Comparative Analysis of Pan-sharpening Techniques on DubaiSat-1 images

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Abstract—This paper evaluates the performance of a set of pan-sharpening methods on DubaiSat-1 images. DubaiSat-1 is a new satellite and the evaluation of pan-sharpening methods shall promote new applications of data. Methods are selected to represent different approaches of pan-sharpening. The methods are the generalized Intensity-Hue-Saturation method, the principle component substitution method, and Gram-Schmidt method from the component substitution category, Brovey transform method, University of New Brunswick method, and smoothing filter based intensity modulation method from the modulation-based category, and basic high-pass filtering method, substitutive wavelet method, and additive wavelet luminance proportional method from the filtering-based category. The pan-sharpened images are quantitatively evaluated for their spatial and spectral quality using a set of well-established measures in the field of remote sensing. The evaluation metrics are ERGAS, Q4, and SAM which measure the spectral quality and a Laplacian-based metric that measures the spatial quality. Results show that images pan-sharpened using additive wavelet luminance proportional method are the best in terms of spatial and spectral quality.

Keywords—Image fusion, remote sensing, image enhancement, high-resolution imaging, pan-sharpening, performance evaluation

I. INTRODUCTION

A remote sensing platform uses a variety of sensors. Of the fundamental ones are PANchromatic (PAN) sensor and Multi-Spectral (MS) sensor. These sensors usually coexist on the same platform since they are of complementary characteristics. Figure 1 shows sample images from both sensors. The PAN sensor has a higher spatial resolution. In other words, each pixel in the PAN image covers a smaller area on the ground compared to the MS image from the same platform. On the other hand, the MS sensor has a higher spectral resolution, which means that it corresponds to a narrower range of electromagnetic wavelengths compared to the PAN sensor. There are several reasons behind not having a single sensor with both high spatial and high spectral resolutions. One reason is the incoming radiation energy. As the PAN sensor covers a broader range of the spectrum, its size can be smaller while receiving the same amount of radiation energy as the MS sensor. Other reasons include limitation of on-board storage capabilities and communication bandwidth [1]. In view of hardware constraints, algorithmic solutions for fusing the complementary characteristics of PAN and MS images into a single image have been developed. These solution are referred to as pan-sharpening methods. Pan-sharpening is one of the most active branches of pixel-level image fusion in remote sensing [2].

Pan-sharpening is defined as the process of synthesizing an MS image at a higher spatial resolution that is equivalent to the one of the PAN image. Pan-sharpening should enhance the spatial resolution of MS image while preserving its spectral resolution. Pan-sharpening continues to receive attention over years. The primary reason is that most existing methods make explicit or implicit assumptions about data. As new sensors get developed, data changes and violates such assumptions leading to results of degraded quality. In addition, methods that are performing well at low spatial resolutions may not perform as well at higher resolutions [3]. Even for satellites with similar characteristics, parameters need to be altered for a better fusion [4]. Therefore, it is necessary to evaluate pan-sharpening techniques as new sensors become available, as in [5]–[7]. One of the new sensors is Dubai Medium Aperture Camera (DMAC). DMAC is the main sensor on-board DubaiSat-1 remote sensing satellite.

The aim of this paper is to compare existing pan-sharpening techniques for the purpose of fusing PAN images with MS images of DubaiSat-1. Section II provides an overview of the pan-sharpening techniques that will be compared. Section III introduces the set of evaluation metrics in addition to the test dataset. Results of spectral and spatial quality metrics are highlighted in Section IV. Finally, Section V concludes with some highlights of potential research directions.

II. A REVIEW OF PAN-SHARPENING TECHNIQUES

Pan-sharpening techniques can be categorized into three broad categories, namely, component substitution, modulation-
based, and filtering-based methods [8]. This categorization is not mutually exclusive as some methods can fall under more than one category.

Component substitution methods are those which rely on the concept of converting the MS image to a different representation, replacing some of the composing elements with elements from the PAN image, and finally transforming the result back to the original representation in order to construct the fused image. An example of methods falling under this category is the simple Intensity-Hue-Saturation (IHS) in [9]. In simple IHS method, the I-component in the IHS domain of the MS image is replaced by the PAN image to yield the pan-sharpened image. Since IHS method is limited to pan-sharpen three-band MS images only, it was extended in [10] in order to fuse MS images with an arbitrary number of bands. The extended method is called the Generalized IHS (GIHS) method. A parametrization of GIHS is introduced in [11] in order to allow a varying degree of injection of spatial details from the PAN image into the MS image. In [12], parameters of GIHS are set using genetic algorithm. Some methods use edge extraction within the IHS framework such as [13] and [14]. Other methods exploit sensor-specific information as in [15]. Another example of a component substitution method is Principle Component Analysis (PCA), as described in [16]. Moreover, some methods exploit Gram-Schmidt (GS) transformation, as in [17]. GS fusion method requires a PAN image to be simulated at a lower resolution. In [18], for example, PAN is simulated from the MS image by adaptive weights. Methods which fall under the component substitution category are widely-used due to their efficiency and ease of implementation [19].

The second category is modulation-based techniques. Techniques in this category are based on the principle of modulating the spatial detail into MS images by multiplying MS images with the ratio of the PAN image to a synthesized image, as in [8]:

\[ F_i = \frac{P}{S} M S_i^{↑} \]  

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( P \) is the PAN image, \( S \) is the synthesized image, and \( M S_i^{↑} \) is the up-scaled \( i \)-th MS band. Multiplication is used as it is the only operation, out of the basic four operations, that is less likely to produce spectral distortions [20]. Methods in this category differ in the methodology of constructing the synthesized image. One of the simplest methods is the Brovey transform method described in [21] where the synthesized image is the average of all MS bands. The synthesized image in [22] is constructed by averaging MS bands that share some of the band with the PAN image. In [23], the synthesized image is a weighted average of the MS bands. The weights are estimated through multiple regression to minimize the difference between the synthesized image and the original PAN image. In [24], the synthesized image is a low-pass filtered version of the PAN image. A modulation technique can be combined with an IHS technique as in [25] where Brovey and IHS methods are combined.

The last category of methods includes those which depend on a filtering process in order to extract spatial details from the PAN image. The details are then injected into MS bands in order to construct the pan-sharpened image. Some methods use a high-pass filter in order to extract spatial detail from the PAN image. In [26], for instance, the PAN image is filtered using a high-pass filter and the result is averaged with the MS image in order to construct the pan-sharpened image. This method is refined in [27] with a weighted addition of PAN detail to the MS image in order to reduce spectral distortions. Other methods utilize a multi-scale transformation (MST). When an image is transformed using a MST, edges of different scales from sharp to blurry are depicted at different levels. Because of their ability to extract edge, MSTs lend themselves for pan-sharpening. In [28], a wavelet multi-scale transform is used to extract spatial details of the PAN image. Then, the details are simply added to each MS band. In the same paper, another variation is presented where spatial details are added to the intensity component in the IHS representation of the MS image. In [29], spatial details are proportionally added to the to the MS image in order to reduce the spectral distortions in the pan-sharpened image. In [30], PAN and MS bands are independently transformed using a pyramid multi-scale transform. Details in a PAN scale are injected into the corresponding scale in an MS band based on the local correlation measure between both scales. In [31], a framework is introduced by which most MST-based methods can be described. The framework is widely known as the ARSIS concept, acronym from its French name, which means ‘spatial resolution enhancement by injection of structures’. Filtering-based methods have additional computational and storage requirements when compared to component substitution and modulation-based techniques [19]. On the other hand, these methods, in general, show the best preservation of spectral resolution [19].

Out of these methods, representative classical and state-of-the-art methods are selected from each category for the sake of comparison: the generalized Intensity-Hue-Saturation method [10], the principle component substitution method [16], and Gram-Schmidt method [17] from the component substitution category, Brovey transform method [10], University of New Brunswick method [32], and smoothing filter based intensity modulation method [24] from the modulation-based category, and basic high-pass filtering method [33], substitutive wavelet method [28], and additive wavelet luminance proportional method [29] from the filtering-based category. In what follows is a brief introduction of each of these methods, in order.

A. The Generalized Intensity-Hue-Saturation Method

The Generalized Intensity-Hue-Saturation (GIHS) method is an extension of the Intensity-Hue-Saturation (IHS) such that an arbitrary number of bands can be fused. The fusion process can be expressed as [10]:

\[ F_i = M S_i^{↑} + (P - S) \]  

\[ S = \frac{1}{N} \sum_{i=1}^{N} M S_i^{↑} \]  

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( M S_i^{↑} \) is the up-scaled \( i \)-th MS band, \( P \) is the PAN image, \( S \) is the synthesized image, and \( N \) is the total number of MS bands. In order to reduce spectral distortions in the fused image, it is recommended to stretch the mean and variance
of the PAN image in order to match those of the \( S \) before fusion. In addition, bands in the MS image that share part of the spectrum with the PAN image are the only ones to be used in order to construct the synthesized image, \( S \).

### B. Principle Component Substitution Method

Principal Component Analysis (PCA) is a statistical-based transformation. It allows the input data to be projected into a domain in which the components are linearly uncorrelated to each other [3]. When the MS image is transformed using PCA, the first principle component is an image that includes information that is common to all inputs, which resembles the PAN image, whereas the spectral details of individual bands are reflected in other components [34]. Hence, PCA provides a basis for pan-sharpening. PCA is proposed in pan-sharpening in [16]. The procedure is as follows. The MS image is first transformed using PCA. Next, the variance and average of the PAN image is changed to match the first principle component [16]. The first component is then replaced by the modified PAN image. Finally, PCA components are transformed back in order to construct the pan-sharpened image. The procedure is depicted in Figure 2. The method can be simplified as follows [35]:

\[
F_i = MS_{i\uparrow} + v_i(P - PC1)
\]

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( MS_{i\uparrow} \) is the up-scaled \( i \)-th MS band, \( v_i \) represents the \( i \)-th element in the most significant eigenvector, \( P \) is the PAN image, and \( PC1 \) represents the first principle component in the transformation of the MS image. In order to reduce spectral distortions, it was suggested to match the mean and variance of the PAN image to those of the first principle component.

### C. Gram-Schmidt Method

Gram-Schmidt (GS) method is depicted in Figure 3 and it can be explained as follows. First, a synthesized PAN image and other MS bands are jointly transformed using GS transform. Second, the PAN image is modified in order to have the mean and variance of the first component in GS transform. Third, the first component of the GS transform is replaced by the modified PAN image. Forth, the new set is inversely transformed in order to produce the pan-sharpened image. There are different approaches in constructing the synthesized PAN image. One approach is where the simulated PAN image is a weighted sum of the up-scaled low resolution MS images.

\[
S = \frac{1}{N} \sum_{i=1}^{N} MS_{i\uparrow}
\]

that is [17]:

\[
S = \frac{1}{N} \sum_{i=1}^{N} MS_{i\uparrow}
\]

where \( S \) is the synthesized image, \( MS_{i\uparrow} \) is the up-scaled \( i \)-th MS band, and \( N \) is the total number of MS bands.

### D. Brovey Transform Method

Brovey transform (BT) is on the classical methods in pan-sharpening. It was developed to enhance the visual appearance of the image [4]. The fusion process can be explained as [10]:

\[
F_i = \frac{P}{S} MS_{i\uparrow}
\]

\[
S = \frac{1}{N} \sum_{i=1}^{N} MS_{i\uparrow}
\]

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( P \) is the PAN image, \( S \) is the synthesized image, \( MS_{i\uparrow} \) is the up-scaled \( i \)-th MS band, and \( N \) is the total number of MS bands. In order to reduce spectral distortions, only MS bands that share part of the spectrum with the PAN image are considered when constructing the synthesized image.

### E. University of New Brunswick Method

University of New Brunswick (UNB) pan-sharpening algorithm is depicted in Figure 4 [32]. The process starts by standardizing the histogram of MS bands and the PAN image. This step assures equal contribution from individual bands into the fused image and therefore help reducing spectral distortions. Then, MS image whose spectral bands share parts of the spectrum with the PAN image are used to generate the synthesized PAN image using the following equation:

\[
S = \sum_{i=1}^{N} w_i MS_{i\uparrow}
\]

where \( S \) is the synthesized image, \( N \) is the total number of MS bands, \( w_i \) is a scalar weight, and \( MS_{i\uparrow} \) is the up-scaled \( i \)-th MS band. The weights, \( w_i \), are determined by minimizing the least square error of \( \|P - S\| \). Finally, all standardized MS bands are fused with the synthetic PAN image using the following equation:

\[
F_i = \frac{P}{S} MS_{i\uparrow}
\]
where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( P \) is the PAN image, \( S \) is the synthesized image, and \( MS_{i↑} \) is the up-scaled \( i \)-th MS band.

**F. Smoothing Filter based Intensity Modulation Method**

Smoothing Filter based Intensity Modulation (SFIM) is a modulation-based fusion technique. The fusion process can be expressed as [24]:

\[
F_i = \frac{P}{(P * h)} MS_{i↑}
\]

(10)

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( P \) is the PAN image, \( * \) is the convolution operator, \( h \) is a low-pass (averaging) filter, and \( MS_{i↑} \) is the up-scaled \( i \)-th MS band. \( h \) should be of a size that is equal or greater than the ratio between the resolution of a pixel in the MS image to the one of the PAN image. For example, in order to fuse two images of 5m and 2.5m pixel sizes, the kernel could be of \( 3 \times 3 \) size as:

\[
h = \frac{1}{9} \begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1
\end{bmatrix}
\]

(11)

**G. Basic High-Pass Filter Method**

HPF (High pass filter) technique was first introduced in [33]. This method can be mathematically described as:

\[
F_i = \frac{[P * g] + MS_{i↑}}{2}
\]

(12)

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( P \) is the PAN image, \( * \) is the convolution operator, \( g \) is the high-pass filter, and \( MS_{i↑} \) is the up-scaled \( i \)-th MS band. The simplest form of the high-pass filter is of size of \( (n \times n) \), where \( n = 2^r + 1 \) and \( r \) is the resolution ratio between the images [27]. The filter has a value \( n^2 - 1 \) at the center and \(-1 \) elsewhere. So for a resolution ratio of two, the following \( 5 \times 5 \) kernel is to be used:

\[
g = \begin{bmatrix}
-1 & -1 & -1 & -1 & -1 \\
-1 & -1 & -1 & -1 & -1 \\
-1 & -1 & 24 & -1 & -1 \\
-1 & -1 & -1 & -1 & -1 \\
-1 & -1 & -1 & -1 & -1
\end{bmatrix}
\]

(13)

**H. Substitutive Wavelet Method**

The Substitutive Wavelet (SW) method was proposed in [28], illustrated in Figure 5. The method works as follows. First, the MS band is up-scaled and the PAN image is modified to match the mean and variance of the MS band. Then, the MS band and the modified PAN image are separately transformed using “a trous” wavelet transform [36] to \( n \)-levels, where \( n = 2 \) or \( n = 3 \). The details of the PAN image replaces those of the MS band to construct the multi-scale representation of the fused band. Finally, the resultant representation is inversely transformed using the inverse wavelet transform in order to construct the fused (pan-sharpened) band in the spatial domain. The whole process needs to be repeated until all bands are fused.

\[\text{Fig. 5. The flow chart of the substitution wavelet fusion.}\]

**I. Additive Wavelet Luminance Proportional Method**

Additive Wavelet Luminance Proportional (AWLP) is a generalization of the Additive Wavelet Luminance (AWL) [29] that allows more than three bands to be fused, as described in the following equation:

\[
F_i = MS_{i↑} + \frac{MS_{i↑}}{N} \sum_{i=1}^{N} \tilde{P}
\]

(14)

where \( F_i \) is the \( i \)-th band in the fused (pan-sharpened) image, \( MS_{i↑} \) is the up-scaled \( i \)-th MS band, \( N \) is the total number of MS bands, and \( \tilde{P} \) is the detail extracted from PAN image. Details of the PAN image are extracted using wavelet analysis of \( n \)-levels, where \( n = \log_2 r \) and \( r \) is the ratio between the size of the MS image to the one of the PAN image. As such, the injection of details does not alter the original relationship between bands.

**III. EVALUATION METRICS AND DATASET**

**A. Evaluation Metrics**

As the field of pan-sharpening expands, the necessity of formal quality metrics increases. The visual comparison between fusion techniques is unreliable since the human visual system is not equally sensitive to different artefacts [37]. It is also a time-consuming process. Hence, quantitative metrics are used. The discussed metrics require the presence of a reference image which, however, does not exist. In order to overcome this problem, the fusion process is performed at a coarser scale, that is the PAN image is reduced to the size of the MS image and the MS image is reduced by the same factor. After these steps, the original MS image would be the reference image for evaluation purposes.

\[\text{a) Relative Dimensionless Global Error in Synthesis:}\]

Relative dimensionless global error in synthesis (ERGAS) metric – acronym of its name in French – indicates the overall quality of the fused image. It is defined as [38]:

\[
\text{ERGAS} = 100 \frac{d_P}{d_{MS}} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \frac{\text{RMSE}_i}{\mu_i} \right)^2}
\]

(15)

\[
\text{RMSE}_i = \frac{1}{X} \sqrt{\sum_{\text{pixels}} (R_i - F_i)^2}
\]

(16)

where \( d_P/d_{MS} \) is the ratio between the pixel sizes of the PAN to MS images, \( N \) is the total number of MS bands, \( \mu_i \) is the mean of the \( i \)-th band in the fused (pan-sharpened) image, \( X \) is the total number of pixels in a multi-spectral band, \( R_i \) is the \( i \)-th band in the reference image, and \( F_i \) is the \( i \)-th band in
the fused (pan-sharpened) image. ERGAS is a distortion index which means the lower the value the better the fusion. ERGAS equals zero in ideal fusion [3] but it has no maximum value.

b) Spectral Angle Mapper: Spectral Angle Mapper (SAM) is an indicator of the spectral distortion. It measures the spectral distortion by calculating the angle between the spectral vector of the fused image and the reference image as in [39]:

$$\text{SAM}(r, f) = \cos^{-1} \left( \frac{\sum_{i=1}^{N} r_i f_i}{\sqrt{\sum_{i=1}^{N} r_i^2 \sum_{i=1}^{N} f_i^2}} \right)$$ (17)

where \( r \) is a spectral vector at the spatial location \((x, y)\) in the reference image, defined as \( r = \{ r_1, r_2, \ldots, r_N \} \) where \( r_i = R_i(x, y) \), \( f \) is a spectral vector at the spatial location \((x, y)\) in the fused image, defined as \( f = \{ f_1, f_2, \ldots, f_N \} \) where \( f_i = F_i(x, y) \), and \( N \) is the total number of MS bands. SAM is averaged to yield a global distortion indicator [19]. The lower the SAM value, the better the preservation of the spectral properties. SAM is an angle that could be expressed in radians or degrees. In this paper, as in [19], degrees are used as units for SAM. Since SAM is the inverse cosine of an always positive value, its ideal value is zero whereas its maximum is 90°.

c) Q4: Quality Index (QI) is a metric that is used in order to evaluate the quality of monochrome images. Q4 is a generalization of QI by extending it to be calculated for hyper-complex numbers, or quaternions, representing the spectral pixel vectors. Q4 is defined as [40]:

$$Q4 = \frac{4|\sigma_{rf}| \cdot |r| \cdot |f|}{\sigma_r^2 + \sigma_f^2 + |r|^2 + |f|^2} \tag{18}$$

$$= \frac{|\sigma_{rf}|^2 |r|^2 |f|^2}{\sigma_r^2 |r|^2 + \sigma_f^2 |f|^2 + 2\sigma_r \sigma_f} \tag{19}$$

where

$$r = r_1 + i r_2 + j r_3 + k r_4 \quad (20)$$

$$r^* = r_1 - i r_2 - j r_3 - k r_4 \quad (21)$$

$$|r| = \sqrt{r_1^2 + r_2^2 + r_3^2 + r_4^2} \quad (22)$$

$$\bar{r} = E[r] \quad (23)$$

$$\sigma_r^2 = E[|r|^2] - |\bar{r}|^2 \quad (24)$$

$$\sigma_{rf} = E[(r - \bar{r})(f - \bar{f})^*] \quad (25)$$

$$r_i = R_i(x, y) \quad (26)$$

Q4 can be rewritten in three terms as in Eq. (19). The first term measures the alignment of the spectral vectors and as such detects where radiometric distortion is accompanied by spectral distortions in a single factor [19]. The second term measures the luminance distortion and the third measures the contrast distortion [41]. Q4 factor is calculated over a window of M-by-M which is normally selected as M=16 or M=32. Q4 is averaged over the whole image to lead a global quality metric. Q4 is in the range [0, 1] where one represents the ideal fusion, that is when the fused image and the reference image are identical [40]. 

d) Spatial Quality Metric: In order to compare the spatial quality of the pan-sharpened image, spatial details in each band in the pan-sharpened image will be compared with those extracted from the respective band in the reference image, as proposed in [29]. The procedure starts by extracting spatial detail from all bands using a Laplacian filter. Then, the correlation coefficient is calculated for corresponding bands. Finally, correlation coefficients are averaged resulting in the overall spatial measure. The procedure can be mathematically described as:

$$\tilde{R}_i = R_i * g \quad (27)$$

$$F_i = F_i * g \quad (28)$$

$$CC_i = \sigma_{\tilde{R}_i, F_i} / (\sigma_{\tilde{R}_i}, \sigma_{F_i}) \quad (29)$$

$$SM = \frac{1}{N} \sum_{i=1}^{N} CC_i \quad (30)$$

where \( R_i \) is the \( i \)-th band in the reference image, \(* \) is the convolution operator, \( g \) is a Laplacian filter, \( \sigma_{\tilde{R}_i}, \tilde{R}_i \) is the covariance, \( \sigma_{F_i} \) is the standard deviation, and \( N \) is the total number of MS bands. In this paper, as in [29], \( g \) is set to:

$$g = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad (31)$$

The spatial quality (SQ) metric results in a value within the range [1, –1] [42] where one indicates the best spatial quality.

B. Test Dataset

Test dataset are captured by DMAC on-board DubaiSat-1 remote sensing satellite. DubaiSat-1 is an Earth observation satellite orbiting at a Low Earth Orbit (LEO). It was launched to orbit on July 29, 2009. The satellite is owned and operated by Emirates Institution for Advanced Science and Technology (EIAST). DMAC has one PAN and four-band MS sensors. The spatial and spectral resolutions of the sensors are described in Table I. Further information about DubaiSat-1 mission can be found at [43]. A test dataset of images having different land covers is used to evaluate the pan-sharpened images. The test dataset is shown in Figure 6 where one row shows a series of four PAN images with their corresponding MS image in the following row. Each PAN image has a spatial dimension of 8192 × 8190 pixels whereas each band in the MS image has a spatial dimension of 4096 × 4095 pixels.

<table>
<thead>
<tr>
<th>Band No. (name)</th>
<th>Spatial Resolution (m)</th>
<th>Spectral Resolution (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAN</td>
<td>2.5</td>
<td>420-720</td>
</tr>
<tr>
<td>MS1 (Blue)</td>
<td>5</td>
<td>420-510</td>
</tr>
<tr>
<td>MS2 (Green)</td>
<td>5</td>
<td>510-580</td>
</tr>
<tr>
<td>MS3 (Red)</td>
<td>5</td>
<td>600-720</td>
</tr>
<tr>
<td>MS4 (Near Infrared)</td>
<td>5</td>
<td>760-890</td>
</tr>
</tbody>
</table>

IV. RESULTS AND DISCUSSIONS

In what follows, pan-sharpening methods are compared using a set of well-established and highly adopted measures in the literature of remote sensing. The metrics are ERGAS, Q4, SAM, which are used to measure the spectral quality.
whereas SQ metric is used to measure the spatial quality. Since these measures require the presence of a reference image, fusion is performed at a coarser resolution where the PAN image is reduced to the resolution of the MS image and the MS image is reduced by the same factor. Thus, the original MS image will be the reference image. Then, the input MS image is up-sampled using bilinear interpolation before fusion. Since, some of the presented methods are computationally expensive, images cannot be processed at full resolution using the development environment. Therefore, input images are divided into 16 equally sized blocks. Fusion and quality evaluation are performed at block level. The reported values in Table II represent the average of the calculated measures for all blocks in the entire dataset. Methods in the table are ordered by the average of their rankings as per each metric. It is worth highlighting that the spatial quality metric compares the pan-sharpened image to the MS reference image. Thus, the introduction of extra edges that are not available within the reference image (over-sharpening) is regarded as a degradation of spatial quality.

Based on objective evaluation metrics, the best method in terms of spatial and spectral quality is the AWLP. The success of AWLP can be traced to several design concepts of the method. First, AWLP is based on a dyadic wavelet decomposition [44] which suits images where the spatial resolution ratio is a power of two as in DubaiSat-1 images [45]. Furthermore, AWLP specifies the number of decomposition levels to be used in terms of the resolution ratio. Thus, AWLP assures injection of spatial details while avoiding over sharpening. In addition, the relative injection of spatial details into each band maintains the relationship between bands. SFIM is the best method in preserving the spectral quality as reported by SAM metric. Other methods showed varying performances in the order shown in Table II from the best to the worst. HPF method

Fig. 6. Test dataset as captured by DMAC on-board DubaiSat-1 (courtesy of EIAST).

Fig. 7. Part of (a) a MS reference image and its corresponding parts from images pan-sharpened using (b) GIHS (c) PCA (d) GS (e) BT (f) UNB (g) SFIM (h) HPF (i) SW (j) AWLP.
TABLE II. VALUES OF OBJECTIVE EVALUATION METRICS USED IN ORDER TO ASSESS THE SPECTRAL AND SPATIAL QUALITY OF DIFFERENT PAN-SHARPENING METHODS

<table>
<thead>
<tr>
<th>Pan-sharpening Method</th>
<th>ERGAS</th>
<th>Q4</th>
<th>SAM</th>
<th>SQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>AWLP</td>
<td>1.621343</td>
<td>0.882134</td>
<td>0.864781</td>
<td>0.796768</td>
</tr>
<tr>
<td>SFIM</td>
<td>2.678925</td>
<td>0.809495</td>
<td>0.863933</td>
<td>0.703027</td>
</tr>
<tr>
<td>UNB</td>
<td>3.854349</td>
<td>0.823201</td>
<td>0.877877</td>
<td>0.69737</td>
</tr>
<tr>
<td>GS</td>
<td>2.416628</td>
<td>0.812702</td>
<td>0.904107</td>
<td>0.664785</td>
</tr>
<tr>
<td>GIHS</td>
<td>2.828743</td>
<td>0.821262</td>
<td>0.947961</td>
<td>0.665341</td>
</tr>
<tr>
<td>BT</td>
<td>4.762657</td>
<td>0.795689</td>
<td>0.870832</td>
<td>0.656584</td>
</tr>
<tr>
<td>SW</td>
<td>3.975775</td>
<td>0.692045</td>
<td>1.941229</td>
<td>0.592987</td>
</tr>
<tr>
<td>PCA</td>
<td>7.030797</td>
<td>0.702483</td>
<td>3.645509</td>
<td>0.655029</td>
</tr>
<tr>
<td>HPF</td>
<td>60.64949</td>
<td>0.136411</td>
<td>8.960828</td>
<td>0.392887</td>
</tr>
</tbody>
</table>

is the worst out of the evaluated methods in terms of spectral and spatial resolution. The method results in an over-sharpened image. This is caused by the addition of PAN details to all bands.

V. CONCLUSION

Pan-sharpening methods show a varying performance in relation to the characteristics of input data. In other words, a pan-sharpening method that shows an excellent performance on images taken from one remote sensing sensor might not perform as good on images taken from other sensors. Therefore, pan-sharpening methods need to be evaluated considering each remote sensing sensor. This study also shows that a pan-sharpening method would perform better when input images exhibit characteristics that match the design principles of the pan-sharpening method.

For DubaiSat-1, nine pan-sharpening methods were evaluated. These methods represent different approaches of pan-sharpening, namely, component-substitution methods, modulation-based methods, and filtering-based methods. Methods were evaluated using a set of well-established metrics to measure the spectral and spatial quality of pan-sharpened image. Spectral quality is measured using ERGAS, Q4, and SAM whereas the spatial quality is measured using a Laplacian-based metric. AWLP outperformed all other pan-sharpening methods in terms of both spectral and spatial quality whereas SFIM showed the second best performance. The worst pan-sharpening methods were PCA and HPF.

This study will be extended to evaluate methods not only on their performance on images from different satellite sensors but also on various land-covers. The complete understanding of the properties of data and the characteristics of sensors is crucial in designing an effective pan-sharpening method.

ACKNOWLEDGMENT

The authors would like to thank EIAST for providing the test dataset. Also, the authors would like to acknowledge the support of H.H. General Sheikh Mohammed Bin Zayed Al-Nahyan Program for Postgraduate Scholarships (Buhooth) under which the current research is conducted.

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