

# Automated Image Registration for Hydrologic Change Detection in the Lake-Rich Arctic

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**Abstract**—Multitemporal remote sensing provides a unique tool to track lake dynamics at the pan-Arctic scale but requires precise registration of thousands of satellite images. This is a challenging task owing to a dearth of stable features to be used as tie points [(TPs), i.e., control points] in the dynamic landscapes. This letter develops an automated method to precisely register images in the lake-rich Arctic. The core premise of the method is that the centers of lakes are generally stable even if their shorelines are not. The proposed procedures first extract lakes in multitemporal satellite images, derive lake centroids and match them between images, and then use the centroids of stable lakes as TPs for image registration. The results show that this approach can achieve subpixel registration accuracy, outcompeting the conventional manual methods in both efficiency and accuracy. The proposed method is fully automated and represents a feasible way to register images for lake change detection at the pan-Arctic scale.

**Index Terms**—Centroids, feature-based, image registration, lake identification, “pseudo” features, subpixel accuracy.

## I. INTRODUCTION

**D**UE TO late Holocene deglaciation and the presence of widespread permafrost, the Arctic and sub-Arctic regions have the highest concentration of lakes in the world today [1], [2]. As a crucial component of the Arctic terrestrial water cycle, Arctic lakes play an integral role in nearly every aspect of the Arctic system. However, it is now recognized that warming Arctic climate is causing significant changes in lake distribution, with lake growth in some areas but drainage or desiccation in others [3]–[5]. However, these studies have tracked lake changes for less than 1.5% of the pan-Arctic land surface, so there is a critical need for a broader inventory of lake changes over the past few decades.

Owing to its broad spatial coverage and monitoring capability, satellite remote sensing is the only feasible approach to achieve this goal. Lake-rich land areas northward of 45° N cover nearly a quarter of the global terrestrial surface area. As one of the early remote sensing satellite series, NASA’s Landsat program that has been operated since July 1972 provides the longest systematic archive of civilian remote sensing images

that are powerful to resolve small Arctic lakes and detect their changes over the past approximately 30 years. The onboard sensors have evolved from the Multispectral Scanner (MSS) on Landsat 1–5 to the Thematic Mapper (TM) on Landsat 4–5 and the Enhanced Thematic Mapper plus (ETM+) on Landsat 7. The acquired satellite images, however, may not be precisely geolocated due to inaccuracies in orbital parameters and the attitude angles, topographic relief, and Earth curvature [6]. A process of geometric correction is therefore needed to georeference the images. Archived Landsat data maintained by the Earth Resources Observation and Science (EROS) Data Center consist of georeferenced image products at various levels of geometric correction, including systematic correction, precision correction, and terrain correction. The terrain-corrected image products are orthorectified satellite images and are the most precisely georeferenced. The Landsat GeoCover data sets archived at the EROS Data Center and also the Global Land Cover Facility (GLCF) are orthorectified image products with a positioning accuracy [root mean square error (rmse)] of about two pixels [7].

To detect temporal changes in lake distribution, images acquired at different times need to be spatially aligned. The alignment process is known as multitemporal image registration, in which one image (i.e., the master) is used as the reference for other images (i.e., slave images). Precise image registration is critical for successful change detection: Even a slight offset between images may induce significant error to change detection [8], [9], particularly for small targets. Due to the abundance of small-sized ponds and lakes in the high latitudes, the two-pixel georeferencing error of the orthorectified Landsat images is unacceptable for detection of pan-Arctic hydrologic change. Instead, subpixel image registration between early MSS, the later TM, and more recent ETM+ imagery is required. The traditional process of image registration is as follows: 1) careful selection of conjugated feature points (such as road intersections) that are visible on both master and slave images to be used as tie points [(TPs), or control points]; 2) development of an optimal registration model by least squares solutions using most TPs; 3) accuracy evaluation of the registration model using the remaining TPs; and 4) performing image registration using the model if satisfactory. TP selection is traditionally done manually [10], leading to inconsistency, low repeatability, and variable accuracy. Moreover, acquiring a large number of reliable TPs is a tedious and labor-intensive task and, therefore, prohibitive for change detection over large areas. A pan-Arctic

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inventory of lake changes will require thousands of Landsat scenes and demands creation of an automated registration procedure.

Automated image registration techniques may be classified into two categories: area based and feature based. In area-based methods, a small window (i.e., template) centered at a location in the slave image is statistically compared with a same-sized window in the master image to compute a similarity measure using the corresponding sets of pixel values. Normalized cross-correlation between the two templates is a widely used measure of similarity. However, similarity measures computed directly from image values are vulnerable to image brightness variations, image rotation, geometric distortions, repetitive patterns, and temporal changes [11]. Compared to the area-based approaches, feature-based registration methods are less influenced by such problems but require additional steps to extract and match common features from both images. Linear features, object edges, and closed contours are widely used matching primitives [6], [12], [13]. However, these methods are challenged by temporal changes of dynamic features, such as lake shorelines, which vary both seasonally and interannually. This letter proposes a “pseudo”-feature-based approach to image registration in dynamic lake-rich environments.

## II. PROPOSED METHODS

It is both desirable and challenging to remove the misregistration between images while retaining the real differences to be examined for subsequent change detection [14]. On one hand, the images must be precisely registered for reliable change detection; on the other hand, the changes themselves interfere with the process of TP selection or feature matching. Despite the existence of sophisticated registration algorithms [14], [15], it is challenging for them to register multitemporal images of dynamic landscapes. This difficulty can be attributed to the lack of stable features in such landscapes. Lakes and their shorelines are the primary features that are visible in satellite images of lake-rich Arctic environments. However, neither of these features can be assumed to be temporally stable. Lakeshores are quite dynamic, subject to changing water balance, shoreline erosion, tapping, and emergent vegetation growth, preventing their use as matching primitives. Feature-based algorithms that use lakeshores as feature primitives are therefore unsatisfactory.

In this letter, we propose the use of lake centroids as “pseudo” features in automated image registration in dynamic lake-rich environments. Centroids of closed contours or regions have previously been used to refer to the location of regions in image registration [16]–[18]. Compared to lakeshores, lake centroids are relatively stable. In low relief areas such as lake-rich Arctic landscapes, lakes shrink or expand quite uniformly in all directions, as shown in Fig. 1. Lakes grow or shrink radially, but their centers tend to remain stable even if their edges migrate significantly. Lake centers can thus be considered as “pseudo” image features, which are not visible directly in the images. However, they can be estimated geometrically once the lakes are delineated. The method presented here associates and matches corresponding lake centroids between images to

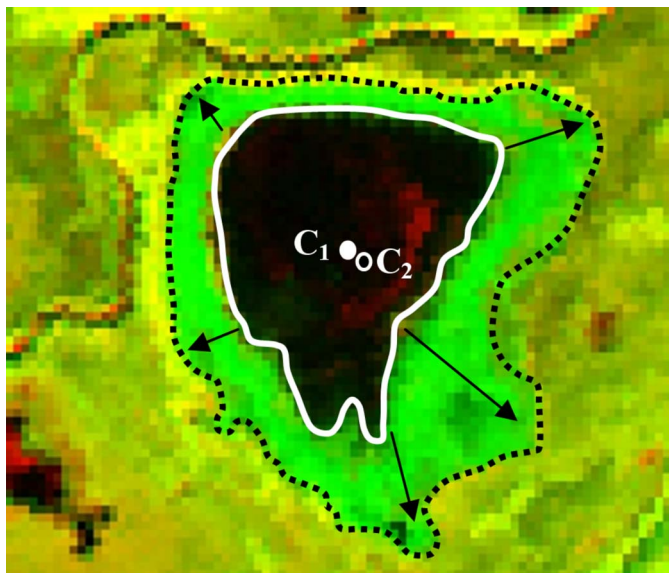


Fig. 1. Dynamic lakes with stable centers. The center of a lake is relatively stable, even though the lake expands or shrinks. The center ( $C_2$ ) of this significantly expanding lake does not move far from its original location ( $C_1$ ).

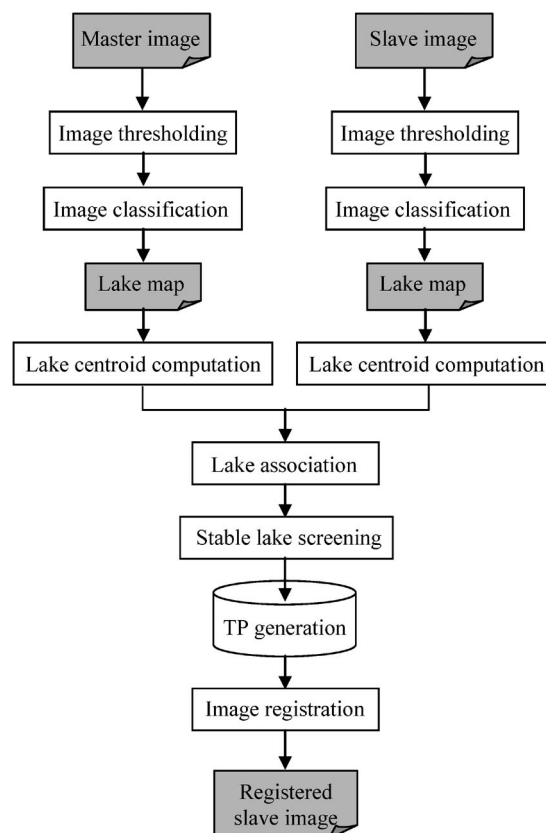


Fig. 2. Flowchart of the proposed method.

generate TPs automatically for thousands of lakes throughout a study area.

The proposed method is shown in Fig. 2. First, histogram thresholding is applied to both the master and the slave images. The segmentation result is then used to create training samples to classify lakes from the land background using multispectral images, allowing the computation of lake centroids at subpixel

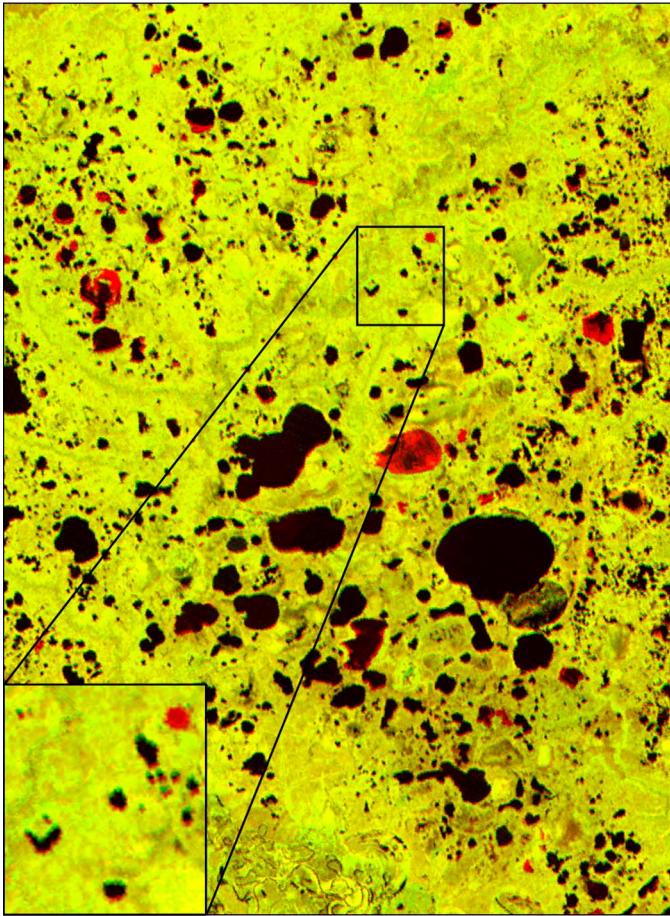


Fig. 3. Color composite image made by displaying the MSS and the TM NIR images in green and red channels, respectively. An  $\sim 3$ -pixel offset is indicated by the red and green edges around lakes.

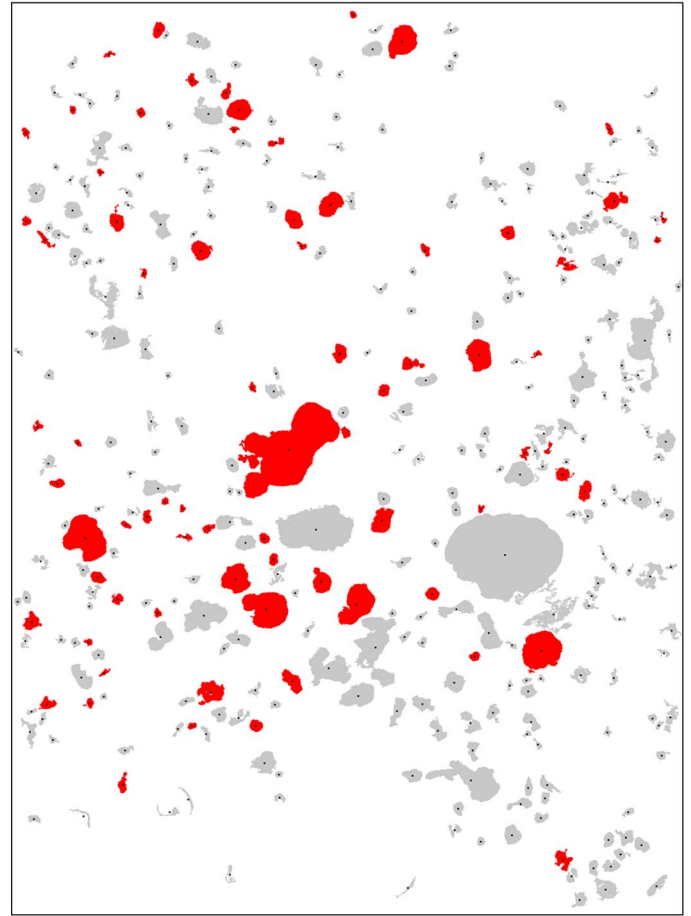


Fig. 4. Computed centroid points of stable lakes for the TM image. The detected stable lakes are illustrated in red, whereas the unstable lakes are shown in light gray. The black dots represent the centroid locations.

precision. This letter assumes that the input images are roughly registered. This assumption is often valid nowadays because many satellite images are provided in roughly georeferenced forms such as the GeoCover archive. In case the input images offset greatly, an automated fast-Fourier-transform-based registration can be first applied to roughly register them [19], [20]. The corresponding lakes on the two input images can be easily identified. For each lake in the master image, the corresponding lake in the slave image is determined by identifying the lake centroid pair with minimum Euclidean distance. Stable lakes are then identified as those with minimal size change, and their centroids are used as TPs in the subsequent image registration. The next section illustrates the procedures using an MSS image and a TM image from West Siberia.

#### A. Images Used

Two summer orthorectified Landsat images from West Siberia ( $66.2^\circ$  N and  $81.2^\circ$  E) are used as a case study. The images were acquired by the MSS sensor on August 22, 1973 and by the TM sensor on September 17, 1987, respectively. Lakes in this area are abundant and dynamic, and experienced significant changes during the 14 years transpiring between the two images. The TM image is assigned as the master image owing

to its better positioning properties [7]. Fig. 3 shows a subset of the color composite image made from the MSS and the TM near-infrared (NIR) images. This false-color image is useful for illustrating true lake changes as well as misregistration errors. Stable lakes appear black, and stable land appears yellow. New lakes appear green, whereas vanished lakes appear red. Close visual inspection of Fig. 3 reveals a misregistration offset of  $\sim 3$  pixels between the two images.

#### B. Lake Identification

The first step is to identify lakes in both images. Open-water surfaces are readily identified owing to their low reflectance in the NIR images ( $0.8\text{--}1.1\ \mu\text{m}$  for MSS and  $0.76\text{--}0.90\ \mu\text{m}$  for TM and ETM+) [21]. Histograms of NIR reflectance in lake-rich areas typically exhibit a strongly bimodal distribution. A threshold between the two peaks can be automatically determined for segmenting the images into water bodies and the land background. This segmentation is further refined by a supervised classification technique using multispectral bands. Areas where pixel values are less than the mean value of the water-body segment serve as the training set for pure-water bodies. Similarly, pixels having values that are greater than the mean background segment value are the training set

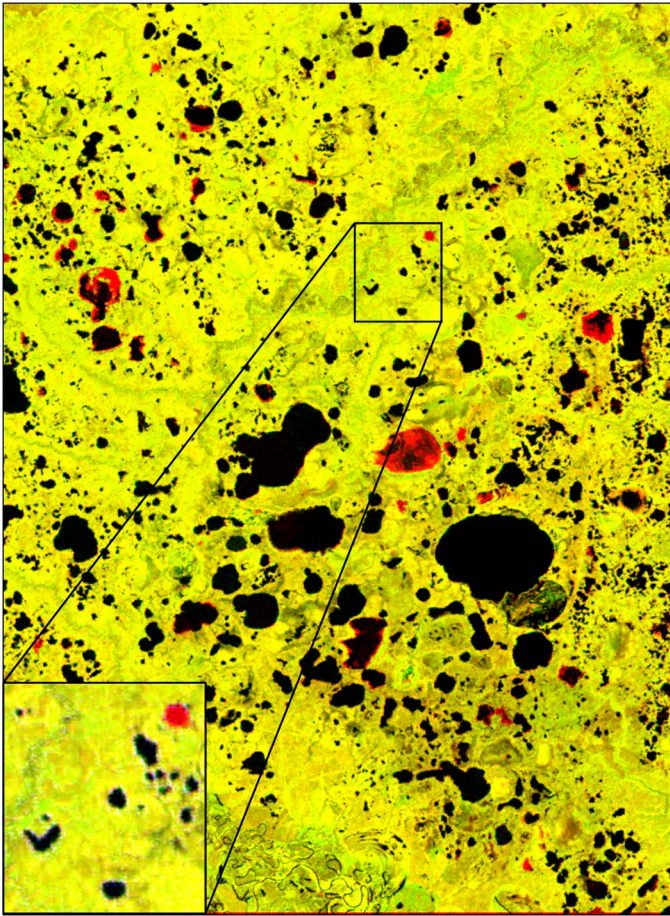


Fig. 5. Color composite image after image registration. Offsets found in the original images have been removed by the proposed registration method.

for the background class. Based on the two training sets, the maximum-likelihood classifier produces a lake map from all the four bands of the MSS image. The TM image is processed in the same way to produce the TM lake map. As such, the lake identification procedure is simple, automated, and effective.

### C. Lake Matching and Generation of TPs

The proposed method selects the centroids of stable lakes as TPs for image registration. The method involves computing the centroid of each lake at subpixel precision, spatially associating identical lakes in the two images, identifying stable lakes, and generating TPs. The centroids of individual lakes in the TM image are shown as black dots in Fig. 4. Because two orthorectified GeoCover images are typically misaligned by only several pixels, identical lakes in the two images are associated by comparing the Euclidean distances between centroid points in the two images. The lakes on the two images are considered to be an identical lake if their centroids are closest on the images and their Euclidean distance is less than the predefined threshold (i.e., five pixels for most GeoCover images). Seventy-four stable lakes (in red) are then identified using lake change criteria (i.e., area change of 3% or less). The centroids of these stable lakes therefore serve as TPs for the subsequent image registration procedure.

### D. Image Registration and Accuracy Assessment

Two-thirds (49) of the generated TPs were randomly selected to develop a linear registration model, and the rest (25) used for registration accuracy assessment. Subpixel accuracy is achieved with a rmse of 0.62 pixels. The MSS image was then registered to the TM image using the derived registration model. The registration result is illustrated in Fig. 5. The noticeable offsets around lake shorelines (Fig. 3) have been successfully removed, and the two images are ready for lake change detection. This automated registration result is even better than that produced by the traditional manual method. Using 49 TPs carefully selected on the two images in the Environment for Visualizing Images (ENVI) through a labor-intensive process, a registration accuracy of 0.79 pixels (rmse) is achieved. The proposed approach also achieved a 0.27-pixel accuracy when applied to register two MSS images acquired in early summer just after snowmelt and late summer just before freezing, respectively.

## III. DISCUSSION AND CONCLUSION

Major hydrological changes are believed to be underway in response to high-latitude climate warming, but their detection will require a massive processing of roughly georeferenced Landsat data at the pan-Arctic scale. Even orthorectified Landsat images may be misaligned by several pixels, which is unacceptable for lake change detection. Traditional automated registration procedures fail in this environment owing to the lack of stable features for use as TPs. It is particularly challenging to remove the misregistration between images while retaining true lake dynamics. The proposed “centroid-matching” method therefore offers broad utility for automated image registration problems in dynamic environments like the Arctic.

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### REFERENCES

- [1] B. Lehner and P. Doll, “Development and validation of a global database of lakes, reservoirs and wetlands,” *J. Hydrol.*, vol. 296, no. 1–4, pp. 1–22, Aug. 2004.
- [2] L. C. Smith, Y. Sheng, and G. M. MacDonald, “A first pan-Arctic assessment of the influence of glaciation, permafrost, topography and peatlands on northern hemisphere lake distribution,” *Permafrost. Periglac. Process.*, vol. 18, no. 2, pp. 201–208, Apr.–Jun. 2007.
- [3] “ACIA,” *Arctic Climate Impact Assessment*, Cambridge Univ. Press, Boston, MA, 2005.
- [4] J. P. Smol and M. S. V. Douglas, “Crossing the final ecological threshold in high Arctic ponds,” *Proc. Nat. Acad. Sci. USA*, vol. 104, no. 30, pp. 12 395–12 397, Jul. 2007.
- [5] L. C. Smith, Y. Sheng, G. M. MacDonald, and L. D. Hinzman, “Disappearing Arctic lakes,” *Science*, vol. 308, no. 5727, p. 1429, Jun. 2005.
- [6] F. Eugenio and F. Marques, “Automatic satellite image georeferencing using a contour-matching approach,” *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 12, pp. 2869–2880, Dec. 2003.
- [7] GLCF, *GeoCover Technical Guide*. Last access in 2007. [Online]. Available: [http://glcf.umiacs.umd.edu/data/guide/technical/techguide\\_geocover.pdf](http://glcf.umiacs.umd.edu/data/guide/technical/techguide_geocover.pdf)
- [8] J. R. G. Townshend, C. O. Justice, C. Gurney, and J. McManus, “The impact of misregistration on change detection,” *IEEE Trans. Geosci. Remote Sens.*, vol. 30, no. 5, pp. 1054–1060, Sep. 1992.

- [9] X. L. Dai and S. Khorram, "The effects of image misregistration on the accuracy of remotely sensed change detection," *IEEE Trans. Geosci. Remote Sens.*, vol. 36, no. 5, pp. 1566–1577, Sep. 1998.
- [10] R. E. Kennedy and W. B. Cohen, "Automated designation of tie-points for image-to-image coregistration," *Int. J. Remote Sens.*, vol. 24, no. 17, pp. 3467–3490, Sep. 2003.
- [11] Y. Sheng and D. E. Alsdorf, "Automated georeferencing and orthorectification of Amazon basin-wide SAR mosaics using SRTM DEM data," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 8, pp. 1929–1940, Aug. 2005.
- [12] L. M. G. Fonseca and B. S. Manjunath, "Registration techniques for multisensor remotely sensed imagery," *Photogramm. Eng. Remote Sens.*, vol. 62, no. 9, pp. 1049–1056, Sep. 1996.
- [13] H. Li, B. S. Manjunath, and S. K. Mitra, "A contour-based approach to multisensor image registration," *IEEE Trans. Image Process.*, vol. 4, no. 3, pp. 320–334, Mar. 1995.
- [14] B. Zitova and J. Flusser, "Image registration methods: A survey," *Image Vis. Comput.*, vol. 21, no. 11, pp. 977–1000, Oct. 2003.
- [15] L. G. Brown, "A survey of image registration techniques," *Comput. Surv.*, vol. 24, no. 4, pp. 325–376, Dec. 1992.
- [16] A. Goshtasby, G. C. Stockman, and C. V. Page, "A region-based approach to digital image registration with subpixel accuracy," *IEEE Trans. Geosci. Remote Sens.*, vol. GRS-24, no. 3, pp. 390–399, May 1986.
- [17] J. C. Ton and A. K. Jain, "Registering Landsat images by point matching," *IEEE Trans. Geosci. Remote Sens.*, vol. 27, no. 5, pp. 642–651, Sep. 1989.
- [18] J. Flusser and T. Suk, "A moment-based approach to registration of images with affine geometric distortion," *IEEE Trans. Geosci. Remote Sens.*, vol. 32, no. 2, pp. 382–387, Mar. 1994.
- [19] H. J. Xie, N. Hicks, G. R. Keller, H. T. Huang, and V. Kreinovich, "An IDL/ENVI implementation of the FFT-based algorithm for automatic image registration," *Comput. Geosci.*, vol. 29, no. 8, pp. 1045–1055, Oct. 2003.
- [20] B. S. Reddy and B. N. Chatterji, "An FFT-based technique for translation, rotation, and scale-invariant image registration," *IEEE Trans. Image Process.*, vol. 5, no. 8, pp. 1266–1271, Aug. 1996.
- [21] L. C. Smith, "Satellite remote sensing of river inundation area, stage, and discharge: A review," *Hydrol. Process.*, vol. 11, no. 10, pp. 1427–1439, Aug. 1997.