Optimal selection of GCPs from Global Land Survey 2005 for precision geometric correction of Landsat-8 imagery

Shanshan Li¹, Man Peng²*, Changshan Wu³, Xuxiang Feng¹ and Yewei Wu¹

¹China Remote Sensing Satellite Ground Station, Institute of Remote sensing and Digital Earth, Chinese Academy of Sciences, No.9 Dengzhuang South Road, 100094, Beijing, China
²State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Datun Road, 100101, Beijing, China
³Department of Geography, University of Wisconsin-Milwaukee, Milwaukee, 53201, Wisconsin, USA

*Corresponding author, e-mail address: Pengman@radi.ac.cn

Abstract
To conduct precision geometric correction of Landsat-8 data, all ground control points from the Global Land Survey (GLS) 2005 are typically selected, thereby making the process time consuming and labor intensive. This paper developed an optimal selection algorithm for choosing representative points. The optimal technique consists of three steps, including 1) evaluating the spatial distribution patterns of points from GLS2005, 2) extracting ideal points positions from each scene based on the spatial distribution patterns obtained in the first step, and 3) selecting real representatives GCPs from the original large number of GCPs based on the positions of ideal points. One hundred individual Landsat-8 images were chosen for precision geometric correction to assess the robustness and efficiency of the method. Experimental result demonstrated that the approach could only consume 1/10 processing time or less when compared to that using the full set of original GCPs while still achieving comparable geometric accuracy. The developed technique will make an important contribution to improving the efficiency of precision geometric product generation systems for Landsat-8 images.

Keywords: Landsat-8, ground control points (GCPs), Global Land Survey 2005, precision geometric correction.

Introduction
Geometric distortions of remote sensing imagery have been one of the major factors that affect image quality, mainly due to the factors associated with the sensor platforms, atmosphere effects and Earth curvature [Jensen, 1996]. These distortions exert influence on many applications, such as image fusion, image classification, data manipulation and analysis, as well as deriving map-based products using geographic information system (GIS). Therefore, one important procedure that must be carried out prior to analyzing remote sensing data is geometric correction. Typically, systematic geometric corrections are conducted based on orbital and attitude data. These systematic corrections minimize the
global image distortions caused by factors related to the satellite platform, sensor, measuring instruments, atmosphere effects, and earth curvature [Toutin, 2004]. The resultant images, however, are still with very low absolute geometric accuracy. Therefore, in order to obtain precise geolocation information, it is necessary to employ ground control points (GCPs) to further rectify the satellite imagery.

Previous research has indicated that the number, precision and spatial pattern of GCPs affect the accuracy and reliability of the corrected image [Jia, 2005; Wang et al., 2005; Zhang et al., 2006; Sertel et al., 2007]. In particular, a number of researchers have explored the effect of the spatial distribution of GCPs during the geometric correction process. For example, Orti [1981] explicitly conducted a quantitative investigation on the relationship between the spatial distribution of GCPs and the geometric correction error of a Landsat image. Zhang et al. [2006] explored the effect of the spatial distribution of GCPs on the accuracy of image rectification. In this study, they applied both area-distributed and linear distributed GCPs obtained by manual selection to rectify Landsat-5 Thematic Mapper (TM) images of a coastal zone. Chen and Lee [1992] presented an original scheme to generate control-point pairs for image rectification using a Voronoi-Delaunay dual diagram. They also carried out an experiment to illustrate the efficiency of the method using SPOT images. Similarly, Zhang et al. [2009] proposed a Voronoi tessellation method to control the GCP distribution. This method proved to be an effective approach for improving the precision of geometric correction. These studies clearly indicate that the spatial distribution of GCPs affects the accuracy of the geometric correction of satellite remote sensing images.

Following these previous studies, this paper aims to develop an optimal selection technique to automatically generate spatially evenly distributed representative GCPs from a large number of feature points for precision geometric correction of Landsat-8 imagery. In particular, the distribution characteristics of original feature points are firstly evaluated using the variance-to-mean-ratio (VMR). Then, a spatial optimization algorithm is applied to select a subset of GCPs from the original feature points based on their spatial distribution. The precision geometric correction is used to determine the mapping function explicitly using the selected GCPs. Finally, the effect of the optimal method is evaluated using 100 individual Landsat-8 images in order to determine whether the number of GCPs can be reduced without significantly affecting the accuracy.

**Landsat-8 satellite**

Landsat-8 was launched on Feb. 11th, 2013 and was once called the Landsat Data Continuity Mission (LDCM). It is the eighth satellite in the Landsat family. Landsat-8 has continued to acquire remote sensing data using a two-sensor payload, the Operating Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The Worldwide Reference System-2 (WRS-2) is used to identify the path and row of each Landsat-8 standard scene. The 233 path is the descending orbit of the satellite, and each path is segmented into 119 rows, from north to south. Full list of Landsat-8’s bands is shown in Table 1.

The China Remote Sensing Satellite Ground Station (RSGS), a member of the Landsat Ground Station Operations Working Group, has been responsible for receiving and processing Landsat-8 satellite data in China. As shown in Figure 1, its two stations at Miyun (range shown by the red circle) and Kashi (range shown by the blue circle) can receive data from the satellite covering the whole territory of China and parts of the rest of Asia.
Table 1 – Full list of Landsat-8’s bands.

| Band Number | Band Name      | Wavelength (um) | Resolution (m) |
|-------------|----------------|-----------------|----------------|
| 1           | Coastal/Aerosol| 0.435-0.451     | 30             |
| 2           | Blue           | 0.452-0.512     | 30             |
| 3           | Green          | 0.533-0.590     | 30             |
| 4           | Red            | 0.636-0.673     | 30             |
| 5           | NIR            | 0.851-0.879     | 30             |
| 6           | SWIR-1         | 1.566-1.651     | 30             |
| 7           | SWIR-2         | 2.107-2.294     | 30             |
| 8           | Pan            | 0.503-0.676     | 15             |
| 9           | Cirrus         | 1.363-1.384     | 30             |
| 10          | TIR-1          | 10.60-11.19     | 100            |
| 11          | TIR-2          | 11.50-12.51     | 100            |

Figure 1 - Geographic range (areas covered by the blue and red circles) from which Landsat-8 data can be received from RSGS.

Global Land Survey (GLS) 2005

The task of carrying out geometric correction of Landsat data is assisted by the assembly of global datasets collected by the United States Geological Survey (USGS) and National Aeronautics and Space Administration (NASA) from existing archives. The Global land survey (GLS) project has established a large number of GCPs as a geometric base for all the current Landsat products, including data from the latest of Landsat-8 satellite. Several freely available Global Land Survey (GLS) datasets are listed in Table 2 [Gutman et al., 2008]. These collections were created by identifying optimal scenes as close to the nominal date of the collection as possible. As shown in Table 2, the GLS datasets are primarily comprised of Landsat images: each of the pre-2005 datasets was produced using images acquired by a single sensor and GLS2005 used a selection of imagery generated by expanding the available data sources to include Landsat 5 TM and Landsat 7 ETM+, as well as images
from the Advanced Land Imager (ALI), Earth Observing Mission 1 (EO-1) satellite. For GLS2005, the 9718 scenes acquired by TM and ETM+ sensors were chosen from the nearly 500,000 Landsat images that were acquired during 2004–2007, based on acquisition date, cloud cover, gap-fill coverage, sensor choice, time of year and geographic uniformity.

Table 2 - Global land survey datasets comprised of Landsat MSS, TM, ETM+ and ALI images.

| Dataset   | Total | MSS | TM | ETM+ | ALI |
|-----------|-------|-----|----|------|-----|
| GLS1975   | 7592  | -   | -  | -    | -   |
| GLS1990   | 7375  | -   | 7375 | -    | -   |
| GLS2000   | 8756  | -   | -  | 8756 | -   |
| GLS2005   | 10273 | -   | 2423 | 7295 | 555 |

GLS2005 provides a complete spatial coverage of almost all land areas - only 0.59% of all continental landmasses is not included. These gaps are mostly located along land–ocean boundaries. The use of GLS2005 datasets is facilitated by the fact that they have been standardized: all images are orthorectified to a Universal Transverse Mercator (UTM) projection using a World Geodetic System 1984 (WGS84) datum. The images have been resampled by cubic convolution and are stored in the GeoTIFF data format. The GCPs are generally located at the positions of the feature points extracted by the Moravec operator from the GLS2005 dataset [Moravec, 1977]. The GCP database is composed of two parts: the GCP library and the chips image. Geographic information including latitude, longitude and elevation as well as projection information etc. are stored in the GCP library. At the same time, as Figure 2 shows, the GCPs and the neighboring 63×63 pixels are included as the GCP chips raster file. Therefore, a GCP chip database helps to make the GCP matching and correlation fast.

Figure 2 - A representative GCPs chips image.

**Geodetic accuracy of GLS2005**

As it is a source of ground control points, the geolocation accuracy of the GLS2005 dataset is an important factor. It was assessed in an earlier study that the average Root Mean Square Error (RMSE) of GLS2000 was within 25 m (13.05 m over the United States, 15.75 m
over Australia and 25.27 m with triangulation analysis). Most of the GLS2005 data were registered to be within 7.5 m of GLS 2000. Furthermore, the overall geolocation RMSE of GLS2005 is 5.9 m when compared to GLS 2000, according to the 7888 images analyzed [Gutman, 2013].

**Coverage of GCPs in China**
The coverage of the GLS2005 dataset and corresponding GCPs in China is shown in Figure 3. The GLS2005 dataset covers the vast majority of the landmass of China and there are more than 200 GCPs for each standard scene defined by a Landsat path/row, except for the eight scenes shown in green. The scenes shown in red each contain more than 500 GCPs.

![Figure 3 - Number and distribution of GCPs for the GLS2005 dataset in China.](image)

**Methodology**
Rigorous 3D physical and deterministic models were adopted to perform the geometric correction of the Landsat-8 images. An iterative least-squares adjustment process was used to estimate the parameters of the model when there were more GCPs than the minimum number required by the model. On the one hand, using all the GCPs from GLS2005 is time-consuming but since more confidence, consistency and robustness could be expected with physical models than with empirical models, it was undesired to increase the number of well-distributed GCPs [Toutin, 2010]. Therefore, an optimal selection of GCPs from GLS2005 becomes important for precision geometric correction. The selection meet two conditions: (1) the selected GCPs should be spread widely on the image and have a uniform distribution; (2) the number of selected GCPs should be a compromise between efficiency and robustness.

**Spatial distribution of GCPs for each scene in China**
Before developing an optimal GCPs selection method, the spatial distribution pattern of GCPs for each scene in China from GLS2005 needed to be evaluated. In this research, we
applied a variance-to-mean-ratio (VMR) to examine the spatial distribution of GCPs [Stiteler and Patil, 1971]. The VMR is equal to zero in the case of a constant random variable. If the event follows a random distribution, it can be modeled by the Poisson process, and the VMR will be 1.0. Larger values (VMR > 1.0) correspond to the existence of clumps in spatial clusters. Smaller values (VMR < 1.0) correspond to a more uniform distribution [Young and Young, 1998]. As Figure 4 shows, a scene was divided into 8 cells which were consisted of four different linear directional elements, including horizontal, vertical, left diagonal, right diagonal. The number of GCPs within each cell was counted that was represented by \( x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8 \) separately, and produced the variable, \( X = (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) \), expressing the statistical distribution feature. The variance \( s^2 \) and mean \( m \) of \( X \), were then used to create the VMR:

\[
VMR = \frac{s^2}{m} \quad [1]
\]

![Figure 4 - Scene division (a) horizontal, (b) vertical, (c) left diagonal, and (d) right diagonal.](image)

![Figure 5 - (a) VMR = 0.158. (b) VMR = 0.432. (c) VMR = 1.056.](image)

Figure 5 shows three scenes and the corresponding VMRs. As can be seen, the value of VMR increases with a decline degree of spatial uniformity. VMR values for scenes in China is calculated and shown in Figure 6. It indicates that over 92% of the images, the VMR was less than 0.6, and only 15 scenes had a VMR of over 1.5 and these covered coastal and desert areas. These results demonstrate that the majority of GCPs in GSL2005 are evenly distributed with an individual image scene in the conterminous China.
Optimal ideal points positions sampling
The selection of GCPs in the image space can be regarded as a spatial coverage sampling (SCS) process. SCS is a sampling method that provides the optimal distribution of sampling points in geographic space. This method partitions the area into compact geographical strata, the centers of which can be selected as the ideal positions of points [Brus et al., 2006]. The equal area spatial coverage sampling (EASCS) algorithm was applied in this study for the selection of optimal points.

For the purpose of improving the efficiency of sampling, regular grids are first established on the reference image: a grid cell size of about 1/2500 to 1/5000 of the size of the study area is considered suitable [Walvoort et al., 2010]. The mean value of the squared shortest distance (MSSD) is used as an objective function for sampling the GCPs using geographically compact areas as strata, and this function can be minimized by the well-known $k$-means clustering algorithm. The geographic coordinates of the center point of each grid cell are regarded as the basic unit of clustering. The objective function can be written as

\[
\text{MSSD} = \frac{1}{G} \sum_{j=1}^{G} \min_i (d_{ij}^2) \quad [2]
\]

where $G$ is the number of grid cells and $\min_i (d_{ij}^2)$ presents the minimum of the squared distance between the $i$-th grid cell center and all cluster centers; $d$ is the Euclidean distance. Spatially compact strata will form an equal division of the image area through cell transfer, and the center of each subarea will be selected as the solution for each of the ideal points. The steps included in this method are listed in Figure 7.
Algorithm: Equal area spatial coverage sampling (EASCS) algorithm

Data: The GLS2005 images

Result: ideal points positions

Step 1: Initial partition. Supposing $k$ points are required, create an initial partition into $k$ clusters by visiting all grid cells in random order and assign cell $i$ to a cluster $(i-1) \mod k+1$.

Step 2: Assign initial centers. Calculate the centers by the centroid of the clusters, $\bar{x}, \bar{x}, \ldots, \bar{x}$.

Step 3: Re-allocation of partition.

   do
   for each grid cell $u$ (vector labels cluster $A$) do
   for each grid cell $v$ (vector $v$ labels cluster $B$) do
   if $d'(\bar{x}, u) + d'(\bar{x}, v) > d'(\bar{x}, v) + d'(\bar{x}, u)$ then
   The labels of the two grid cells were swapped, i.e. the cell $u$ in cluster $A$ was transformed to $B$ and the cell $v$ in cluster $B$ was transformed to $A$;
   end
   end
   Re-calculate the centroid for each clusters.
   while (Any two grid cells was swapped)

Step 4: The resulting partition and cluster centers constitute the ideal points position until none of the grid cells are being swapped anymore.

Figure 7 - Equal area spatial coverage sampling (EASCS) algorithm.

The $k$-means of EASCS algorithm is a deterministic search technique. The initial clustering may affect the minimization of the objective function and mean that the final clustering can be a local minimum instead of the global minimum. Therefore, it is recommended to apply the algorithm to several initial clusters to obtain optimal sampling in practice. As Figure 8 shows, the number of ideal points increased from 7 to 25 in the scene to which EASCS was applied before reliable and robust locations were obtained.

Figure 8 - Ideal points positions from (a) N=7 to (k) N=25 obtained using Equal Area Spatial Coverage Sampling.
Real GCPs selection
It is important to note that real GCPs are located at feature points, such as the crossing of roads or the corner of a building, which can be clearly identified and marked in practice. Therefore, if the ideal points are not located at such points, a small adjustment is needed to ensure that the real GCPs are located at feature points that are the closest to the positions of the ideal points, as measured by the Euclidean distance.

Experiments and results
Data and geometric accuracy assessment
As Figure 9 shows, 500 standard scenes of Landsat-8 images were received at the Miyun station, located in the suburb of Beijing. These scenes were acquired over China from January 22 to April 10, 2014, and the cloud cover was less than 10%. Twenty percent of those scenes (100 scenes) were used in experiments. 50 of them are with VMR values between 0 and 0.3, 43 scenes are with VMR in range of 0.3 and 0.6, and remaining 7 scenes are with VMR between 0.6 and 1.0. The objective of this experiment is: (1) to identify the optimal number of GCPs for different values of the VMR, (2) to make a comparison on computation expense needed for the precision geometric modeling of a standard scene between using the original full set of GCPs and the selected optimal GCPs.

The flowchart of the precision geometric correction method for Landsat-8 images is shown in Figure 10. First, the least-squares matching algorithm was applied as the image correlation techniques to determine the locations of the optimal selected GCPs on the systematic image. A sub-pixel matching accuracy was obtained by fitting a polynomial around matching
windows centered on the correlation peak. Although six GCPs are adequate for physical model parameter estimation for a Landsat-8 standard scene, extra points provide more observations and lead to a better estimate via the least-squares solution. Therefore, the adequate number of GCPs was used to estimate the robust geometric model parameters and residual errors arrived at minimum before spatial transformation and resampling.

Finally, for each scene, 30% points from the remaining GCPs of the original GLS2005 were selected as validation points (VPs), which were widely spread across the image. The numbers of VPs of over 90% of these scenes are between 100 and 180, which can be considered adequate to evaluate the accuracy of the geometric correction images [Aguilar et al., 2008]. The accuracy of the geometric correction was determined by calculating the RMSE of the validation points [Toutin, 2004; Hansan, 2012]. The RMSE is define as

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\sigma_{xi}^2 + \sigma_{yi}^2)}$$  \[3\]

where $n$ is the number of VPs, and $\sigma_{xi}^2$ and $\sigma_{yi}^2$ represent the $x$- and $y$-coordinate residuals of the $i$th VP, respectively. $\text{RMSE}_x$ and $\text{RMSE}_y$, which represent the root-mean-square error in the $x$ and $y$-coordinates, can be calculated in a similar way.

We took three standard images as examples, based on their VMR values. Detailed information about these three scenes is given in Table 3. Sampling designs could be evaluated through visualization of the spatial distribution of GCPs in the imagery [Shi and Pang, 2000].

**Table 3 – Image, GCPs and spatial distribution for three scenes in the experiments.**

| Image | Scene (Path/Row) | Acquisition Time | Number of GCPs | VMR |
|-------|-----------------|-----------------|----------------|-----|
| 1     | 123/36          | 2014/4/29 2:54:52 | 440            | 0.17|
| 2     | 123/32          | 2014/4/29 2:53:17 | 500            | 0.51|
| 3     | 121/34          | 2014/5/1 2:41:41 | 429            | 0.93|
Figure 11 - Optimal selected GCPs from scene 123/36 (VMR = 0.17). (a) band 5,4,3 color infrared image, (b) location of original set of GCPs, ideal points and real selected GCPs for image 1.

Figure 12 - Optimal selected GCPs from scene 123/32 (VMR = 0.51). (a) band 5,4,3 color infrared image, (b) location of original set of GCPs, ideal points and real selected GCPs for image 2.
Figure 13 - Optimal selected GCPs from scene 121/34 (VMR = 0.93). (a) band 5,4,3 color infrared image; (b) location of original set of GCPs, ideal points and real selected GCPs for image 3.

In Figure 11, Figure 12 and Figure 13, the distribution of original set of GCPs on images are shown as black open circles. The yellow filled rectangles represent the locations of the ideal sampling points in the reference image and the red filled circles represent the location of the selected GCPs after adjustment. X and Y axes represent the projection coordinate system of the images. With the proposed approach, the positions of the optimal ideal points were calculated, followed by the selection of real representative points from the feature points. Therefore, the selected GCPs were sufficiently dispersed and distributed evenly in the reference image. The calculated VMR values of the optimally selected are lower than those with complete set of GCPs.

The required number of GCPs was increased one at a time and joined precision correction model constructing until the geometric accuracy error (RMSE) reached minimum using the least-squares iterative method. Since errors are unavoidable when determining the locations of the selected GCPs on the systematic image. Firstly, the pointing accuracy of the selected GCPs was evaluated for each scene. Figure 14 reports that pointing error of the selected GCPs is in the range of 0.2 to 0.4 pixels (6 to 12 m for Landsat 8 imagery) and is practically irrelevant for number of GCPs.

Secondly, the RMSE statistics were calculated using the VPs and the results are shown in Figure 15 for three images. Table 4 gives the required number of GCPs by optimal selection needed to achieve the RMSE that reached a minima using adequate VPs. 10 GCPs selected by the proposed method were used to correct image 1 (scene 123/36). 12 GCPs were used for image 2 (scene 123/32) and 25 for image 3 (scene 121/34). The accuracies of the precision geometric correction were consistent with the values obtained using the complete set of GCPs.
Figure 14 - Number of GCPs versus pointing error for three images.

Figure 15 - Required number of GCPs versus RMSE for three images.

Table 4 - Required number of GCPs by optimal selection needed to achieve the RMSE that reached minima.

| Image | Scene (path/row) | Required number of GCPs | Number of VPs | RMSE (m)  |
|-------|------------------|-------------------------|---------------|-----------|
| 1     | 123/36           | 10                      | 132           | 9.22      |
| 2     | 123/32           | 12                      | 150           | 13.73     |
| 3     | 121/34           | 25                      | 130           | 18.75     |

Finally, Figure 16 shows the number of selected optimal GCPs versus the VMR, the statistics were calculated using 100 scenes, the solid red line represents VMR in (0,0.3) of scenes, the solid blue line represents VMR in (0.3, 0.6) of scenes and the solid black line represents VMR in (0.6,1.0) of scenes. Table 5 gives the optimal ranges of the number of selected GCPs for these scenes. The average selected numbers of GCPs using the proposed optimal method were 12, 18 and 25 for the three ranges of VMR shown.
Figure 16 - Values of VMR versus the optimal number of selected GCPs for 100 scenes.

Table 5 - Average selected numbers of GCPs for 100 scenes for VMR.

| VMR     | Range of number of original GCPs | Range of optimal number of selected GCPs | Average optimal number of selected GCPs |
|---------|----------------------------------|----------------------------------------|----------------------------------------|
| (0, 0.3)| 407–536                          | 8–14                                   | 12                                     |
| (0.3, 0.6)| 413–494                       | 13–21                                  | 18                                     |
| (0.6, 1.0)| 136–486                        | 21–30                                  | 25                                     |

**Efficiency improvement**

When comparing the efficiency using the different numbers of GCPs, an important issue is the computation cost needed. Here, we compare the average computation times for 100 scenes. We conducted the experiments on an Intel(R) Xeon(R) CPU X5650 2.66-GHz processor with 48-GB RAM. The average processing time of least-square matching and least-square iterations for geometric model estimation was 2.0 s with the original GCPs for each scene, meanwhile, the time was deceased to 0.16s with the proposed technique including spatial distribution computing and optimal GCPs selection. Neither of the algorithms was implemented in parallel. The optimal selection method could, therefore, be significant in terms of the reliability of its geometric accuracy as well being able to improve the efficiency of satellite product generation by a factor of at least 10.

**Discussion and conclusions**

An optimal GCPs selection technique was employed for the precision geometric correction of Landsat-8 images. Under the condition that we have no prior information about the geometric correction model parameters, the technique could be regarded as a model-independent optimal selection approach from a large number candidates without generating new points. Therefore, the method was affected by VMR that expressed the spatial distribution pattern of original set of GCPs. The resulting design tends to be spatially regular in appearance and achieves even coverage of the entire reference image.
of GLS2005. The experiments demonstrated that the more uniform of original full set of GCPs, the fewer representative GCPs could be selected by the optimal technique. On the contrary, the complete set of GCPs was spatially clustering, and then more selected GCPs are required as redundant observations to obtain robustness precise geometric correction model. In terms of the statistics derived from 100 scenes used in experiments, using the optimal selected GCPs from GLS2005 can improve the efficiency of geometric correction while still achieving comparable geometric accuracy. Statistics of VMR demonstrate that the majority of original set of GCPs are evenly distributed in China, the optimal selected GCPs could save the 9/10 processing time or more comparing with that using original full set of GCPs.

Since the China Remote Sensing Satellite Ground Station processes more 160GB Landsat-8 data each day of a satellite periods, the proposed approach could greatly reduce computation cost and improve the efficiency of precision geometric product generation systems. Therefore, the GCP optimization selection method is recommended for the rectification of Landsat-8 images and for use in the Landsat continuity GCP improvement mission.

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