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Performance of Landsat 8 Operational Land Imager for Mapping Ice Sheet Velocity

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Abstract

Landsat imagery has long been used to measure glacier and ice sheet surface velocity, and this application has increased with increased length and accessibility of the archive. The radiometric characteristics of Landsat sensors, however, have limited these measurements generally to only fast-flowing glaciers with high levels of surface texture and imagery with high sun angles and cloud-free conditions, preventing wide-area velocity mapping at the scale achievable with synthetic aperture radar (SAR). The Operational Land Imager (OLI) aboard the newly launched Landsat 8 features substantially improves radiometric performance compared to preceding sensors: enhancing performance of automated Repeat-Image Feature Tracking (RIFT) for mapping ice flow speed. In order to assess this improvement, we conduct a comparative study of OLI and the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) performance for measuring glacier velocity in a range of surface and atmospheric conditions. To isolate the effects of radiometric quantization and noise level, we construct a model for simulating ETM+ imagery from OLI and compare RIFT results derived from each. We find that a nonlinearity in the relationship between ETM+ and OLI radiances at higher brightness levels results in a particularly large improvement in RIFT performance over the low-textured interior of the ice sheets, as well as improved performance in adverse conditions such as low sun-angles and thin clouds. Additionally, the reduced noise level in OLI imagery results in fewer spurious motion vectors and improved RIFT performance in all conditions and surfaces. We conclude that OLI imagery should enable large-area ice sheet and glacier mapping so that its coverage is comparable to SAR, with a remaining limitation being image geolocation.

Keywords

Landsat 8; OLI; LDCM underfly; glacier flow; feature tracking

1. Introduction

The accessibility, long historical archive, frequent repeat cycle and high spatial resolution of Landsat imagery make them an excellent resource for Earth surface change detection over timescales of weeks to decades. Landsat has been used to observe glacier and ice sheet surface motion, through the use of automated Repeat Image Feature Tracking (RIFT), for over two decades (e.g. Bindshadler and Scambos, 1991; Scambos et al., 1993). This

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application has expanded over the past few years following the opening of access to the USGS Landsat archive, and Landsat is now a primary tool for monitoring ice sheet change (e.g. Enderlin et al., 2014). The utility of Landsat, and other optical-band imagery, for measuring ice flow, however, has been generally restricted to cloud free, daytime imagery over areas of high surface texture. These conditions are required to provide enough spatial variability in pixel brightness to enable successful cross-correlation-based matching of features between images. This limitation is largely dependent on the radiometric precision of the imagery. Increasing the precision tends to decrease the ambiguity of the cross-correlation maxima, improving match success. The 8 bit precision of Landsat radiometers through the Landsat 7 Enhanced Thematic Mapper-Plus (ETM+) tends to be inadequate for tracking features over snow-covered terrain and in imagery with low illumination levels and/or with cloud or fog cover; conditions especially common at high latitudes. The Operational Land Imager (OLI) sensor aboard Landsat 8, launched in February 2013, provides imagery with 12-bit precision, a 16-fold increase over ETM+ and its predecessors. A study by Morfitt et al. (2015) positively identified that the radiometric performance such as signal-to-noise ratio (SNR) and dynamic range of OLI outperforms that of ETM+. We would therefore expect the OLI to have improved performance in feature tracking over low contrast surfaces compared to previous Landsat sensors. Here we assess this improvement.

Comparison of OLI and ETM+ performance is complicated by differences in optical band widths. The relative spectral response curves and band indices for these sensors are illustrated in Figure 1. RIFT is most often applied to panchromatic band (number 8 for both sensors) imagery due to its higher (15 m) spatial resolution. The OLI panchromatic band spans approximately half the spectral range of the ETM+ instrument, with a resulting lower wavelength peak in response. While this narrower bandwidth is expected to increase the contrast between vegetated and non-vegetated surfaces (Irons et al., 2012), it is unclear how this difference will impact RIFT performance over ice and snow.

A further complication in comparing sensor performance stems from the Scan Line Corrector (SLC) failure on the ETM+ in May 2003. Following SLC failure, all imagery contains void stripes, resulting in approximately 30% data loss. While the SLC failure did not impact radiometric performance (Markham et al., 2005), the presence of void stripes makes RIFT more challenging, requiring specialized processing schemes (Ahn and Howat, 2011; Warner and Roberts, 2013).

Here we compare the performance of ETM+ and OLI for RIFT of glacier flow speeds in order to assess how the increase in radiometric precision and signal-to-noise ratio impacts the quality of cross-correlation-based feature tracking. The intent is that improved understanding of the sensitivity of results to these differences will guide future sensor development and applications for change detection.

2. Method and Data

Any comparative assessment of ETM+ and OLI characteristics or performance is best achieved using coincident imagery in order to ensure consistent illumination, atmospheric and ground conditions. For this purpose, ETM+ and OLI were flown in tandem mode

between 29 and 30 March 2013, resulting in image acquisitions approximately three to seven minutes apart. This tandem acquisition enables comprehensive cross validation and calibration of ETM+ and OLI radiance measurements (e.g. Mishra et al., 2014). RIFT of glacier motion using Landsat, however, requires a longer temporal separation between repeats than obtainable from the tandem mode dataset and substantial changes in environmental conditions can occur during the eight day lag between Landsat 7 and 8 passes. Thus we adopt an approach in which we compare ice flow velocity results using OLI and simulated ETM+ images. The simulated ETM+ images are created from OLI images using an ETM+/OLI radiance conversion obtained from analysis of tandem mode imagery. By using simulated imagery, we can isolate the combined effects of radiometric precision and signal to noise ratio on RIFT-derived results while ensuring equivalent illumination and environmental conditions and eliminating the influence of data gaps due to SLC failure.

2.1 OLI/ETM+ Conversion and Simulation

We derive a method for converting OLI quantized and calibrated digital numbers (DN) to their ETM+ equivalent using their cross relationship in the measured at-sensor radiance as observed during the 29–30 March 2013 tandem mission. Flood (2014) performed cross comparison of reflectance of each corresponding bands of ETM+ and OLI and used linear regression to estimate ETM+ reflectance from that of OLI in order to estimate biases from the normalized difference vegetation index (NDVI). In that study, the tandem underflight pair was not available due to cloud cover. Moreover, linear regression would not capture possible non-linear camera response (e.g. Dierks, 2004) in the OLI/ETM+ relationship, especially for bright pictures like snow cover.

We utilize 11 near-coincident pairs of OLI and ETM+ images obtained during the tandem mission over the Greenland Ice Sheet (Figure 2). Coregistration errors between image pairs are determined from normalized cross correlation-based image matching (e.g. Scambos et al, 1992) of image corners detected using the method of Shi and Tomasi (1994). The images and the coregistration error statistics are listed in Table 1.

Each panchromatic image pair is converted from DN to radiance using the conversion parameters in the metadata. The overlapping area of each image pair was regridded to the same map coordinate system using bilinear interpolation, excluding void pixels. As the pixels near both ends of the swath of ETM+ are already contaminated by the void values, they were also excluded. A Gaussian filter (21×21 pixels of kernel size with $\sigma^2=15$) was applied to mitigate effects of noise.

Due to the non-linearity in the relationship between OLI and ETM+ radiance we do not use linear regression to derive a conversion model. Instead we construct a Lookup Table (LUT) for each tandem pair by calculating mean and number of OLI samples corresponding to ETM+ spatial bins that are equally spaced. Standard deviations of samples in each bin were also calculated to estimate the uncertainty. The mean values of each pair were weight-summed by the number of samples per bin to build a global LUT. The uncertainty of the global LUT was calculated based on that of the local curves and their weight. The mean bias in the LUT result for the eleven pairs is -0.17 and the standard deviation is $11.96 \text{ W/(m}^2\text{sr}\mu\text{m)}$. These are equivalent to -0.17 and 12.26 in DN of ETM+ in low-gain mode.

Considering that this bias is less than quarter of the DN quantization, and that the standard deviation is mainly due to image noise and misalignment, we observe no significant error in the LUT-based conversion.

Another difference in radiometric performance is the amount of sensor noise. Noise is considered as the standard deviation of observed radiance from a target with known constant irradiance. Scaramuzza et al. (2004) and Morfitt et al. (2015) modeled the radiance-dependent noise equivalent change in radiance of certain wavelength λ ($NE\ L(R_\lambda)$) as:

$$NE\Delta L(R_\lambda) = \sqrt{a + bR_\lambda} \quad (1)$$

where a and b are coefficients with different values for each ETM+ and OLI band. The noise is also affected by image smoothing from interpolation during reprojection and increased by quantization to 8-bit DN image. Including these effects into the noise model gives:

$$v_T(R_\lambda) = \sqrt{m \cdot NE\Delta L(R_\lambda)^2 + q^2} \quad (2)$$

where m is a factor for resampling noise scaling, 0.81 for bicubic convolution, and q is 8-bit quantization noise which is 0.281 W/(m²srμm) for panchromatic band of ETM+ in low gain (Scaramuzza et al., 2004).

The increase in $NE\ L$ with the square root of radiance in equation (1) suggests that fluctuations in the number of detected photons, which follows a Poisson distribution, is the primary source of noise. However, due to the large of number of photons detected per sample, and the contribution of other error sources, the noise is typically considered to follow a Gaussian distribution (e.g. Liu et al., 2008; EMVA 2010; Hasinoff, 2014). Thus, the measured radiance was assumed to follow a normal distribution with mean of $\mu_{R\lambda}$ and variance of $v(R_\lambda)^2$, thereby its mean value becomes the “measured” radiance and dispersion becomes the noise. In the noise simulation, q in equation (2) was set to zero because the ETM+ simulation already incorporates the effect of quantization.

2.2 Feature Tracking Test Cases

We perform RIFT on OLI and corresponding simulated ETM+ image pairs to extract glacier velocity maps for three major and well-studied glacier systems as test cases:

Kangerdlugssuaq (KL) and Jakobshavn Isbræ (JI) in Greenland and Pine Island Glacier (PIG) in Antarctica (Figure 2). We purposefully selected image pairs with conditions typically considered adverse to RIFT, including low-contrast and uncrevassed snow surfaces (all scenes), varying degrees of cloud cover (KL and PIG) and low-light conditions in ascending orbit (JI and PIG) (See Table 2 for details). The selected images are as listed in the first three items in Table 2. All pairs were reprojected to polar stereographic and clipped to areas of overlap. The preprocessed images in the adverse conditions are as presented in Figure 3.

In the case of KL, (first column of Figure 3) the earlier image in the pair is covered by cloud so that the surface texture is almost invisible without any enhancement. The pair for JI (second column of Figure 3) have a relatively small DN range, as they were acquired with a low sun angle. Surface texture is still visible, however, despite the low light conditions. The image pair for PIG (third column of Figure 3) includes both extensive cloud cover and low sun angle conditions. The first image in the pair has scattered cloud cover at the end of the ice stream and thick cloud cover on the margins. The latter image of the pair is brighter than the earlier one, but clouds substantially obscured the ice stream.

To serve as a benchmark of comparison, we also applied RIFT to high quality (cloud-free image with sufficient contrast) image pairs from the same locations and near the same acquisition times as with the adverse-conditions set. Thus, these pairs represent an ideal case from which to isolate the effects of the adverse scene conditions on RIFT performance for both simulated ETM+ and OLI (See Table 2 for details). These benchmark pairs are listed in lower three items in Table 2. We note that although the KL pair was acquired in ascending orbit, we visually confirmed that the images display an abundance of trackable surface textures.

The complete procedure for the ETM+ simulation and RIFT application is illustrated in Figure 4. The radiance of OLI is converted to that of ETM+ using the derived global LUT. The random noise based on the normal distribution of R_{λ} discussed in section 2.1 was added to the converted ETM+ radiance. The simulated ETM+ radiance was converted to DN using the coefficients in the metadata and quantized to 8 bit unsigned integer. RIFT was then applied to both OLI and simulated ETM+ pairs and their quality was assessed. Additionally, in order to isolate the effects of radiometric precision and noise level on RIFT performance, RIFT was applied to simulated ETM+ pairs both with and without noise added.

2.3. RIFT processing

We utilized the Multi-Image Multi-Chip (MIMC) RIFT algorithm originally devised by Ahn and Howat (2011) and improved by Jeong et al. (submitted) to track glacier surface motion. The MIMC algorithm locates the peak in normalized cross-correlation between subsets of coregistered imagery (i.e. image chips) testing multiple convolution filters, using a range of chip sizes and by swapping the images (i.e. Quadramatching). The most probable correct match is then selected from the population of displacement estimates for each reference chip. Additionally, an existing velocity maps (i.e. Rignot et al., 2011; Joughin et al., 2010) are used as *a priori* to constrain the match space within a tolerance.

The largest error source in RIFT of glacier flow speed using Landsat imagery orthorectified by the USGS is typically the error in image coregistration. Coregistration errors arise from the difference in incidence angles between images and errors in the Digital Elevation Model (DEM) used to orthorectify the images (Scherler et al., 2008). Coregistration errors are largely mitigated by using image pairs acquired from the same path/row, so that most of the errors arising from both sources cancel out when measuring displacement. We correct for any remaining coregistration error by subtracting the average measured displacement over stationary (i.e. ice free land) surfaces. If no control points can be located, coregistration is performed over slow flowing (less than 10 m/yr) areas identified in existing, SAR-derived

maps (Rignot et al. 2011, Joughin et al. 2010). Following these corrections, the standard deviation of the control points' displacements ranged approximately from 0.12 to 0.52 pixels, which corresponds to approximately 110 ± 70 m/yr of coregistration error to the observed velocity for a 16-day repeat cycle.

Additionally, the MIMC algorithm provides a metric of match reliability, termed the matching ratio, which is the ratio (0–1) of successful matches to all multiple matching attempts in each measurement grid (Jeong et al., submitted). A larger matching ratio indicates more consistency among the population of matches for each grid point, so that the match is more reliable. A smaller matching ratio indicates a large variation in the match solution for different attempts, and thus a less reliable match. We use this metric, along with the velocity field, as indicators of RIFT performance.

3. Results and discussion

3.1. LUT and test image pairs

The radiance of each ETM+ and OLI pair are plotted against each other in Figure 5. We find a consistent relationship between the radiance of OLI and ETM+ presented in the series of plots in Figure 5, which includes a nonlinearity in the brighter region (radiance > 270 W/m²sr μ m). This nonlinearity is due to narrower range in ETM+ radiance than OLI for bright areas, which is most prominent over clouds, icebergs and shadows.

Compared to vegetated areas, ice sheets have simpler composition of land cover (i.e. rocks, snow and ice). Also considering the consistency in the local LUTs regardless of their respective locations and land cover variance, it can be assumed that our test sites will also have similar ETM+/OLI radiance pattern as the tandem pairs.

Except for the images in subplots of 006/002, all ETM+ radiances shown in Figure 5 reach saturation whereas the maximum OLI radiances are approximately 300 W/m²sr μ m below saturation. This demonstrates the tendency of ETM+ to saturate over snow or glaciers while OLI provides an expanded range at higher radiances.

The image pair from path 6, row 12 has a narrower range in radiance because this image covers only ice sheet without moraines or bedrock outcrops. The anomalously high scatter for path 230, row 13 is the result of a large coregistration error, causing misalignment of pixels between pairs and spurious comparisons of radiance.

Cloud cover in Figure 3, as seen in the earlier image in adverse KL pair and latter image in adverse PIG pair, can partially obscure the surface, resulting in either spurious or failed matches. However, OLI's improved radiometric resolution may increase the likelihood of successfully detecting surface texture through partially transparent cloud cover.

Low illumination conditions demonstrated in the adverse JI and PIG pairs also affect RIFT performance. The performance in such conditions is dependent on sensor gain, signal-to-noise ratio (SNR), dynamic range and radiometric resolution, all of which determine sensor sensitivity. Quality will also be affected by large shadows, which obscure the surface and/or cause spurious matches.

3.2. OLI RIFT Results

We analyzed RIFT performance for observing glacier motion using the three OLI image pairs obtained in adverse image conditions (upper three pairs in Table 2) in comparison with an identical, benchmark set obtained in near ideal conditions (lower three pairs in Table 2). Speed maps and flow line profiles obtained from the OLI imagery pairs are shown in Figure 6. Nearly complete, high quality coverage is obtained from the benchmark OLI pairs (Figure 6(d)-(f)), even over low contrast (snow) surfaces further into the interior of the ice sheets. The only areas yielding consistently poor matching results are areas of rotational displacements, such as along shear margins (A1 in Figure 6(d)) and the bend in flow (A2 of Figure 6(e)). This is due to the inability of the RIFT algorithm to resolve non-translational flow and/or loss of coherence in features. To validate RIFT performance with OLI in adverse conditions, we compare velocities extracted along the central flow line from both the adverse and near-ideal pairs (Figure 6(g)-(i)). The difference between the overlaid speed profiles are presented in Table 3 in terms of bias and root mean squared error (RMSE). Since these pairs were acquired within weeks of each other, little change in ice flow velocity is expected, with the exception of changes close to the calving front. We find close agreement between speed profiles in all cases, indicating that successful matches are obtained in both cloudy and low-light conditions, as well as over the low-texture interiors. Noise in the PIG speed profile corresponds to the areas of most opaque cloud cover.

3.3 ETM+ Simulation

In order to compare OLI and ETM+ performance for RIFT measurements of glacier motion, we simulated ETM+ images from the adverse-conditioned OLI test pairs using the LUT described in section 2.1. Figure 7 presents the with and without added noise ETM+ simulation results derived from the OLI images shown in upper two rows in Figure 3. We expect the decrease in radiometric precision to result in a substantial decrease in image texture, which is most clearly evident in the saturation of brighter surfaces in Figure 7.

The “texturedness” (Shi and Tomasi, 1994) of an image can be measured by calculating the minimum eigenvalue of structure tensor Z of image $I(x,y)$, defined as:

$$Z = \sum_w \begin{bmatrix} g_x^2 & g_x g_y \\ g_x g_y & g_y^2 \end{bmatrix} \quad (3)$$

in which $\sum_w$ means to sum all values in a moving window w , and

$$\begin{bmatrix} g_x \\ g_y \end{bmatrix} = \nabla I(x, y) \quad (4)$$

The minimum eigenvalues of the images in each case (OLI, simulated ETM+ without noise, and simulated ETM+ with noise) are presented in Figure 8, showing substantial degradation in texturedness between OLI and ETM+ due primarily to loss of radiometric resolution.

Brighter areas, such as fresh snow, show the largest degradation in texturedness. This can be explained, firstly, by saturation, as seen in the comparison of cloudy and snow covered regions in Figures 8(a, d) and their texturedness in Figure 8(g, j). Also contributing to the loss of texturedness over bright areas is the non-linear relationship between OLI and ETM+ radiance for the brighter end of the spectrum. For brighter radiances, ETM+ spans a relatively narrower range of radiance, causing a relatively higher loss in gradation and texturedness. Substantial losses in texturedness are also found on the side of main trunk of JI in Figure 8(k) in a region with low brightness and gradation in the DN, as shown in Figure 7(e). In the case of PIG (Figure 8(i, l)), the texturedness of upglacier regions was mostly reduced by discretization while the texturedness of low-contrast areas associated with narrow DN distributions was reduced due to the low brightness.

Comparison of the Eigenvalue images for test images with and without added noise in Figure 8 reveals the strong effect of noise on texturedness. For example, texturedness in noiseless images in Figure 8 (g, k, and i) is almost removed entirely by the addition of random noise in Figure 8(m, q, and o), indicating that the signal to noise ratio is not high enough to preserve textures distinguishable from noise. In order to obtain useable RIFT results, both of the eigenvalues of the structure tensor need to be larger than noise level (Shi and Tomasi, 1994). We therefore expect that the lower signal to noise ratio of ETM+ would result in substantially lower RIFT performance.

The resulting RIFT speed map from each test pair and the matching ratio are presented in Figure 9. The velocity results obtained from the OLI pairs have the fewest numerical artifacts and provide the most continuously high matching ratios, with high confidence results obtained over snow covered terrain in low light conditions and through thin clouds. Figure 9 and the maps of speed difference in Figure 10 confirm that RIFT performance was substantially degraded in up-glacier regions for the simulated ETM+ pairs without added noise, where the loss of texturedness was most substantial as shown in Figure 8. Moreover, significant difference in the measurement was found from bedrock outcrop region in Figure 10(b), which means the texture on this dark surface is not trackable using ascending images of ETM+. Good results, however, were still obtained on the glacier trunks in areas of fast flow where high texturedness was maintained from the noiseless pairs. This figure also identifies additional performance loss from the noise-added ETM+ pairs, even on the main trunks. The speed differences in Table 4 also show that the noise-added images had lower performance than the noiseless images. As shown in the texturedness plot in Figure 8(m)-(r), the level of noise is as high as that of texture, preventing successful matches.

For RIFT velocities obtained from the noiseless ETM+ simulated image pairs, the largest loss in matching ratio occurred over low-contrast snow and thin cloud surfaces. This implies that the difference in radiometric resolution is the major control on performance in those regions. In contrast, adding noise reduces the matching ratio over the entire area and was most severe in areas of clouds and in low-light conditions. It is notable that the degradation in matching ratio over textured surfaces due to increased noise is of a similar magnitude to the degradation over low contrast regions due to loss in radiometric precision.

4. Conclusions

We have demonstrated the improved performance of OLI over ETM+ in extracting surface velocity of glaciers using RIFT due to an increased radiometric precision and lowered noise levels. Comparison of images acquired during the tandem-mission OLI and ETM+ underfly revealed a non-linearity in the relationship between the two sensors' radiances at the brighter end of the range, indicating that OLI is better able to resolve gradations in radiance over bright terrains, such as snow, and it is less prone to saturation. We derived a LUT method for simulating ETM+ from OLI imagery to assess the degradation in radiometric and RIFT performance over an image test suite of major glaciers and using imagery obtained in both adverse and near-ideal conditions for RIFT. We found that OLI is able to obtain high-confidence RIFT results over low contrast surfaces, such as snow, through thin clouds and in low-light conditions. The ETM+ images simulated from the OLI without synthetic noise yielded RIFT results that were substantially degraded over low-contrast and bright (i.e. snow covered) terrain owing to the reduced radiometric precision. Adding synthetic noise to the simulated ETM+ imagery resulted in further RIFT quality loss over the main trunks of the glaciers, in areas of high texture, affected mostly by the adverse image conditions.

The relatively high performance of OLI suggests that it will provide substantially more useful velocity measurements over glaciers and ice sheets than its predecessors, allowing for large-area velocity mapping in regions that optical methods were previously not able to resolve. Although precise (sub-meter) displacement measurement is still challenging with OLI, its wider coverage is expected to enable complete, continental-scale ice flow velocity maps comparable to those produced from active microwave sensors, such as RADARSAT (e.g. Rignot et al., 2011; Joughin et al., 2010). Further, RIFT quality from OLI appears to be far less sensitive to light conditions and cloud cover, allowing for more frequent repeats over a longer period of the year, enabling measurement of changes in glacier motion corresponding to seasonal conditions. The largest remaining challenges for OLI's application to RIFT in polar areas are the high co-registration errors resulting from poor ground control and digital elevation models used for image orthorectification. These can provide errors of 10's of meters or more for image pairs acquired from different orbits. This error can lead to very large velocity errors in regions of slow flow in ice sheet interiors and prevent change detection. It is crucial that strategies be pursued to reduce or mitigate these co-registration errors in order to unlock OLI's potential for ice sheet and glacier observations.

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Figure 1. Relative response curves for ETM+ (top, increasing y-axis) and OLI (bottom, decreasing y-axis) in visible and near/mid infrared range. The band designations of each sensors are as labeled on the curves.

Figure 2.

Tandem mode image pairs over Greenland during the underfly event of LDCM (Landsat 8) and Landsat 7, showing the coverage of tandem pairs. Path / Row of image tiles are as labeled in each rectangles. Image details are listed in Table 1. Note that no tandem data was available for the Antarctic study area (inset). Points and labels show the locations of glaciers targeted in this study: Jakobshavn Isbrae (JI), Kangerdlugssuaq (KL) and Pine island glacier (PIG).

Figure 3.

Clipped and reprojected OLI Image pairs presented in Table 2. The first, second, and third columns are images for KL, JI and PIG respectively. The upper two rows are images in adverse conditions, while the ones in lower two rows are in ideal conditions. Their DAQ times are provided at top of each plot. The scale of DN's are as presented in grayscale bar in each plot.

Figure 4. Procedure for ETM+ simulation and feature tracking. Regions enclosed with dashed lines are part of the simulation.

Figure 5.

Scatter plots of radiance in panchromatic bands of ETM+ and OLI for each test pair, labeled by path/row. The LUT curves derived from each are overlaid. The bottom right panel is the global LUT, which is weighted sum of the local LUTs. Standard deviations of R_{oli} corresponding to each R_{ETM+} bin are plotted on each y axes of each. The upper limit of horizontal and vertical axes approximates saturation radiance of each sensor presented in Morfitt et al. (2015).

Figure 6.

Comparison of speed profiles along streamline measured from the OLI pairs listed in Table 2. (a)-(c): Speed maps of KL, JI, and PIG from the ideal-case pairs in Table 3. (Color is in log scale) and (d)-(f): their corresponding matching ratio maps. (g)-(i): Speed profiles of KL, JI and PIG respectively extracted from the flow lines shown in (a)-(c). The extracted streamlines are plotted on speed maps of each site. The DAQ times of the speed profiles are presented in legends. Areas of shear margin (A1 in (d)) and bending flow (A2 in (e)) are marked with green circles. Noisy speed profile in (i) was obtained from the area of thick cloud cover.

Figure 7.

Simulated ETM+ image pair of Kangerdlugssuaq, Jakobshavn and Pine island glacier from OLI images presented in adverse-condition pairs in Figure 3.

Figure 8.

Minimum Eigenvalues of image structure tensors as indicator of the texturedness of the image. The first, second and the third columns are maps from KL, JI and PIG respectively. The first and the second rows are the texturedness of the adverse-conditioned OLI images. The third and fourth rows are the ones of the simulated ETM+ image without noise. The fifth and sixth rows are the measurements of the noise-added ETM+ simulation results. The odd rows are the results from the earlier image in each pair, and even rows are from the latter one. The value was color-coded in log scale.

Figure 9.

Speed map and matching ratio of KL, JI and PIG, derived from simulated ETM+ pairs (noiseless and noise-added). Each rows represents KL, JI and PIG. The first and the second rows are results from the original OLI pairs. The third and the fourth rows are ones from the noiseless ETM+ simulated pairs. The fifth and the sixth are the measurements from the noise-added ETM+ pairs. Odd and even rows are plots of speed and matching ratio respectively. Speeds are plotted in log scale.

Figure 10.

Speed difference of the simulated ETM+ image pairs of (a,d): KL, (b,e): JI, and (c,f): PIG, with respect to the original adverse-conditioned OLI pairs. (a-c) are from noiseless simulated ETM+ images, and (d-f) are those of nose-added simulated images.

Table 1.

Underfly tandem image pairs used for the LUT generation.

Path/Row	Sensor	Scene ID	Data acquisition (DAQ) time (scene center)	Coreg. err. (m)	
				$\mu x, \mu y$	σ_x, σ_y
006/ 012	ETM+	LE70060122013088EDC00	29 March, 2013, 14:38:31	16.56	53.86
	OLI	LC80060122013088LGN03	29 March, 2013, 14:45:50	161.14	30.28
006/ 013	ETM+	LE70060132013088EDC00	29 March, 2013, 14:38:55	-4.14	17.65
	OLI	LC80060132013088LGN03	29 March, 2013, 14:46:14	-3.46	9.32
006/ 014	ETM+	LE70060142013088EDC00	29 March, 2013, 14:39:18	-0.76	17.18
	OLI	LC80060142013088LGN03	29 March, 2013, 14:46:38	-3.62	16.34
006/ 015	ETM+	LE70060152013088EDC00	29 March, 2013, 14:39:42	-5.22	8.95
	OLI	LC80060152013088LGN03	29 March, 2013, 14:47:01	0.91	6.23
013/ 009	ETM+	LE70130092013089EDC00	30 March, 2013, 15:20:34	1.94	39.77
	OLI	LC80130092013089LGN01	30 March, 2013 15:23:13	-2.18	36.94
013/ 010	ETM+	LE70130102013089EDC00	30 March, 2013 15:20:58	6.98	11.72
	OLI	LC80130102013089LGN01	30 March, 2013 15:23:37	-4.96	8.99
013/ 011	ETM+	LE70130112013089EDC00	30 March, 2013 15:21:22	17.41	21.12
	OLI	LC80130112013089LGN01	30 March, 2013 15:24:01	16.06	27.98
230/ 010	ETM+	LE72300102013089ASN00	30 March, 2013 13:42:06	-2.76	21.03
	OLI	LC82300102013089LGN01	30 March, 2013 13:45:03	2.72	15.30
230/ 011	ETM+	LE72300112013089ASN00	30 March, 2013 13:42:30	-7.10	40.65
	OLI	LC82300112013089LGN01	30 March, 2013 13:45:27	-8.08	34.32
230/ 012	ETM+	LE72300122013089ASN00	30 March, 2013 13:42:53	-3.82	12.87
	OLI	LC82300122013089LGN01	30 March, 2013 13:45:50	-3.13	8.82
230/ 013	ETM+	LE72300132013089ASN00	30 March, 2013 13:43:17	35.73	48.45
	OLI	LC82300132013089LGN01	30 March, 2013 13:46:14	61.35	24.93

Table 2.

OLI image sources utilized for feature tracking.

Scenario (Location)	Path/ Row	Scene ID	DAQ time (scene center)
Cloud cover (KL)	230/ 012	LC82300122014148LGN00	28 May, 2014, 13:46:24
		LC82300122014164LGN00	13 June, 2014, 13:46:32
Ascending image (JI)	081/ 233	LC80812332014192LGN00	11 July, 2014, 23:53:59
		LC80812332014208LGN00	27 July, 2014, 23:54:03
Marginal winter w/ cloud cover (PIG)	232/ 113	LC82321132014258LGN00	15 September, 2014, 14:39:37
		LC82321132014274LGN00	01 October, 2014, 14:39:38
Ideal images (KL)	073/ 232	LC80732322014152LGN00	01 June, 2014, 23:03:54
		LC80732322014168LGN00	17 June, 2014, 23:04:00
Ideal images (JI)	008/ 011	LC80080112014193LGN01	12 July, 2014, 14:54:17
		LC80080112014209LGN00	28 July, 2014, 14:54:21
Ideal images (PIG)	232/ 113	LC82321132014322LGN00	18 November, 2014, 14:39:39
		LC82321132014338LGN00	04 December, 2014, 14:39:39

Table 3.

Bias and RMSE of speed profiles from adverse OLI pairs with respect to ideal OLI pairs.

Measure	KL	JI	PIG
Bias (m/yr)	205.22	11.96	9.37
RMSE (m/yr)	120.56	338.66	256.02

Table 4.

Bias and RMSE of speeds between original OLI and simulated ETM+ images (with and without noise). All values are in unit of m/yr.

Measure / condition	KL	JI	PIG
Bias / without noise	179.00	142.28	187.49
Bias / with noise	256.60	667.12	270.27
RMSE / without noise	405.70	447.83	623.26
RMSE / with noise	444.69	592.65	800.15