ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 4) Pages (172-183)
IJREB
Journal home page: www.ijreb.org

ADAPTIVE SMOOTH FILTERING BASED ON INTENSITY MODULATION FOR SATELLITE IMAGE PAN-SHARPENING

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ABSTRACT

Image fusion techniques are widely used to integrate a lower spatial resolution multispectral image with a higher spatial resolution panchromatic image. The fusion of these channels is called Pan sharpening. Even though the existing pan sharpening techniques have several advantages, there exist many disadvantages such as spectral distortion, implementation expense, computational complexity and time consuming decomposition and reconstruction process. This paper proposes an advanced technique called Smooth filter based intensity modulation (SFIM) based on simplified solar radiation and land surface reflection model. This technique improves spatial resolution and also minimizes the spectral distortion of the satellite images.

KEYWORDS: multispectral image, panchromatic image, Pan sharpening, SFIM

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

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Journal home page: www.ijreb.org

INTRODUCTION

Satellite is an artificial object which has been intentionally placed into the orbit. Such objects are sometimes called artificial satellites to distinguish them from natural satellites such as moon. Earth observation satellites such as IKONOS, Quick bird, Geoeye are composed of a panchromatic channel and multispectral channel. The remote sensing image data acquired by the sensors of these satellites have been widely used. The sensors have a physical link between the spatial and the spectral resolutions. The method of integrating the geometric detail of a high resolution panchromatic image and the spectral information of a low resolution multispectral image to produce a high resolution multispectral image are called Pan-sharpening.

Pan-sharpening is mainly used in land use classification, change detection, map updating. Land use involves the management and modification of natural environment or wilderness into built environment such as fields, pastures, and settlements. It also provides a provision of new or revised information to a digital road. Pan-sharpening can overcome the limitations of individual sources information and obtain a better understanding of observed scene. Simple pan-sharpening methods aim at providing a color image of pleasing and sharp appearance. Human visual perception has an LR in the three color channels than in the black and white (panchromatic) channel. Evaluation of remote sensing data, calls for more sophisticated methods. The aim of pan-sharpening is to obtain HR multispectral image with same spectral response as the multispectral sensors but the spatial resolution of the panchromatic sensors. A particular difficulty is that, in general, the panchromatic pixel value cannot be considered to be simply the linear combinations of one in the spectral bands. The reason is that the spectral bands may not add up to the panchromatic sensitivity band.

Among the existing hundreds of various pan-sharpening methods, the most popular ones are IHS [1] (Intensity hue saturation technique). In color image three bands of a multispectral image are considered. The transformation of intensity -hue-saturation is performed, which separates the intensity information from the color information (hue and saturation).Then the panchromatic image replaces the intensity image. Pan-sharpened image is created by inverse IHS transform. The drawback of this

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

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Journal home page: www.ijreb.org

method is that it is only suitable to a three-band multispectral image.

Another conventional method of pan-sharpening is PCA[2] (Principal Component Analysis).To the original image PCA is applied, then the first principle component (PC) image is replaced by the panchromatic image. First principal component image with largest variance contains the major information in the original image. However, data information is distributed among several PCs. So this method brings about spectral distortion.

Brovey transform is another technique in pan-sharpening, which is actually a band-multiplicative method. For i-th band, it is generated by: Fused band i = Pan * Band i / (band 1+ band 2+ ……+ band N).

The computation is on pixel by pixel basis. A wavelet based method [3] includes three steps: forward transform, coefficient combination, and backward transform. Different ways are there to fuse the wavelet coefficients of the original image and panchromatic image. For example, one fusion rule takes the vertical, horizontal, and detail coefficients from the multispectral image. Another rule takes the average of vertical, horizontal, and diagonal coefficients of the panchromatic and multispectral images, and takes the approximation coefficients from the multispectral image. S.li and Bin Yang [4] addresses the remote sensing image pan-sharpening problem from the perspective of compressed sensing (CS) theory. First ,the degradation model from high-to-low resolution multispectral image and panchromatic image is constructed as a linear sampling process which is formulated as a matrix. Finally, the basis pursuit algorithm is also used to resolve the restoration problem. Another compressed sensing based pan-sharpening method [5] which views the image observation model as a measurement process in the CS theory and constructs a joint dictionary from LRM and HRP images in which the HRM is sparse. X Zhu and Richard Balmer [6] address another problem of resolving two closely spaced complex-valued points from N irregular Fourier domain samples.

Another algorithm used for pan-sharpening is SPARSEFI algorithm [7]. It is based on the compressive sensing theory explores the sparse representation of HR/LR multispectral image patches in the dictionary pairs co trained from the panchromatic image

IJREB

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and its down sampled LR version. Sparsefi algorithm includes mainly three steps a) dictionary learning b) sparse coefficients estimation c) HR multispectral image.

Sparse FI explores the sparse representation of multispectral image patches in a dictionary trained only from the panchromatic image at hand. Therefore, no HR multispectral images from other sensors are required. The Sparse FI algorithm also does not assume any spectral composition model of the panchromatic image and gives robust performance against spectral model errors. Compared with conventional methods, sparse reconstruction based methods "learn" from, i.e., adapt themselves to, the data. Due to the super-resolution capability and robustness of the used sparse reconstruction technique, these methods are expected to give higher spatial and spectral resolution with less spectral distortion compared with other existing methods.

ADAPTIVE SMOOTH FITER BASED INTENSITY MODULATION

The digital number (DN) value of a daytime optical image of reflective spectral band is mainly determined by two factors: the solar radiation impinging on the land surface, irradiance, and the spectral reflectance of the land surface $\rho(\lambda)$.

$$DN(\lambda) = \rho(\lambda)E(\lambda) \qquad (1)$$

The SFIM aims at producing synthetic images (fused products) having the highest spatial resolution in the same multispectral bands of the original low resolution images. The SFIM technique is defined as

$$DN(\lambda)_{SIM} = \frac{DN(\lambda)_{low}\, DN(\gamma)_{high}}{DN(\gamma)_{mean}}$$

$$\frac{\rho(\lambda)_{low}\, E(\lambda)_{low}\, \rho(\gamma)_{high} E(\gamma)_{high}}{\rho(\gamma)_{low}\, E(\gamma)_{low}}$$

$$\approx \rho(\lambda)_{low}\, E(\lambda)_{high} \qquad (3)$$

Where(digitalnumber) $DN(\lambda)$sim is the simulated higher resolution pixel corresponding to $DN(\lambda)low$ and $DN(\gamma)_{mean}$ the local mean of $DN(\gamma)high$ over a neighborhood equivalent to the resolution .

For a given solar radiation, irradiance upon a land surface is controlled by topography. If the two images are quantified to the same DN range, we can presume $E(\lambda) \approx E(\gamma)$ for any given resolution because both

ISSN 2321-743X
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vary with topography in the same way. We can also presume $\rho(\gamma)_{low} \approx \rho(\gamma)_{high}$ if there is no significant spectral variation within the neighborhood for calculating DN (λ) mean. Thus in

$$\frac{\rho(\lambda)_{low}\,E(\lambda)_{low}\,\rho(\gamma)_{high}E(\gamma)_{high}}{\rho(\gamma)_{low}\,E(\gamma)_{low}} \qquad (4)$$

The local mean $DN(\lambda)_{mean}$ is calculated for every pixel of the higher resolution image using a smoothing convolution filter. The filter kernel size is decided based on the resolution ratio between the higher and lower resolution images. For instance, to fuse a 30m resolution TM band image with a 10m resolution SPOT Pan image, the minimum smoothing filter kernel size for calculating the local mean of the SPOT Pan image pixels is 3x 3 defined as

$$\frac{1}{9}\begin{pmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{pmatrix}$$

This is the key difference between the SFIM and PBIM. For PBIM, $DN(\lambda)_{mean}$ is calculated only once for each lower resolution pixel block as an average of all the higher resolution pixels within the block. It does not change within a pixel block because the TM6 DNs are identical in the block. However, convolution smoothing has to be performed to calculate$DN(\lambda)_{mean}$ for every higher resolution pixel in the SFIM technique because there is not pixel block structure between the warping co-registered lower resolution image and the higher resolution image.

As the spectral difference between the lower and the higher resolution images is not fundamental to the operations, can be further simplified as a general processing algorithm of the SFIM:

$$IMAGE_{SFIM} = \frac{IMAGE_{low}\,IMAGE_{high}}{IMAGE_{mean}} \qquad (5)$$

where IMAGE $_{low}$ is a pixel of a lower resolution image co-registered to a higher resolution image of IMAGE $_{high}$, IMAGE $_{mean}$ a smoothed pixel of IMAGE $_{high}$ using averaging filter over a neighborhood equivalent to the actual resolution of IMAGE $_{low}$. The SFIM is therefore reliable to the spectral properties as well as contrast of the original lower resolution image.

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ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

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Journal home page: www.ijreb.org

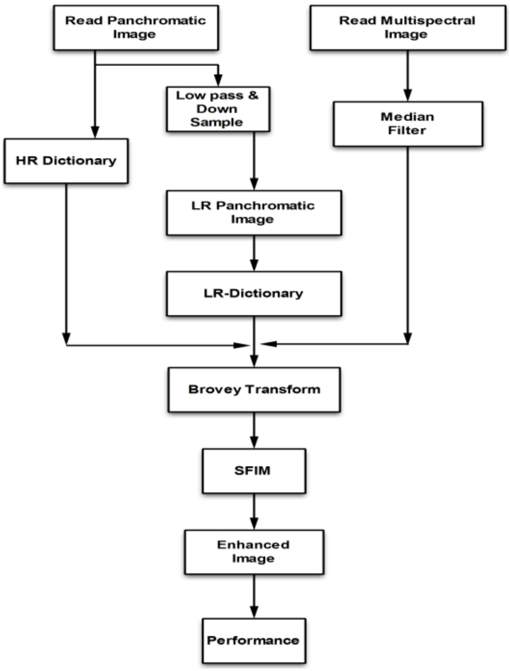

Figure 1. SFIM process

SFIM technique involves mainly some process such as dictionary learnig of both high resolution and low resolution image,brovey transform etc.

1) *Read panchromatic image and multi spectral image*

The panchromatic image and multi spectral image are read from the database. Multispectral images are the main type of images acquired by remote sensing (RS) radiometers. Dividing the spectrum into many bands, multispectral is the opposite of panchromatic, which records only the total intensity of radiation falling on each pixel.

2) *Low pass and down sample*

The HR pan image X_0 is low-pass filtered and down sampled by a factor of FDS (typically 4–10) such that it has a final point spread function similar to a sampling grid identical to the multispectral channels. The resulting LR version of X_0 is called Y_0. This down sampling step may be combined with the co registration of the different channels that is required, anyway.

3) *LR panchromatic image*

The LR pan image Y_0 and the LR multispectral image Y are tiled into small (typically 3 × 3to9 × 9) possibly, but not necessarily, partially overlapping patches y_0 and y_k, where k stands for the kth channel and k =1,..., N.

4) *LR-directory*

All LR patches y_0 with pixel values arranged in column vectors form the matrix D_l called the LR dictionary.

5) *HR-directory*

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ISSN 2321-743X

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The HR dictionary D_h is generated by tiling the HR pan image X_0 into patches x_0 of FDS times the size as the LR pan image patches, such that each HR patch corresponds to an LR patch.

6) *Median filter*

Median filtering is a nonlinear process useful in reducing noise. It is also useful in preserving edges in an image while reducing random noise. A slide along the image and the median intensity value of the pixels within the window becomes the output intensity of the pixel being processed.

7) *Brovey transform*

Brovey transform involves a red-green-blue (RGB) color transform method. It retains the corresponding spectral feature of each pixel, and transforms all the luminance information into a panchromatic image of high resolution.

8) *SFIM*

For every higher resolution pixel in the SFIM technique because there is not pixel block structure between the warping co-registered lower resolution image and the higher resolution image. The SFIM is therefore reliable to the spectral properties as well as contrast of the original lower resolution image.

9) *Enhanced image*

The process of improving the quality of a digitally stored image by manipulating the image. To make an image lighter or darker, or to increase or decrease contrast.

10) *Performance*

We compare the existing method with the proposed method in terms of its efficiency for performance analysis.

11). *Individual band fusion and filter kernel size optimization*

One advantage of the SFIM technique is that it can perform data fusion for individual spectral band images. Figure 2 shows SPOT Pan and TM band 5 fusion result. The TM band 5 was chosen for illustration because it shows more spectral variety of lithology than other bands. Thus the fidelity of the technique to the original spectral property can be effectively demonstrated using this band. The TM5/SPOT Pan fused image using the SFIM with a 3* 3 smoothing filter (figure 2(*d*)) presents much more spatial details than the TM5 (figure 2(*c*)) without noticeable spectral distortion. However, the improved texture features are

IJREB
ISSN 2321-743X
International Journal of Research in
Engineering and Bioscience
Volume 2 (Issue 4) Pages (172-183)
Journal home page: www.ijreb.org

blurred by slightly mismatched edges. The SFIM is sensitive to the accuracy of image co-registration. Edges with imperfect co-registration will be displayed as faint double lines because the cancellation between E(l) low and E(c) low in formula (4) is not complete in such a case. Unfortunately, it is difficult to achieve very high co-registration accuracy between images with different spatial resolutions based on manually selected ground control points using commercial image processing software packages for remote sensing applications.

The problem of edge blurring can be overcome by using a smoothing filter with a larger kernel than the resolution ratio. In such a case, E(c) low is lower frequency information than E(l) low in formula (4). The division between the two does not lead to a complete cancellation and the residual is the high frequency information of the lower resolution image relating to edges. Thus, in the fused image, the major edges appearing in both images will be sharpened while the subtle textural patterns, which are recognizable only in the higher resolution image, will be retained. Figure 2(e) is processed using the SFIM with a 5×5moothing filter; the blurring effects are effectively suppressed while the spatial details are significantly improved. For example, the river channels along the south of the mountain foot are blurred in figure 2(d) but become clear and sharp in figure 2(e). The problem is therefore resolved without further refining the co-registration.

The improvement of spatial details from figure 2(c)–(e) is eminent but the further increase of kernel size to 7 ×7 does not make much difference (figure 2(f)) and it brings in slight effect of edge enhancement that is not necessarily wanted. To find out the optimal kernel size for TM/SPOT Pan fusion, statistical correlation analysis has been carried out between the TM5, SPOT Pan and the SFIM images using different filter kernel sizes. The image correlation between the TM5 and the SFIM is much higher than that between SPOT Pan and SFIM for the theoretical kernel size 3 ×3 but with the increase of the kernel size from 3 ×3 to 31 ×31, the former decreases steadily while the later increases. The correlation coefficients are nearly even for kernel size 31× 31. This means that a very large filter kernel will distort the TM5 spectral property towards SPOT Pan. This phenomenon can be explained by formula (4) in which the assumption of

IJREB

ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

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$\rho(\gamma)_{low} \approx \rho(\gamma)_{high}$ is unlikely to hold for a large neighbourhood, thus the local residual of SPOT Pan spectral reflectance,, will affect the spectral property of the TM5/SPOT Pan fused image. It is interesting to notice that as fusion products, all the SFIM images have higher correlation with both the TM5 and SPOT Pan than the correlation between the TM5 and SPOT Pan. The total correlation reaches the maximum when the kernel size is 5 ×5. From visual judgement, it is obvious that increasing the kernel size from 3× 3 (the theoretical kernel size) to 5× 5 improves the edge quality of the SFIM image significantly without introducing non-negligible spectral distortion. The further increase of the kernel size increases spectral distortion steadily without real gain in spatial textural information. The kernel size 5× 5 is therefore recommended for TM/SPOT Pan image fusion using the SFIM.

The HR pan image **X**0 is low-pass filtered and down sampled by a factor of *F*DS (typically 4–10) such that it has a final point spread function similar to a sampling grid identical to the multispectral channels. The resulting LR version of **X**0 is called **Y**0. This down sampling step may be combined with the co registration of the different channels that is required, anyway. The LR pan image **Y**0 and the LR multispectral image **Y** are tiled into small (typically 3 × 3 to 9 × 9) possibly, but not necessarily, partially overlapping patches **y**0 and **y***k*, where *k* stands for the *k*th channel and *k* = 1, . . . , *N*. All the LR patches **y**0 with pixel values arranged in column vectors form the matrix **D***l* called the LR dictionary. Likewise, the HR dictionary **D***h* is generated by tiling the HR pan image **X**0 into patches **x**0 of *F*DS times the size as the LR pan image patches, such that each HR patch corresponds to an LR patch. These image patches are called "atoms" of the dictionaries. atoms from the dictionary pair **D***h* and **D***l*. In this example, the LR and HR patches are of sizes 5 × 5 and 50 × 50 pixels, respectively, i.e., down sampling factor *F*DS = 10. We use this extreme down sampling factor for the later experiments and to test the limits of the proposed algorithm.

It is worth mentioning that, for the image sharpening tasks where dictionaries are trained from external image the LR images. In our method, the dictionary pair is learnt directly from the image itself. Due to the fact that the dictionaries are built up from the pan image observing the same area and acquired at the same time as the multispectral channels, the LR

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ISSN 2321-743X

International Journal of Research in

Engineering and Bioscience

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multispectral image patches **y***k* and their corresponding HR patches **x***k* to be reconstructed are expected to have a sparse representation in this LR/HR dictionary pair. Furthermore, the corresponding **y***k* and **x***k* share the same sparse coefficients in **D***h* and **D***l*.

The advantage of the SFIM over the HSI and Brovey transform fusion techniques for spectral preservation can be convincingly demonstrated with colour composites. The colour composite of TM bands 5, 4 and 2 in red, green and blue (TM542 RGB) is chosen for the illustration because the spectral range of these three bands is very different from that of SPOT Pan and thus the possible spectral distortion can effectively tested.

The SFIM is more sensitive to image co-registration accuracy than the HSI and Brovey transform. Inaccurate co-registration may result in blurring edges in the fused images. This problem can be resolved using a smoothing filter with a kernel larger than the resolution ratio between the higher and lower resolution images. The requirement for co-registration accuracy of the SFIM can thus be relaxed to permit image co-registration based on manually selected ground control points and the exhausting process for refining the co-registration is therefore not necessary. According to the statistical analysis, the optimal SFIM smoothing filter kernel size for TM/SPOT Pan fusion is 5× 5 that is one step larger than the 3 ×3 kernel based on TM/SPOT Pan resolution ratio. The HSI and Brovey transform fusion techniques are not sensitive to the co-registration accuracy as the topographic/textural features are totally replaced by the intensity replacement (or modulation) image. This may not necessarily be an advantage. The possible displacements between spectral (colour) features and textural features are not apparent in HSI and Brovey fusion images and often overlooked by users. The SFIM technique is not applicable for fusing images that are fundamentally different in illumination conditions or physical properties, such as the fusion between optical images and radar images or geophysical/geochemical data.

Figure 2. The TM/SPOT Pan image fusion for TM band 5 using the SFIM technique. (*a*) A 350× 450 SPOT Pan sub-scene. (*b*) The *SPOT P*/*SPOT P*mean ratio image, where *SPOT P*mean is derived from *SPOTP* using a 3× 3 smoothing filter. (*c*) The co-registered TM band 5 image with 10m pixel

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International Journal of Research in
Engineering and Bioscience
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size. (*d*) The TM5/SPOT Pan fused image using the SFIM with a 3× 3 smoothing filter. (*e*) The TM5/SPOT Pan fused image using the SFIM with a 5× 5 smoothing filter. (*f*) The TM5/SPOT Pan fused image using the SFIM with a 7×7 smoothing filter.

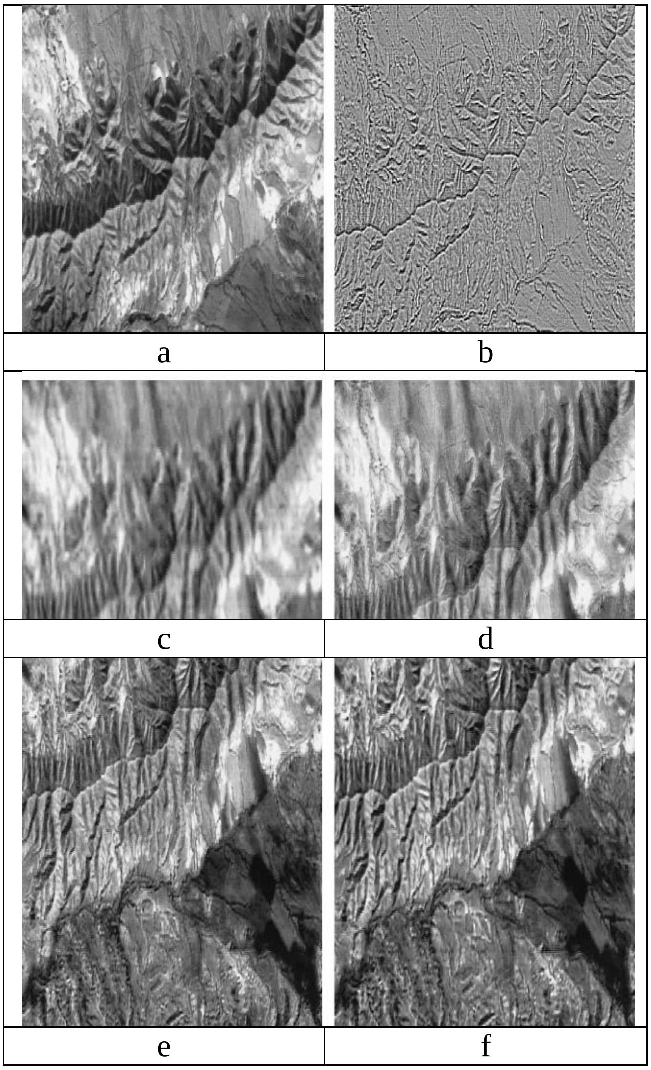

Table 1: comparison between RMSE and SPATIAL values of different pan sharpening methods

REFERENCE VALUE	0	1
HIS	5.93	0.981
IKONOS IHS	5.0	0.984
ADAPTIVE IHS	4.47	0.96
WAVELET	4.1	0.80
PCA	4.8	0.97
P+XS	4.0	0.77
VWP	2.9	0.83
SFIM	1.4	0.987

Table 1 shows the comparison between RMSE and SPATAIL values for different images.In this adaptive IHS have more spatial details comparing with other method.

CONCLUSIONS

The SFIM is a further development of the PBIM technique based on the same physical principle. The advantage of the SFIM over the HSI and Brovey transform fusion technique is that it improves spatial details with the fidelity to the image spectral properties and contrast. The spectral preservation property of the SFIM is proved from both physical principles and image statistics and well demonstrated by a

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Engineering and Bioscience
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TM/SPOT Pan fusion example. The statistical data show that the SFIM preserves spectral properties even better than the much more complicated wavelet transform for TM/SPOT Pan fusion. This very simple technique can be easily implemented into commonly used image-processing packages to perform high speed real-time image fusion process and visualization for either individual bands or colour composites.

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