; and RMSE&lt;sub&gt;ey&lt;/sub&gt; (cm)</td>
<td>RMSE&lt;sub&gt;r&lt;/sub&gt; (cm)</td>
</tr>
<tr>
<td>X-cm</td>
<td>≤X</td>
<td>≤1.41*X</td>
</tr>
</tbody>
</table>

Based on Table 1, data users, when they request products such as digital orthoimagery or digital planimetric data, can specify that the data must be produced to meet ASPRS Accuracy Standards for the RMSE<sub>ex</sub> and RMSE<sub>ey</sub> Horizontal Accuracy Class he or she is interested in. If 10 cm accuracy is desired, then the statement can be written as “the data set should be produced to meet ASPRS Positional Accuracy Standards for Digital Geospatial Data (2014) for 10.0 (cm) RMSE<sub>ex</sub> and RMSE<sub>ey</sub> Horizontal Accuracy Class”. The standards, Table 2, lists 24 common accuracy classes for orthoimagery and planimetric maps.

Table 2 Common Horizontal Accuracy Classes according to the new standards

<table>
<thead>
<tr>
<th>Horizontal Accuracy Class</th>
<th>RMSE&lt;sub&gt;ex&lt;/sub&gt; and RMSE&lt;sub&gt;ey&lt;/sub&gt; (cm)</th>
<th>RMSE&lt;sub&gt;r&lt;/sub&gt; (cm)</th>
<th>Orthoimage Mosaic Seamline Maximum Mismatch (cm)</th>
<th>Horizontal Accuracy at the 95% Confidence Level (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.63</td>
<td>0.9</td>
<td>1.3</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>1.25</td>
<td>1.8</td>
<td>2.5</td>
<td>3.1</td>
<td>3.1</td>
</tr>
<tr>
<td>2.50</td>
<td>3.5</td>
<td>5.0</td>
<td>6.1</td>
<td>6.1</td>
</tr>
<tr>
<td>5.00</td>
<td>7.1</td>
<td>10.0</td>
<td>12.2</td>
<td>12.2</td>
</tr>
<tr>
<td>7.50</td>
<td>10.6</td>
<td>15.0</td>
<td>18.4</td>
<td>18.4</td>
</tr>
<tr>
<td>10.00</td>
<td>14.1</td>
<td>20.0</td>
<td>24.5</td>
<td>24.5</td>
</tr>
<tr>
<td>12.50</td>
<td>17.7</td>
<td>25.0</td>
<td>30.6</td>
<td>30.6</td>
</tr>
<tr>
<td>15.00</td>
<td>21.2</td>
<td>30.0</td>
<td>36.7</td>
<td>36.7</td>
</tr>
<tr>
<td>17.50</td>
<td>24.7</td>
<td>35.0</td>
<td>42.8</td>
<td>42.8</td>
</tr>
<tr>
<td>20.00</td>
<td>28.3</td>
<td>40.0</td>
<td>49.0</td>
<td>49.0</td>
</tr>
<tr>
<td>22.50</td>
<td>31.8</td>
<td>45.0</td>
<td>55.1</td>
<td>55.1</td>
</tr>
<tr>
<td>25.00</td>
<td>35.4</td>
<td>50.0</td>
<td>61.2</td>
<td>61.2</td>
</tr>
<tr>
<td>27.50</td>
<td>38.9</td>
<td>55.0</td>
<td>67.3</td>
<td>67.3</td>
</tr>
<tr>
<td>30.00</td>
<td>42.4</td>
<td>60.0</td>
<td>73.4</td>
<td>73.4</td>
</tr>
<tr>
<td>45.00</td>
<td>63.6</td>
<td>90.0</td>
<td>110.1</td>
<td>110.1</td>
</tr>
<tr>
<td>60.00</td>
<td>84.9</td>
<td>120.0</td>
<td>146.9</td>
<td>146.9</td>
</tr>
<tr>
<td>75.00</td>
<td>106.1</td>
<td>150.0</td>
<td>183.6</td>
<td>183.6</td>
</tr>
<tr>
<td>100.00</td>
<td>141.4</td>
<td>200.0</td>
<td>244.8</td>
<td>244.8</td>
</tr>
<tr>
<td>150.00</td>
<td>212.1</td>
<td>300.0</td>
<td>367.2</td>
<td>367.2</td>
</tr>
<tr>
<td>200.00</td>
<td>282.8</td>
<td>400.0</td>
<td>489.5</td>
<td>489.5</td>
</tr>
<tr>
<td>250.00</td>
<td>353.6</td>
<td>500.0</td>
<td>611.9</td>
<td>611.9</td>
</tr>
<tr>
<td>300.00</td>
<td>424.3</td>
<td>600.0</td>
<td>734.3</td>
<td>734.3</td>
</tr>
<tr>
<td>500.00</td>
<td>707.1</td>
<td>1000.0</td>
<td>1223.9</td>
<td>1223.9</td>
</tr>
<tr>
<td>1000.00</td>
<td>1414.2</td>
<td>2000.0</td>
<td>2447.7</td>
<td>2447.7</td>
</tr>
</tbody>
</table>

"the new standards are published to meet the dire needs of new era for the geospatial community."
Table 3 Digital Orthoimagery Accuracy Examples for Current Large and Medium Format Metric Cameras

<table>
<thead>
<tr>
<th>Common Orthoimagery Pixel Sizes</th>
<th>Recommended Horizontal Accuracy Class RMSE_ and RMSE_y (cm)</th>
<th>Orthoimage RMSE_x and RMSE_y in terms of pixels</th>
<th>Recommended use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.25 cm</td>
<td>≤1.3 ≤1-pixel</td>
<td></td>
<td>Highest accuracy work</td>
</tr>
<tr>
<td></td>
<td>2.5 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥3.8 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>2.5 cm</td>
<td>≤2.5 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥7.5 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>5 cm</td>
<td>≤5.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥15.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>7.5 cm</td>
<td>≤7.5 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>15.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥22.5 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>15 cm</td>
<td>≤15.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>30.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥45.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>30 cm</td>
<td>≤30.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>60.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥90.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>60 cm</td>
<td>≤60.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>120.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥180.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>1 meter</td>
<td>≤100.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>200.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥300.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>2 meter</td>
<td>≤200.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>400.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥600.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
<tr>
<td>5 meter</td>
<td>≤500.0 ≤1-pixel</td>
<td>Highest accuracy work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1,000.0 2-pixels</td>
<td>Standard Mapping and GIS work</td>
<td></td>
</tr>
<tr>
<td></td>
<td>≥1,500.0 ≥3-pixels</td>
<td>Visualization and less accurate work</td>
<td></td>
</tr>
</tbody>
</table>

The standards also provide users with guidelines for associating orthoimagery pixel sizes and associated RMSE_x and RMSE_y accuracy, Table 3. As stated in the new standards, the associating pixel size and products accuracy are largely based on experience with current sensor technologies and primarily apply to large and medium format metric cameras. The table is only provided as a guideline for users during the transition period to the new standards. These associations may change in the future as mapping technologies continue to advance and evolve.

The new standards also provide the following examples to guide the user to relate the new standards to the legacy standards. Such examples are important for the users to prevent confusion and to assure a smooth transition to the new standards.

**Example 1: Converting the horizontal accuracy of a map or orthoimagery from the new 2014 standards to the legacy ASPRS map standards of 1990**

**Given:** A map or orthoimagery with an accuracy of $\text{RMSE}_x = \text{RMSE}_y = 15 \text{ cm}$ according to the new 2014 standards, compute the equivalent accuracy and map scale according to the legacy ASPRS map standards of 1990, for the given map or orthoimagery.

**Solution:**

1) Because both standards utilize the same RMSE measure, then the accuracy of the map according to the legacy ASPRS map standards of 1990 is $\text{RMSE}_x = \text{RMSE}_y = 15 \text{ cm}$

2) To find the equivalent map scale according to the legacy ASPRS map standards of 1990, follow the following steps:

   a. Multiply the $\text{RMSE}_x$ and $\text{RMSE}_y$ value in centimeters by 40 to compute the map scale factor (MSF) for a Class 1 map, therefore:

   $$\text{MSF} = 15 \text{ (cm)} \times 40 = 600$$

   The map scale according to the legacy ASPRS map standards of 1990 is equal to:

   i. Scale = 1:MSF or 1:600 Class 1;

   ii. The accuracy value of $\text{RMSE}_x = \text{RMSE}_y = 15 \text{ cm}$ is also equivalent to Class 2 accuracy for a map with a scale of 1:300.

(TO BE CONTINUED)

"Many of the data acquisition and mapping technologies that legacy standards were based on are no longer used in today's mapping process."

The contents of this column reflect the views of the author, who is responsible for the facts and accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the American Society for Photogrammetry and Remote Sensing and/or Woolpert, Inc.
24° E. Rikuraru, code RIK, $\Phi_o = 10^\circ 01' 28.34''$ N, $\Lambda_o = 169^\circ 00' 47.77''$ E. Rongelap, at Observation Spot, $\Phi_o = 11^\circ 08' 02.5''$ N, $\Lambda_o = 166^\circ 53' 35''$ E. Rongelap (1952), code ROP, at 25. Astro, $\Phi_o = 11^\circ 09' 27.8''$ N, $\Lambda_o = 167^\circ 30' 59.0''$ E, $\alpha_o = 174^\circ 00' 56.2''$ to 2a from south, International, $H_o = 2.5$ m. Rongelap (1952), at 1a. Astro station, $\Phi_o = 11^\circ 26' 43.62''$ N, $\Lambda_o = 167^\circ 03' 27.56''$ E. Rongerik (1952), at 25. Astro station, $\Phi_o = 11^\circ 22' 27.8''$ N, $\Lambda_o = 166^\circ 52' 03.2''$ E, $\alpha_o = 75^\circ 03' 50.1''$ to 24 from south, International, $H_o = 1.9$ m. Rube Point, code RUA, at Observation Spot, $\Phi_o = 4^\circ 35' 13''$ N, $\Lambda_o = 168^\circ 13' 23''$ E. Takowa Island, code TAA, at Observation Spot, $\Phi_o = 6^\circ 13' 36''$ N, $\Lambda_o = 171^\circ 48' 14''$ E. UK requested change from Takowaka. Taongi Astro 1952, code TAO, at 2. Astro, $\Phi_o = 14^\circ 37' 43.5''$ N, $\Lambda_o = 169^\circ 01' 04.0''$ E, $\alpha_o = 20^\circ 00' 23.5''$ to 1 from south, International, $H_o = 5.6$ ft. Taroa Island Trig Station, $\Phi_o = 9^\circ 46' 07.1''$ N, $\Lambda_o = 160^\circ 59' 10.2''$ E, International, elevation = 5.2 ft. Ujelang, at Observation Spot, $\Phi_o = 9^\circ 46' 29''$ N, $\Lambda_o = 160^\circ 57' 43''$ E. USAF 1959, at WAKE (8), $\Phi_o = 19^\circ 16' 19.637''$ N, $\Lambda_o = 166^\circ 39' 21.745''$ E, $\alpha_o = 273^\circ 29' 34.503''$ Bikini (4) to Rolap (2), Hough. Preliminary determination of position of Initial Point. Utirik (1951), at 2. Astro, $\Phi_o = 11^\circ 13' 08.5''$ N, $\Lambda_o = 169^\circ 50' 42.5''$ E, $\alpha_o = 73^\circ 04' 55.0''$ to 1 from south, International, $H_o = 5.9$ ft. Wotje, at Observation Spot, $\Phi_o = 9^\circ 27' 58.6''$ N, $\Lambda_o = 170^\circ 14' 09.7''$ E, $\alpha_o = 320^\circ 12' 34.7''$ to 42 azimuth mark from south, International, $H_o = 6.4$ ft. Wotje, at Observation Spot, $\Phi_o = 9^\circ 27' 31''$ N, $\Lambda_o = 170^\circ 14' 32''$ E. I never was aware of any classified datums in the area. There could have been but it would have been on a need-to-know basis. There could well be duplicates in this list. JWH"
This book addresses fundamental and foundational theories and principles of photogrammetry and its advancements. The target audience varies with students and users of imagery for measurement purposes. The book is organized into basic concepts including coordinate systems, stereoscopic techniques, laser scanning, GIS applications using photogrammetry, and advanced topics of photogrammetry.

The book is divided into sections and chapters as follows:

- Foundational principles of photogrammetry
  - Principles of photography and imaging
  - Cameras and other imaging devices
  - Image measurements and refinements
  - Object space coordinate systems
- Angle of tilt and types of photographs
  - Vertical photographs
  - Stereoscopic viewing
  - Stereoscopic parallax
  - Stereoscopic plotting instruments
  - Tilted and oblique photographs
- Terrestrial and close-range photogrammetry
- New technological advancement
  - Laser scanning systems
- Mapping and GIS
  - Elementary methods of planimetric mapping for GIS
  - Introduction to analytical photogrammetry
  - Topographic mapping and spatial data collection
  - Fundamental principles of digital image processing
  - Photogrammetric applications in GIS
- Control surveys in photogrammetry
  - Control for aerial photogrammetry
  - Aerotriangulation
  - Project planning

This text has been very well written with precise information. The fourth edition has been thoroughly revised from its previous edition. This edition has a new chapter called Laser Scanning Systems, emphasizing its timely technological advancement. This is a significant change in the realm of photogrammetry. The problems in the examples provide and clarify the computational procedures. The various images, maps and figures illustrate the information provided. The language utilized is very simple for even novice practitioners attempting to learn photogrammetry. The references are comprehensive for each chapter and well updated. The organization of the book is well structured and easy to follow.

In my opinion, the Elements of photogrammetry with Application in GIS have accomplished its goal defining photogrammetric foundational principles while also addressing the advanced concepts of photogrammetry. This text is much more comprehensive in photogrammetric principles than other similar books that I have evaluated. The authors, well established experts in the field of photogrammetry, provide a text that is well suited for any audience interested in photogrammetry. The book is well written in terms of layout, binding, typography, notes, figures, diagrams, maps, imagery, appendices and index. Imagery technical specifications and example problems were accurate per this reviewer’s spot check.
**ASPRS HAS A NEW REGION!**

During the Board of Directors meeting for all of ASPRS, the Southwest US Region was dissolved and their territory was re-assigned to the Northern California Region. The next piece of business was the renaming of the newly expanded Region to the Pacific Southwest Region.

For those of you unfamiliar with the geographic coverage of both the old Northern California and Southwest US Regions, our new Region includes the entire states of California, Nevada, Arizona and Hawaii.

The next piece of business will be the adoption of new by-laws and the election of a new slate of officers to govern the new Region. That will be followed up with an election early in 2015.

The officers of both the old Northern California and Southwest US Regions would like to extend a big THANK YOU to all who have involved in the leadership in the last few years and those involved in overseeing the formation of the new Pacific Southwest Region.

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**Letter for the Executive Director**

continued from page 4

bership in an organization that values quality workmanship, adherence to principles of managed precision and accuracy, dedication to detail, and the deeply seated notion of giving to others what the profession has given to us.

Take a look around. There is no other professional organization that offers this to people with our skills and capabilities. Doesn’t it just make sense for you to be a member of that kind of organization?

You may be thinking, “Is there really a need for me to be part of this group?” Indeed there is; the need for this organization may be greater than it ever has been before. The growing commercialization of geospatial information over the last decade has created a deep societal dependence upon the work of our members. Our contributions may be unknown and unappreciated by most citizens and policy makers, but they are necessary to the functioning of modern society.

As a member of ASPRS you will have a much greater opportunity to inform people about what we do. Society needs us, our expertise, our standards, our publications, our support for education, and our professional engagement. Our members understand and expertly address the big issues of our time – from agriculture to defense, from climate change to transportation planning, and from water resources to energy management, to name just a few.

Even as the work of our members has become increasingly important, the challenges faced by members have also increased. Members face cheap labor outsourcing from abroad, broken government contracting models, gaps in our educational system, the ever-constant pressure to lower costs, and the urgent need to innovate business models. Globalization and commoditization challenge traditional services and products, while, ironically, the new technologies we create to stay competitive also disrupt our existing businesses. We face these and other challenges in common, so we are stronger if we identify them and address them together.

Getting our ship ready to sail on its most important voyage in many years is taking some time, of which we have precious little. The tides and currents around us are flowing at a rapid pace. Our ship’s design is outdated. Nonetheless, our members know how to fit a ship for sailing, and they are busy making the necessary changes. (See sidebar.) Even the officers have rolled up their shirt sleeves and are doing carpentry, sheeting sails, and hauling supplies on board. We are almost ready. Within a few months, our plan is to set sail from Tampa, the site of our annual meeting.

Where shall we sail? Should we simply allow the wind and tide carry us where they will? Of course not! Should we chart a course for a known land and prove that we can reach a shore that others have found before us? Perhaps. Or, will we instead boldly point the helm into uncharted waters in search of something entirely new, unknown, and possibly tremendously rewarding?

Consider the example of HMS Endeavour, which set sail in 1768 on a mission to explore Terra Australis Incognita ("unknown southern land"). After she nearly sank on the Great Barrier Reef, Lieutenant James Cook beached her for repairs. Cook wrote, “...it was happy for us that a place of refuge was at hand, for we soon found that the ship would not work...” Endeavour proceeded to sail around the Cape of Good Hope and complete her journey home. The spirit of HMS Endeavour lives on today. Over 200 years later her namesake also circled the earth – but this time from space – OV-105 Space Shuttle Endeavour.

Those who sail with ASPRS on our new endeavor will be in for an adventure in all senses of the word – anticipation, challenge, excitement, exhilaration, education, and perhaps even fame and fortune. We promise not only an adventure, but also the chance to accomplish something that is bigger than any one of us can achieve on our own.

New frontiers await us in the next 80 years, I am certain of it. This ship is sea-worthy, but it needs a good complement of passengers and crew. Please, board the ship with me and let us sail together toward a bright future.

Dr. Michael Hauck, ASPRS Executive Director
WELCOME TO THE NEW YEAR, STUDENT MEMBERS!

The Student Advisory Council (SAC) along with executive members of ASPRS have begun to make incredible changes to the organization to benefit student members. We are thrilled to be implementing new policies and programs to improve how students experience membership—now is the time and 2015 is the year to engage with ASPRS!

In the months to come, the SAC will be extending support to ASPRS Student Chapters on campuses throughout the US and Canada. Please be on the lookout for Student Advisory Councilors who will be contacting your Student Chapter, or contact us if you are interested in establishing a Chapter on your campus! If you are planning any university-sponsored ASPRS events, we would love to feature your chapter on our online blog Signatures: The ASPRS Student Newsletter at www.asprssignature.blogspot.com and in our online social media pages.

Your student membership will be the passport to a host of new incentives and opportunities. We want to ensure that you receive the best value from your membership and are an active student member in the Society. Most importantly, we want you to be interactive with your fellow ASPRS members nationally, in your region, and on your campus. To get the most of your ASPRS Student Membership, we encourage you to:

◊ Attend national conferences—it is easiest thing to do!
  ASPRS conferences function to introduce and connect students to the geospatial community. When we attend conferences, we are able to:
  • Meet the leaders who are innovating geospatial technology and may have written our textbooks!
  • Find potential employers at the Student-Employer Meet & Greet and throughout the conference
  • Present our research and receive feedback from industry and research professionals
  • Have fun with other students who share our interests and will be collaborators for years to come!

◊ Enroll in the Geospatial Intern Program (GIP)!
The Geospatial Intern Program puts you on the path to professional certification as a scientist or a technician. Since 2014, GIP applicants no longer require on-the-job experience, the requirement can be delayed up to 5 years after receiving the GIP for full certification. Geospatial Interns can be certified as Photogrammetrists, Remote Sensing or GIS/LIS Mapping Scientists, or as Lidar Scientists (NEW for 2015)!

◊ Submit articles here in Photogrammetric Engineering and Remote Sensing (PE&RS)!
This is an amazing opportunity for any student! PE&RS is a widely read, peer-reviewed technical journal in the geospatial sciences, featuring important breakthroughs and best practices. In fact, the Impact Factor of the journal is steadily rising, meaning that the article that you submit will be read and cited!

◊ Participate in the GeoLeague Competition!
GeoLeague is a competition between ASPRS student chapters who participate as teams to solve a problem with geospatial tools! The teams are provided a study site and relevant geographic data from which they must conduct research and geospatial analysis to solve an existing problem. This year, the competition is based on preserving trails and campsites for the Boy Scouts. Please assemble your campus team and register for GeoLeague by January 26!

By taking these steps, you will not only take the best advantage of ASPRS student-focused events and programs, you will gain desirable skills and experiences to enhance your career! We hope that you start by coming to the next national conference in Tampa, Florida, the Imaging and Geospatial Technology Forum (IGTF) taking place May 4-8, 2015. We also invite you to respond to the Call for Papers this month with your abstracts to be included in the conference program!

Best wishes for the New Year,
The Student Advisory Council
JACIE JOINS ASPRS AGAIN!

This May, for the second year, the American Society for Photo Grammetry and Remote Sensing (ASPRS) and the Joint Agency for Commercial Imagery Evaluation (JACIE) will be co-located!

The Joint Agency Commercial/Civil Imagery Evaluation (JACIE) effort formed to leverage Federal agencies’ resources for the characterization of commercial remote sensing data and to share those results across the Federal Government and beyond. Consisting of representatives from the U.S. Geological Survey (USGS), the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the U.S. Department of Agriculture (USDA), the JACIE team performs product analysis of commercial and other remote sensing data and information products, providing earth scientists and other users with awareness and independent verification of commercial imagery data quality.

Ever increasing numbers of available commercial sources for remotely sensed data offers users more choices than historically possible. The ability to use data from these new sources hinges on understanding their characteristics, capabilities, and quality of data they produce.

The JACIE team provides independent characterizations of delivered image and image-derived end products. Each team member brings their resources and strengths to this task, providing Federal users in-depth assessments of commercial imagery quality. The JACIE team efforts have been instrumental in several improvements to commercial image quality and have enhanced working relationships between government and the commercial remote sensing industry.

JACIE works to provide insights into the capabilities of upcoming and recently launched remote sensing systems. This years’ 14th Annual JACIE Workshop will feature presentations from vendors and users describing new systems and reporting on their data quality and capabilities.

CLASSIFIEDS

EMPLOYMENT

The Department of Geomatics at the University of Alaska Anchorage invites applicants for a full-time tenure-track Assistant/Associate Professor position.

The primary duty of this position is full-time teaching for the ABET accredited BS in Geomatics. Courses may include surveying, GPS, GIS, geodesy, map projections, photogrammetry, LiDAR, remote sensing, boundary law, adjustments, hydrographic surveying, land development design, and CAD. The position may include a research component depending on the background of the successful applicant.

To apply go to www.uakjobs.com, Posting Number 0069856.
ASPRS MEMBERSHIP

ASPRS would like to welcome the following new members!

**At Large**
Lizy Abraham
Amr Al-Hamad
Muwaffaq Alqurashi
Naif Muidh Alsubaie
Rizwan Ahmed Ansari
Chi Chen
Zhen Dong
Anna Fryskowska, Ph.D.
Marqqa Rosa Varela Gonzalez
Bianca Hoersch
Martin Kada
Maria Gabriela Lenzano
Zeyu Li
Yuehan Li
Julien Li-Chee-Ming
Dorota Iwaszcuk
Werner Mayr
Somyeh Mollaee
Marcus V T Monteiro
Navid Mostofi
Arnadi D. Murtiyoso
Agata Orych
Andrej Peisker
Saied Pirasteh
Kurtis Poettcker
Ralf Reulke
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Berthold Winck
Bisheng Yang
Yunsheng Zhang, Ph.D.
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Carla Castillo
Fils Dieu-Conserve
Nicole Gamboa
James Henn
Paul Keays
Danielle Kittredge
Kate Kraynak
Kaylee LaManna
Lynda Mamasse
Alyssa Murakami
Mark Rochelo
Paige Rogolino
Augustus O. Slaven
Brian Smith
Molly Elizabeth Smith
Leonardo V. Trejo
Natasha Vidal
Darren Zap

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Evan Applegate
Lori Baer
Christopher Barnes
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Michael Budde
Michael Chaoate
Jon B. Christopherson
Catherine Costello
Angie Diefenbach
Sean Dinsmore
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Colin Leslie
Holly Miller
Ron Morfitt
Jim Nelson
Kurtis Nelson
Birgit Peterson
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Gabriel Rousseau
Sarah Ryker
Aparajithan Sampath
Kristi Sayler

**Heartland**
Evan Menke
Robert C. Anderson
Craig Edward Hoover
David Meyer
Matthew Trani
Tim D. Washechek

**Mid-South**
Rachel Snively
Laila Almutairi
Elivelton Fonseca, Ph.D.
Pan Gao
Maryellen Sault

**Northern California**
Matthew Bromley

**New England**
Sean Cunningham
Faith Justus
Qian Lei
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Brian Buechler
Megan Kathleen Caldwell
Joseph Clark
Christopher Cole
Thomas Fogarty, Jr.
Jason Freels
Wendy Goetz
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Tammira Taylor
Jennifer Turner-Valle
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**Southwest US**
Sarah Shivers

**West Great Lakes**
Zoltan Koppanyi
Susan Wirth

FOR MORE INFORMATION ON ASPRS MEMBERSHIP, VISIT HTTP://WWW.ASPRS.ORG/JOIN-NOW/

Your path to success in the geospatial community

Erik Brewster  |  Bon Dewitt  |  B. Haack
Jonathan Li  |  Sudhagar Nagarajan  |  Xiaojun Yang

FOR SPONSORING SOME OF OUR NEW MEMBERS!

Thank You!
PRODUCTS

Optech is pleased to announce the latest addition to its innovative line of airborne laser terrain mappers (ALTM), the Optech Titan, launching a new era in remote sensing. For the first time ever, multispectral active imaging of the environment can occur day or night, enabling new vertical applications and information extraction capabilities for lidar.

In the past, single or dual-wavelength sensors were developed for specific market verticals and application requirements. Titan breaks away from this convention by combining three beams with separate wavelengths, increasing the information content that can be derived from the target surface and allowing surveying professionals to address many more applications using a single sensor solution. Whether the goal is high-precision, high-density topographic surveying, land cover classification, vegetation mapping, or shallow water bathymetry, the Optech Titan can accommodate them all.

Titan incorporates three independent laser beams at different wavelengths, with a combined ground sampling rate approaching 1 MHz. The sensor includes full gyro-stabilization compatibility for predictable point distribution and a fully-programmable scanner for significant point density increases at narrower FOVs. Passive imagery support is available via fully-embedded high-resolution metric mapping cameras, including multispectral, thermal, NIR and RGB. For applications that demand it, Titan also includes full-waveform recording capability for each independent lidar wavelength.

Workflow is a critical component of any successful remote sensing solution. Standard software deliverables with Titan include Optech FMS, a fully-featured flight management system that enables integrated mission planning for both lidar and camera, aircraft navigation, and real-time monitoring of the 3D active point clouds from each data channel alongside passive image thumbnails for in-air collection confidence. Also included is Optech’s Lidar Mapping Suite (LMS), an industry benchmark for production lidar processing and accuracy quantification across the entire project extent. Unique to Titan is an LMS software extension that provides enhanced map product deliverables for bathymetric and land cover classifications by leveraging Titan’s multispectral capability.

For further information, please contact your Regional Sales Manager or www.optech.com.

GeoCue Group Inc. is pleased to announce the release of GeoCue 2014.1. This release includes many new features, performance improvements and stability enhancements. A number of features are aimed specifically at supporting LAS 1.4 data while easing usability and installation of GeoCue’s client and server components.

Highlights of the new release include:
• Dramatically Simplified Installation and Client Start-Up
• Improved Performance of Distributed Workflows
• Email Alerts on Dispatched Jobs
• New Window Arrangement Feature
• New Coordinate Reference Systems and Vertical Datum
• Comprehensive support for LAS 1.4. (LIDAR 1 CuePac)
• Additional Options for DirectDrive of MicroStation/Terrasolid
• Improved Look Up Table (LUT) Support (DMC PPS CuePac)
• Enhanced FramePro Data Import and Streamlined Workflow (RCD30 CuePac)

In addition to the major new features highlighted above, we have also addressed many areas of the software to improve both performance and stability.

Everyone who has GeoCue on current maintenance will receive the release on DVD. We will send out an email blast when the new release has been posted to the download server.

For more information, visit www.GeoCue.com.
Correction of Distortions in YG-12 High-Resolution Panchromatic Images

Yonghua Jiang, Guo Zhang, Deren Li, Xinming Tang, Wenchao Huang, and Litao Li

Abstract
Design deficiencies and hardware limitations cause a number of issues with the images acquired by Chinese satellites launched before 2012, such as YG-12. The geometric quality of the images recorded by YG-12 cannot match its high resolution because of serious time-synchronization errors and interior distortions. To improve the geometric quality of YG-12 images, this paper proposes a method of interior calibration for the YG-12 panchromatic sensor. In addition, an innovative method is proposed to eliminate time-synchronization errors using parallel observations of the panchromatic sensor onboard YG-12. The experimental results indicate the interior parameters of the panchromatic sensor are determined with an accuracy of better than 0.32 pixels, and seamless mosaic images can be obtained after the elimination of distortions. Furthermore, the positioning accuracy with relatively few ground control points is shown to be better than 1.5 pixels.

Introduction
The high-resolution YaoGan-Weixing 12 (YG-12) satellite was launched by China in November, 2011, and is located in a 500 km circular orbit. It is intended for scientific experiments, land surveys, crop yield assessments, and disaster monitoring (Barbosa, 2011). YG-12 can acquire panchromatic images with a resolution of 1 m using a pushbroom camera, whose focal plane is briefly illustrated in Figure 1. Detailed camera information is provided in Table 1.

The positioning accuracy of YG-12 using ground control points (GCPs) is known to be very poor due to large distortions, and this seriously restricts the satellite’s applications. As an example, Figure 2 shows the positioning errors after using sufficient GCPs to compensate for systematic orbit and attitude errors, with the image line (representing scanning time) on the horizontal axis and residual errors on the vertical axis. Obviously, the residual errors vary randomly with scanning time, so increasing the number of GCPs will not improve the geometric accuracy. The reasons for such large distortions in YG-12 panchromatic images are as follows: (a) The time system is not unified onboard YG-12. Therefore, time-synchronization errors exist because of delays between the time of orbit data, attitude data, and scanning time. The magnitude of the error was found to be several ms (for comparison, the average integral time of the panchromatic sensor is about 0.13 ms); (b) The panchromatic sensor of YG-12 was designed as a large-distortion optical system, meaning that high-order distortions exist in panchromatic images without precise interior calibration; and (c) there may be some large random errors in the measurements of orbit and attitude data.

While scanning in orbit, YG-12 uses a single-frequency GPS system to measure the satellite position and velocity relative to the WGS84 coordinate system with accuracies

FIGURE 1. CCD array placement of panchromatic sensor.
0.15 m/s, and the satellite attitude is determined by onboard star-trackers and gyroscopes with an accuracy of better than 5°. The sampling frequencies are about 1 Hz and 4 Hz for the orbit and attitude data. The orbit and attitude data for a certain scanning time are calculated by the Lagrange interpolation method and linear interpolation method, respectively. During the design phase of YG-12, the random errors of these measurements were made as small as possible. In addition, these measurements mainly behave systematically during a very short period, such as the period of one image (<2.5 s), so item (c) can be neglected. Therefore, in this paper, we focus on methods to resolve (a) and (b). Regarding (b), many researchers have studied methods of distortion elimination by improving interior calibration, and good results have been achieved for the SPOT5, IKONOS, ALOS, and Ziyuan-3 satellites, among others (Bouillon et al., 2003; Breton et al., 2002; Gachet, 2004; Leprince et al., 2008; Grodecki and Dial, 2002; Tadono et al., 2006; Tadono et al., 2009; Yonghua et al., 2013; Guo et al., 2013; Mulawa, 2004; Radhadevi and Solanki, 2008). Different from previous studies, determining the precise interior parameters of YG-12’s panchromatic sensor is difficult because of the time-synchronization errors. As for the elimination of time-synchronization errors, related studies have been carried out for the sensors onboard the international space station (Dou et al., 2013). However, they aimed at the frame camera that instantaneously scans an entire image. Time-synchronization errors of frame camera can equal to systematic orbit errors and attitude errors, which are totally different with the errors of CCD push-broom sensors. Moreover, few studies have been carried out on the elimination of time-synchronization errors for the CCD push-broom sensors.

The influence of time-synchronization errors on positioning is analyzed in detail, based on which we determine the precise interior parameters of the panchromatic sensor by shortening the calibration period. Further, an innovative method is proposed that eliminates time-synchronization errors using parallel observations of the panchromatic sensor. The overlaps between adjacent CCD arrays are sensitive to the imaging side-angle and terrain (De Lussy et al., 2005). As an example, the ellipse in Figure 3 shows the lack of overlap between adjacent CCD images caused by large imaging side-angles. A virtual imaging method that is independent of the overlap is introduced to generate mosaic images. We conduct a series of experiments by collecting several YG-12 panchromatic images and corresponding control data to verify the feasibility and validity of the proposed method. The results indicate that the interior parameters of the panchromatic sensor are determined with an accuracy of better than 0.32 pixels, and seamless mosaic images can be obtained after eliminating distortions. Furthermore, the positioning accuracy using a few GCPs is shown to be better than 1.5 pixels, and equivalent to the accuracy of the GCPs.
Methodology

Characteristics of the Time-Synchronization Errors

The rigorous geometric model of the panchromatic sensor can be established as Equation 1 based on the geometric parameters of the panchromatic sensor and the measurements of orbit data and attitude data (Poli, 2012; Xinming et al., 2012):

\[
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix} =
\begin{bmatrix}
X_S \\
Y_S \\
Z_S
\end{bmatrix} + mR_{\text{body}2\text{wp}}R_{\text{camera2body}}
\begin{bmatrix}
x - \Delta x \\
y - \Delta y \\
f
\end{bmatrix}
\]  

where \((X, Y, Z)\) is the object position vector in the WGS84 coordinate system; \((X_S, Y_S, Z_S)\) is the position vector of the satellite with respect to the WGS84 coordinate system; \(R_{\text{camera2body}}\) denotes the rotation matrix to convert the satellite body coordinate system to the WGS84 coordinate system; \((x, y, f)\) is the position vector in the camera coordinate system; \((\Delta x, \Delta y)\) is the distortion of pixel \((x, y)\); and \(m\) denotes the scaling factor.

Suppose the time-synchronization error among orbit data, attitude data, and scanning time is \(\Delta t\). When processing the image line scanned at time \(t\), Equation 1 can be used to derive:

\[
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix}_t =
\begin{bmatrix}
X_S \\
Y_S \\
Z_S
\end{bmatrix} + mR_{\text{body}2\text{wp}}R_{\text{camera2body}}
\begin{bmatrix}
x - \Delta x \\
y - \Delta y \\
f
\end{bmatrix}
\]  

From Equation 2, the position and attitude data of the satellite measured at time \(t + \Delta t\) are used to process the image line at time \(t\). Therefore, the time-synchronization errors essentially affect the positioning, and these can be regarded as position errors and attitude errors that vary with scanning time. These variational position errors and attitude errors can be expressed as:

\[
\Delta p = v\Delta t, \quad \Delta a = a\Delta t
\]  

where \(\Delta p\) denotes the variational position error, \(v\) is the satellite’s velocity at time \(t\), \(\Delta a\) denotes the variational attitude error, and \(a\) is the satellite’s angular velocity.

Furthermore, the time-synchronization errors can be simplified based on the equivalent relationship between orbit positioning error and attitude error under the condition of a small field of view, as illustrated in Figure 4. In this Figure, \(S\) denotes the correct position of the satellite, \(S'\) denotes the wrong position, and \(SO\) points from the satellite to the earth’s center of mass. In Figure 4a, the position error along the track \(\Delta X\) is equivalent to a pitch angle error \(\Delta \phi\), because an almost identical value of pitch angle \(\phi\) is the response to all detectors in the CCD arrays. However, the situation in Figure 4b is more complex, as different roll angles \(\omega\) correspond to different detectors. The positioning error caused by a roll angle error \(\Delta \omega\) can be calculated as:

\[
\Delta Y = H \tan(\omega) - H \tan(\omega + \Delta \omega)
\]  

and taking the partial derivative of \(\Delta Y\) with respect to \(\omega\):

\[
d(\Delta Y) = H[(\tan^2(\omega) - \tan^2(\omega + \Delta \omega))d\omega
\]
According to the design of the YG-12 panchromatic sensor (Table 1), let $\cos1.4^\circ$ (the field of view of the panchromatic sensor), $\Delta\leq32^\circ$ (the largest side angle of YG-12), $\Delta\leq5^\circ$, and $H \approx 500$ km. This implies that $d(\Delta')$ is less than 0.51 m under the worst conditions, so a roll angle error can generally be considered as a constant positioning error for all detectors, and this is approximately equivalent to the position error across the track $\Delta'$. In Figure 4c, the positioning error $\Delta P$ caused by the radial position error $\Delta Z$ can be very small, as shown in Equation 6, while scanning downward. According to the inference on Figure 4b, $\Delta Z$ can also be regarded as a constant positioning error, even when scanning with a large side angle, owing to the small field of view, based on which this is equivalent to a corresponding angle error:

$$\Delta P = \Delta Z \tan(\omega) \leq 10 \cdot \tan(1.4/2) = 0.12 m$$

(6)

For this reason, time-synchronization errors can be regarded as variational attitude errors, since position errors are equivalent to corresponding attitude errors.

**Interior Calibration of YG-12 Panchromatic Sensor**

The time-synchronization errors can be counted as systematic errors over very short time periods, because the satellite can maintain a steady velocity and angular velocity during such short time-frames. As shown in the example of Figure 5, the positioning errors in the black box caused by time-synchronization errors can be eliminated by several GCPs. This means interior calibration is no longer affected by time-synchronization errors. Therefore, we can shorten the calibration period by selecting an appropriate image area for the acquisition of interior calibration is no longer affected by time-synchronizations. The time-synchronization errors can be counted as systematic errors in the black box caused by time-synchronization errors can be eliminated by several GCPs for calibration, because time-synchronization errors can be eliminated in this area. This will ensure the precision of the calibration.

To eliminate systematic installation errors of onboard equipment (camera, star sensor, etc.) and attitude errors during the calibration period, a matrix is introduced into Equation 2 (Radhadevi et al., 2011):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} X_s \\ Y_s \\ Z_s \end{bmatrix} + m(R_{body2exp})_{t+d} R_t R_{camera2body} \begin{bmatrix} x - \Delta x \\ y - \Delta y \\ f \end{bmatrix}$$

(7)

where $R_t$ denotes the matrix to be resolved. As the positioning errors in the black box in Figure 5 shows a linear change with time, $R_t$ can be defined as:

$$R_t = \begin{bmatrix} \cos(\phi + \gamma t) & 0 & \sin(\phi + \gamma t) \\ 0 & 1 & 0 \\ -\sin(\phi + \gamma t) & 0 & \cos(\phi + \gamma t) \end{bmatrix} \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

(8)

Then, $\phi$, $\omega$, $\kappa$, $\psi$, and $\nu$ can be calculated with several GCPs after linearizing Equation 7.

The panchromatic sensor of YG-12 consists of multiple linear CCD arrays. Each may have different interior errors due to the different arrangement in the focal plane. Therefore, we adopt the following look-angle model for interior calibration to avoid establishing different distortion models for each CCD array (Leprince et al., 2008):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} X_s \\ Y_s \\ Z_s \end{bmatrix} + m(R_{body2exp})_{t+d} R_t R_{camera2body} \begin{bmatrix} \tan \psi_x \\ \tan \psi_y \\ 1 \end{bmatrix}$$

(10)

Hence, the look-angles ($\psi_x$, $\psi_y$) can be calibrated for a certain detector using only one GCP in the corresponding row. When more than one GCP is obtained, the look-angles can be determined based on the least-squares method. However, there must be some error in parts of the obtained look-angles if no restrictions are adopted to restrain the effects caused by inaccurate GCPs. Therefore, a suitable smoothing fit is required to eliminate these errors. For a linear CCD array look-angle with a principal point offset ($\Delta x$, $\Delta y$), focus-length bias $\Delta f$, zooming scale error $s_z$, CCD chip rotation error $\theta$, radial distortion ($k_1$, $k_2$), and decentering distortion ($p_x$, $p_y$) (Brown, 1971; Fryer and Brown, 1986):
where \( r = \sqrt{x^2 + y^2} \).

For a linear CCD array, \( x \) is constant, so Equation 7 can be approximated as (Yonghua et al., 2013):

\[
\begin{align*}
\tan(\psi_x) &= a_0 + a_1s + a_2s^2 + \cdots + a_is^i \quad \text{for } i \\
\tan(\psi_y) &= b_0 + b_1s + b_2s^2 + \cdots + b_is^i
\end{align*}
\]

(12)

where \( s \) denotes the image row. The variables \( a_0, a_1, \ldots, b_0, b_1, \ldots, b_i \) are obtained using the direct calibrated look-angles on the basis of polynomial regression analysis for each CCD array.

**Elimination of the Time-Synchronization Errors Based on Parallel Observations**

As shown in Figure 6, the adjacent CCD arrays scan the same ground object within a very short period of time \( \tau \), which is determined by the shift between the adjacent CCD arrays of the panchromatic sensor (\( \tau \approx \frac{5000 \times 0.00013}{\sin 0.20°} = 0.65s \), where 0.00013 is the average integral time).

![Figure 6. Schematic diagram showing parallel observations.](image)

If there are no errors in the imaging geometry during the period \( \tau \), the conjugate points \( p_0 \) and \( p_i \) should be positioned on the same ground object \( S \), as shown in Figure 6. This can be expressed as:

\[
\begin{align*}
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix}
= & \begin{bmatrix}
X_S \\
Y_S \\
Z_S
\end{bmatrix} \\
+ & m_t \begin{bmatrix}
R_{body2earth}R_{cam2body} \\
\tan \psi_x \\
\tan \psi_y
\end{bmatrix}
\end{align*}
\]

(13)

After precisely determining the interior parameters of the panchromatic sensor, the unknown height of \( S \) and the timesynchronization errors invalidate Equation 13. The influence of height error on Equation 13 is illustrated in Figure 7 where panel 7a shows the stereoscopy error across the track, and panel 7b shows the stereoscopy error along the track. In Figure 7, \( \Delta h \) is the height error of the ground object \( S \), \( \alpha_0 \) and \( \alpha_1 \) are the side angles of the conjugate points in adjacent CCD arrays, while \( \theta_0 \) and \( \theta_1 \) are the angles of pitch; \( \Delta X \) and \( \Delta Y \) denote the stereoscopy errors across and along the track, respectively. For the panchromatic sensor of YG-12, the overlap between adjacent CCD arrays is less than 40 pixels and the focal length is about 5 m. In the extreme case, the sensor is assumed to scan with a maximum side-angle of 32°. Considering the maximum difference between \( \alpha_0 \) and \( \alpha_1 \) in Figure 1, we let \( \delta \) be the side angle of the left-most pixel in the CCD2 array, and \( \alpha_i \) be that of the conjugate pixel in CCD1:

\[
\begin{align*}
\alpha_0 & \approx 32° + \tan^{-1}(0.00001 \times 3072/5) = 32.352° \\
\alpha_1 & \approx 32° + \tan^{-1}(0.00001 \times 3072 + 40) = 32.356°
\end{align*}
\]

The maximum stereoscopy error across the track (\( \Delta X \)) can be calculated as:

\[
\Delta X = \Delta h(\tan(32.356°) - \tan(32.352°)) = 0.00098 \Delta h
\]

(14)

Similarly, we let \( \theta_0 \approx 0.20° \) and \( \theta_1 \approx 0.20° + \tan^{-1}(5000 \times 0.00001/5) = 0.77° \) according to Figure 1, and calculate the stereoscopy error along the track (\( \Delta Y \)) as:

\[
\Delta Y = \Delta h(\tan(0.77°) - \tan(0.20°)) = 0.01 \Delta h
\]

(15)

![Figure 7. Stereoscopy errors during parallel observations: (a) across the track, and (b) along the track.](image)
The direct positioning accuracy of YG-12 without GCPs can be <90 m. When a 90 m shuttle radar topography mission (90 m SRTM) digital elevation model (DEM) is used for correction, the height error of ground objects is less than 30 m (Consortium for Spatial Information, 2012), and the stereosey errors are both less than 0.3 m according to Equations 14 and 15, so the influence on Equation 13 caused by height error can be neglected. Therefore, Equation 13 is only affected by the time-synchronization errors. To regard the time-synchronization errors as a variational attitude error, it can be eliminated by introducing an attitude offset matrix into Equation 13 (Yonghua et al., 2014), giving:

\[
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix} = \begin{bmatrix}
X^i_S \\
Y^i_S \\
Z^i_S
\end{bmatrix} + m_t R^i_{\text{body2geom}} R^i_{\text{offset}} R^{\text{cam2body}} \begin{bmatrix}
\tan \psi_x \\
\tan \psi_y \\
\end{bmatrix}
\]

where \( R^i_{\text{offset}} \) denotes the attitude offset matrix at time \( t \), which can be defined as:

\[
R^i_{\text{offset}} = R_0 R_s R_t = \begin{bmatrix}
\cos \phi_0 & -\sin \phi_0 & 0 \\
\sin \phi_0 & \cos \phi_0 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\cos \omega_0 & -\sin \omega_0 & 0 \\
\sin \omega_0 & \cos \omega_0 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\cos \kappa & -\sin \kappa & 0 \\
\sin \kappa & \cos \kappa & 0 \\
0 & 0 & 1
\end{bmatrix}
\]

where \( \phi, \omega, \kappa \) denote the variables which are indeed resolved.

There are two main problems if we solve \( R^i_{\text{offset}} \) directly using Equation 16 when the ground object location \( (X,Y,Z) \) is unknown: (a) too many calculations are required, because six unknowns \( (\phi, \omega, \kappa, X,Y,Z) \) must be found for each conjugate point; (b) the accuracy of \( (X,Y,Z) \) obtained by the forward intersection is severely affected by the extraction accuracy of the conjugate points when there is only a very low base-height ratio between adjacent CCD arrays, which may reduce the correction accuracy of time-synchronization errors. To overcome these problems, the location \( (X,Y,Z) \) of a ground object can be calculated at time \( t_i \) with an identity offset matrix and a 90 m SRTM, and the attitude offset matrix at time \( t_i \) can then be computed. If the attitude offset matrix is solved for each conjugate point in this manner, there will be errors in parts of the attitude offset matrixes due to unavoidable mismatched points. Thus, techniques to reduce the detrimental effects of mismatched points should be applied. Given that the errors may remain regular over a very short period, we can divide all of the conjugate points into different groups. We then need only solve an attitude offset matrix for one group to suppress the mismatched points, because the majority points in a group will be correctly matched. If we suppose that \( n \) conjugate points \( (x^c_{i,j}, y^c_{i,j}, z^c_{i,j}, \theta^c_{i,j}, \psi^c_{i,j}) \), \( 1 \leq n \leq N \), have been obtained from adjacent CCD arrays \( CCD_i \) and \( CCD_{i+1} \), the division process proceeds as follows (Yonghua et al., 2014).

1. First, calculate the location \( (X,Y,Z) \) that corresponds to \( (x^c_{i,j}, y^c_{i,j}) \) with a 90 m SRTM, and calculate the image coordinates \( (x^c_{i,j}, y^c_{i,j}) \) in \( CCD_i \) that correspond to \( (X,Y,Z) \).
2. Calculate the conjugate positioning errors for all points as follows: \( \Delta x = x_{i,j} - x^c_{i,j}, \Delta y = y_{i,j} - y^c_{i,j} \), \( j \leq N \) (17).
3. Set a threshold \( r \) such that if two conjugate points satisfy \( \sqrt{\Delta x^2 + \Delta y^2} \leq r \), they should be placed in the same group. Otherwise, generate a new group.
4. Eliminate the group for which the number of points is very small (e.g., <5). We then solve the attitude offset matrixes for each group.

Virtual Imaging Method to Generate Mosaic Image Products

Finally, after determining the interior parameters and eliminating time-synchronization errors, a virtual imaging method is adopted to generate the mosaic image products of the panchromatic sensor. The virtual imaging method proceeds as follows (Hongbo et al., 2013):

1. A geometric model of the virtual CCD is established on the basis of the interior orientation defined by its position in the focal plane (shown in Figure 8). The object coordinates \( (X,Y,Z) \) of any pixel \( (x',y') \) in the virtual CCD are then obtained using the model and the corresponding height from 90 m SRTM.
2. The image coordinates \( (x,y) \) in the original image corresponding to \( (X,Y,Z) \) in Step 1 are calculated using the geometric model for the original image.
3. The gray value of a pixel \( (x,y) \) in the original image, obtained by resampling with a raised cosine function (Cho et al., 2005), is assigned to pixel \( (x',y') \) in the virtual CCD.
4. The mosaic image is generated by repeating Steps 1, 2, and 3 for all pixels.
5. The rational polynomial coefficients (RPCs) are then generated based on the geometric model of the virtual CCD obtained in Step 1.

Results and Analysis

Study Area and Data Sources

To validate the feasibility of the proposed method, we collected 1:2000 scale digital orthophoto maps (DOMs) and DEMs as shown in Figure 9 and the corresponding panchromatic images of YG-12. The Tianjin data contain flat regions and a height range of 12 m. The Henan region covers a 50 km × 50 km area with a small mountainous region in the southwest, and has a height range of about 600 m. Information on the YG-12 images is listed in Table 2.

<table>
<thead>
<tr>
<th>Area</th>
<th>Imaging time</th>
<th>Side-angle (°)</th>
<th>Max / Ave (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-3-27-Henan</td>
<td>2012-3-27</td>
<td>-3.05</td>
<td>641.78/400.34</td>
</tr>
<tr>
<td>2012-4-17-Tianjin</td>
<td>2012-4-17</td>
<td>17.89</td>
<td>9.74/1.24</td>
</tr>
<tr>
<td>2012-5-8-Tianjin</td>
<td>2012-5-8</td>
<td>8.13</td>
<td>10.82/29.81</td>
</tr>
<tr>
<td>2012-10-18-Henan</td>
<td>2012-10-18</td>
<td>-19.51</td>
<td>541.76/664.88</td>
</tr>
<tr>
<td>2012-11-16-Henan</td>
<td>2012-11-16</td>
<td>0.16</td>
<td>513.68/709.93</td>
</tr>
</tbody>
</table>

* Max denotes maximum altitude difference and Ave denotes average altitude.
First, the interior parameters of the panchromatic sensor were determined using the 27 March 2012 Henan image. Using these, the proposed method of eliminating time-synchronization errors was applied to the other images. Finally, the mosaic image products were generated, and their accuracy was estimated to verify the feasibility and validity of the proposed method.

**Correction of Distortions for the Panchromatic Sensor**

According to the characteristics of the positioning errors in 2012-3-27-Henan, the appropriate image area was determined from lines 12 000 to 14 000. GCPs were obtained for every third row from the 1:2000 scale DOM using a high-accuracy matching method with a theoretical accuracy of better than 0.02 pixels (Leprince et al., 2008). Finally 9,982 evenly distributed GCPs were acquired. The distribution of the GCPs is shown in Figure 10.

The interior calibration accuracy is given in Table 3, where the maximum along- and across-track residual errors are both less than 1.5 pixels, and the overall accuracy is better than 0.32 pixels. This indicates two points: (a) the systematic errors can be totally eliminated with the proposed calibration model, and (b) the influence on interior calibration of the time-synchronization errors can be restrained by shortening the calibration period. The residual errors after calibration are shown in Figure 11 where the left panel denotes the variation rule of the residual errors along the CCD direction, and the right panel denotes that with respect to scanning time. It can be seen that time-synchronization errors are completely eliminated since there is no trend in the variation with scanning time, unlike in Figure 2, which further verifies the equivalence between the time-synchronization errors and systematic attitude errors within the short calibration period.
Figure 11. Residual errors after interior calibration.

Figure 12. Comparison of the conjugate positioning errors: (a) 2012-4-17-Tianjin, (b) 2012-5-8-Tianjin, (c) 2012-10-18-Henan, and (d) 2012-11-16-Henan;
A total of 30,420, 66,493, 117,860, and 21,174 conjugate points were obtained by the matching method (Yonghua et al., 2014) for 2012-4-17-Tianjin, 2012-5-8-Tianjin, 2012-10-18-Henan, and 2012-11-16-Henan, respectively. These conjugate points and the calibrated interior parameters from 2012-3-27-Henan were applied to eliminate the time-synchronization errors in the other images. Because only variational attitude errors invalidate Equation 13, we calculated the conjugate positioning errors based on Equation 17 to estimate the elimination accuracy of the time-synchronization errors. The conjugate positioning errors before and after eliminating time-synchronization errors are compared in Table 4.

From Table 4, we can see that the conjugate positioning errors after eliminating the time-synchronization errors are less
Figure 15. Positioning accuracy with four GCPs: (a) 2012-4-17-Tianjin, (b) 2012-5-8-Tianjin, (c) 2012-10-18-Henan, and (d) 2012-11-16-Henan.
than 0.3 pixels both along and across the track, which proves the time-synchronization errors were well compensated by the attitude offset matrices. On the other hand, the appearance of the time-synchronization errors shown in Figure 12 accords with the characteristic mentioned above, that random variation occurs in the steady state during very short periods. This is so complex and random that we cannot establish a rigorous model for it.

**Evaluation Based on the Mosaic Image Products**

The mosaic image products of all images were generated after eliminating distortions. A comparison of the mosaic effect before and after these distortions were removed is shown in Figure 13.

The mosaic effect of the mosaic images mainly depends on the accuracy of the geometric model. In Figure 13, only very poor mosaic effects were achieved using the original geometric model that suffers from time-synchronization errors. However, seamless mosaic effects were achieved with the accurate geometric model after eliminating all distortions. Further, 35, 33, 30, and 28 GCPs were manually extracted from the 1:2000 scale DOMs and DEMs over Henan and Tianjin to validate the positioning accuracy with a few GCPs (shown in Figure 14). The accuracy of the image coordinates of all GCPs is better than 1.5 pixels. The affine model based on RPC was taken as the exterior orientation model (Fraser and Hanley, 2003; Hanley et al., 2002):

\[
x + a_x + a_x x + a_y y = RPC \text{ (lat, lon, h)}
\]

\[
y + b_x + b_x x + b_y y = RPC \text{ (lat, lon, h)}
\]

From Table 5, we can see that the positioning accuracy using a few GCPs improves considerably after the elimination of distortions. The accuracy with four GCPs is better than 1.5 pixels, and is equivalent to the accuracy of the GCPs. Because the DOMs and DEMs over Henan and Tianjin were taken in 2010 and 2007, respectively, the obvious variation in ground features reduces the accuracy of the manually extracted GCPs. With more accurate GCPs, the numbers in Table 5 would approach the accuracy levels in Table 3. However, because of the limited number of GCPs and their distribution, the accuracies given in Table 5 do not reflect the actual distortions in the mosaic image products, and hence Table 5 differs from Table 4.

The residual errors with four GCPs are shown in Figure 15, where the left panels denote the accuracies before elimination and the right panels are the accuracies after elimination. It can be seen that no systematic errors exist after exterior orientation with four GCPs in the right panels, which proves that the internal accuracy of the panchromatic sensor onboard YG-12 was improved significantly by the proposed method.

**Conclusions**

This paper has presented a method for the correction of large distortions in the panchromatic images of YG-12 caused by time-synchronization errors and interior distortions. The influence of time synchronization errors on positioning was analyzed in detail, and their effects were removed by shortening the calibration period, allowing interior parameters to be precisely calibrated. In addition, we proposed an innovative technique to eliminate time-synchronization errors using parallel observations from the panchromatic sensor onboard YG-12. The experimental results indicate that the interior parameters of the panchromatic sensor can be determined with an accuracy of better than 0.32 pixels, and seamless mosaic images were obtained after eliminating the time-synchronization errors. Furthermore, the positioning accuracy with a few GCPs was shown to be better than 1.5 pixels, and equivalent to the accuracy of the GCPs. However, further study is required to determine whether the proposed method can be applied in practice to ensure the geometric quality of YG-12 panchromatic images, which depends on a tradeoff between the computational cost and the number of matching points acquired.

**Acknowledgments**

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**References**


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**Table 4. Comparison of Conjugate Positioning Errors**

<table>
<thead>
<tr>
<th>Area</th>
<th>Before solving attitude error</th>
<th>After solving attitude error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unit: pixels</td>
<td>Unit: pixels</td>
</tr>
<tr>
<td></td>
<td>RMS(x)</td>
<td>RMS(y)</td>
</tr>
<tr>
<td>2012-4-17-Tianjin</td>
<td>11.33</td>
<td>5.67</td>
</tr>
<tr>
<td>2012-5-8-Tianjin</td>
<td>7.31</td>
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</tr>
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<td>2012-10-18- Henan</td>
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<td>3.46</td>
</tr>
<tr>
<td>2012-11-16- Henan</td>
<td>2.34</td>
<td>4.67</td>
</tr>
</tbody>
</table>

**Table 5. Positioning Accuracy Using Different Numbers of GCPs**

<table>
<thead>
<tr>
<th>Area</th>
<th>Number of GCPs</th>
<th>Accuracy (RMSE: pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level-l image</td>
<td>Line</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Original</td>
</tr>
<tr>
<td>2012-4-17- Tianjin</td>
<td>4</td>
<td>4.11</td>
</tr>
<tr>
<td>2012-5-8- Tianjin</td>
<td>4</td>
<td>3.61</td>
</tr>
<tr>
<td>2012-10-18- Henan</td>
<td>4</td>
<td>2.47</td>
</tr>
<tr>
<td>2012-11-16- Henan</td>
<td>4</td>
<td>5.39</td>
</tr>
</tbody>
</table>

* Original: before eliminating distortions, Corrected: after eliminating distortions.


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Optimal Land Cover Mapping and Change Analysis in Northeastern Oregon Using Landsat Imagery

Michael Campbell, Russell G. Congalton, Joel Hartter, and Mark Ducey

Abstract
The necessity for the development of repeatable, efficient, and accurate monitoring of land cover change is paramount to successful management of our planet’s natural resources. This study evaluated a number of remote sensing methods for classifying land cover and land cover change throughout a two-county area in northeastern Oregon (1986 to 2011). In the past three decades, this region has seen significant changes in forest management that have affected land use and land cover. This study employed an accuracy assessment-based empirical approach to test the optimality of a number of advanced digital image processing techniques that have recently emerged in the field of remote sensing. The accuracies are assessed using traditional error matrices, calculated using reference data obtained in the field. We found that, for single-time land cover classification, Bayes pixel-based classification using samples created with scale and shape segmentation parameters of 8 and 0.3, respectively, resulted in the highest overall accuracy. For land cover change detection, using Landsat-5 TM band 7 with a change threshold of 1.75 standard deviations resulted in the highest accuracy for forest harvesting and regeneration mapping.

Introduction
Remote sensing technologies are unparalleled in their ability to monitor and analyze Earth’s natural resources rapidly, cost-effectively, and with ever-increasing levels of precision and accuracy (Jensen, 2005). Although a number of high spatial resolution imagery platforms have emerged in recent years (e.g., Ikonos, QuickBird), the Landsat program has greatly benefited the remote sensing community by providing consistently high quality, medium spatial resolution imagery since 1972 (Green, 2006). Landsat-5 Thematic Mapper (TM) has proven particularly valuable, having contributed almost 30 years worth of essentially uninterrupted data (well beyond its expected life span of three years) at a bi-monthly temporal resolution (Chander and Markham, 2003). With Landsat data now freely available, the potential for remote sensing studies of all kinds has exploded as indicated by a 60-fold increase in data downloads since January, 2009 (NASA).

Central to the study of natural resource management is the ability to monitor changes in the landscape over time. The remote sensing community is constantly seeking newer and better ways to accomplish this very goal. Programs like the National Land Cover Database (NLCD) are extremely valuable in providing a baseline of data which can be utilized in studies spanning an array of disciplines (Homer et al., 2004). Additionally, the NLCD provides a generalized framework by which similar land cover assessments can be accomplished, including a tried-and-true methodology for land cover change analysis (Xian et al., 2009). Similarly, the National Oceanic and Atmospheric Administration’s (NOAA) Coastal Change Analysis Program (C-CAP) has informed this study and others by suggesting a number of standardized techniques by which land cover change can be monitored (Dobson et al., 1995).

Traditionally, land cover mapping and analysis was performed on a pixel basis, i.e., a purely spectral approach wherein reflectance values for each pixel (and derivative information) of an image are the sole basis for classifying the imagery into a map. Within the last decade, object-based image analysis (OBIA, also called GEOBIA) has gained momentum in the remote sensing community (Blaschke, 2010). OBIA is based on segmenting images (i.e., grouping of pixels) into meaningful areas of spatial and spectral homogeneity called “objects” (Jensen, 2005). There is a great degree of user flexibility in generating these objects, guided by the manipulation of three parameters: scale, shape, and compactness to produce meaningful areas of spatial and spectral homogeneity called “objects” (Jensen, 2005). While the results tend to be case-specific, there appears to be general agreement that images can be over-segmented (objects are too small) and under-segmented (objects are too large) (Kim et al., 2008; Holt et al., 2009; Liu and Xia, 2010; MacLean and Congalton, 2011).

While the majority of OBIA studies tend to focus on feature extraction from high-resolution image data (e.g., Moran, 2010; Alganci et al., 2013), a few have explored its applications on medium-resolution data sources such as Landsat (e.g., Geneletti and Gorte, 2003; Gamanya, 2009). An increasing number of studies are inquiring into the feasibility of using OBIA techniques to analyze land cover change (e.g., Lam et al., 2008; Chen et al., 2012), but we have found few studies that link object-based land cover change and Landsat-5 TM data; Robertson and King (2011) is a notable exception.

While the remote sensing community has consistently pushed the limits of technical and computational capacity, seeking to develop new and improved methodologies, there is a critical need for the implementation of broad-scale monitoring operations that employ relatively simple, repeatable, and comprehensible processes. The focus of this study is precisely that: to establish an analytical and processing workflow for...
a land cover change assessment upon which future studies can be based. In so doing we compare a number of well-established techniques with some new methods using a two-county area in northeastern Oregon as a case study. The objectives of this study are to (a) evaluate pixel-based versus object-based image analysis for a generalized land cover change assessment of medium resolution data (i.e., Landsat Thematic Mapper) at the landscape level, (b) explore a variety of change analysis techniques including a modified principal component analysis to provide the best change maps of the area, and (c) use the optimal/best change analysis method to conduct an assessment of forest harvesting and regeneration from 1986 to 2011.

**Study Area**

Union and Baker Counties in northeastern Oregon, USA are large counties (13,267 km²) with a combined population of 41,882, as of the 2010 Census (Figure 1). The region is characterized by a highly varied topography ranging from very mountainous terrain to expansive valley bottoms. Elevations range from 512 m at the lowest point to 2,915 m in the Wallowa Mountains. This region is relatively dry, receiving less than 50 cm average annual precipitation on the valley floors. Large water bodies are relatively few and far between, with only a few notably-sized lakes and rivers being present throughout the two-county area. As a result, forested environments are found only in the higher elevations, where temperatures remain consistently cool enough and the evapotranspirative balance enables tree growth. Despite this relative aridity, cropland is plentiful on the valley bottoms (hay, alfalfa), benefitting from heavy irrigation and fertile Mount Mazama ash soils. In between these two extremes, there is a dominance of two land cover types: grassland and shrub/scrub. The former tends to fill the elevation transition zone between cropland and forest and is often found in drier patches and south-facing slopes within the forested areas. The latter dominates the middle elevations of the southern portion of the study area, forming vast expanses of rolling hills dominated by sagebrush with little to no undergrowth. Almost 40 percent (5,111 km²) of the land in Union and Baker counties is public land, managed by the USDA Forest Service, 522 km² of which falls within the Eagle Cap Wilderness area. For the purposes of this study, elevations above 2,000 m and designated wilderness areas were removed from consideration because they are excluded from active forest management and wildfire suppression. It is believed that land cover changes that occur in these areas are simply the result of differential presence/absence of snow and/or other natural disturbance events (e.g., fire). Of interest to this study are only the anthropogenic effects on regional land cover.

**Methods**

**Reference Data**

Ground-based land cover reference data were collected between the months of June and August in 2011. Global Positioning System (GPS) data were captured using a Trimble YUMA unit and Esri ArcPad 10 software. Sample units were selected based on a few criteria: (a) the sample unit must be ≥90 m x 90 m in size (3 x 3 Landsat pixels) (as per the recommendation of Congalton and Green (2009)) (most units were significantly larger and then the collection was done at or near the center), (b) the entire area must be visually (and spectrally) homogeneous within the unit, (c) the areas must be heterogeneous between units (capturing maximum variability), and (d) the sampling units must be spatially distributed throughout the entire study area.

**Image Data**

Two Landsat-5 TM scenes were needed to encompass the vast majority of Union and Baker counties: Path 43, Row 28 (approximate scene center: 46°1’50.9”N, 117°46’19.2”W) and Path 43, Row 29 (44°36’43.9”N, 118°17’9.6”W). A temporal series of late spring to early fall images (May through October) with <5 percent cloud cover were obtained at a five-year interval.
between the years of 1986 and 2011. In order to capture the seasonality of the highly moisture- and temperature-
dependent land cover classes in this region, two images were
used for each year of interest. An “early summer,” or growing
season image and a “late summer,” or senescence image were
used in the classification process (Table 2). As the late sum-
mer images ultimately played a more significant role in the
classification process, every effort was made to utilize near-
anniversary images at or around the end of August into early
September. The exception to this rule was the year of 1986,
during which the cloud-free, senescence image availability
was limited to October. The time frames of the early summer
images were more variable, given the typically higher cloud
cover present during the growing season.

Table 2. Landsat-5 TM Image Dates

<table>
<thead>
<tr>
<th>Year</th>
<th>Early Summer</th>
<th>Late Summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>07/09</td>
<td>08/26</td>
</tr>
<tr>
<td>2006</td>
<td>06/25</td>
<td>08/28</td>
</tr>
<tr>
<td>2001</td>
<td>05/10</td>
<td>08/30</td>
</tr>
<tr>
<td>1996</td>
<td>06/13</td>
<td>09/01</td>
</tr>
<tr>
<td>1991</td>
<td>07/02</td>
<td>09/04</td>
</tr>
<tr>
<td>1986</td>
<td>07/20</td>
<td>10/08</td>
</tr>
</tbody>
</table>

Image Preprocessing

For each image date, six of the seven spectral bands (Bands
1 to 5 and 7) were stacked together and adjacent path-rows
were mosaicked together. In order to enhance image compara-
bility between dates and reduce the effects of differential
topographic illumination, topographic normalization was
performed on these mosaicked images. The C-Correction
algorithm (Meyer et al., 1993) was selected as the normaliza-
tion algorithm of choice, given its demonstrated effectiveness
(Riaño et al., 2003). The first step in the C-Correction process
is to determine the magnitude of illumination across the en-
tire study area, as defined by:

\[
\text{Illumination} = \cos \gamma_i = \cos \theta_i \cos \alpha_i + \sin \theta_i \sin \alpha_i \cos (\delta_i - \delta_s) \tag{1}
\]

where \( \gamma_i \) is the solar incidence angle relative to the sloped
ground surface, \( \theta_i \) is the solar zenith angle, \( \alpha_i \) is the slope of
the ground surface, \( \delta_i \) is the solar azimuth angle, and \( \delta_s \) is
the aspect of the ground slope. In order to create an illumination
surface, slope and aspect layers were derived from a USGS
30-m Digital Elevation Model (DEM). The solar zenith angle
and azimuths for each image date were obtained from their
respective Landsat header files. In order to assess the effect of
illumination on the Landsat DN values, a random sample of
10,000 points was used to extract the spectral and illumination
values at each point. A linear regression was run to deter-
mine the relative effect of illumination on the “brightness” of
the pixel in each spectral band. The purpose of C-Correction
(and other non-Lambertian normalization techniques) is to
normalize the data such that the presumed positive relation-
ship between illumination and DN value would be reduced to
a null effect (Meyer et al., 1993). In order to do so, the C-
Correction algorithm was used:

\[
\text{DN}_{i,h} = \text{DN}_{i,a} \left( \frac{\cos \theta_i + c_i}{\cos \gamma_i + c_i} \right) \tag{2}
\]

where \( \text{DN}_{i,a} \) is the DN value of a pixel (\( i \)) in a given spe-
\text{c}tral band (\( i \)) on a horizontal surface (\( h \)) (with no influence
of solar illumination), \( \text{DN}_{i} \) is the value of that pixel on a
sloped surface (subject to illumination influence), and \( c_i \) is a
band-specific parameter defined by slope (\( m_i \)) and \( y \)-intercept
(\( b_i \)) of the linear regression line between illumination and DN
values, such that:

\[
c_i = \frac{b_i}{m_i} \tag{3}
\]

To further enhance image comparability and eliminate the ef-
facts of atmospheric interference on image data, atmospheric
correction was performed on all images. The COST corrected
surface was calculated as follows (Chavez, 1988):

\[
\rho = \left[ e^{\delta} \left( I_{\text{max}} - I_{\text{min}} \right) \frac{I_{\text{max}} - I_{\text{min}}}{\text{DN}_{\text{max}} - \text{DN}_{\text{min}}} \right] \frac{0.01 + \cos \theta}{e^{\cos \theta}} \tag{4}
\]

where \( d \) is the sun-earth distance, \( L_{\text{min}} \) and \( L_{\text{max}} \) are spectral
radiance calibration factors, \( \text{DN} \) is the DN value at a given pixel
\( i \), \( \text{DN}_{\text{max}} \) is the maximum possible DN value (255 for 8-bit data),
\( \text{DN}_{\text{min}} \) is the hand-specific minimum DN value found through
an exploration of the layer histogram (smallest value with \( \geq
1000 \) pixels), and \( E_{\text{sun}} \) is the solar spectral irradiance, \( L_{\text{min}}, L_{\text{max}} \),
\( E_{\text{sun}} \), and \( d \) can all be found in Chandler & Markham (2003).

In order to improve the accuracy of resultant classifications,
a number of commonly used derivative image layers were
generated from the topographically and atmosphere-
corrected images, including the Normalized Difference
Vegetation Index (NDVI) and the Tasseled Cap transformation
features (Brightness, Greenness, and Wetness).

The ten resulting bands (six raw, four derivatives) were then
stacked together into a single image. For each year of interest,
the early and late summer ten-band images were then stacked
together to form a 20-band image. Finally, given the important
link between land cover and topography in this region, slope,
aspect, and elevation layers were stacked with the 20-band
image to create a 23-band spectral and topographic image.

Image Segmentation and Classification

All subsequent image processing and classification took place
using Trimble eCognition® Developer 8.7. An analysis was
performed to determine the optimal segmentation param-
eters needed to attain the highest land cover classification
accuracy. Of interest in the segmentation process were two
parameters: (a) scale, and (b) shape. Using the multi-
resolution segmentation algorithm, a series of image segmenta-
tions were performed on the 2011 23-band image. Assigning equal
weights to all 23 spectral, derivative, and topographic bands,
the image was segmented at every combination of the follow-
ing parameter settings:

- Scale 2-20, intervals of 2
- Shape 0.0-0.5, intervals of 0.1

There were a number of considerations that went into the
determination of these test ranges. In terms of scale, a visual
exploration of images segmented at a variety of scales facil-
itated the determination of 20 as a suitable high-end extreme.
Beyond a scale of 20, the segments became exceedingly large
and quickly began to lose their within-segment land cover ho-

d\( \text{mogeneity} \) (i.e., at a scale of 30, a single polygon could contain
Forest, Shrub/Scrub and Grassland). In terms of shape/color, it
was believed that spatial qualities of a segment (shape) should
never have a stronger influence on determining the size and
shape of the segments than the 23 “spectral” bands (color).
Accordingly, the high end of shape influence was determined to
be 0.5 or 50 percent of the segmentation weight.

Each of the resulting segmentations was examined closely
for the input parameters’ effects on segment size, and other
spatial and spectral characteristics. Of interest to this study
was not only the general effect of scale parameter on seg-
ment size, but also the relative variation in segment size that
resulted at each scale level. Accordingly, an analysis was performed to explore the relationship between segment size relative standard deviations (RSD) and the scale parameter. Because the segment sizes at large scale parameters will have significantly larger standard deviations, the normalized or relative standard deviation was deemed an appropriate representation of within scale segment size variation. RSD was calculated as such:

\[ RSD = \frac{s_{ij}}{\mu_{ij}} \]  

where \( s_{ij} \) is the sample standard deviation of segment size (in pixels) at a given scale parameter \( i \) and shape parameter \( j \), and \( \mu_{ij} \) is the mean size at those same parameters. The mean RSDs by scale parameter were then calculated.

Each of the image segmentations then underwent a separate land cover classification. Land cover classifications were performed in both a pixel- and object-based environment, using a non-parametric classification algorithm (Classification and Regression Tree (CART)) and a parametric classification algorithm (Bayes - Maximum Likelihood). These two approaches were selected because both are commonly used in land cover mapping. The Bayes-Maximum Likelihood classification technique is by far the most used traditional pixel-based method, while CART has gained wide use in the last five years. Taking into account all of the segmentation and classification permutations, 240 classifications of the 2011 imagery were performed (10 scale × 6 shape × 2 environments × 2 algorithms = 240 classifications in total). An important distinction between what was being tested in the pixel- and object-based environments must be made here. For both pixel- and object-based classifications, image segments were intersected with training data sample unit centroids (as created through field reconnaissance and photo interpretation) to determine the segment training units. This approach is not unlike using a region-growing algorithm or visually defining a training area boundary to maintain homogeneity in the training data selection. In both cases, the classification algorithm was trained with the resultant image segment sample data. In the object-based environment, this trained model was then applied to the remaining, unclassified image segments. In the pixel-based environment, however, the trained model was then applied to the remaining, unclassified pixels on the image, effectively ignoring the boundaries of the remaining segments. So, in essence, the impact of the segment characteristics has a twofold impact on the resultant classification accuracy (training samples and segment classification) in the object-based environment. In the pixel environment, however, the impact is singular, merely affecting the nature of the training data. Additionally, in the object-based environment, a host of segment features can be used to both train the model and classify the imagery, whereas pixels rely purely on the training data’s per-band mean values and variances. The input features for object-based analysis were computed in eCognition as follows:

- Mean layer value of each of 23 bands by object
- Standard deviation for each band by object
- Skewness
- Brightness
- Maximum pixel value
- Minimum pixel value
- Mean of object inner border
- Mean of object outer border
- Contrast to neighboring pixels
- Mean difference to neighboring objects
- Hue, saturation, intensity transformations (early & late image dates, original image bands only)
- Gray Level Co-occurrence Matrix (GLCM) homogeneity
- Area
- Border length
- Compactness
- Roundness
- Rectangular fit
- Shape index

**Accuracy Assessment**

Error matrices (Congalton et al., 1983) were constructed to determine which combination of segmentation parameters, analytical environment and classification algorithm attained the highest accuracies. Overall accuracies, class-specific user’s and producer’s accuracies, and Kappa were all calculated for each of the 240 classifications (Congalton and Green, 2009). An area-based error matrix (MacLean and Congalton, 2012) was used for the 120 object-based classifications. For each combination of CART versus Bayes and object versus pixel, a mean overall accuracy was computed across each scale and shape parameter. The combination of segmentation parameters, classification type, and classification algorithm that produced the highest overall accuracy for the 2011 land cover classification was selected for use in all subsequent classifications (2006, 2001, 1996, 1991, and 1986) following the change detection process described below. Lastly, each land cover map was filtered to a minimum mapping unit of 4,500 m² to remove mostly spurious single pixels remaining in the map.

**Change Detection**

In order to assess changes in the land cover, an image difference was performed. For each five-year interval of interest a ten-band differenced image was created based on a simple pixel-by-pixel subtraction between sequential image dates (i.e., image differencing). Following a methodology introduced by Gong (1993), a principal components analysis (PCA) was performed on the ten-band difference image to create a single principal component (PC1) that would account for most of the variability (change) found in all ten bands. All ten change bands and PC1 were then used individually as the bases for change-based image segmentations to create 11 separate sets of “potential change segments” for comparison. Using two standard deviations from the mean as the base threshold for delineating change areas within each land cover class, segments were classified into change and non-change areas.

The 11 different change area delineations were the evaluated for correctness. Using a 15,000 ha heavily-logged area in northern Union County as a reference area, change polygons were manually digitized for the 2006 to 2011 interval at a scale of approximately 1:15,000. This scale was selected because it provided sufficient detail for the change analysis. These reference polygons were then compared to each of the 11 change classifications and an area-based 2 × 2 change-no change error matrix was produced (Congalton and Green, 2009). With these error matrices, overall accuracies, user’s accuracies (errors of omission) and producer’s accuracies (errors of commission) were computed to determine which change image produced the best representation of “actual” change. Of interest to this study were change detection algorithms with high overall accuracies, and similar user s and producer s accuracies (in the interest of avoiding vast over- or under-estimation of change). The highest accuracy/best change detection band was then selected for further analysis.

Given the relatively high overall omission errors using the two-standard deviation threshold across all bands, an analysis of optimal threshold selection was performed using the most accurate single-band change detection method. Assuming that higher thresholds would only result in greater omission errors, four smaller standard deviation-based thresholds were tested for change detection accuracy: 1 SD, 1.25 SD, 1.5 SD and 1.75 SD. Using the same change detection accuracy methods described above, the highest accuracy threshold was chosen for use in the change detection and subsequent classification process.

**Change Classification**

With the optimal/best change detection methodology in place, a full change classification was performed using the C-CAP change classification protocol (Dobson et al., 1995). According to this methodology, each image was classified separately backwards in time using training data from non-change
areas. For example, the 2011 classification was created using all of the original training data. However, given the land cover changes that occurred between 2006 and 2011, some of the training data collected in 2011 may no longer be valid because of new forest harvesting or younger trees growing into forests. As such, in order to classify the 2006 image, those data that fell within the change areas were removed and replaced via image interpretation. The new training dataset was then used to classify only those areas where change has occurred. This change area classification was then merged back with the non-change-area 2011 classification to form a wall-to-wall 2006 land cover classification. This process was repeated for each interval of interest.

Additionally, the same change detection accuracy assessments were performed on each interval, comparing the automatically-detected change areas to manually digitized areas of similarly high logging activity. Last, all of the land cover classifications were compared by five-year interval to determine the changes that have occurred in the landscape. Change matrices were created to assess the types of change occurring and their magnitudes. These changes were also assessed according to the land ownership type in which they fell, including public lands, private industrial lands, and private non-industrial lands. As the changes in the forested environment are of key importance to this study, the 6 × 6 land cover change matrices were reduced to simple 2 × 2 forest-non forest matrices to assess forest harvesting and regeneration trends, both across the entire landscape and across different ownership classes.

Results and Discussion

The scale segmentation parameter has a substantial and direct effect on resultant image segment size. In order to obtain a quantitative estimate of this impact, an analysis was performed using the accuracy assessment sample data. For each segmentation performed at incremental levels of the scale parameter, the accuracy assessment sample data were used to obtain a mean value of segment size (in pixels). Figure 2 shows segment size displayed by scale parameter, with each point representing a different shape parameter input. A power function trend line was fitted to the model and a R² value was computed. There is a positive relationship between scale parameter and segment size at least up to a scale parameter of 20 for Landsat TM imagery. Beyond a certain scale parameter value, we anticipate that the distribution of resultant segment sizes will reach an asymptote. Where this leveling off occurs, however, will depend on image spatial extent and resolution, and no evidence of an asymptote is apparent over the range of the scale parameter used here.

A test was performed to explore the relationship between the scale parameter and segment size variability, as measured by the segment size RSD. The results of this test can be seen in Figure 3, where two notable trends emerge. The first is a peak RSD at the lowest scale parameter of 2 (RSD = 1.03). This suggests that at a scale of 2, high variability in segment size can be expected. This trend declines to a trough at scale of 8, where segment size was the most consistent. Following this low RSD, a slow steady rise in variability emerges as the segment size increases up to the scale parameter maximum of 20.

The manipulation of the shape parameter did not result in a predictable distribution of segment sizes. Instead, the tradeoff between shape and color parameters primarily affected the segments’ spatial and spectral characteristics, as would be expected. For every combination of scale and shape parameter segmentations, a classification was performed using all four combinations of CART versus Bayes and pixel-based versus object-based classification. Henceforth, CART object-based = CO, CART pixel-based = CP, Bayes object-based = BO, and Bayes pixel-based = BP. As a result, 240 classifications in all were performed and their thematic accuracies were assessed using the traditional error matrix (Congalton et al., 1983). The overall accuracies for CO, CP, BO and BP were averaged for each different scale parameter segmentation. The resulting mean accuracies can be seen in Figure 4. In every case, BP produced the highest classification accuracies, with a peak at a scale parameter of 8 and a mean overall accuracy of 90.68 percent. Interestingly, CP, also pixel-based, although consistently less accurate than BP, shares a similar trend, albeit less smooth, with a peak occurring at or around a scale of 8 and a trough at 18. The two object-based classifications, CO and BO similarly share a generalized trend in accuracy across the range of scale parameters. In both cases, there appears to be a fairly distinct positive relationship between the scale parameter and overall classification accuracy. The relationship is certainly stronger in BO than in...
CO, but in BO there is a sharp decrease in accuracy at the very last scale parameter tested, 20. While BP greatly outperformed CP, CO almost exclusively outperformed BO, if only slightly.

Similarly, the overall accuracies for CO, CP, BO, and BP were averaged for each of the different shape parameter segmentations. The resulting mean accuracies can be seen in Figure 5. It is important to note that Figures 4 and 5 should be considered together, rather than in isolation of one another, particularly when comparing between classification method accuracies, because these results tend to be similar across the entire ranges of scale and shape parameters, with the order of descending accuracy being roughly equivalent to BP (best), CP, CO, and BO (worst). That being said, these graphs do function as good indicators of within classification method accuracies. The trend lines of scale versus accuracy themselves are believed to be the most revealing. Accordingly, some important trends emerge in Figure 5 as well. The most accurate method, BP, appears to function almost entirely independent of shape, with functionally equal accuracies across the board. However, the marginally highest mean accuracy was produced at a shape parameter of 0.3 (accuracy of 89.96 percent). Conversely, CP, CO, and BO all appear to have an accuracy peak in the 0.1 to 0.3 ranges and a trough in the 0.4 to 0.5 range, with a slight uptick in accuracy at shape 0.5.

Taking all of these accuracies into consideration, a selection of segmentation parameters (scale and shape), image analysis environment (pixel versus object) and classification algorithm (CART versus Bayes) was made. The optimal combination was found to be Bayes pixel-based classification with training samples segmented at a scale of 8 and a shape of 0.3 (overall accuracy of 91.48 percent, and Kappa = 0.897). The error matrix with class-specific user's and producer's accuracies can be seen in Table 3. The final 2011 land cover classification can be seen in Plate 1.
### Table 3. Error Matrix for Highest Accuracy Land Cover Classification (Sample Unit Tallies)

<table>
<thead>
<tr>
<th></th>
<th>Reference Data</th>
<th>Map Data</th>
<th>Sum Units</th>
<th>User Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cropland</strong></td>
<td></td>
<td></td>
<td>45</td>
<td>95.56%</td>
</tr>
<tr>
<td>Developed</td>
<td></td>
<td></td>
<td>43</td>
<td>86.05%</td>
</tr>
<tr>
<td>Forest</td>
<td></td>
<td></td>
<td>50</td>
<td>98.00%</td>
</tr>
<tr>
<td>Grassland</td>
<td></td>
<td></td>
<td>45</td>
<td>88.89%</td>
</tr>
<tr>
<td>Shrub/Scrub</td>
<td></td>
<td></td>
<td>57</td>
<td>84.21%</td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td></td>
<td>30</td>
<td>100.00%</td>
</tr>
<tr>
<td><strong>Sum Units</strong></td>
<td>50</td>
<td>40</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td><strong>Producer Accuracy</strong></td>
<td>86.00%</td>
<td>92.50%</td>
<td>96.00%</td>
<td>90.00%</td>
</tr>
</tbody>
</table>

Plate 1. 2011 land cover classification of the study area.
To determine the optimal change detection technique, the first change interval of interest, 2006 to 2011 was used for analysis. Ten separate difference images and one principal components image were tested to see which produced the best change detection accuracy. The PCA was performed on the ten-band difference image to capture as much change across all of the input bands as possible into a single band (approximately 70 percent of the change variance is captured in PC1). Using the most accurate 2011 land cover classification, a within-class segmentation was performed for each of the 11 change bands of interest (ten difference bands and PC1). From the resultant segments, a distribution of class-specific change values emerged. For each band and class, the change distributions resembled a normal distribution and the class-specific differences visualized in the spread of change magnitudes. In order to determine change thresholds, the class-specific change means and standard deviations were calculated for each band.

Using two standard deviations from the mean as a base threshold for change, each band was then tested for its ability to accurately detect change. These class-specific band threshold values were applied to the binary classification of change versus non-change for the 2006 to 2011 interval. As a result, 11 different classifications were performed and assessed for accuracy using an error matrix approach. Band 7 (middle infrared) was determined to be the optimal band for use in the change analysis given the preferential emphasis placed on minimizing errors of omission and highest overall performance. Given that change omission and commission errors can be seen as a direct product of the change threshold used (i.e., a higher standard deviation-based change threshold will likely produce greater omission error and a lower threshold will produce increased errors of commission), band 7 was then further evaluated for a range of standard deviation change thresholds (1 SD to 2 SD, intervals of 0.25 SD). The results show that the best change analysis occurred at 1.75 SD, and this threshold was selected for all further use (Table 4).

<table>
<thead>
<tr>
<th>Map</th>
<th>Change</th>
<th>No Change</th>
<th>Sum Area</th>
<th>User</th>
<th>Producer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 7 Threshold 1.75 SD (Area in Hectares)</td>
<td>1,356.38</td>
<td>415.69</td>
<td>1,772.07</td>
<td>76.54%</td>
<td>77.68%</td>
</tr>
<tr>
<td>Band 7 Threshold 1.75 SD (Area in Hectares)</td>
<td>389.74</td>
<td>14,726.92</td>
<td>15,116.67</td>
<td>97.42%</td>
<td>97.25%</td>
</tr>
<tr>
<td>Sum Area</td>
<td>1,746.13</td>
<td>15,142.62</td>
<td>16,888.74</td>
<td>95.23%</td>
<td></td>
</tr>
</tbody>
</table>

Band 7 was used to classify change and non-change areas for each five-year interval of interest iteratively backwards in time starting with 2006 to 2011 and ending with 1986 to 1991. Based on this change analysis, land cover classifications were performed only on the detected change areas for each year. These change area classifications were then merged with the corresponding year’s classification to attain wall-to-wall classification. The resulting classifications were intersected to assess class-specific land cover classification changes. Areas were calculated in hectares to determine change magnitude. These change maps were then simplified to forest and non-forest changes in order to further study forest harvesting and regrowth patterns. Four combinations resulted: forest to forest (non-change), forest to non-forest (change), non-forest to non-forest (no change), and non-forest to forest (change). Forest to non-forest changes were assumed to be the result of harvesting and non-forest to forest changes were assumed to represent forest regeneration. These totals were then intersected with land ownership data to determine owner-specific changes. The forest to non-forest totals and ownership breakdown can be seen in Figure 6. A few definitive trends emerge. In terms of overall forest harvesting, the first two time intervals (1986 to 1991 and 1991 to 1996) saw very similar total hectares removed at slightly below 8,500 ha each. Following these early highs, a precipitous drop occurred between 1996 and 2001, when only 2,126 ha were removed in total. The final two intervals saw consistently increasing totals with 5,477 ha removed between 2001 and 2006, and 9,227 ha removed in the most recent interval, reaching the highest total of any interval tested. In terms of ownership-specific patterns, some clear trends can be seen as well. A notable decrease in harvesting on public land occurred between 1986 and 2001 (1986 to 1991: 6,242 ha; 1991 to 1996: 3,434 ha; 1996 to 2001: 749 ha), followed by a less aggressive, steady increase between 2001 and 2011. Harvesting on private industrial land saw significant increases between the 1986 to 1991 interval (402 ha removed) and the 2006 to 2011 interval (3,975 ha removed). Private non-industrial land typically saw relatively low harvesting totals, with the one exception being between 1991 and 1996 where 3,603 ha were removed.

These results however, should be viewed with the understanding of differential total forest land ownership. For example, in 2011, there were 418,144 ha of forested land throughout the entire study area, 312,284 ha (74.68 percent) is owned by public entities (most of which is USFS), followed by private, non-industrial land owners (77,732 ha, 18.59 percent), and last, private industrial (26,127 ha, 6.73 percent). Accordingly, these removal totals were divided into total forested land ownership to compute the “normalized” or percent by ownership removal. The resulting removal percentages can be seen in Figure 7.

The forest and non-forest change classification process not only yields change areas that suggest forest removal, but additionally forest areas that are regenerated (non-forest to forest). From the forest management perspective, this variable is in many ways as valuable, if not more so, than the harvesting totals. Accordingly, forest regeneration totals were calculated across the entire study area and, again, broken down by land ownership class. The results of these analyses can be seen in Figure 8. The total forest regeneration across all ownership classes does not take on any major trend in the positive or negative direction, with the exception of a steep decline in the 1991 to 1996 interval, which makes sense, given the heavy harvesting that occurred in that year. The ownership-specific trends, however, are of interest. For instance, again with the exception of 1991 to 1996, regeneration on public land has steadily declined. Conversely, both kinds of private land have seen somewhat steady growth in forest regeneration from the 1991 to 1996 interval to 2006 to 2011.

Conclusions
This study had a wide-ranging set of objectives, in terms of both remote sensing methods and real world applications; the study utilized a largely exploratory approach to determining the optimal conditions for conducting efficient land cover classification and change detection. In incremental fashion, each procedure in the process was carefully vetted for optimal accuracy. Only when conditions were met to attain an acceptably high analytical accuracy was forward progress made. While the specific results of any remote sensing study are only immediately applicable to that study, certain broader trends can emerge upon which future analyses can be based. The incremental approach used here can function not only as a framework for future investigation, but because the methods were explored using such a wide range of input parameters, a number of the specific results can help inform future research as well.
Of particular interest in this study is the analysis of pixel-based versus object-based image classification. While OBIA has become often used for high spatial resolution imagery, few studies have documented the utility of using OBIA on medium resolution image datasets such as Landsat-5 TM. This absence is not without justification; Landsat’s 30 m pixels are, in many ways, image objects in their own right and have historically been very successful in land cover analyses of all kinds. For a land cover study conducted over a relatively small area with a fairly detailed classification scheme, a 30 m pixel may sufficiently reduce the spectral noise contained within an image to produce accurate, functional ground units, despite their indiscriminant spatial placement. At the regional or landscape scale with more generalized classes...
such as this study, however, perhaps the noise reduction caused by grouping of pixels over large areas (OBIA) would produce a more desirable result. This study was not intended to determine outright whether pixel-based analysis or object-based analysis is preferable. The results depended heavily on the classification algorithm used. Across the entire range of scale and shape parameters, Bayes pixel-based classification significantly outperformed Bayes object-based classification and had the highest overall accuracy. However, the relationship between CART pixel-based and object-based classifications was much more heavily influenced by the segmentation parameters used.

Finally, detailed, quantitative accuracy assessment formed the basis for not only the individual date land cover maps, but also the land cover change detection analysis and the detailed forest harvesting and regeneration conducted as part of this study. The primary application of interest in this study involved detecting and classifying changes in the forested environments of a two-county area in northwestern Oregon. The results highlight predominant trends in overall and ownership-specific changes in total forested area throughout this region over a 25-year time span at five-year intervals. Three main trends in forest harvesting practices emerge. In terms of overall change, we see that the greatest amount of forest removal occurred in the most recent interval, 2006 to 2011; in total, 9,227 ha of forest were removed. This total decreases to 1996 to 2001 where an estimated 2,127 ha of forest was removed. This total then climbs back up to a plateau for the intervals of 1986 to 1991 and 1991 to 1996 where 8,311 ha and 8,394 ha were removed, respectively. In addition to the overall forest harvesting trends, two ownership-specific trends emerge: (a) an increase in private industrial harvesting, and (b) an initial decrease in public land harvesting followed by a slower increase from 1986 to 2011. These trends are likely the result of a variety of factors. Speculation into the social, economic, and political mechanisms at work that have resulted in this shift from predominantly public land harvesting to primarily private industrial warrants an entire study in and of itself. However, one important geospatial factor that is immediately relevant is that all timberlands are not equally harvestable. The ability to harvest timber from a given location in a forest depends primarily on three factors: (a) accessibility, (b) topography, and (c) rules and regulations. Accessibility is simply the ability for a logger to reach a given area of timber, i.e., a factor that is controlled by the specific locations and densities of the forest road network. Closely related to accessibility is the quality of the terrain, or topography, of the timberlands. Some areas are simply too steep or otherwise impeded by natural, geologic features to harvest timber. And last, there are a variety of legislative and regulatory road blocks to a variety of logging operations, particularly relating to the preservation of wilderness and protection of endangered species. For instance, riparian environments are often protected against logging due to their importance in the preservation of certain fish species that could be harmed by increased runoff and/or other industrial pollutants thought to be caused by logging operations. Taking all of these factors together, a scenario can readily be imagined wherein private industrial timberlands, which tend to be on lower-lying elevations with less dramatic topography, having higher road densities and fewer regulatory impediments, are simply more harvestable than, for example, public lands. Accordingly, this study reveals ownership-specific trends that are related to the degree to which forested areas are harvestable.

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Reliable Spatial Relationship Constrained Feature Point Matching of Oblique Aerial Images

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Abstract
This paper proposes a reliable feature point matching method for oblique images using various spatial relationships and geometrical information for the problems resulted by the large view point changes, the image deformations, blurring, and other factors. Three spatial constraints are incorporated to filter possible outliers, including a cyclic angular ordering constraint, a local position constraint, and a neighborhood conserving constraint. Other ancillary geometric information, which includes the initial exterior orientation parameters that are obtained from the platform parameters and a rough DEM, are used to transform the oblique images geometrically and reduce the perspective deformations. Experimental results revealed that the proposed method is superior to the standard SIFT regarding both precision and correct matches using images obtained by the SWDC-5 system.

Introduction
Beginning in 2000, oblique aerial camera systems garnered attention from the photogrammetry community due to their ability to capture the facades of buildings and their ability to be briefly interpreted (Petrie, 2009). Many penta-view camera systems that feature four 45° oblique cameras and one nadir camera, including Pictometry (Gerke and Kerle, 2011), MIDAS (Madani, 2012), and SWDC-5 that are used in this paper, have collected numerous datasets. However, traditional photogrammetry techniques and software are designed primarily for nadir images and are difficult to adapt for oblique aerial images. New challenges have been posed to photogrammetry practitioners to integrate all of the images to extract more geometrical information for the problems resulted by the wide baseline and large tilting angles (Yao and Cham, 2007; Yang et al., 2012). Additionally, in production practice, an existing solution with traditional software is to process images for each camera separately and then manually select enough inter-camera tie points to assemble different blocks of images together. However, this solution is not only time consuming, but it is also prone to inter-camera inconsistencies due to the lack of accurate tie points.

It turns out that feature matching between nadir images and oblique images is astonishingly difficult because of the obvious difference in their appearances, which consists of occlusions, perspective deformations, light conditions, and blur that are caused by the wide baseline and large tilting angles. It is obvious that the appearance information of the images is different, which consists of occlusions, perspective deformations, light conditions, and blur that are caused by the wide baseline and large tilting angles. In our previous work (Zhu et al., 2007), a filter strategy using information content is proposed to improve the repeatability of the interest points and the reliability of the matches, which is also based on the appearance information. However, when the images are essentially dissimilar in appearance, the quality of the bundle adjustment will decrease. To improve the quality of bundle adjustment, we need to consider the spatial relationships of feature points into the process to increase the reliability of the matches.

In this paper, we propose a reliable feature point matching method for oblique images using spatial relationships and geometrical information. The proposed method is superior to the standard SIFT regarding both precision and correct matches using images obtained by the SWDC-5 system.

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the spatial relationships are more important cues that are responsible for reliable feature correspondence. Furthermore, the spatial relationship constraint has been confirmed to be a powerful method for wide baseline-dense matching in our previous work.

In the next section, feature matching methods based on appearance and spatial relationships are briefly introduced. Then, we present two core innovative steps of the proposed methods followed by information for the configurations of the oblique camera system and the datasets obtained. The performance of the proposed methods is subsequently evaluated leading to concluding remarks.

Related Works

In an early investigation of image matching, three fundamental properties of the correct correspondences were set up (Ullman, 1979). Similarity: the correspondences must be similar in appearance among the matching images. Proximity: the correspondences must have tenable spatial relationships. For example, in the situation of repeated patterns, images of textureless, spatial relationships provide clues for establishing correspondences or removing outliers among identical features. Exclusion: the final feature matches should be established one-on-one and can simply be enforced by cross check, which is a two-step procedure of forward and backward matching.

In the photogrammetry and computer vision communities, feature matching methods have been prosperous; most of these methods resorted to appearance information alone to identify correspondences. To the best of our knowledge, the earliest feature matching method dates to the Moravec (1981) corner detector and normalized cross correlation (NCC). Since then, the robust pyramid matching strategy (Wang, 1990) has been the software standard, which uses intersecting points to detect corners (Moravec, 1981; Förstner and Gülch, 1987; Harris and Stephens, 1988) and NCC to match the features from coarse to fine. In applications where accuracy is important, the least square matching (LSM) strategy is also mandatory for locating the matches in a sub-pixel position (Grüen, 1985). The sophisticated paradigm that uses pyramid matching and LSM is widely adopted in both aerial and close range applications. Liang and Heipke (1996) integrate an automatic relative orientation method with a modified Moravec detector and a coarse-to-fine matching strategy into their method. Several hundreds of well distributed correspondences are found, and the results indicate that internal accuracies reached less than 0.3 pixels, even in scanned digital images. Lerma et al. (2013) compare different matching strategies for close range applications, in which artificial retro-reflect targets are not used. They confirm that NCC and LSM result in better accuracies for images with near parallel bore-sight directions.

The methods that match features with NCC can be considered to use the appearance information in a fixed square window around the corners. Consequently, NCC is essentially sensitive to scale and rotation changes (Lowe, 2004). Lindeberg (1993) proposes to detect blob-like features that are stable in the scale space, and the same author also provides a practical solution to build the scale space that is the Laplacian of Gaussian (Lindeberg, 1998), which has triggered the development of numerous invariant features. Based on the scale space theory, Lowe (2004) presents the milestone work of scale invariant feature transform (SIFT), which detects features in the scale space using the difference of Gaussian and describes the image blob with the histograms of gradients. Mikolajczyk and Schmid (2005) compare various features against different situations and claim that SIFT presents the best performances, except for the case of large affine deformations. Some approaches attempt to restrict the features to be affine-invariant (Matas et al., 2004; Mikolajczyk and Schmid, 2004); however, these approaches can cause either decreases in the amount of detected features or performance losses in the cases of small affine deformations (Lowe, 2004). Attempts to surpass the performance of SIFT have focused on descriptor dimensions (Ke and Sukthankar, 2004), speed (Bay et al., 2008) and affinity (Morel and Yu, 2009).

The methods described above use appearance information either in a square window or in a salient blob. The extracted feature descriptors are matched using NCC and Euclidean distances, respectively. When the appearances of the images are fundamentally dissimilar, their performances will predominantly decrease and cause a huge amount of false correspondences. Spatial relation constraints are herein adopted to guide the matching process and remove outliers. Zhang (1988) invented a feature matching method called a “bridging mode” which is still widely used in the VirtuoZo software. The bridging mode assumes that a single feature point is not capable of describing a feature; thus, three points that form an image segment are adopted: two protruding points with a minimal intensity gradient and one point with a maximal gradient. The matching window is formed by the relation in the image segment. Zhang et al. (1991) extend the bridging mode to support search in two directions to enrich the matching information and use dynamic programming to increase the global consistency. Although the matching window is adapted by the spatial relationships, the matching criterion is still determined by the NCC; therefore, the issues of the NCC still exist for this method.

Unlike the low-level feature descriptors, which have similarity measurements that can be simply defined by Euclidean distances, the high-level spatial relations are complex to quantify. Existing methods that combine blob-like feature descriptors and spatial relations are usually formulated as a graph matching problem (Caetano et al., 2009). Li et al. (2005) use a Bayesian formulation, which is modeled by a Markov random field (MRF). The likelihood term enforces the similarities of the feature appearance/descriptors, and the a priori term encodes the cyclic order constraint of the Delaunay triangulations. The model is casted to the corresponding factor graph and solved with the max-product algorithm. Torresani et al. (2006) formulate the feature matching problem as a unified energy minimization task that encodes additional information, including feature appearance, geometric compatibility, spatial coherence, and is solved using dual decomposition. The authors noticed that their method was equivalent to the graph matching problem that embodies pairwise constraints in edges and similarity measurements in the vertices of graphs. Liu et al. (2012) propose a similar method and consider the optimization problem as finding two matched graphs with minimum non-rigid transformation errors. However, these graph matching approaches, which combine appearance and structure information in a unified framework, are NP-hard because all of the combinations of the binary labels that denote true/false matches must be exhausted to find the global solution (Li et al., 2005; Caetano et al., 2009). The space complexity of the algorithm is generally $O(n^3)$ (Caetano et al., 2009; Torki and Elgammal, 2010), and the time complexity is $O(n^3)$ (Liu et al., 2012), where $n$ is the number of features; this approach is often not appropriate for aerial images. Even 100 correspondences will take almost 1,200 seconds to solve the problem (Liu et al., 2012), compared to nearly real time with the standard RANSAC approach. In our practical experience, the number of correspondences of a single stereo pair result in a magnitude of $10^4$ to $10^6$. 
Methodology

Algorithm Principle
As shown in Figure 1. We add two steps, which are detailed in the following Section, into the standard feature matching procedure. First, we use geometric transformation to relieve the perspective deformation between the oblique image and nadir images. Second, three spatial relation constraints are adopted to remove the remaining outlier by the random sample consensus (RANSAC) approach using epipolar information. Because epipolar constraint is only imposed on a line, there are still possibilities for unfiltered false correspondences when the image format is large. In this situation, additional constraints to filter off remaining outliers are necessary.

Preprocessing
Before detection and matching of the feature points, we exploit the initial EO parameters to geometrically transform the images in order to relieve the perspective deformations as shown in Figure 1. Assuming the terrain is exactly a plane, a one-to-one correspondence can be established between the nadir and the oblique images. After defining a plane $\pi \rightarrow z - h_{\text{flight}} = 0$ to roughly approximate the terrain in the coordinate system of vertical camera, a homography matrix $H$ is estimated between the image plane of the vertical and oblique images. The homography matrix $H$ is calculated in Equation 1 (Hartley and Zisserman, 2004) after giving calibrated camera matrix $K_{v}$ and $K_{o}$ for the vertical and oblique cameras, respectively:

$$H = K_{o} \left[ R + t_{n} \right] K_{v}^{-1}$$  \hspace{1cm} (1)

where $n_{d} = n/d$, $n$ is the normal vector of plane $\pi$ in the coordinate system of the nadir image, $d$ is the distance between its center and $\pi$, and $[R,t]$ is the relative rotation and translation between the nadir and oblique images. Using the homography matrix $H$, the image coordinate of the oblique camera $m_{o}$ can be mapped to the vertical view by $m_{o} = Hm_{v}$. Using a specific resampling method, such as bilinear interpolation or bicubic interpolation, the pixels of the oblique image can be remapped to match the vertical view. Therefore, the perspective deformation in the oblique image is relieved.

To compensate for the differences of approximately 180° in the yaw angle between strips, a special method that treats all three rotation angles of the nadir images as zeros is adopted. Therefore, similar geometric transformations also apply to all of the nadir images. To enclose all of the transformed pixels, the rectified images must be enlarged and shifted according to the transformed boundaries. In this way, we can assume that the scale, rotation, and other perspective deformations have been eliminated.

The features are then detected, described and matched on the rectified images as shown in Figure 1; however, the point coordinates are reverse transformed to the original image coordinates because the geometric transformation defined by the homography matrix is invertable. Then, the follow-up outlier removal steps are performed because some constraints are only justifiable in the original image, such as the epipolar constraint. Because no invariant ability should be imposed on the features, we chose to use the FAST corner detector (Rosten et al., 2010) as suggested by Jazayeri and Fraser (2010) and a BRIEF descriptor (Calonder et al., 2012) for efficiency consideration. The binary descriptors are then matched in hamming distance using approximate nearest neighbor search techniques (Muja and Lowe, 2012), then reverse transformed to the original image coordinates. We also adopt the RANSAC approach to initially remove outliers; however, dozens of false correspondences out of the 10^4 matches still exist, even if the RANSAC threshold is set to 1 pixel, which will sometimes prevent the bundle adjustment from converging.

Spatial Relationship Constrained Outlier Removal
In this study we impose three more constraints on the initial correspondences based on spatial relations and classify them as inliers or outliers after quantifying the constraints, including the cyclic angular order constraint, local position consistency constraint, and neighborhood conserving constraint. The first constraint assume that any non-rigid transform of the correspondences will not change the cyclic angular order between them; the second assumes that the positions of the correspondences in a local neighborhood should not abruptly change; and the last constraint that the
neighborhood relationship should be conserved in correspondences. It should be noted that all the three constraints are not processed sequentially, but in parallel with the refined correspondences after RANSAC outlier removal as shown in Figure 1. After executed in parallel, we removed the union set of the outliers detected in each constraint.

Cyclic Angular Order Constraint
In this study, the angular order of a feature point \( i \) in the reference image is denoted as \( S_i \), where \( i \) is the point number, and that in the matching image is denoted as \( S'_i \). \( S \) is formatted as the sequence of point numbers of the \( K \) nearest neighbors (denoted as \( N(i); k = 6 \) is adopted in this study), which is ordered clockwise. For example, as shown in Figure 2a the angular order for point No. 96 is \( S_{96} = \{103,96,94,95,97,104\} \) and that in the matching image (Figure 2b) is \( S'_{96} = \{97,104,103,95,96,94\} \). Similarly, for the false correspondence point No. 94, the angular orders are \( S_{94} = \{97,104,103,95,96,98\} \) and \( S'_{94} = \{104,103,97,96,95,98\} \).

The residual for a correspondence \( i \), \( r(p_i) \), is calculated as the following 2 \( \times \) 1 residual vector of \( r(p) \):

\[
r(p) = p' - T(p). \tag{3}
\]

The local position consistency constraint is based on the assumption that after the affine transformation, the residuals should be consistent across a local area. More explicitly, for a point \( p_i \) and its KNN \( \{p_k | k \in N(i)\} \), we calculate the average residuals of the neighbors \( \mu = \frac{1}{k} \sum r(p_k) / K \), and the mean and standard deviation of their lengths as \( \sigma = \frac{1}{k} \sum |r(p_k)| / K \) and \( \sigma = \frac{1}{k} \sum |r(p_k)| / K \) respectively. It should be noted that, in most cases, \( |\mu| \neq |\sigma| \). The local position consistency constraint imposes the following statement on the residual length and direction:

Local Position Consistency Constraint: The residual for a point \( p_i \) in the reference image should satisfy the following constraint, otherwise label it as an outlier.

\[
\begin{align*}
|r(p_i)| &< \mu + \frac{3\sigma}{\mu} \\
|r(p_i)| &> |\mu| - \frac{3\sigma}{\mu} \\
\end{align*} \tag{4}
\]

where the first restricts the residual to be approximately in the same direction of its neighbors and the second impose constrain on the size of the residuals.

Neighborhood Conserving Constraint
The neighborhood conserving constraint is based on the assumption that the neighbors of a point in the reference image are also the neighbors in the matching image. Therefore, we compute both the KNN of \( p_i \) and \( p'_i \) as \( N(i) \) and \( N'(i) \), respectively. Ideally, the two ID sets should coincide with each other. The similarity of two sequence vectors of the points can simply be measured by their intersection, which is denoted as \( |N(i) \cap N'(i)| \). Similar to the second constraint, the statistical average \( \mu \) and standard deviation \( \sigma \) are obtained, and the third constraint is formally stated as follows:
Neighborhood Conserving Constraint: The intersection number for the KNN of the two points in a correspondence, \(|p, p'|\), should satisfy the following:

\[ |p, p'| > \mu_i - 3\sigma_i \] (5)

Algorithm Complexities
As described above, previous matching algorithms that adopted spatial constraints often resort to the graph matching method, thus resulted in prohibitively expensive time and space complexities at the magnitude of \(O(n^3)\), where \(n\) is the number of correspondences or even higher (Torki and Elgammal, 2010), which was unable to extend to aerial images applications. It can be noted that for all the three constraints, KNN search for all the correspondences are adopted and its time complexity is \(O(n\log n)\) in average. For the first constraint, we need to calculate the cyclic edit distance for each points at the time complexity of approximate \(O(Kn)\), where \(K\) is the selected number of nearest neighbors. For the second constraint, we need to calculate the statistical information of each cliques at the complexity of \(O(Kn)\). And for the last one, only global statistical information is needed with time complexity of \(O(n)\). Considering that \(K\) is a relative small number, the total time complexity is only at \(O(n\log n)\) level. Furthermore, it is obviously that the space complexity is \(O(n)\). So the low algorithm complexities have guaranteed the extendibility of our method.

Experimental Evaluations
Configurations and Dataset
In this study, the oblique imagery system, SWDC-5, adopts the “Maltese Cross” configuration (Petrie, 2009). This type of configuration consists of five cameras: a single camera (CamE) pointing at nadir and four oblique cameras (CamA, CamB, CamC, and CamD). One pair of oblique cameras (CamA and CamC) point in opposite directions across the strips, whereas the other pair of cameras (CamB and CamD) view the same strip. Using a cross configuration system, the intuitive merits of having oblique views from four different directions are clearly emphasized by the ability to capture all of the possible facades of the buildings as shown in Figure 3.

The entire dataset consists of 27 strips that are collected during several flights by LEADOR SPATIAL over Jinyang, which is new development in the mountainous city of Guiyang. In fact, the flight conditions over the area were not good due to air movement and cloudy skies. The complete block contains 1,711 images for each camera at a strip overlap of 60 percent and side overlap of 50 percent, from which only some continuous strips of the fifth flight were chosen here. The average elevation of the coverage area is approximately 1,300 m, and the expected relative flight height is 600 m. The principal distances of the camera are approximately 50 mm for the nadir images and 80 mm for the oblique images. With this configuration, the ground sample distance (GSD) is approximately 0.08 m. In this study, the image distortion and principle point are pre-rectified to zero and to the image center, respectively. Additionally, a bundle adjustment of all of the nadir images was previously conducted using the integrated sensor orientation (Ip et al., 2007). The initial EO information was obtained from the GPS/IMU devices and several manually selected ground control points to eliminate the datum shift. The mean square error of unit weight \(\sigma_u\) is 0.3 pixels, and we treat triangulated 3D points from nadir images as control points in the experiments because no ground control points were available. Furthermore, the theoretical positioning error of the nadir images are at centimeters level. The platform parameters are calibrated in a calibration field as shown in Table 1. The initial EO parameters for CamA to CamD are estimated

Figure 3. The same building viewed from the nadir and four oblique views.
with the platform parameters and the adjusted EO for CamE. Due to reinstallation and other miscellaneous reasons, the initial EO parameters may cause meters-level 3D positioning errors. However, the initial accuracies for the oblique EO parameters are enough, because they only contribute to the geometrical transformations.

Table 1. Platform Parameters of the Camera System; the Eulerian Angles are in the Order of $\omega \rightarrow \phi \rightarrow \kappa$. Camera is Pointing at Nadir and Camera to CamD are the Four Oblique Cameras

<table>
<thead>
<tr>
<th>Translation $P_{OE}$</th>
<th>Rotation $R_{OE}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$X$(m)</td>
</tr>
<tr>
<td>CamA-CamE</td>
<td>0.109</td>
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<tr>
<td>CamB-CamE</td>
<td>0.019</td>
</tr>
<tr>
<td>CamC-CamE</td>
<td>-0.111</td>
</tr>
<tr>
<td>CamD-CamE</td>
<td>-0.002</td>
</tr>
</tbody>
</table>

To qualitatively and quantitatively evaluate the performance of the proposed methods, two types of experiments are conducted on two small subsets of images from the fifth flight, which include a dense built-up area and a rural area with vegetation and bare soil, as shown in Figure 4. First, we visually and statistically compare the match results with the standard SIFT methods using the two datasets. Next, we apply bundle adjustment to a block of 150 images and evaluate the quality of the bundle adjustment to quantify the performance of the correspondences.

Performance Evaluation of the Matching Results

In Plate 1, the match results of the proposed method and the standard SIFT method are displayed. For both methods, the ratio match (Lowe, 2004) is adopted, which detects the two nearest neighbors and only reserves those correspondences that exhibit a distance ratio between the two neighbors of less than 0.75. Furthermore, the cross check described previously is also adopted to ensure the one-on-one matching property. The successive RANSAC approach using a fundamental matrix follows the ratio match with a threshold of 1 pixel. To present a better understanding of the matching results, the key points and the images of the oblique views are geometrically transformed without a shift such that the correspondences are approximately parallel to each other. Otherwise, the correspondences will intersect and distort the meaning of the visual comparisons. The results of the proposed method are shown in Plate 1a and 1c. For the others, the matching results are obtained with the SIFT on the original images. The first column in each row provides the intuitional distributions of the correspondences, and the second column provides the matching results. The number of correspondences and the distribution are superior to those using SIFT, especially in the built-up areas where SIFT encountered enormous outliers after the RANSAC approach and most matches are centralized at few areas (Plate 1b). Furthermore, even in seriously occluded areas, such as the built-up areas in Plate 1a, we are also able to detect enough well-distributed tie points on building roofs when the shape of the roofs are relatively regular and simple.

To present a more comprehensive understanding of the performance of the proposed method, the matching results
for the two areas are listed in Table 2. The number of final matches, the outliers detected by the spatial relationships constraint and the false alarms are presented. The false alarms are obtained by manual inspecting the detected outliers; specifically, they are the number of correct correspondences that are labeled as outliers. The false alarms rate is very low, partly because of the sparseness of the remaining outliers after previous outlier handling steps, such as cross check, ratio match and RANSAC. Another characteristic observed is that the performances for the images of the urban areas are slightly inferior to those of the rural areas. This is because occlusions are more severe in the previous scenario.

Turning into compare with other methods or software, we also use SIFT, VisualSFM (Wu, 2011) and Photoscan to test matching results with the same images. In the experiments, the SiftGPU (Wu, 2007) is adopted for the SIFT implementation, which is also used in VisualSFM for feature detection. It can be noted that whereas the performance of SIFT decreases dramatically in the urban areas, the proposed method performs considerably well; the geometric transformation relieves the perspective deformation, especially for regions that are parallel to the horizontal ground (i.e., the building roof and planar ground). In fact, in the urban area, more correspondences are detected on the building roofs than on the ground, which are more inclined to be occluded and textureless. Furthermore, in the case of matching between images of different oblique cameras, SIFT will totally fail after RANSAC outlier removal and VisualSFM also will not perform well, as shown in the last two rows of Table 2a and 2b. The translational tilting angles (Morel and Yu, 2009) between the images are approximately 90°, which makes it almost impossible for the partially affine invariant SIFT descriptor to establish correct correspondences. However, the proposed method is also capable of handling these cases. Although Photoscan is able to obtain enough tie points, its performance is still inferior to the proposed method and after careful examinations, we discover that Photoscan will produce enormous false matches. In fact, when images is significantly different, large amount of outliers are expected if not handled appropriately.

Furthermore, one of the major considerations on the performance for practical applications is the runtime speed. As described above, some previous works on feature points matching with spatial relationship constraints are impracticable in applications of aerial images due to prohibitively high space and time complexities (Liu et al., 2012). In order to provide some perspectives into the algorithm details, we

Plate 1. Comparison of the matching results with the proposed method and the SIFT. The feature distribution and matching results for 05021AR0004 and 05019ER0006 with (a) the proposed method, and (b) SIFT; and the same results for 05015ER0023 and 05017AR0023 with (c) the proposed method, and (d) SIFT.
demonstrate the runtime speed with respective to different modules of the method. As summarized in Table 3, although we have carefully chosen the feature detection method and diligently optimized the KNN search, which is specially tuned for speed, the bottleneck still lies in feature detection and KNN search for the match candidates. The first two steps operate on all the feature points, whose amount is at the level of 10^5, however the RANSAC filter and spatial filter proposed in this paper operate on the matching candidates succeeded to previous steps. This helps to explain the performance. Due to the low time complexities of the spatial filter as described above, the runtime of the three constraints are nearly negligible when compared to the hotspots in the procedures.

### Performance Evaluation of Bundle Adjustment

To further evaluate the accuracies of the matching results, we select 150 images from seven strips (30 images for each camera) and conduct a bundle adjustment on the block of images using tie points that are generated and filtered by the proposed method. In the bundle adjustment, the EO parameters for the nadir images (CamE) are held fixed because these images have already been oriented with ground control points. Because all of the strips are from the same flight, we considered that the platform parameters at all of the exposure positions are the same and unknown in the adjustment (Jacobsen, 2009). Among all of the images, we created 3,390 pair-wise images matches because of the dense overlap ratio for the oblique camera system. After connecting all of the matches, we select hundreds of points that are evenly distributed within each image. In the selection, we prefer the points that connect more images, and the maximum tied points even linked 31 images. Overall, there are 8,339 object points that formulate 47,522 image tie points for the bundle adjustment. The mean square error of the unit weight is \( \sigma = 0.46 \) pixels after the bundle adjustment, and the adjusted platform parameters together with their internal accuracies are listed in Table 4. The internal accuracies for the adjusted platform parameters are quite good because of the well-distributed block

<table>
<thead>
<tr>
<th>Pair</th>
<th>Proposed Method</th>
<th>SIFT</th>
<th>VisualSFM</th>
<th>Photoscan</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-A</td>
<td>3595</td>
<td>215</td>
<td>413</td>
<td>1369</td>
</tr>
<tr>
<td>E-B</td>
<td>9017</td>
<td>1730</td>
<td>182</td>
<td>2913</td>
</tr>
<tr>
<td>E-C</td>
<td>6498</td>
<td>2277</td>
<td>248</td>
<td>2145</td>
</tr>
<tr>
<td>E-D</td>
<td>7026</td>
<td>2315</td>
<td>294</td>
<td>2434</td>
</tr>
<tr>
<td>A-C</td>
<td>1253</td>
<td>N/A</td>
<td>N/A</td>
<td>78</td>
</tr>
<tr>
<td>B-D</td>
<td>1181</td>
<td>N/A</td>
<td>N/A</td>
<td>612</td>
</tr>
</tbody>
</table>

**Table 2. Matching Results for the Two Test Areas; the 'E' denotes the nadir images and A to D denote oblique images**

- a) Tests in the rural area, which features vegetation, bare earth and roads.
- b) Tests in the built-up area, which features dense and tall buildings.

<table>
<thead>
<tr>
<th>Pair</th>
<th>Proposed Method</th>
<th>SIFT</th>
<th>VisualSFM</th>
<th>Photoscan</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-A</td>
<td>3398</td>
<td>36</td>
<td>61</td>
<td>940</td>
</tr>
<tr>
<td>E-B</td>
<td>3943</td>
<td>138</td>
<td>62</td>
<td>934</td>
</tr>
<tr>
<td>E-C</td>
<td>4461</td>
<td>43</td>
<td>36</td>
<td>1730</td>
</tr>
<tr>
<td>E-D</td>
<td>4688</td>
<td>49</td>
<td>34</td>
<td>1096</td>
</tr>
<tr>
<td>A-C</td>
<td>726</td>
<td>N/A</td>
<td>N/A</td>
<td>286</td>
</tr>
<tr>
<td>B-D</td>
<td>2596</td>
<td>N/A</td>
<td>N/A</td>
<td>231</td>
</tr>
</tbody>
</table>

**Table 3. Performance Results for the Runtime Speed of the Proposed Method**

<table>
<thead>
<tr>
<th>Pair</th>
<th>Feature detection (ms)</th>
<th>KNN search (ms)</th>
<th>RANSAC filter (ms)</th>
<th>Spatial filter (ms)</th>
<th>Miscellaneous (ms)</th>
<th>Total (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-A</td>
<td>8847</td>
<td>8290</td>
<td>9</td>
<td>26</td>
<td>102</td>
<td>17274</td>
</tr>
<tr>
<td>E-B</td>
<td>10607</td>
<td>10329</td>
<td>618</td>
<td>26</td>
<td>99</td>
<td>21679</td>
</tr>
<tr>
<td>E-C</td>
<td>10034</td>
<td>9038</td>
<td>30</td>
<td>28</td>
<td>107</td>
<td>19237</td>
</tr>
<tr>
<td>E-D</td>
<td>10814</td>
<td>9587</td>
<td>380</td>
<td>32</td>
<td>13</td>
<td>20826</td>
</tr>
</tbody>
</table>

**Table 4. Adjusted Results of the Platform Parameters for the Oblique Images; the bold values denote the internal accuracies of the platform parameters**

<table>
<thead>
<tr>
<th>CamA-CamE</th>
<th>X(m)</th>
<th>Y(m)</th>
<th>Z(m)</th>
<th>( \phi ) (°)</th>
<th>( \omega ) (°)</th>
<th>( \kappa ) (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.107</td>
<td>0.003</td>
<td>0.038</td>
<td>-0.770</td>
<td>44.820</td>
<td>90.720</td>
<td></td>
</tr>
<tr>
<td>3.20E-03</td>
<td>3.29E-03</td>
<td>3.26E-03</td>
<td>3.07E-04</td>
<td>2.30E-04</td>
<td>4.31E-04</td>
<td></td>
</tr>
<tr>
<td>CamB-CamE</td>
<td>0.018</td>
<td>0.118</td>
<td>0.051</td>
<td>-44.583</td>
<td>-0.155</td>
<td>180.223</td>
</tr>
<tr>
<td>2.93E-03</td>
<td>2.27E-03</td>
<td>2.87E-03</td>
<td>1.83E-04</td>
<td>1.78E-04</td>
<td>2.12E-04</td>
<td></td>
</tr>
<tr>
<td>CamC-CamE</td>
<td>-0.094</td>
<td>-0.012</td>
<td>0.024</td>
<td>0.751</td>
<td>-44.974</td>
<td>-89.306</td>
</tr>
<tr>
<td>2.81E-03</td>
<td>3.14E-03</td>
<td>2.96E-03</td>
<td>2.91E-04</td>
<td>2.19E-04</td>
<td>2.90E-04</td>
<td></td>
</tr>
<tr>
<td>CamD-CamE</td>
<td>-0.001</td>
<td>-0.116</td>
<td>0.039</td>
<td>45.319</td>
<td>0.374</td>
<td>0.295</td>
</tr>
<tr>
<td>2.98E-03</td>
<td>2.43E-03</td>
<td>2.98E-03</td>
<td>1.79E-04</td>
<td>1.73E-04</td>
<td>2.50E-04</td>
<td></td>
</tr>
</tbody>
</table>
network with multiple tie points among all of the images. The platform parameters changed only slightly compared to those before the adjustment as shown in Table 1.

To evaluate the consistencies in the block, we select another 3,000 sets of tie points from the remaining correspondences after removing the points used for the bundle adjustment. Each set must connect at least two nadir images and two oblique images. Thus, we treat the 3D points triangulated by the nadir images as ground control points. The projection errors and the 3D position errors of the oblique images are listed in Table 5, including the root mean square errors (RMSE) of the image coordinates and object space. The projection errors decreased nearly an order of magnitude, even with the small changes in the platform parameters. The position errors are reduced to approximately 1.5 GSD. When taking the flight height into account, the relative accuracies (RMSE divided by relative flight height) are shown as the bolded rows in Table 5b, which is sufficient for subsequent processing considering the precision of the triangulated control points and the small baseline-height ratio of the medium format oblique images (Colomina and Molina, 2014).

Conclusions

We determined that translational shifts and rotational skewing exist in the platform parameters for the SWDC-5, even if the parameters are expected to be fixed after offline calibration, which will cause tens of pixels misalignments on the oblique images and more than one-meter positioning errors. Due to occlusions and perspective deformations, tie point matching for the images of oblique camera systems are extraordinarily difficult. To surmount this problem, we exploited the initial geometric information to rectify the images and reduce the perspective deformations. Furthermore, spatial relationship constraints are incorporated into the feature matching procedures and serve as important clues to remove outliers, which still exist after using the common approach to handling outliers because of the consequences of the essential image dissimilarities in appearances. Experimental evaluations and comparisons reveal that the proposed method outperforms the standard SIFT in both the numbers and distributions of the correspondences. After a bundle adjustment with the connected points that are generated by the proposed method, the translation and skewing of the platform parameters are remedied. Furthermore, the internal inconsistencies of the block are reduced to a satisfactory level. An obvious trend in processing oblique images is to exploit the measurement potentials (Haala, 2013), and our future works will focus on developing efficient and suitable method for the dense image matching of oblique images.

Acknowledgments

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References


Sub-pixel-scale Land Cover Map Updating by Integrating Change Detection and Sub-Pixel Mapping

Xiaodong Li, Yun Du, and Feng Ling

Abstract
Coarse-resolution remotely sensed images are high in temporal repetition rates, but their low spatial resolution limits their application in updating land cover maps. Our proposed land cover updating method involves the use of coarse-resolution images to update fine-resolution land cover maps. The method comprises change detection and sub-pixel mapping methods. The current coarse-resolution image is unmixed, and the previous fine-resolution map is spatially degraded to produce current and previous class fraction images. A change detection method is applied to these fraction images to create a fine-resolution binary change/non-change map. Finally, a sub-pixel mapping method is applied to update the fine-resolution pixel labels that are changed in the change/non-change map. The proposed method is compared with a pixel-based classification method and two sub-pixel mapping methods. The proposed method maintains most of the spatial patterns of land cover classes that are unchanged in the previous and current images, whereas other methods cannot.

Introduction
Remotely sensed images can provide reliable land cover information at different scales and are the primary data utilized in the production and updating of land cover maps. At the global scale, coarse-resolution images, such as those obtained with a moderate-resolution imaging spectroradiometer (MODIS), have been applied to build land cover products, such as the MODIS land cover product (Friedl et al., 2002). Coarse-resolution images are high in temporal repetition rates, which allow the timely updating of land cover maps and the creation of long-term land cover products. However, the spatial resolution of coarse-resolution images is low. Coarse-resolution land cover products fail to satisfy regional-scale land cover resource and landscape analyses. At the regional scale, fine-resolution remotely sensed images are the primary data utilized to generate land cover maps. For instance, Landsat images at a spatial resolution of 30 m are utilized to produce and update the National Land Cover Database (NLCD) of the United States (Homer et al., 2007). However, owing to the tradeoff between spatial and temporal resolution, fine-resolution images have their limitations because they are often acquired at a relatively low temporal resolution. The land cover products from fine-resolution images are derived only from remotely sensed data acquired during one or several years, and these products represent the land cover characteristics of a specific period. Therefore, they lack not only long-term but also timely land cover change information.

Using a current coarse-resolution image and a previous fine-resolution map to timely update fine-resolution land cover products at the regional scale is meaningful and challenging. This task necessitates the use of multi-resolution images, which provide mutually supplementary land cover information at different scales. A popular approach that combines fine-resolution and coarse-resolution images is the use of coarse-resolution images that cover the entire area as the primary data source, as well as fine-resolution images that cover a part of the area as training samples. Braswell et al. (2003) combined coarse-resolution and fine-resolution images to extract land cover fraction images at the sub-pixel scale using soft classification, which predicts land cover class fractional information within each coarse-resolution pixel. The fine-resolution images were utilized to train endmember signatures, and the coarse-resolution images were utilized for spectral unmixing. Lu et al. (2011) integrated MODIS and Landsat images to map a fractional forest cover in the Brazilian Amazon. MODIS images were unmixed to forest fraction images, whereas Landsat images were utilized to calibrate the forest fraction images. However, the aforementioned methods can only detect land cover fraction within each coarse-resolution pixel and cannot produce fine-resolution land cover maps.

Sub-pixel mapping (SPM) or super-resolution mapping is a technique that transforms a coarse-resolution image or a spectral unmixing result into a fine-scale hard classification map by dividing pixels into sub-pixels and assigning different classes to these sub-pixels (Foody, 2006; Atkinson, 2009). SPM provides more information than spectral unmixing during the downscaling of coarse-resolution images because SPM can specify the location of each class within the coarse pixels. Generally, SPM adopts mono-temporal coarse-resolution remotely sensed images as input. In fact, SPM is an ill-posed inverse problem of transforming a coarse-resolution fraction image to a fine-resolution land cover map, and SPM accuracy is influenced by the uncertainty in determining fine-resolution pixel labels (Nguyen et al., 2006; Ling et al., 2010). The combination of a current coarse-resolution image and a previous fine-resolution land cover map is useful in reducing SPM uncertainty. Ling et al. (2011) developed a sub-pixel scale land cover change mapping method by using a current coarse-resolution remotely sensed image and a previous fine-resolution land cover map. This method was directly used on land cover fraction images obtained by spectral unmixing applied to remotely sensed images; fraction image errors reduced the accuracy of the result.

The integration of a previous fine-resolution land cover map into land cover classification and map updating accuracy

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has been developed in recent years. Previous studies have shown that pixel-based classification methods that integrate previous land cover map information outperform methods that independently classify images. Xian et al. (2010) updated 2001 NLCD impervious surface products to 2006 through a change detection method with Landsat imagery. Chen et al. (2012) proposed an automatic approach to update land cover maps. With the application of a change detection method to the previous map and current image (Chen et al., 2011), the aforementioned land cover map updating approaches are simplified to update only the labels of changed pixels in the current image. However, these methods require that current remotely sensed images have a spatial resolution as fine as that of the previous land cover map and that the advantage of coarse-resolution images with a high temporal resolution be ignored.

This study proposes a novel land cover map updating method that involves the use of a current coarse-resolution image and a previous fine-resolution land cover map to update fine-resolution land cover maps. The proposed method comprises a change detection method and an SPM method. The change detection method is utilized to detect which fine-resolution pixels are changed in each coarse-resolution image pixel, whereas SPM is used to label only the changed fine-resolution pixels instead of all the fine-resolution pixels in the image. The proposed method was validated on the basis of synthetic multi-spectral and Landsat images by comparison of the proposed method with a hard classification method and two SPM methods.

**Methods**

The proposed method comprises a change detection method and an SPM method. The change detection method is used to produce a fine-resolution binary change/non-change map. SPM is utilized to label only the changed fine-resolution pixels according to the binary change/non-change map.

**Change Detection Method**

Change detection techniques can be grouped into two categories. One category involves detecting binary change/non-change information, and the other category involves detecting the “from-to” change trajectory. In this study, fine-resolution pixel change/non-change information is detected on the basis of coarse- and fine-resolution images. Although several remote sensing techniques have been successfully used in change detection, most of them focus on the change “between” classes measured in a crisp way through which each pixel label is changed or unchanged in different images. When the spatial resolution of a remotely sensed pixel is coarse, the pixel is usually not pure and comprises different land cover classes. Therefore, crisp change detection methods are inappropriate for coarse-resolution image change detection. Rather, the significance arises in the way that land cover fractions within each pixel may change in different images. Spectral unmixing applied to coarse-resolution images can generate land cover fraction images that represent land-cover area proportions within each pixel at the sub-pixel scale. Fraction image-based change detection methods quantify the change in different classes within each pixel by comparing the fraction images acquired at different times, so these methods are suitable for the change detection of coarse-resolution remotely sensed images (Lu et al., 2004a). In this study, the fraction image-based change detection method is applied to detect sub-pixel land cover change information by comparing a pair of current and previous fraction images.

Current fraction images are produced by applying spectral unmixing to the current coarse-resolution image. Previous studies have confirmed that linear spectral mixture analysis (LSMA) can extract land cover fractions that represent area proportions of the endmembers within the pixel and can be applied in land cover fractional change detection (Roberts et al., 1996; Ju et al., 2003; Lu et al., 2004b). In this study, LSMA is applied to current coarse-resolution images to generate current land cover fraction images.

The previous coarse-resolution fraction images are spatially degraded on the basis of the previous fine-resolution land cover map with the use of a mean filter (Foody et al., 2002; Tatem et al., 2003; Wang et al., 2014). We assume $C$ classes in the previous map. $C$ fine-resolution binary category maps are first produced. In the $k^{th}$ ($k = 1, ..., C$) fine-resolution land cover category map, a value of 1 is assigned to the fine-resolution pixel if it belongs to class $k$; otherwise, a value of 0 is assigned to it. The scale factor between the size of the coarse-resolution image pixel and the pixel in the fine-resolution map is defined as $s$, and each coarse-resolution pixel contains $s^2$ fine-resolution pixels (sub-pixels). Each of the $C$ fine-resolution binary category maps is then spatially degraded with a mean filter that has an $s \times s$ fine-resolution pixel window to generate a previous coarse-resolution fraction image of that class.

After the current and previous coarse-resolution fraction images are produced, the change/non-change information of each class in every coarse-resolution pixel can be obtained. A fraction differencing image for each class is produced by application of a subtraction operation to the current and previous fraction images of that class. Assume that $F_{k,pre}$ and $F_{k,cur}$ are the previous and current fraction images of class $k$. $\Delta F_k$ is the fraction differencing image of class $k$ and is calculated as follows:

$$\Delta F_k = F_{k,pre} - F_{k,cur} .$$  \hspace{1cm} (1)

In implementing change/non-change detection on each fraction differencing image, establishing a threshold level to define the land cover change of that class in each coarse-resolution pixel is necessary. In this study, the threshold is determined through the use of training images (Lu et al., 2004b). These training images include a pair of a previous fine-resolution map and a current coarse-resolution remotely sensed image of a training region. The previous training image is acquired temporally close to the previous data as the input of proposed model, and the current training image is acquired temporally close to the current data as the input of proposed model. The previous fine-resolution training map is spatially degraded into the previous training fraction images, and the current coarse-resolution training image is unmixed into the current training fraction images. The training fraction differencing images are obtained from the pair of previous and current training fraction images according to Equation 1. The selection of thresholds for each class is based on statistical analysis of unchanged land-cover sample plots within the training fraction differencing image of that class, in consideration of the fact that unchanged land covers have normally distributed histograms in fraction differencing values (the mean value is close to zero), whereas changed land covers do not. Assume that $SD_i$ is the standard deviation of the values of pixels that cover the unchanged sample plots in the training fraction differencing image of class $k$. The land cover fraction change/non-change threshold value for class $k$, called $T_{k,i}$, equals to $3 \times SD_i$ (Lu et al., 2004b).

The fine-resolution binary change/non-change map is created after the fraction change/non-change threshold for each class is determined with the use of the training data. The change or non-change of each fine-resolution pixel is determined as follows. We assume that $b_i$ is the $i^{th}$ coarse-resolution pixel in the current image, and $a_j$ is the $j^{th}$ fine-resolution pixel in $b_i$. We also assume that the label of $a_j$ in the previous map is class $k$. First, we determine whether the fraction value of class $k$ in $b_i$ is changed by comparing the value of coarse-resolution $i$ in the fraction differencing image.
ΔF_k (called ΔF_{ik}) and the threshold value \( T_k \). If \( ΔF_k \) falls in the range of \(-T_k\) to \( T_k\), the fraction value of class \( k \) in \( b_i \) is unchanged; otherwise, the fraction value of class \( k \) in \( b_i \) is changed. We make the simple assumption that if the fraction value of class \( k \) in \( b_i \) is unchanged, then all the fine-resolution pixels labeled as class \( k \) in \( b_i \) in the previous map are unchanged; therefore, the fine-resolution pixel \( a_{i,j} \) is labeled as “unchanged” in the fine-resolution binary change/non-change map. Likewise, if the fraction value of class \( k \) in \( b_i \) is changed, all the fine-resolution pixels labeled as class \( k \) in \( b_i \) in the previous map are changed, and the fine-resolution pixel \( a_{i,j} \) is labeled as “changed” in the fine-resolution binary change/non-change map.

Sub-pixel Mapping

SPM is an approach to predict fine-resolution pixel (or sub-pixel) labels within each coarse-resolution pixel. SPM is essentially a hard classification technique at a finer spatial resolution than that of the input coarse-resolution remotely sensed image. Several SPM methods have been proposed in recent years (Table 1). These methods include pixel-swapping algorithm (Atkinson, 2005; Foody and Doan, 2007; Makido et al., 2007; Li et al., 2011; Tong et al., 2013; Xu and Huang, 2014), Hopfield neural networks (Tatem et al., 2003; Ling et al., 2010; Muaa and Foody, 2012), spatial attraction model (Ge, 2013), particle swarm optimization (Wang et al., 2011), indicator kriging (Boucher and Kyriakidis, 2007; Wang et al., 2013), interpolation model (Ling et al., 2013; Tolpekin and Stein, 2009; Ardila et al., 2012; Li et al., 2012), Wang and Wang, 2013), spatial-spectral managed model (Ling et al., 2012; Li et al., 2014), spatial regularization (Villa et al., 2011), indicator kriging (Boucher and Kyriakidis, 2007; Wang et al., 2014), interpolation model (Ling et al., 2013; multiple-point simulating model (Ge, 2013), particle swarm optimization (Wang et al., 2012), and supervised fuzzy c-means-based model (Li et al., 2012).

Spatial-spectral managed algorithm (SSMA) is a simple yet effective method that can be applied directly to remotely sensed images. SSMA is utilized in this study to label current fine-resolution pixels marked as changed pixels in the fine-resolution change/non-change map, rather than labeling all current fine-resolution pixel labels in the entire image as traditional SPM methods do. SSMA comprises three parts: a spatial term, a spectral term, and a balance parameter. The spatial term is the regularization term aiming to make the solution smooth. The spectral term is the data term to preserve information of the original coarse-resolution image. The balance parameter is utilized to balance the contribution of the spatial and spectral terms.

We assume that the coarse-resolution image is \( y \), and \( y \) contains \( B \) bands with each band containing \( n \) pixels. The output of SPM is a fine-resolution land cover map \( c \). The goal function \( E \) of SSMA is characterized as:

\[
E = \lambda \cdot E_{\text{spatial}} + E_{\text{spectral}}
\]

where \( E_{\text{spatial}} \) is the spatial term, \( E_{\text{spectral}} \) is the spectral term, and \( \lambda \) is the balance parameter.

The SSMA spatial term aims to maximize the spatial correlation of neighboring fine-resolution pixels based on the assumption that spatially proximate observations of a given property are more similar than distant observations (Verhoeye and De Wulf, 2002; Makido and Shortridge, 2007; Atkinson, 2009). The spatial term for fine-resolution pixel \( j \) in coarse-resolution pixel \( i \), \( a_{i,j} \), is computed as:

\[
E_{\text{spatial}}(c(a_{i,j})) = \sum_{(i \in N(a_{i,j}))} \frac{1}{d(al_{i,j})} \delta(c(a_{i,j}), c(al))
\]

where \( N(a_{i,j}) \) is a symmetric neighborhood system that includes all fine-resolution pixels inside a square window whose center is \( a_{i,j} \), itself is not included in the window; \( d(al_{i,j}) \) is the Euclidian distance between \( a_{i,j} \) and \( al \); \( c(al) \) and \( c(a_{i,j}) \) are the land cover class labels of fine-resolution pixels \( a_l \) and \( a_{i,j} \); \( \delta(c(a_{i,j}), c(al)) \) is defined as:

\[
\delta(c(a_{i,j}), c(al)) = \begin{cases} -1 & c(al) = c(a_{i,j}) \\ 0 & c(al) \neq c(a_{i,j}) \end{cases}
\]

The spectral term is utilized to preserve information of the original coarse-resolution image. Assume that \( y \) is the observed pixel spectral value of pixel \( b_i \) in \( y \). \( \mu \) is the synthetic coarse-resolution pixel spectral vector of pixel \( b_i \). Assume that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel, \( \mu \), is calculated as:

\[
\mu = \sum_{k=1}^{c} \theta_k \mu_k
\]

where \( \theta_k \) is the proportion of class \( k \) in pixel \( b_i \); \( \theta_k \) is calculated from label map \( c \) which is the SSMA intermediate result in each iteration, by dividing the number of fine-resolution

---

**TABLE 1. SUB-PIXEL MAPPING (SPM) METHOD NAMES AND IMPORTANT MATHEMATICAL VARIABLES DEFINITION**

<table>
<thead>
<tr>
<th>SPM and variables names</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSA</td>
<td>Pixel-swapping algorithm based SPM</td>
</tr>
<tr>
<td>SSMA</td>
<td>Spatial–spectral managed SPM</td>
</tr>
<tr>
<td>CD_SSMA</td>
<td>Land cover map updating method that incorporates change detection and SSMA</td>
</tr>
<tr>
<td>MDC</td>
<td>Minimum distance classifier</td>
</tr>
<tr>
<td>y</td>
<td>Current coarse-resolution image</td>
</tr>
<tr>
<td>c</td>
<td>Current fine-resolution land cover map outputted from SPM</td>
</tr>
<tr>
<td>ΔF_k</td>
<td>Fraction differencing image of class ( k )</td>
</tr>
<tr>
<td>( T_k )</td>
<td>Land cover fraction change/non-change threshold value for class ( k ) in ΔF_k</td>
</tr>
<tr>
<td>( b_i )</td>
<td>The ( i )-th coarse-resolution pixel in the current image</td>
</tr>
<tr>
<td>( a_{i,j} )</td>
<td>The ( j )-th fine-resolution pixel in ( b_i )</td>
</tr>
<tr>
<td>( c(a_{i,j}) )</td>
<td>The land cover class label of the fine-resolution pixel ( a_{i,j} )</td>
</tr>
<tr>
<td>s</td>
<td>Scale factor between the size of the coarse-resolution image pixel and the pixel in the fine-resolution map</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>Balance parameter in SSMA and CD_SSMA</td>
</tr>
</tbody>
</table>
pixels labeled as class $k$ in pixel $b_i$ by total fine-resolution pixel number, i.e., $s^k$, in $b_i$ and $\mu_k$ is the endmember spectral vector of class $k$. The SSMA spectral term for pixel $b_i$ is expressed as

$$E_{\text{spectral}}(b_i) = (y_i - \mu_i)^T (y_i - \mu_i)$$

where $T$ is the transposition operation. Therefore, the goal function ($E$) of SSMA is calculated as:

$$E = \lambda \cdot \sum_{i,j} E_{\text{spatial}}(c_{ij}) + \sum_i E_{\text{spectral}}(b_i).$$

SSMA optimization is achieved by minimizing the goal function through simulated annealing (Geman and Geman, 1984).

**Land Cover Map Updating by Integrating Change Detection and SPM**

The proposed land cover map updating method that incorporates change detection and SSMA (CD_SSMA) is a modification of SSMA. Compared with SSMA, CD_SSMA adopts the fine-resolution binary change/non-change map and the previous fine-resolution map as base maps to update the fine-resolution pixel labels. CD_SSMA determines if the fine-resolution pixel is changed before labeling this fine-resolution pixel. If a fine-resolution pixel is detected as “changed” in the binary change/non-change map, this fine-resolution pixel is labeled according to the SSMA goal function; if a fine-resolution pixel is detected as “unchanged” in the binary change/non-change map, this fine-resolution pixel is labeled according to the previous fine-resolution land cover map. The flowchart of CD_SSMA is shown in Figure 1.

**Methods for Comparison**

CD_SSMA was compared with a hard classification method and two SPM methods. Minimum distance classifier (MDC) was employed as the hard classification method to generate the pixel-based classification map. The pixel-swapping algorithm (PSA) (Atkinson, 2005) and SSMA were utilized as SPM methods for comparison. PSA is a widely used SPM method. In the PSA initialization step, the fine-resolution pixels of each class within each coarse-resolution pixel are randomly labeled according to the numbers calculated with the use of land cover fraction images, which are the output of a spectral unmixing model. In each iteration, two fine-resolution pixels with different land cover labels are randomly selected from each coarse-resolution pixel. If swapping these two fine-resolution pixels increases the land cover spatial dependence of the land cover map, these two fine-resolution pixels are swapped. PSA stops when a fixed number of iteration is reached. MDC, PSA, and SSMA adopt a coarse-resolution mono-temporal image as input.

**Experimental Results**

**Experiment on Synthetic Multi-spectral Images**

A synthetic multi-spectral image was used as the current coarse-resolution image to avoid spectral signature bias in deriving the endmember signatures. The previous and current
The parameters of the different SPM methods were set. Neighborhood window size, which is the length of the square side of the neighborhood, was set to 5 in PSA (Makido and Shortridge, 2007) and 7 in both SSMA and CD SSMA (Ardila et al., 2011). Balance parameter \( \lambda \) in SSMA and CD SSMA was set empirically. If \( \lambda \) is small, the result maps are unsmoothed with isolated patches; if \( \lambda \) is large, the result maps are over-smoothed with rounded patches. In this study, \( \lambda = 80 \) was set at \( s = 5 \), and \( \lambda = 5 \) was set at \( s = 10 \).

The CD SSMA training images are shown in Plate 1. A mean filter was used to spatially degrade the previous fine-resolution training image. LSMA was utilized to unmix the current coarse-resolution training image. Comparing the previous and current fraction images obtained from the training images and applying the supervised change detection method (Lu et al., 2004b) to the images helped determine the land cover fraction change/non-change threshold values of the fractional change for each class (Table 2).

Plate 1 also shows the classification and SPM results, which differ significantly. The class boundaries in the MDC result are serrated and rough because the hard classification map is produced at the pixel scale and the mixed pixels are labeled as monotypes regardless of the spatial patterns of land cover classes within mixed pixels. In the PSA and SSMA results, the land cover patches are aggregated into rounded patches because SPM maximizes the spatial correlation of neighboring fine-resolution pixels. Many speckle artifacts in salt-and-pepper appearance can be seen in the PSA result. This is because the fine-resolution pixel number of a class, which is determined by class fractions of that class in the coarse-resolution pixel, is very few, and these fine-resolution pixels are characterized as speckle artifacts in the result map. In PSA, swapping a pair of fine-resolution pixels within the coarse-resolution pixel does not change class fractions. By contrast, such speckle artifacts are mostly eliminated by SSMA in which the land cover fractions can be changed before and after SPM (Kasetkasem et al., 2005; Tolpekin and Stein, 2009; Ling et al., 2012; Li et al., 2014). The CD SSMA result matches the reference map better than the other results. The speckle artifacts are eliminated, and the spatial pattern of the linear-shaped Developed-Barren class, which is unchanged in the previous and current maps, is preserved in the zoomed area because CD SSMA incorporates a change detection method and preserves the unchanged fine-resolution pixel labels. The scale factor plays an important role in the results. With the increase in the scale factor, the MDC map becomes coarse and the PSA and SSMA maps acquire more aggregated patches. By contrast, the CD SSMA result does not change significantly.

A quantitative comparison was conducted with Kappa value, quantitative disagreement (QD), and allocation disagreement (AD) to assess the match between the reference land cover map and the resulting land cover map. QD is the difference between the reference and resulting maps caused by a less-than-optimal match in the proportions of categories. AD is the difference between the reference and resulting maps caused by a less-than-optimal match in the spatial allocation of categories given the proportions of the categories in the reference and resulting maps. Low values of QD and AD show a good match between the resulting and reference maps (Pontius and Milliones, 2011). Overall accuracy (OA) calculated from the change/non-change matrix was utilized to quantify the match between the real change/non-change map and the resulting change/non-change map. The real change/non-change map is produced by a per-pixel comparison of the reference and previous maps, whereas the resulting change/non-change map is produced by a per-pixel comparison of the resulting and previous maps. The accuracies of the different methods are shown in Table 3. The Kappa and OA values for all the methods are higher at \( s = 5 \) than at \( s = 10 \), and the QD and AD values for all the methods are lower at \( s = 5 \) than at \( s = 10 \) except for the QD value for SSMA. This result shows that coarsening the current coarse-resolution remotely sensed image always reduces the accuracy of different methods in land cover map updates. The Kappa values of CD SSMA are approximately 0.20 higher than

![Table 2. Land Cover Fraction Change/Non-Change Threshold Values for Different Classes for Synthetic Images](image)

<table>
<thead>
<tr>
<th>Class</th>
<th>Threshold Value</th>
<th>QD</th>
<th>AD</th>
<th>OA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water-Wetlands</td>
<td>0.0143</td>
<td>0.0612</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Developed-Barren</td>
<td>0.1995</td>
<td>0.1301</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>0.0432</td>
<td>0.0290</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubland-Herbaceous</td>
<td>0.0835</td>
<td>0.0543</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Planted/Cultivated</td>
<td>0.0618</td>
<td>0.0473</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Table 3. Accuracies of the Different Methods Using Synthetic Images](image)

<table>
<thead>
<tr>
<th>Method</th>
<th>Kappa</th>
<th>QD</th>
<th>AD</th>
<th>OA</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDC</td>
<td>0.6753</td>
<td>0.0289</td>
<td>0.2050</td>
<td>0.7806</td>
</tr>
<tr>
<td>PSA</td>
<td>0.7071</td>
<td>0.0088</td>
<td>0.2055</td>
<td>0.8008</td>
</tr>
<tr>
<td>SSMA</td>
<td>0.7200</td>
<td>0.0390</td>
<td>0.1619</td>
<td>0.8110</td>
</tr>
<tr>
<td>CD SSMA</td>
<td>0.9172</td>
<td>0.0088</td>
<td>0.0513</td>
<td>0.9507</td>
</tr>
<tr>
<td>MDC</td>
<td>0.5336</td>
<td>0.0535</td>
<td>0.2660</td>
<td>0.7094</td>
</tr>
<tr>
<td>PSA</td>
<td>0.5188</td>
<td>0.0094</td>
<td>0.3442</td>
<td>0.6747</td>
</tr>
<tr>
<td>SSMA</td>
<td>0.5527</td>
<td>0.0211</td>
<td>0.3016</td>
<td>0.6997</td>
</tr>
<tr>
<td>CD SSMA</td>
<td>0.7774</td>
<td>0.0103</td>
<td>0.1514</td>
<td>0.8575</td>
</tr>
</tbody>
</table>
Plate 1. Training images, previous map, reference map, change map, and result maps of different methods using a synthetic multi-spectral image: (a) Training images, (b) Previous map, reference map, and change map, and (c) Results map.
those of the other methods, and the OA values of CD_SSMA are approximately 0.15 higher than those of the other methods at $s = 5$ and $s = 10$. The QD and AD values for MDC are high; this finding reveals the influence of the mixed pixel problem on pixel-based classification. The AD value for PSA is extremely high; this result shows that the uncertainty of the spatial locations of different land cover classes is the main factor that affects accuracy. The QD and AD values for CD_SSMA are lower than those of SSMA, MDC, and PSA at $s = 5$ and $s = 10$ (except for the QD value of PSA). Thus, CD_SSMA is effective to predict the locations of land cover classes at the sub-pixel scale.

**Experiment on Landsat Images**

CD_SSMA was validated on Landsat multi-spectral imageries in this experiment. The study area is located near Sorriso (12°33'21"S and 55°42'31"W) in Mato Grosso State, Brazil. This area is in the Brazilian Amazon Basin, which is mainly covered by tropical forests and has undergone a massive deforestation process in recent years. A Thematic Mapper (TM) image acquired on 11 July 1988 with a spatial resolution of 28.5 m was employed to produce the previous land cover map. A Landsat Enhanced Thematic Mapper+ (ETM+) image acquired on 18 July 2005 with a spatial resolution of 30 m was utilized to produce the reference land cover map. The TM

![Figure 2. SPM and classification results of different methods using Landsat images.](image-url)
image was geo-registered to the ETM+ image and resampled at a spatial resolution of 30 m. The registration error between the TM and ETM+ images was less than 0.5 pixel. The TM and ETM+ images were subset with 2,880 × 2,000 pixels and then manually digitized to the previous and reference maps with forest and non-forest classes in the maps. In addition, the ETM+ image (red and near-infrared bands) was spatially degraded into the coarse-resolution image with a mean filter with the scale factor $s = 8$ to simulate the first two bands of MODIS image at a spatial resolution of 250 m.

The previous and current fine-resolution training images with 1,600 × 1,600 fine-resolution pixels were obtained from the same TM and ETM+ images located near the study area. The previous fine-resolution training image was manually digitized to the previous training land cover map, which was then spatially degraded into the previous fine-resolution images with a mean filter at $s = 8$. The current fine-resolution training image was spatially degraded into the coarse-resolution multi-spectral images with a mean filter at $s = 8$, which was then unmixed into current fine-resolution images with the use of LSMA. Comparison of the pair of previous and current training fraction images with the use of the supervised change detection method (Lu et al., 2004b) shows that the land cover fraction change/non-change threshold values were 0.1585 for both forest and non-forest. The neighborhood window size values in PSA, SSMA, and CD_SSMA were set similar to those in the synthetic image experiment. $s = 1$ was set in SSMA and CD_SSMA through numerous trials.

As can be seen in Figure 2, MDC generates aggregated and discontinuous patches. The small linear object in the zoomed area is eliminated because of the coarse resolution of the remotely sensed image. In the PSA result, the linear object is discontinuous. In the SSMA result, the linear object is eliminated because of the spatial smoothing effect. By contrast, the linear object is mostly preserved in the CD_SSMA result. Quantitative analysis shows that the land cover fraction change/non-change threshold values of CD_SSMA are higher than those of other methods (Table 4). Although the QD value of CD_SSMA is approximately 0.003 higher than that of MDC and SSMA, the AD value of CD_SSMA is approximately 0.01 lower than that of the other methods.

<table>
<thead>
<tr>
<th>Table 4</th>
<th>ACCURACIES OF THE DIFFERENT METHODS USING LANDSAT IMAGES</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Kappa</td>
</tr>
<tr>
<td>MDC</td>
<td>0.8862</td>
</tr>
<tr>
<td>PSA</td>
<td>0.8890</td>
</tr>
<tr>
<td>SSMA</td>
<td>0.8993</td>
</tr>
<tr>
<td>CD_SSMA</td>
<td>0.9116</td>
</tr>
</tbody>
</table>

Conclusions

CD_SSMA, a sub-pixel scale land cover map updating method that integrates change detection and SPM, was developed in this study. CD_SSMA utilizes current coarse-resolution images with high temporal resolution and previous land cover maps with fine spatial resolution to update land cover maps with high temporal and fine spatial resolutions. Unlike other SPM methods that directly label all the fine-resolution pixels in the image, CD_SSMA employs a change detection method to produce a fine-resolution binary change/non-change map and only updates the fine-resolution pixels that are changed in the binary change/non-change map through the use of SSMA. The spatial patterns of the unchanged fine-resolution pixels in the previous map can be preserved in the CD_SSMA result.

The proposed method was tested on synthetic multi-spectral and Landsat images by comparing the proposed method with a hard classification method and two SPM methods, namely, PSA and SSMA. The results show that the hard classification method generates land cover maps with serrated boundaries because of the coarse resolution of the remotely sensed image. PSA generates land cover maps with speckle artifacts, and SSMA generates land cover maps with over-smoothed boundaries. CD_SSMA generates land cover maps that are close to the reference map and preserves most of the spatial patterns of the unchanged classes. Quantitative analysis shows that the CD_SSMA results have higher Kappa values and lower allocation disagreement values in all experiments by comparison with the results of the other methods.

The accuracy of CD_SSMA is related to the number of constraints. First, CD_SSMA requires that the registration error between the previous fine-resolution land cover map and the current coarse-resolution image be strictly controlled because mis-registration will reduce the change detection accuracy. Furthermore, training images are necessary to obtain the threshold value for the identification of unchanged classes in every coarse-resolution pixel. Unsupervised threshold determination methods that can be applied without image training must be developed. Finally, the balance parameter in the SPM procedure of CD_SSMA was set by trials. A comprehensive study that involves the automatic estimation of the optimal balance parameter value is required in the future.

Acknowledgments

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References


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Mapping Wetlands and Phragmites Using Publically Available Remotely Sensed Images

Yichun Xie, Anbing Zhang, and William Welsh

Abstract
Using publically available remotely sensed images to map wetlands and invasive plants is attractive to ecologists, environmental scientists, and managers. However, wetland and invasive plant mapping on the basis of low-cost images has been challenged by the variability of mapping accuracy. In this paper, we are developing an innovative wetland and invasive plant mapping technique characterized with three integrations: the integration of image interpretation with feature extraction, the integration of high spatial-resolution images with high spectral-resolution images, and the integration of field reference data with interpreted and classified images. This technique advocates standard procedures for integrating NAIP (National Agriculture Imagery Program) and Landsat images with multiple processes of ground truthing, image classification, and validation. The case study conducted in the Detroit River International Wildlife Refuge concludes that the integration of NAIP and Landsat images provides sufficient spatial and spectral information for mapping coastal wetlands and Phragmites.

Introduction
Wetlands provide critical ecosystem services, such as support of biodiversity, improvement of water quality, flood abatement, and carbon sequestration (Mitsch and Gosselink, 2007). Despite their value, wetlands have often been filled, drained, or otherwise destroyed. Wetland losses in Michigan over the past two centuries are estimated at over 50 percent (Dahl, 1990; Reyer et al., 2009). The wetlands that remain often face severe stressors, especially in urban landscapes. These stressors include altered hydrology, increased loads of nutrients and contaminants from within the watershed, fragmentation, and invasion of non-native species. The Great Lakes region has a long history of biological invasions, with over 40 percent of invasive species in this region caused well-documented environmental problems and substantial economic losses (Mills et al., 1993). At least 10 percent of invasive species in this region have caused wetland plant communities (Corcoran et al., 2007; Pignattia et al., 2006; Ustin et al., 2007; Lopez et al., 2006; Ustin et al., 2002; Zhang and Xie, 2014). Radar data have also been used to identify wetland plant communities (Corcoran et al., 2011; Henderson and Lewis, 2008; Kasischke and Bourgeau-Chavez, 1997), including Phragmites in the Great Lakes Basin (Bourgeau-Chavez et al., 2004). Radar’s active sensors emit energy at a very low angle and create backscattered energy. The backscattered energy is sensitive to the dielectric constant and is primarily affected by the volume, physical structure, and amount of moisture in a material (Kozlov et al., 2001; Kwon and Lu 2009; Skolnick, 2008). However, in general, the accessibility to hyperspectral and radar data is limited and the associated costs of acquiring and processing are very high.

Multispectral images are the largest family among remotely sensed images. Many among them are free for public access. For instance, NAIP imagery is available from the National Agricultural Imagery Program (http://www Farm Service Agency.gov). Landsat images provide spatial-resolution images with high spectral-solution images, and the integration of field reference data with interpreted and classified images. The case study conducted in the Detroit River International Wildlife Refuge concludes that the integration of NAIP and Landsat images provides sufficient spatial and spectral information for mapping coastal wetlands and Phragmites.

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bands 10 and 11 (100 m). Landsat imagery, through its 16 to 18 day fixed temporal resolution, has a great potential to provide intra-annual image time series. In other words, Landsat imagery has a medium spectral resolution and a high temporal resolution. However, its spatial resolution is often not sufficient for identifying plant species. Although Landsat imagery has long been used to detect wetland vegetation types (Lunetta and Balogh, 1999), high spatial resolution images have been preferred as image datasets for detecting invasive plants by some researchers (Everitt et al., 2005; Walsh et al., 2008). Image vegetation classification over grassland and wetland from Landsat images is often a challenge (Baker et al., 2006; Sohn and Qi, 2005). Over the land covers with mixed vegetation compositions, the same vegetation type may exhibit different spectral features while different vegetation types may show similar spectra. It is common that plant communities present mosaic-like patterns, which can make it difficult to extract vegetation information from images with acceptable accuracy (Cingolani et al., 2004; Stuart et al., 2006; Lan and Xie, 2013; Xie et al., 2010). This challenge is mainly caused by image resolutions (spatial, spectral, and temporal) when the cost of image acquisition is a limiting factor. For public projects, such as mapping wetlands over a large area for the purpose of natural resource management or ecosystem restoration, the cost of image acquisition can be a critical obstacle. It would be an ideal situation if freely-accessible imagery sources could be used to produce wetland or Phragmites maps that are as good as (or close to) those produced with high-resolution commercial images. Therefore, we proposed to fuse the publically-available, no-cost NAIP and Landsat images to overcome the limitations of the spectral resolution of NAIP and the spatial resolution of Landsat imagery for mapping wetlands.

The second challenge is to get a sufficient number of high-quality reference points in order to obtain training signatures and to validate classification results. Lack of coincident ground information with which either to establish discrete land cover classes or to assess the accuracy of their identification has been demonstrated to be a serious limitation for effective use of remotely sensed imagery (Xie et al., 2010). There are three approaches of collecting training samples, either through ground truthing to gather ground reference points (GRPs) or by image data extraction to obtain the surrogates of GRPs, or in combination (Zhang and Xie, 2014). It is usually an expensive and time-consuming task to collect a large number of high-quality field samples (Chi and Bruzzone, 2005). This issue is particularly critical when mapping coastal wetlands and invasive plant species. In these areas, harsh terrain, standing water, rotting plants and litters hinder observers’ accessibility. Because of the confined impact of inaccessibility and high cost, it is often impossible to get a sufficient number of training samples for supporting a proper training of a classification algorithm or validating it.

Another challenge is to determine which image classifier is most successful to extract or identify various plant communities. Numerous image classifiers have been developed to improve classification accuracy, generally divided into unsupervised and supervised approaches (Langley et al., 2001). For supervised classification, a maximum likelihood (ML) classifier is usually regarded as a classic and mostly used for image classifications resting on the normal curve statistical distribution pattern (Higdon and Schafer, 2001; Sohn and Rebello, 2002; Xu et al., 2005). However, ML has its limitation for classifying mixed land uses (or covers) since the assumption of ML that the data follow Gaussian distribution may not always be the case in heterogeneous areas.

A growing volume of literature on new approaches to classification for mapping wetlands or invasive plants has been seen in recent years. In general, these new classifiers fall into three groups: (a) object-based classifications (OBC) (Benz et al., 2004; Lu and Weng, 2007; Rampi et al., 2014); (b) rule-based classifiers (RBC), which usually involve some type of learning process in image classification, such as fuzzy rules and functions, neural network algorithms, decision trees (Guo et al., 2008; Lan and Xie, 2013; Malon et al., 2008); and (c) the algorithms derived from support vector machine (SVM). Artificial neural network (NET) and fuzzy logic classifiers are representatives of the RBC. Although the NET method is appropriate for most types of data irrespective of their statistical properties, the interpretability of the results as well as the probability of local minima restrains its application (erni and Chytrý, 2005). Fuzzy logic classification is a kind of probability-based classification rather than a hard classification (Triepeke et al., 2008; Sha et al., 2008). Moreover, there are a growing number of RBC classifiers. In fact, there is a new trend taking place within this category, in which several rules are integrated to form newly improved classifiers called hybrid or multiple classifiers (Baraldi, 2011; Maulik and Saha, 2010; Mittrakis et al., 2008; Stavrakoudis et al., 2012). Due to a broad scope of RBC, the artificial neutral network (NET) algorithm was adopted in this paper as a representative RBC.

Recently, the support vector machine (SVM) has been introduced as a new technique for solving a variety of learning, classification and prediction problems (Guo et al., 2008; Malon et al., 2008; Zhao et al., 2008). SVM-based approaches have also been applied for the classification of remotely sensed data (Mitra et al., 2004). Unlike the aforementioned classifiers, SVM is a state-of-the-art learning algorithm having a solid theoretical foundation in statistical learning theory (Vapnik, 1995; Vapnik, 1996). SVM fixes decision functions based on structural risk minimization (SRM) instead of minimizing the misclassification on the training set to avoid overfitting (Du and Sun, 2008). It solves a binary classification problem by searching for maximal margin hyperplanes in terms of a subset of the input data (also referred to as support vectors) between different classes (Wu et al., 2008). Although both NET and SVM are regarded as learning machines and the capability of NET for image classification is well known, empirical testing showed that SVM performance in most cases is better than that of NET in terms of accuracy (Chen et al., 2005). Another advantage of SVM over other classifiers is attributed to its lower sensitivity to the overall size of training samples. Given the fact that the cost of acquiring GRPs to train image classifiers is often a concern (Chi and Bruzzone, 2005), SVM is prominent since, theoretically, SVM can use a smaller size of training samples and is able to achieve higher accuracy than similar classifiers, e.g., NET (Nemmour and Chibani, 2006).

In this paper, efforts are made to develop an innovative and synthetic procedure to meet the aforementioned challenges by answering the questions: how best to use NAIP imagery to extract GRPs for training and validation; how best to take advantage of NAIP high spatial resolution when processing Landsat imagery; and how to obtain higher classification accuracy from Landsat imagery.

Methodology

Study Area and Data Description

The study area, Detroit River International Wildlife Refuge (DRWR), is situated 41°43’ to 42°16’N and 83°06’ to 83°30’W (Figure 1). DRWR occupies 48 miles of Lake Erie shoreline and contains thousands of acres of wetlands. DRWR is well vegetated with Phragmites australis (giant reed cane), grass, shrubs, trees, cattail, marshland, cropland, and various other types. Many of these wetlands have been invaded by Phragmites in recent years. Previous studies and onsite survey showed that the invasion of Phragmites presents a severe threat to the
indigenous plants of the wetland ecosystem. Wetland mapping and the collection of the present and historical vegetation cover through remote sensed images could provide critical information to support the research of the Phragmites invasion.

Data used in this case study includes aerial NAIP images, Landsat-5 Thematic Mapper (TM) images, and field habitat survey data. Fifteen NAIP images over the study area were interpreted and processed to provide reference data for this case study. Moreover, 22 transects of field habitat surveys were conducted in July 2010, which served as important ground reference data along with the interpreted NAIP images. A Landsat-5 TM scene acquired on 10 September 2010, covering the entire study area, was obtained and preprocessed. We searched Landsat-5 images from the later-spring leave-on season to the early-fall leave-on season. From the viewpoint of phenology, Phragmites was easily separable from other tall shrubs and plants in the early-fall season. Moreover, it was easier to find cloud-free Landsat images during the early-fall season. This Landsat image was then classified to extract vegetation information for mapping Phragmites and wetland plant communities.

One of the important purposes of this research is to design and experiment a standard technique, through which the publicly available imagery sources, NAIP and Landsat, can be processed to extract vegetation data for wetland and invasive plant mapping with a reasonable accuracy level (at least above 80 percent). This procedure should be transparent and repeatable by other groups with a similar set of information and applicable in other regions. The procedure worked out through the Detroit River case study includes nine steps, grouped into three phases (Figure 2): Phase 1 (Steps 1 through 4): Data Preparation and Imagery Preprocessing; Phase 2 (Step 5): Ground Reference Data Extraction; and Phase 3 (Steps 6 through 9): Image Classification and Validation.

Data Preparation and Imagery Preprocessing

This case study was part of the DRIWR NOAA research project conducted by Eastern Michigan University. A component of this project included the field collection of vegetation and habitat data using the transect sampling approach. A total of 22 vegetation/soil transects were staked and plant sample data were collected at 22 sites over 13 DRIWR units, including: Humbug Marsh and Island (3), Strong (1), Gibraltar Bay (2), Gibraltar Marsh (2), Fix (1), Burke (1), Pte. Aux Peaux (1), Plum Creek (1), Our Lady of the Lake (1), Brancourt (2), Lake Erie Metropark (3), Ford Marsh (2), and Pte. Mouillee (2). The locations of transect stakes, plant community types and boundaries, soil samples, and field photos were georeferenced using GPS. Detailed transect field data collection forms were devised and implemented by the data collection team. All data were compiled into fully digital forms after the conclusion of the field season, and were quality checked. The field transect samples were an important source of GRPs for developing training signatures. However, due to the limitations of the spatial distribution and the quantity of the field transects, additional GRPs were needed in order to increase the number and the quality of classification training signatures as well as testing samples.

The Landsat-5 TM scene was located at Path 20/Row31 of the WRS2. NAIP images were warped to the Landsat image by using the first order polynomial rectification with the accuracy of the root mean squared error of less than half a pixel with the ground control points gathered at the field transects. Since we had no in-situ atmospheric measurements, image-based atmospheric corrections were applied to remove haze effects. So, a strictly image-based atmospheric correction, as proposed by Chavez (1996), was followed to remove atmospheric haze impact. The atmospheric correction was done with the flash module in ENVI. The reflective bands (band 1, 2, 3, 4, 5, and 7) of Landsat-5 TM image were used for classification.

Ground Reference Data Extraction

A four-step process was designed to extract the ground reference data for classifying and validating the Landsat-5 image (Figure 2):

1. NAIP images at selected scenes (i.e., two of the DRIWR management units, Humbug and Strong) were interpreted with traditional aerial photo interpretation techniques; and
2. a set of training and testing signatures were obtained from the interpreted NAIP images in conjunction with
3. the remaining NAIP images were classified by various classifiers and validated with the reference signatures, and, then, the best classification outcome was chosen; and
4. a final set of reference points was determined based on visual comparison of the classified NAIP images and the preprocessed Landsat image.

First, a classic aerial photo interpretation was conducted over two NAIP images covering the DRIWR management units, Humbug and Strong. Next, the interpreted NAIP maps were used as the primary source to extract a preliminary set of GRPs for classifying the NAIP images. The preliminary GRPs were extracted from a set of image area of interest (IAOI). The strategy of using small areas instead of single pixels is based on two considerations (Chen and Stow, 2002): (a) single pixels are hardly capturing spectral and spatial information for spatially heterogeneous classes; and (b) the IAOI method reduces the amount of searching time for image analysts to find representative samples for spatially heterogeneous classes. An IAOI was determined by the following rules:

- An IAOI should be representative of a feature of interest.
- The shape of an IAOI should follow the shape of the feature of interest and is contained within the boundary of that feature.
- An IAOI usually contains at least ten pixels.
- An IAOI for each class signature should be comprised of pixels with similar tone/color, texture, and other relevant interpretative elements of the class.
- Multiple IAOI were chosen for each class feature to ensure representative training signatures were obtained.
- The whole set of IAOI should be distributed evenly over the study area.

Third, the set of IAOI was randomly divided into the

### Table 1. The Distribution of Training and Validation Samples in the DRIWR Study Area*

<table>
<thead>
<tr>
<th>Class / Location</th>
<th>Grassy Island</th>
<th>Humbug</th>
<th>Lake Erie</th>
<th>Strong</th>
<th>Fermi</th>
<th>Erie Marsh</th>
<th>Gibraltar Marsh</th>
<th>Pointe Mouillee</th>
<th>Other locations</th>
<th>Total training samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>10</td>
<td>0</td>
<td>10</td>
<td>14</td>
<td>10</td>
<td>6</td>
<td>0</td>
<td>26</td>
<td>40</td>
<td>116</td>
</tr>
<tr>
<td>Cattails</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>3</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>9</td>
<td>34</td>
</tr>
<tr>
<td>Open water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>76</td>
<td>94</td>
</tr>
<tr>
<td>Cropland</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>16</td>
<td>5</td>
<td>4</td>
<td>0</td>
<td>24</td>
<td>57</td>
</tr>
<tr>
<td>Aquatic plants</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>66</td>
<td>81</td>
</tr>
<tr>
<td>Urban land</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>2</td>
<td>13</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>35</td>
</tr>
<tr>
<td>Pond and lake</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>14</td>
<td>34</td>
<td>58</td>
</tr>
<tr>
<td>Forested wetlands</td>
<td>6</td>
<td>7</td>
<td>3</td>
<td>7</td>
<td>6</td>
<td>0</td>
<td>14</td>
<td>0</td>
<td>59</td>
<td>102</td>
</tr>
<tr>
<td>Shrub wetland</td>
<td>0</td>
<td>8</td>
<td>4</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>15</td>
<td>39</td>
</tr>
</tbody>
</table>

* The upper section is the distribution of training samples, while the lower section is for validation samples.

### Table 2. The Error Matrix of the SVM Classifier for NAIP Imagery in Strong Unit

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>85.1</td>
<td>84.9</td>
<td>3930/4616</td>
<td>3930/4631</td>
</tr>
<tr>
<td>Cattails</td>
<td>91.2</td>
<td>91.7</td>
<td>1239/1359</td>
<td>1239/1351</td>
</tr>
<tr>
<td>Wet meadow</td>
<td>99.9</td>
<td>99.9</td>
<td>4788/4794</td>
<td>4788/4792</td>
</tr>
<tr>
<td>Shrubs</td>
<td>85.1</td>
<td>86.1</td>
<td>4544/5342</td>
<td>4544/5278</td>
</tr>
<tr>
<td>Open water</td>
<td>98.5</td>
<td>96.0</td>
<td>5055/5131</td>
<td>5055/5264</td>
</tr>
<tr>
<td>Pond and lake</td>
<td>95.5</td>
<td>98.3</td>
<td>4426/4635</td>
<td>4426/4502</td>
</tr>
<tr>
<td>Forested wetland</td>
<td>92.8</td>
<td>94.9</td>
<td>1059/1141</td>
<td>1059/1116</td>
</tr>
</tbody>
</table>

Overall Accuracy = (32329/34467) 93.8%
Kappa Coefficient = 0.93

### Table 3. The Error Matrix of the SVM Classifier for NAIP Imagery in Humbug Unit

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>99.6</td>
<td>85.5</td>
<td>679/682</td>
<td>679/794</td>
</tr>
<tr>
<td>Urban land</td>
<td>94.7</td>
<td>100.0</td>
<td>1220/1288</td>
<td>1220/1220</td>
</tr>
<tr>
<td>Cropland</td>
<td>98.5</td>
<td>80.8</td>
<td>399/405</td>
<td>399/494</td>
</tr>
<tr>
<td>Open water</td>
<td>100.0</td>
<td>100.0</td>
<td>4569/4569</td>
<td>4569/4569</td>
</tr>
<tr>
<td>Pond and lake</td>
<td>100.0</td>
<td>99.9</td>
<td>4120/4120</td>
<td>4120/4124</td>
</tr>
<tr>
<td>Forested wetland</td>
<td>95.5</td>
<td>99.9</td>
<td>2985/3125</td>
<td>2985/2988</td>
</tr>
</tbody>
</table>

Overall Accuracy = (13972/14189) 98.5%
Kappa Coefficient = 0.98
training and the testing subsets following the ratio 3:1. NAIP images were then classified by adopting a selected classifier (which will be described in a latter section) with the training subset. The classification results were validated by using the testing IAOI subset. Fourth, when the classification accuracy met the predetermined expectation (>80 percent), a comparison of the interpreted NAIP images with the preprocessed Landsat-5 image was conduct to select a new set of image area of interest. The same procedures used for selecting the preliminary set of IAOI from the NAIP images were applied over the Landsat image to identify the new set of IAOI. Finally the centers of the new set of IAOI were picked as the final set of GRPs. As a result, 546 GRPs, which were originally derived from the NAIP imagery, were identified on the Landsat image.

With an additional 70 ground reference points chosen from the field transects, a total of 616 reference points covering eight different covers was obtained. These 616 reference samples were randomly divided into the training set and the
testing set at the ratio about 3:1. As the result, 418 samples were in the training set and 198 samples were in the testing set (Table 1). In the following sections, all image analyses were conducted based on the training samples, while the accuracy assessment was carried out from the testing samples. One critical point that needs to be mentioned is the reference points derived from the NAIP imagery were selected with a comparative visual analysis of the differences between the NAIP imagery and the Landsat-5 imagery. Only pure (not mixed) pixels found on both NAIP and overlain Landsat-5 images were selected as reference points. Through the tests conducted in this case study, the selection of pure pixels as training sets dramatically improved the outcomes of image classification.

Table 4. The Accuracy Statistics of the SVM Classifier for Landsat Imagery over the Entire Study Area

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>100.0</td>
<td>85.0</td>
<td>34/34</td>
<td>34/40</td>
</tr>
<tr>
<td>Cattails</td>
<td>66.7</td>
<td>85.7</td>
<td>6/9</td>
<td>6/7</td>
</tr>
<tr>
<td>Open water</td>
<td>100.0</td>
<td>100.0</td>
<td>25/25</td>
<td>25/25</td>
</tr>
<tr>
<td>Cropland</td>
<td>100.0</td>
<td>100.0</td>
<td>22/22</td>
<td>22/22</td>
</tr>
<tr>
<td>Aquatic plants</td>
<td>96.9</td>
<td>73.8</td>
<td>31/32</td>
<td>31/41</td>
</tr>
<tr>
<td>Urban land</td>
<td>76.9</td>
<td>100.0</td>
<td>10/13</td>
<td>10/10</td>
</tr>
<tr>
<td>Pond and lake</td>
<td>47.6</td>
<td>90.9</td>
<td>10/21</td>
<td>10/11</td>
</tr>
<tr>
<td>Forested wetlands</td>
<td>97.0</td>
<td>94.1</td>
<td>32/33</td>
<td>32/34</td>
</tr>
<tr>
<td>Shrub wetlands</td>
<td>66.7</td>
<td>85.7</td>
<td>6/9</td>
<td>6/7</td>
</tr>
</tbody>
</table>

Overall Accuracy = (52/61) 88.89%
Kappa Coefficient = 0.87

Image Classification and Validation

Image classification over grassland or shrubland, which is often the predominant land cover in coastal wetlands, involves much more complexities than over forested areas (Xie et al., 2010). Based on the literature review of various classifiers and the characteristics of wetland and invasive plant mapping, SVM was chosen as the primary classifier, while neural net and ML were adopted for the purpose of comparison and validation in this paper. Some specifics of adopting SVM were provided below.

SVM is built with a solid theoretical foundation in statistical learning theory (Vapnik, 1995; Vapnik, 1998; Su, 2009). SVM solves a binary classification problem by searching for maximal margin hyperplanes in terms of a subset of the input data (also referred to as support vectors) between different classes (Wu et al., 2008). SVM is a supervised learning method used mainly for data classification and has been applied in various fields (Pal, 2008; Zhang and Xie, 2014). In SVM, the input data is viewed as two sets of cases (denoted as 1 or −1, indicating that any case can be classified as positive or negative) in an n-dimensional space. Building a SVM model involves finding a separating hyperplane in n-dimensional space to maximize the margin between the two sets of cases and thus derive a classification machine for new input cases. Theoretically, a reasonable separation is achieved by the maximum-margin hyperplane that has the largest distance to the neighboring data points of both classes, since the larger the margin, the lower the generalization error of the classifier. In most cases, the input data may not be linearly separated by a hyperplane. In building an effective SVM model, a key concern is to select an appropriate kernel. The SVM kernel tries to map the input vectors through SVM kernel into a very high-dimensional feature space in which data can be linearly separated.

A kernel function and its related kernel parameters are required to design an SVM. We chose the radial basis function (RBF) in this study and the parameters to be optimized include the penalty parameter C and the kernel function parameter, namely gamma (γ). The RBF kernel has better accuracy than the three other kernels (Linear, Polynomial, and Sigmoid) (Tan and Du, 2009; Du et al., 2010). A grid algorithm, or cross-validation, was adopted to select appropriate values for γ and C (Hsu and Lin, 2002). Specifically, we systematically changed the values for γ and C from low to high. For each combination of γ and C, considering the possible side effect caused by the uneven sizes of positive cases and negative cases, we followed the method, as proposed by Huang and Du (2005), by setting the ratio of penalties for different classes (positive and negative) with the inverse ratio of the training class sizes of positive to negative. This weighted SVM could compensate for the undesirable effects caused by the uneven training class sizes among various habitat types.

Outcomes and Maps

NAIP Images

The maps produced using aerial photo interpretation over NAIP images were used as surrogates of the training and validation sets. The interpretations and classifications were carried out in two DRIWR management units, Humbug and Strong. The experiments were carried out with three
classifiers, Maximum-likelihood (ML), Neural NET, and SVM in ENVI. We constructed the confusion matrices to compare the classification results with the ground reference points. For the ML method, the classification accuracy is 84.7 percent; kappa coefficient is 0.819; and Phragmites user accuracy is 83.63 percent (Story and Congalton, 1986). The classification accuracy of Neural NET is 78.1 percent; kappa coefficient is 0.734; and Phragmites user accuracy is 66.3 percent. The overall accuracy and Kappa coefficient are important statistics assessing whether general accuracy requirements are met. In particular, Kappa coefficient reflects the difference between the actual agreement and the agreement expected by chance. A Kappa value of 0.80 means there is 80 percent better agreement than by chance alone. The higher a Kappa value, the higher is the confidence concerning the accuracy assessment (Congalton, 1991). The Kappa values of the SVM classifications were higher than 0.92 (Table 2 for the Strong Unit and Table 3 for the Humbug Unit). By comparing the different results, it is clear that the SVM classifier obtained the best classification accuracy. Figure 3 shows the NAIP composite image, the interpreted map, and the SVM classified image of Strong Unit based on the NAIP image. Similarly, Figure 4 is Humbug Unit original and SVM classified images. Different gray-scale regions on these images represent different land cover types.

Landsat-5 TM Image

Landsat-5 TM image was processed for mapping invasive plant and wetlands over the entire study area, the Detroit River International Wildlife Refuge. The reflective bands (band 1, 2, 3, 4, 5, 7) of Landsat-5 TM were used for the classification experiments. Three classifiers, ML, NET (Figure 5) and SVM (Figure 6), were applied. For the ML, the classification accuracy is 82.8 percent, kappa coefficient is 0.8030, and Phragmites user accuracy is 91.67 percent. For NET, the classification accuracy is 86.36 percent, kappa coefficient is 0.8412, and Phragmites user accuracy is 91.89 percent. The results of SVM classification was reported in Table 4 and displayed in Figure 6. The SVM classifier attains the classification accuracy 88.89, the kappa coefficient 0.87 and the user accuracy of Phragmites 85.00 percent. By comparison, SVM obtains the best classification accuracy statistics.

Discussions and Conclusion

A reliable but low cost technique was developed to map coastal wetlands and invasive plant species, Phragmites, to support decision making in ecological restoration and environmental management projects. In terms of cost, two types of images that were easily accessible and had no or very low costs were tested. One was the airborne four-band NAIP image and the other was the satellite Landsat image. The NAIP image had higher spatial resolution but lower spectral resolution; it was a good image source for image interpretation to extract ground reference points and to validate other image classification outcomes. Moreover, the NAIP images covered smaller areas, i.e., the Strong unit and the Humbug unit in our case studies. The spatial and spectral information of NAIP were sufficiently good for site-specific mapping purposes. In addition, the experiments conducted in this paper also revealed that classification results based on NAIP images were usually better over a small area in comparison to Landsat images that covered a much larger area. It was also logical to assume that it would be labor-intensive to use the NAIP image, including four bands and covering small areas, for differentiating spectral
variations of land covers and uses over a large heterogeneous region, in comparison to Landsat TM.

In terms of reliability, it was recommended to achieve higher classification outcomes on publically available images by taking advantage of the “high (in relative sense)” spatial resolution of NAIP image to extract sufficient GRPs and then using them to classify the “high (in relative sense)” spectral resolution Landsat image with effective classifiers. The most important technique was to repetitively conduct data mining on the high spatial resolution of NAIP image to extract a sufficiently large size of GRPs or samples for classification training and validation. It was a critical step to extract GRPs of different classes as training and validation datasets when studying land cover and land use changes using remotely sensed data (Zhang and Xie, 2014). In the experiments, 546 pure pixels were obtained as GRPs from the extracted image areas of interest on both interpreted and processed NAIP images, in addition to 70 GRPs from the ground transects.

Three types of classifiers, ML, Neural Net, and SVM, were experimented in this case study. Over two small NAIP images, the ML, and SVM methods (especially the SVM classifier) performed much better than Neural Net. On the other hand, for the Landsat-5 image that covers the entire study area, the classification accuracy statistics of Neural Net and SVM methods were better than that of the ML method. Similarly to both NAIP and Landsat images, the SVM method had the highest overall accuracy statistics. Therefore, two conclusions could be drawn here: (a) the method for obtaining a large size of GRPs from NAIP images in combination with field observations, worked reasonably well; and (b) the SVM classifier performed better than ML and NET. Another note is that no ancillary information (except for a small number of GRPs from the ground transects) was taken into consideration in the current classifiers. The primary goal of this paper was to develop a low cost, easily reproducible technique to map wetland vegetation. The exclusion of ancillary information was to focus on the key techniques described in this paper. However, it is worth pointing out that many vegetation mapping projects strongly suggested to include ancillary datasets. When ancillary datasets, such as soil, landform, bedrock geology, terrain, hydrology, and climate data were added into classification processes, the classification accuracy was significantly improved in comparison with the sole consideration of Landsat derived variables (Wright et al., 2007). When a large number of ancillary data layers were available, decision-tree-based image classification algorithms were able to produce accurate vegetation maps (Baker et al., 2006; Davranche et al., 2010).

Finally, although the classification outcomes were satisfactory based on the accuracy assessments, there were limitations that need to be addressed. For instance, we only selected seven types of land covers/uses based on what we found in the Strong Unit to classify habitats over the entire study area. In fact, some habitat types were neglected in our study, such as shrub, wet meadow, and others. In order to verify or validate the classification accuracy for various types of vegetation or invasive plant species, more experiments and tests should be repeated in other study areas or in other ecosystems. In addition, it might help if some systematic approaches of collecting ground reference samples and deriving surrogate reference data from aerial photos were designed or implemented. All of these suggested will be our efforts at near future.

**Acknowledgments**

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Appreciation also goes to Dr. Eugene Jaworski, Ms. Xiaolin Ge, Ms. Lisa Denys, Mr. Greg Stevens, Mr. Jason Tallant, and Mr. Michael Dueweke at Eastern Michigan University for field data collection and aerial image interpretation.

**References**


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