An Improved Method for Destriping of VIIRS Day/Night Band Images

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ABSTRACT The VIIRS Day/Night Band (DNB) images have opened a new era of nocturnal monitoring of global ocean, lands, and atmospheric activities at a reasonably high spatial resolution of 742 m. However, the quality of VIIRS day/night band images is seriously affected with periodic horizontal stripe noises. The image quality is further reduced on the along-track scene edges due to the complex banding effects. The noise pattern and amplitude vary according to the observation time, background light condition, and the pixel position/characteristics. To enhance the utility of VIIRS day/night band image data, we developed an improved method to reduce the noise effects and evaluate the denoised output data to ensure its radiometric integrity and quality. The noise pattern is multiplicative in nature and generated due to the detector-to-detector response variation depending on the incident light condition across the scene. Accordingly, the observed pixels in the day and night images were separated into several classes using the Otsu’s threshold value. The images recorded during twilight were classified using the solar zenith angles. Pixel-by-pixel correction of the noise effects was done by multiplying the row-wise detector gains and column-wise error factors for each class. This method was tested on several day/night and twilight images captured over the different regions with varying light conditions. The results are excellent in terms of successfully removing the striping noise and reconstructing the denoised images without spatial discontinuity across the scene regardless of its observation condition.

INDEX TERMS Remote sensing, VIIRS, day/night band, stripe noise, destriping, oceanography.

I. INTRODUCTION
The Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (SNPP) satellite consists of 22 spectral bands in the wavelength region of 0.410-12.013 µm. The VIIRS spectral bands include fourteen reflective solar bands, seven thermal emissive bands, and a panchromatic Day/Night band (DNB). These bands are designed to observe large-scale global dynamics, contemporary to the Moderate Resolution Imaging Spectroradiometer (MODIS) with a similar reflective and thermal band configuration. However, the cross-track scanning mechanisms of MODIS and VIIRS are different such that MODIS uses a scanning mirror and VIIRS uses a rotating telescope to suppress the stray light contributions [1].

The daytime VIIRS DNB is less useful as many narrow VIIRS VNIR bands provide high-quality observation data. In the absence of these narrow bands at nighttime, the broad VIIRS DNB channel provides high-quality nighttime observation data suitable for many oceanic, atmospheric, and terrestrial applications, such as nocturnal fire detection [2], boat detection [3], identification of sea surface oil slicks [4], tropical cyclone tracking [5], algal bloom patch and sediment dynamics observation [6], oceanic internal solitary waves detection [7], [8], and bioluminescent milky sea observations [9]. The nighttime light data such as Black marble products [10] generated from the nightly VIIRS DNB images are increasingly utilized in many critical applications, including socioeconomic studies [11], natural disaster assessment [12],
TABLE 1. Details of the pixel numbers associated with aggregation zones in the along-scan direction.

| Aggregation zones | The right side of the nadir | Aggregation zones | The left side of the nadir |
|-------------------|----------------------------|-------------------|---------------------------|
|                   | Pixel start | Pixel end | Pixel start | Pixel end |
| 1                 | 0           | 79       | 33          | 2031      | 2215      |
| 2                 | 79          | 95       | 34          | 2215      | 2287      |
| 3                 | 95          | 159      | 35          | 2287      | 2375      |
| 4                 | 159         | 223      | 36          | 2375      | 2447      |
| 5                 | 223         | 287      | 37          | 2447      | 2527      |
| 6                 | 287         | 319      | 38          | 2527      | 2599      |
| 7                 | 319         | 343      | 39          | 2599      | 2663      |
| 8                 | 343         | 415      | 40          | 2663      | 2727      |
| 9                 | 415         | 455      | 41          | 2727      | 2791      |
| 10                | 455         | 511      | 42          | 2791      | 2855      |
| 11                | 511         | 551      | 43          | 2855      | 2919      |
| 12                | 551         | 599      | 44          | 2919      | 2999      |
| 13                | 599         | 631      | 45          | 2999      | 3055      |
| 14                | 631         | 679      | 46          | 3055      | 3135      |
| 15                | 679         | 711      | 47          | 3135      | 3207      |
| 16                | 711         | 783      | 48          | 3207      | 3279      |
| 17                | 783         | 855      | 49          | 3279      | 3351      |
| 18                | 855         | 927      | 50          | 3351      | 3383      |
| 19                | 927         | 1007     | 51          | 3383      | 3431      |
| 20                | 1007        | 1063     | 52          | 3431      | 3463      |
| 21                | 1063        | 1143     | 53          | 3463      | 3511      |
| 22                | 1143        | 1207     | 54          | 3511      | 3551      |
| 23                | 1207        | 1271     | 55          | 3551      | 3607      |
| 24                | 1271        | 1335     | 56          | 3607      | 3647      |
| 25                | 1335        | 1399     | 57          | 3647      | 3719      |
| 26                | 1399        | 1463     | 58          | 3719      | 3743      |
| 27                | 1463        | 1535     | 59          | 3743      | 3775      |
| 28                | 1535        | 1615     | 60          | 3775      | 3839      |
| 29                | 1615        | 1687     | 61          | 3839      | 3903      |
| 30                | 1687        | 1775     | 62          | 3903      | 3967      |
| 31                | 1775        | 1847     | 63          | 3967      | 3983      |
| 32                | 1847        | 2031     | 64          | 3983      | 4064      |

nighttime light pollution monitoring [13], and urban built-up area mapping [14], [15].

The VIIRS DNB is a successor of the panchromatic visible/near-infrared (VNIR) band of the Defense Meteorological Satellite Program’s Operational Line Scanner (DMSP/OLS) sensor. It has the full-width half-maximum for the measured spectral response of 500-900 nm with a center wavelength of 705 nm, comparable to the DMSP/OLS VNIR band (470-950 nm). However, the VIIRS DNB offers enhanced radiometric and spatial resolutions (i.e., 14 bit and 742 m) as compared to the DMSP/OLS VNIR band (6 bit and 2.8 km). The VIIRS DNB has a greater dynamic range that allows radiance measurements down to $2 \times 10^{-11}$ W cm$^{-2}$ sr$^{-1}$ relative to the DMSP/OLS measurements down to $5 \times 10^{-10}$ W cm$^{-2}$ sr$^{-1}$ [16]. In addition, the VIIRS DNB on-orbit calibration mechanism has evolved from the modern calibration methodology for making nighttime observations over the globe [17].

The signal-to-noise ratio (SNR) of the VIIRS DNB sensor is increased by four different gain stages based on the time delay integration mode [18], such as 2 High-Gain stages (HGS), one Mid-Gain stage (MGS), and one Low-Gain Stage (LGS). The gain-calibrated data is aggregated into 64 along-scan aggregation zones with an adjustable instantaneous field of view (IFOV). For this purpose, the IFOV of the detectors was made larger at the nadir and narrower at the scene edges [19]. This clever IFOV adjustment avoids the bowtie effect and maintains an equal spatial resolution of 742 m across the entire VIIRS DNB scene. The details of aggregation zones according to the pixel position are given in Table 1.

The VIIRS DNB sensor records data using a charge-coupled device (CCD) with 672 subpixels detectors, and these
FIGURE 1. The effect of horizontal striping and banding on the VIIRS DNB nighttime $L_t$ scene. (a) Nighttime $L_t$ image captured on 2 January 2020, covering the Bay of Bengal and the South China Sea at 19:09 UTC. The bright white pixels indicate light from floating vessels and cities. The two green arrows show the dark bands produced due to the electronic hysteresis. (b) An enlarged view of the scene (marked with a yellow box) over the South China Sea demonstrates the striping and banding effects at the right edge of the scene. (c) Column-wise median of the pixels inside the yellow box shows the periodic striping noise of periodicity 16.

data are combined onboard into 16 along-track detectors [18]. Because the detector-to-detector response of these 16 detectors is not equal, periodic horizontal striping effects become pronounced across the scene. The striping effects are more noticeable over the smooth surface (e.g., over the top of the clouds and water bodies), and it significantly degrades the quality of the DNB images. Moreover, the detector-to-detector response differs in aggregation zones, producing vertical banding effects at the right and left edges of the scene.

Figure 1 (a) shows a nighttime VIIRS DNB top of the atmosphere radiance ($L_t$) scene covering the Bay of Bengal and the South China Sea on 2 January 2020. This image was recorded near the first quarter of the Lunar phase and hence the significantly low SNR. The entire image is affected with horizontal stripes and the image quality is further degraded with banding effects at the scene edges (Fig. 1(b)). The median $L_t$ values across the column (as shown in Fig. 1(b)) show the periodic striping noise patterns repeated after every 16 rows (Fig. 1(c)). Fig. 1(a) displays few narrow dark bands on the left side of the image produced due to the electronic hysteresis effect (pointed with green arrows). This issue can be rectified using the appropriate stray light correction algorithms [20], which is beyond the scope of the present work.

The striping noise is a common artifact in most satellite images provided by the push-broom sensors such as Ocean Color Monitor (OCM 1 and 2), Compact High-Resolution Imaging Spectrometer (CHRIS), Hyperion, Landsat Thematic Mapper (TM), and Landsat Multispectral Scanner (MSS), and the whiskbroom sensors with scanning mirror mechanisms such as MODIS Aqua and Terra. In addition to VIIRS DNB, the reflective and thermal bands of VIIRS are also affected by striping noise [21], [22]. Notable destriping techniques applied to various daytime satellite data include histogram matching [23], [24], Total Variational (TV) method [25], frequency domain filtering [26], moment matching [27], Unidirectional Variational Model [28], wavelet transformation [29], Bayesian Dictionary Learning algorithm [30], Low-Rank Single Image Decomposition (LRSID) method [31], Inverted Gaussian Averaging Window smoothening method [32], neural network [33], sparse matrices approximation [34], and Zero Gradient method [35].

The only destriping technique applied to the VIIRS DNB images was proposed by Mills and Miller [36] using the Histogram Moment Matching method (HMM). The HMM method calculates the gain factors of 16 detectors for each aggregation zone and multiplies them to the noise-affected image. For this method, the striping noise patterns were assumed to be constant over the particular aggregation zone. However, this assumption is not effective at the scene edges, where the image noise frequently changes on the image column. This correction requires a different set of detector gains for each image column instead of a constant gain applied over the aggregation zone. The HMM technique effectively removes horizontal stripes in the VIIRS DNB images, but it becomes ineffective in dealing with the detector crosstalk artifacts (e.g., zigzag lines) produced due to the LGS calibration error for daytime scenes. Moreover, the HMM method calculates the detector gain based on the mean value which can be affected by outlier/fluctuating pixels.
In this study, we developed an improved algorithm to overcome the shortcomings of the HMM technique. This algorithm also considers horizontal stripes as a multiplicative noise and uses a median value to calculate the detector gain factors for the VIIRS image. Unlike HMM, the new algorithm estimates the gain factors for all 4064 image columns instead of 64 aggregation zones and also removes the crosstalk artifacts from the daytime scenes and other nonuniformities on the along-track scene edges due to the banding effects. The outputs of this algorithm are also evaluated using several VIIRS images from different regions around the globe.

The other parts of the manuscript describe the datasets and the correction scheme in section II, demonstrate the results of the proposed method as applied to several images under different environmental conditions in section III, and summarize the outcome of this study in section IV.

II. DATA AND METHODS

A. SPACE-BORNE DATA

The VIIRS SNPP provides data in three levels: Level 0 data or Raw Data Records (RDR), Level 1 data or Sensor Data Records (SDR), and Level 2 data or Environmental Data Records (EDR). The SDR contains the calibrated and geolocated top-of-the-atmosphere radiance (\(L_t\)) products generated from RDR data. For this study, VIIRS SNPP DNB SDR data (Product name: NPP_VDNES_L1) were downloaded from the NASA LAADS DAAC website (https://ladsweb.modaps.eosdis.nasa.gov/). Each VIIRS DNB scene consists of 3232 rows and 4064 columns covering a swath width of 3000 km with a spatial resolution of 742 m.

B. DESCRIPTION OF THE DESTRIPING TECHNIQUE

The horizontal striping noise in the VIIRS DNB image presents periodic variations with a periodicity of 16 caused by the signal-based mismatches of 16 along-track detectors. The noise pattern is nearly identical for an aggregation zone located at the center of the image; however, it varies even with every image column near the right and left edges of the image. The proposed destriping technique considers the striping patterns due to multiplicative noise and estimates the variable gain factors corresponding to 16 detectors for each image column. These gain factors are then multiplied with the original image to make corrections for the striping noise effects.

The proposed method estimates gain factors based on the median from a histogram of the pixel intensity values, which may not coincide with the broader and multimodal histogram peaks. For this purpose, the proposed method utilizes Otsu’s automatic thresholding algorithm [37] for image classification. The Otsu’s algorithm finds an optimum threshold value by minimizing the weighted sum of intra-class variance by considering the image histogram following the binomial distribution. As the Otsu’s algorithm works well on smaller size images, the VIIRS image is divided into 64 small image sections based on the aggregation zones and then the Otsu threshold values are estimated separately for these 64 image sections.

The accuracy of Otsu’s method gets better by removing the outlier pixels from the image. These outliers are mainly caused by the impulse noise (e.g., salt and pepper), and are located on the right and left edges of the image histogram. These outliers are assumed to have a low occurrence (frequency <10), and are detected by constructing a histogram of 1024 bins. Such outlier pixels are then replaced by the median of the surrounding 8 pixels.

The number of classes required for a VIIRS image is determined based on the histogram shape. For example, two clearly separate classes can be discernible in a histogram having a bimodal distribution. The Otsu-based threshold method was tested over hundreds of images and worked reasonably well for all the images acquired during daylight hours and nighttime hours. However, this method fails severely for highly skewed and wider histogram distributions associated with the twilight images. The calibration procedures for the twilight images are usually more complex than those for the daylight and nighttime images, which are calibrated based on the LGS and HGS methods, respectively. The twilight scenes are calibrated by combining MGS, LGS, and HGS methods. As a result, the noise patterns and SNR values for the twilight scenes vary in the image column across the LGS-to-MGS and MGS-to-HGS transition boundaries. Mills and Miller [36] observed this issue and segmented the image into multiple image sections based on the solar zenith angles and destriped the image sections using different gain factors. Our analysis showed that an equal segmentation of solar zenith angles into 20 or more intervals is adequate for removing the different forms of artifacts in VIIRS DNB twilight images. The present method includes two schemes for correcting the horizontal (row-wise) and vertical (column-wise) striping noises in the VIIRS image.

1) HORIZONTAL STRIPE NOISE CORRECTION

Horizontal stripe noises/lines are the most common artifacts in the VIIRS DNB \(L_t\) image data. The horizontal lines have a periodicity of 16 and are corrected by employing a moving median filter of window size 16. The median filter moves along the row and produces a smooth \(L_{ts}\) image while independently operating across all 4064 image columns

\[
L_{ts} = \{\text{movmedian} \ L_t(1 : 3232, j)]1 \leq j \leq 4064 \}
\]  

(1)

The \(L_{ts}\) image is free from horizontal stripe lines; however, this image also lacks high-frequency details present in the original \(L_t\) image. A ratio of \(L_{ts}\) and \(L_t\) provides a rough estimation of horizontal striping error \(\varepsilon\).

\[
\varepsilon = \frac{L_{ts}}{L_t}
\]  

(2)

The \(\varepsilon\) image is divided into 202 horizontal blocks with a shape of 16 × 4064, equivalent to each scan window of the VIIRS DNB sensor where the row numbers coincide with the detector numbers. All elements of the \(j^{th}\) row of every
The estimated gain array has a shape of 16 × 4064, equal to the VIIRS scan window, and multiplication of these gain values with \( L_t \) data according to the detector and column numbers yields the horizontal line corrected \( L'_t \):

\[
L'_t = \left[ L_{ti} \times \text{Gain}_{Detector_j} \right]_{1 \leq i \leq 16} \quad 1 \leq j \leq 4064
\]  

(4)

The complete overview of the horizontal line correction procedure is shown in Figure 2.

2) VERTICAL STRIPE NOISE CORRECTION

The horizontal line correction technique removes all the horizontal stripe lines along the row. However, this correction technique fails to eliminate the effects of vertical nonuniformities/lines from the aggregation zones 1 to 5 and 60 to 64, respectively. A similar moving median filter of window length 64 is designed to rectify this issue. The median filter moves along the column and produces a smoothened \( L''_t \) image while independently operating across all 3232 image rows.

\[
L''_t = \left[ \text{movmedian} \left\{ L'_t(i, 1 : 4064) \right\} \right]_{1 \leq i \leq 4064}
\]  

(5)

The \( L''_t \) image is free from vertical stripe lines, and a ratio of \( L''_t \) and \( L'_t \) provides the rough estimation of vertical stripe error.

\[
\frac{L''_t}{L'_t}
\]

(6)

The error pattern of \( L''_t \) changes according to the image columns, but remains the same across all image rows; Thus, a median of all rows corresponding to the \( j \)th column gives the error factor \( \xi_j \) of the \( j \)th column.

\[
\xi_j = \left[ \text{median} \{ \xi(:,j) \} \right]_{1 \leq j \leq 4064}
\]  

(7)

The estimated error factor array has a shape of 1 × 4064, equal to the size of the image row. As mentioned earlier, the vertical lines are only noticeable for few aggregation zones at the right and left edges of the image; Hence, the vertical line correction is not required for the image pixels that belong to other aggregation zones. So \( \xi_j \) corresponding to the aggregation zones 6 to 59 are assigned as 1.

\[
\xi(287:3775) = 1
\]  

(8)

Finally, multiplication of \( L'_t \) with the error factor, \( \xi \) corresponding to the image column provides the vertical line correction to the image column.
FIGURE 4. A flowchart showing the complete destriping process for the VIIRS DNB $L_t$ images.

corrected $L_t''$ image.

$$L_t'' = \left[ L_t'(\cdot, j) \times \xi(j) \right]_{1 \leq j \leq 4064} \quad (9)$$

The complete overview of the vertical line correction procedure is shown in Figure 3.

3) COMBINED CORRECTION SCHEME

The striping noise level and histogram shape of VIIRS DNB images universally vary depending on the background light conditions. A typical daytime or nighttime image histogram may have 1-4 recognizable modes based on the type of object being recorded. In contrast, twilight image histograms are more skewed and broad in shape without the distinct modes.

Although both day/night and twilight image types are destriped with the successive horizontal and vertical line correction steps, the image classification approach for day/night and twilight images is not the same. For day and night images, the number of image classes is equal to the histogram mode numbers and classified based on the Otsu’s threshold values. For twilight images, the number of image classes is considered $\geq 20$ (depending upon the dynamic range of the scene) and classified based on solar zenith angles.

The SDR data files categorize the VIIRS DNB images in 3 timeframes: ‘Day’ for daytime, ‘Night’ for nighttime, and ‘Both’ for twilight images. The present method uses this day/night flag for diurnal separation, destripes all classes separately, and later combines these classes to produce the complete destriped $L_t$ image. Figure 4 summarizes the correction steps in detail.

C. QUALITY ASSESSMENT OF THE DESTRIPED IMAGE

The noise level of the VIIRS DNB image varies significantly with the observation time and type of recorded pixels, makes an image quality analysis more challenging over the sensors operational during daytime only. In the proposed destriping technique, a constant gain factor is multiplied to the image pixels associated with each detector based on the linear relationship of the destriped image with the original image. Hence, to examine the dependency between the input and output images, the Correlation coefficient ($R^2$), Slope, and Intercept are calculated. The relative error analysis is done using the Mean Relative Error (MRE), Normalized Root Mean Square Error (NRMSE), and Normalized Mean Absolute Error (NMAE). The normalization of RMSE and MAE is executed based on the Inter Quartile Range (IQR) values to avoid the extreme outliers present in the image. The details of these error metrices are summarized in Table 2, where $X$, $Y$, and $n$ represent the input $L_t$ image, destriped $L_t$ image, and total pixel counts, respectively.

The metrices defined earlier cannot assess the perceptual quality of the image; thus, two separate metrics such as Universal Image Quality Index (UIQI) [38] and the Structural Similarity Index Measure (SSIM) [39], are considered in this study. These metrices can evaluate the image quality based on the apparent change of luminance, contrast, and structural similarity, and they offer a better idea about the perceptual variations between the neighboring pixels. The desirable value of UIQI and SSIM should be close to 1.0 for keeping the perceptual information intact. Table 2 shows the formulation of these metrices between $X$ and $Y$ data, where $\sigma_X$, $\sigma_Y$, and $\sigma_{XY}$ are the standard deviation of $X$, $Y$, and the covariance between $X$ and $Y$, respectively. $\bar{X}$ and $\bar{Y}$ are the mean of $X$ and $Y$ data. The two variables, $c_1$ and $c_2$ in

| Estimator | Formula | Desired |
|-----------|---------|---------|
| MRE       | $MRE = \frac{1}{n} \sum_{i=1}^{n} (Y - X)^2$ | 0 |
| NRMSE     | $NRMSE = \frac{1}{IQR} \sum_{i=1}^{n} (Y - X)^2$ | 0 |
| NMAE      | $NMAE = \frac{1}{IQR} \sum_{i=1}^{n} |Y - X|$ | 0 |
| UIQI      | $UIQI = \frac{4c_1c_2\sigma_X \sigma_Y}{(\sigma_X^2 + \sigma_Y^2)(\bar{X}^2 + \bar{Y}^2)}$ | 1 |
| SSIM      | $SSIM = \frac{2\bar{X}\bar{Y} + c_1(2\sigma_X^2 + \sigma_Y^2) + c_2(2\sigma_Y^2 + \sigma_X^2)}{(\bar{X}^2 + \bar{Y}^2)^2 + \sigma_X^4 + \sigma_Y^4}$ | 1 |
| NIF       | $NIF(X,Y) = \left( \int (X - Y)^2 dx \right) \left( \int (X - X)^2 dx \right)^{-1}$ | 0 |
| NDF       | $NDF(X,Y) = 1 - \left( \int (X - Y)^2 dx \right) \left( \int (X - X)^2 dx \right)^{-1}$ | 1 |
SSIM formulation, stabilize the output value against a weak denominator.

In addition, the Normalized Improvement Factor (NIF) and Normalized Distortion Factor (NDF) defined by Bouali and Ignatov [40] are also included as an essential error metrics for the destriping efficiency assessment. The NIF and NDF represent the spatial change of the destriped image compared to the original scene in the along-track and cross-track directions. The ideal value of NIF should be close to zero for good horizontal destriping results, whereas a negative NIF value indicates the outcome of a poor destriping technique. The NDF is used to analyze the destriped image quality vertically; Its value of close to 1.0 represents that the destriped image loses very little information compared to the original image. Table 2 shows the NIF and NDF formulation for X and Y data, where $\delta_x$ and $\delta_y$ represent the partial derivative operator along the x-direction (cross-track) and y-direction (along-track) applied over an image subset $\Omega$.

The destriped images are also analyzed with the Peak Signal-to-Noise Ratio (PSNR). However, the PSNR values become more unreliable for extreme low light conditions (New Moon nights) due to the dominance of Salt and Pepper noise over stripe noise. Thus, the PSNR results are not included in the manuscript.

III. RESULTS AND DISCUSSION
A. THE CONCEPTUAL DESTRIPING OUTPUTS

The horizontal stripe noise observed in the VIIRS DNB image is repetitive and follows an identical noise pattern with a periodicity of 16 for a particular image column for day and nighttime scenes. The proposed destriping algorithm initially attempts to smoothen the image horizontally and later calculate a variable gain factor for all 4064 image columns. The horizontal stripe corrected image is further smoothened at the left and right scene edges to remove the undesired vertical lines.

Figure 5 shows the destriping results for the daytime VIIRS DNB $L_\tau$ subset image, which covers a portion of the Mediterranean Sea on 14 August 2021. The quality of this image is highly degraded at the left side of the scene due to the banding...
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FIGURE 6. Destriping of VIIRS DNB nighttime $L_t$ image, covering hurricane Irma over the Caribbean Sea on 7 September 2017 at 06:57 UTC. (a) Original $L_t$ image subset cropped from the right edge of the image. (b) Horizontal line corrected $L_t$ image. (c) $L_t$ image after incorporating both horizontal and vertical line correction. (d) The estimated noise patterns. (e) Row-wise variation of the median of all columns for the original and destriped $L_t$ data. (f) Column-wise variation of the median of all rows for the original and destriped $L_t$ data. (g) Histograms of the original and destriped $L_t$ data.

effects (Fig. 5(a)). Implementing the horizontal line correction technique over the $L_t$ image successfully removes fluctuations along the rows; however, traces of vertical lines are still noticeable (Fig. 5(b)). The vertical line correction technique eliminates these vertical stripes and produces a clean stripe-free image (Fig. 5(c)). The noise pattern of this image is retrieved from the ratio of destriped to the original $L_t$ image (Fig. 5(d)). The noise artifacts, including the zigzag lines and horizontal stripes visible in the original image, are reproduced in Figure 5(d). The variation of median $L_t$ data in horizontal and vertical directions also shows that the proposed destriping technique works well in removing fluctuation from the image (Figs. 5(e) and 5(f)). Moreover, the histogram of the destriped and original $L_t$ data is also identical in shape, which ensures that the image features present in the original data are not lost during the destriping process (Fig. 5(g)).

Figure 6 shows another example of the effectiveness of the proposed destriping technique over the nighttime VIIRS DNB $L_t$ scene, which covers the eye of Hurricane Irma over the Caribbean Sea on 7 September 2017. The image quality at the left side of this image is deteriorated due to the banding effects (Fig. 6(a)). The histogram of this image is bimodal in shape; the lower mode of the histogram corresponds to the land and water pixels, and the higher mode is due to cloud pixels in the image (Fig. 6(g)). Thus, the image pixels are categorized into two classes using the Otsu’s threshold method. Pixels from these two classes are separately corrected by the horizontal and vertical line correction technique and combined later to produce a stripe-free denoised image (Figs. 6(b) and 6(c)). Note that the noise amplitude and patterns over the cloud and land/water pixels are not the same because of the difference between the estimated gain factors resulting from the significant variation of the pixel values (Fig. 6(d)). The median of $L_t$ data across the column and rows shows that the proposed technique can effectively remove the noise from the image (Figs. 6(e) and 6(f)).
B. PERFORMANCE ANALYSIS BETWEEN THE DIFFERENT DESTRIPING METHODS

The proposed destriping method is an upgraded version of the existing HMM method. The HMM method assumes the same noise pattern for an entire aggregation zone and calculates 64 gain factors corresponding to 64 aggregation zones. In contrast, the proposed method considers noise pattern changes based on all 4064 image columns and estimates 4064 gain factors. Moreover, this method calculates the detector gain using the pixel median, whereas the HMM method uses the pixel mean to achieve the stripe-free image products. In the dark environment (e.g., New Moon night image), the salt and pepper noise is more dominant over the striping noise. Under this situation, the median values are more stable and reliable compared to the mean values.

To evaluate the relative performance of the existing and proposed methods, a VIIRS DNB daytime $L_t$ image subset over the Sahara Desert and the Mediterranean Sea on 14 August 2021 was processed using LRSID [31], HMM [36], TV [25], and the proposed method (see Fig. 7). Note that the HMM destriping code is not publicly available, so it was rewritten based on the methodology of Mills and Miller [36], and the destriping code for LRSID and TV method used in the comparison were downloaded from the repository of existing literature [41]. The image quality of the original $L_t$ data is degraded by both striping and banding effects (Fig. 7(a)). The LRSID method can correct the stripe lines, but it fails to correct the banding noise-affected regions (Figs. 7(c) and 7(g)). Moreover, this method estimates a uniform noise pattern for both land and water pixels. In general, the noise level varies based on the strength of the $L_t$ signal, and it depends

![Figure 7](image-url)
FIGURE 8. Destriping comparison results between the proposed and HMM methods. (a) VIIRS DNB nighttime $L_t$ image subset (in nW-cm$^{-2}$sr$^{-1}$), captured over the Sahara Desert on 9 September 2014 at 00:32 UTC. This subset is cropped from the center (at nadir) of the image. (b) Destriped $L_t$ image using the HMM method. (c) Destriped $L_t$ image using the proposed method. (d) Enlarged view of the original $L_t$ image (inside the red box in 8(a)). (e) Enlarged view of the $L_t$ image destriped using the HMM method (inside the red box in 8(b)). (f) Enlarged view of the $L_t$ image destriped using the proposed method (inside the red box in 8(c)). (g) VIIRS DNB daytime $L_t$ image subset (in mW-cm$^{-2}$sr$^{-1}$), captured over Sahara Desert on 28 May 2014 at 12:32 UTC. This subset is cropped from the left edge of the image. (h) Destriped $L_t$ image using the HMM method. (i) Destriped $L_t$ image using the proposed method. (j) Enlarged view of the original $L_t$ image (inside the blue box in 8(g)). (k) Enlarged view of the $L_t$ image destriped using the HMM method (inside the blue box in 8(h)). The red arrow shows the image section, heavily affected by the banding effects. (l) Enlarged view of the $L_t$ image destriped using the proposed method (inside the blue box in 8(i)). (m) The estimated noise patterns from 8(a) using HMM method. (n) The estimated noise patterns from 8(a) using proposed method. (o) The estimated noise patterns from 8(d) using HMM method. (p) The estimated noise patterns from 8(d) using proposed method. (q) The estimated noise patterns from 8(g) using HMM method. (r) The estimated noise patterns from 8(g) using proposed method. (s) The estimated noise patterns from 8(j) using HMM method. (t) The estimated noise patterns from 8(j) using proposed method.

primarily on the pixel types. The correction using the HMM method is better, but it is unable to correct the banding noise accurately (Figs. 7(d) and 7(h)). The TV method successfully removes both striping and the banding noises (Figs. 7(e) and 7(i)). However, it over-smoothes the image during the correction process, which results in the loss of high-frequency details. Compared to these methods, the proposed method gives a much cleaner image, free from all artifacts (7(f) and 7(j)). Figure 7(b) reveals that the histograms generated from the images destriped using the HMM and proposed method closely follow the original image histogram. In contrast, the histograms of the destriped image by LRSID and TV show significant variation around the water and land boundary regions.
FIGURE 9. Destriping comparison results between the proposed and HMM methods. (a) A subset of the VIIRS DNB nighttime Lt image, covering the Bay of Bengal and the South China Sea on 2 January 2020 at 19:09 UTC. (b) Destriped Lt image using the HMM method. (c) Destriped Lt image using the proposed method. (d) Location of the image affected by both striping and banding noise (marked with yellow box). (e) Estimated noise pattern using HMM method. (f) Estimated noise pattern using proposed method. (g) Row-wise variation of the pixel values generated from the original, HMM, and proposed destriped image data located inside the yellow box region. (h) Histogram plot for pixel values using the original, HMM, and proposed destriped image data located inside the yellow box region.

The error metric values calculated from the original and destriped images (see Fig. 7) are shown in Table 3. The HMM and proposed method yield nearly identical error values because of their good performance in maintaining the image quality and data integrity, when compared to the other two destriping methods. The poor performance of the TV and LRSID methods is not surprising, as these methods are more generalized and formulated primarily to correct the striping noise only. In contrast, the proposed method and HMM are specifically developed to rectify the stripe and banding noises in the DNB images.

The error values calculated for the proposed and HMM methods are nearly similar and inconclusive enough to decide which method works better. So for better analysis, two specific cases from HMM paper are chosen for visual assessment and shown in Figure 8. Figure 8(a) shows a subset of a nighttime Lt image captured over the Sahara Desert on 9 September 2014. This subset is cropped from the center part of the original image, and it is only affected with horizontal stripe lines (see Figs. 8(m) to 8(p) for comparison of the noise pattern retrieved using two methods). The destriping results of HMM (Fig. 8(b)) and the proposed method
FIGURE 10. Destriping of VIIRS DNB nighttime $L_t$ image, covering cyclone Phailin over the east coast of India on 11 October 2013 at 19:45 UTC. (a) Original $L_t$ image. (b) Destriped $L_t$ image. (c) Histogram of the original and destriped $L_t$ data. (d) Scatterplot comparison between the original and destriped $L_t$ data. (e) Enlarged view of the original $L_t$ image marked with a yellow box in 10(a). (f) Enlarged view of the destriped $L_t$ image marked with a yellow box in 10(b). (g) Enlarged view of the original $L_t$ image marked with a green box in 10(a). (h) Enlarged view of the destriped $L_t$ image marked with a green box in 10(b).

are similar (Fig. 8(c)), indicating both these methods work equally well in removing horizontal lines from the image (Figs. 8(e) and 8(f)).

The other subset image was recorded over the Sahara Desert during the daytime on 28 May 2014, and it is a subset from the left side of the original image (Fig. 8(g)). The noise pattern of this image is more complex compared to the previous image (Fig. 8(a)), and both horizontal stripes and banding effects are equally responsible for the degradation of this image (see Figs. 8(q) to 8(t) for comparison of the noise pattern retrieved using two methods). The HMM method successfully removes the horizontal lines from the scene (Fig. 8(h)); however, it fails to correct the artifacts produced in the boundary areas of the aggregation zones (notice red arrows in Figure 8(k)). An apparent mismatch of the radiance values between the two heavily degraded aggregation zone is also noticeable from this image. In contrast, the destriped

| Estimator          | LRSID | HMM | TV   | Proposed |
|--------------------|-------|-----|------|----------|
| $R^2$ (Unitless)   | 0.9981| 0.9994| 0.9969| 0.9993   |
| Slope (Unitless)   | 0.9959| 0.9995| 0.9942| 0.9998   |
| Intercept (mW-cm$^{-2}$-sr$^{-1}$) | 0.0104| 0.0027| 0.0175| 0.0001   |
| MRE (Unitless)     | 0.0111| 0.0096| 0.0216| 0.0010   |
| NRMSE (Unitless)   | 0.0203| 0.0116| 0.0259| 0.0123   |
| NMAE (Unitless)    | 0.0078| 0.0073| 0.0174| 0.0074   |
| UIQI (Unitless)    | 0.9991| 0.9997| 0.9985| 0.9997   |
| SSIM (Unitless)    | 0.9846| 0.9624| 0.5625| 0.9969   |
| NIF (Unitless)     | 0.1045| 0.1156| 0.2708| 0.0936   |
| NDF (Unitless)     | 0.8970| 0.8844| 0.7339| 0.9060   |
FIGURE 11. Destriping of VIIRS DNB nighttime $L_t$ image, covering hurricane Blanca over the Baja California coast, the United States of America on 4 June 2015 at 08:33 UTC. (a) Original $L_t$ image. (b) Destriped $L_t$ image. (c) Histogram of the original and destriped $L_t$ data. (d) Scatterplot comparison between the original and destriped $L_t$ data. (e) Enlarged view of original $L_t$ image marked with a yellow box in 11(a). (f) Enlarged view of the destriped $L_t$ image marked with a yellow box in 11(b). (g) Enlarged view of the original $L_t$ image marked with a green box in 11(a). (h) Enlarged view of the destriped $L_t$ image marked with a green box in 11(b).

The image produced by the proposed method is cleaner and free from all such artifacts (Fig. 8(i) and 8(l)).

Figure 9 (a) shows a nighttime $L_t$ image subset captured over the Bay of Bengal and East China Sea region on 2 January 2020. The image was captured during low light conditions and affected by both striping and banding noises. The HMM method successfully corrects horizontal stripes from this image (Fig. 9(b) and 9(e)); however, it fails to correct the right edge of the image, which is heavily affected by the banding noise (marked with a yellow box in Fig. 9(d)). In contrast, the proposed method effectively rectifies both the horizontal stripes and banding noise in the $L_t$ data and produces a cleaner image (Fig. 9(c) and 9(f)) without distorting the image quality and data integrity. Moreover, it improves the overall signal-to-noise ratio of the image even in the heavily noise-affected region (inside the yellow box) (Fig. 9(g) and 9(h)).

C. DESTRIPEING RESULTS IN DIFFERENT CONDITIONS

The noise pattern in the VIIRS DNB image is more complex than the stripe noise present in satellite images from the MODIS, OCM 1 and 2, or Hyperion sensors. The VIIRS DNB sensor has a better dynamic range and can record signals over the different ambient light conditions during the daytime, nighttime, and even twilight phase. The noise pattern and amplitude change drastically depending on the observation time (day/night/twilight), object type (e.g., land/cloud/water/ice), and location of a
FIGURE 12. Destriping of VIIRS DNB nighttime $L_I$ image, covering the Bay of Bengal and the South China Sea on 2 January 2020 at 19:09 UTC. (a) Original $L_I$ image. (b) Destriped $L_I$ image. (c) Histogram of the original and destriped $L_I$ data. (d) Scatterplot comparison between the original and destriped $L_I$ data. (e) Enlarged view of the original $L_I$ image marked with a yellow box in 12(a). (f) Enlarged view of destriped $L_I$ image marked with a yellow box in 12(b). (g) Enlarged view of the original $L_I$ image marked with a green box in 12(a). (h) Enlarged view of the destriped $L_I$ image marked with a green box in 12(b).

particular pixel within the image (e.g., pixels near the right and left edges are noisier than the pixels near the scene center). Thus, it is necessary to analyze the destriped image acquired under different environmental and lighting conditions.

Figure 10 displays a nighttime $L_I$ image covering the cyclone Phailin over the east coast of India on 11 October 2013. The Lunar illumination in this image is low as this image was acquired near the first quarter of the Lunar phase (Figs. 10(a) and 10(b)). This image is not divided into different classes as the histogram is unimodal in shape (Fig. 10(c)). Close inspection reveals that stripe noises are corrected reasonably well at the center and edges of the image (Figs. 10(e) to 10(h)). The scatterplot and histogram plots of the original and destriped images show an excellent correlation between these two images (Figs. 10(c) and 10(d)). A detailed error analysis between the original and destriped image is added in section III(D).

Figure 11 shows a nighttime $L_I$ image covering the hurricane Blanca over the Baja California coast, USA, on 4 June 2015. Lunar lights significantly illuminated the cloud tops of this image as this image was acquired near the Full moon phase (Figs. 11(a) and 11(b)). The image pixels are categorized into two classes based on the bimodal structure of the image histogram (Fig. 11(c)). The horizontal stripe noise around the hurricane’s eye and the banding noise at the right side of the image are corrected well using the proposed destriping technique (Figs. 11(e) to 11(h)). The scatterplot
also reveals the high correlation between the original and destriped images (Fig. 11(d)).

Figure 12 shows a nighttime $L_t$ image over the Bay of Bengal and the South China Sea on 2 January 2020. This image was acquired near the first quarter of the Lunar phase, exhibiting a significantly low Lunar light across the scene (Figs. 12(a) and 12(b)). As a result, this image becomes more noisy than the images captured near the Full Moon phase. In this case, the pixel values were not categorized as the image histogram followed a unimodal shape (Fig. 12(c)). The bright features due to lightning (Fig. 12(e) and 12(f)) and urban/boat lights (Figs. 12(g) and 12(h)) become more pronounced in the destriped image. The two images also showed a high correlation, which indicates good performance of the proposed destriping technique in terms of the quality and integrity of the output products (Fig. 12(d)).

Figure 13 depicts another example of a lowlight nighttime $L_t$ image captured near the New Moon phase over the northeast Indian Ocean on 4 August. The lower portion of this image (Figs. 13(a) and 13(b)) contains a bioluminescent patch near Java, visible only in nighttime imagery [9]. The proposed destriping technique successfully corrects the horizontal lines visible over this patch (Figs. 13(e) and 13(f)) and the nonuniformities near the edge of the image (Figs. 13(g) and 13(h)) after considering all pixels under the same category (Fig. 13(c)). The scatterplot also shows negligible variations in pixel values between the original and destriped images (Fig. 13(d)).
Figure 14 shows a daytime $L_t$ image over the Sahara Desert on 14 August 2021. The image histogram follows a bimodal shape (Fig. 14(c)), and hence the pixels are categorized into two classes using the Otsu’s threshold value and corrected separately according to the water and land/cloud classes (Figs. 14(a) and 14(b)). The destriping results over the water pixels of this image are already shown in Figure 5. The correction over the land and cloud pixels is also accurately done, where the nonuniformities at the right and left edges of the scene were caused due to the banding effects (Figs. 14(e) to 14(h)). The destriped image shows an excellent correlation with the original $L_t$ image (Fig. 14(d)).

Figure 15 shows an example of a twilight $L_t$ image captured over the Arctic region on 1 April 2021. The pixel values of this image show a very high variation and produce a highly skewed histogram with unidentifiable modes (Fig. 15(c)). A careful observation at the left side of the scene further reveals the different noise patterns and graininess (see at the top and bottom of the green arrow in Fig. 15(e), where the green arrow indicates the separation between the LGS-to-MGS transition boundary).

The Otsu’s threshold method showed poor performance for the highly skewed histograms, and hence the solar zenith angle was considered to divide this image into smaller subsets. The solar zenith angle for this scene varied between 74-103 degrees. Accordingly, this scene is segmented into 20 smaller image sections based on the 20 equally spaced solar zenith angle intervals, and then the proposed destriping technique was applied to each image section independently.
FIGURE 15. Destriping of VIIRS DNB twilight image over the Arctic on 1 April 2021 at 23:21 UTC. (a) Original $L_t$ image. (b) Destriped $L_t$ image. (c) Histogram of the original and destriped $L_t$ data. (d) Scatterplot comparison between the original and destriped $L_t$ data. (e) Enlarged view of the original $L_t$ image marked with a green box in 15(a). The green arrow shows the boundary between the high-gain and mid-gain stages. (f) Enlarged view of the destriped $L_t$ image marked with a green box in 15(b). (g) Enlarged view of the original $L_t$ image marked with a green box in 15(a). (h) Enlarged view of the destriped $L_t$ image marked with a green box in 15(b).

TABLE 4. The error metric values estimated from the original and proposed destriped images for Figures 10-15.

| Estimator       | Fig. 10 | Fig. 11 | Fig. 12 | Fig. 13 | Fig. 14 | Fig. 15 |
|-----------------|---------|---------|---------|---------|---------|---------|
| $R^2$ (Unitless)| 0.9964  | 0.9996  | 0.9951  | 0.9967  | 0.9993  | 0.9991  |
| Slope (Unitless)| 0.9980  | 1.0002  | 0.9692  | 0.9980  | 1.0009  | 0.9994  |
| Intercept (nW·cm⁻²·sr⁻¹) | 0.0024 | -0.0019 | 0.0160  | 0.0046 | -3556.49 | 633.06 |
| MRE (Unitless)  | 0.0356  | 0.0110  | 0.0938  | 0.2641  | 0.0039  | 0.0114  |
| NRMSE (Unitless)| 0.2539  | 0.0137  | 0.8510  | 0.3934  | 0.0332  | 0.0203  |
| NMAE (Unitless) | 0.0975  | 0.0070  | 0.2966  | 0.1902  | 0.0132  | 0.0068  |
| UIQI (Unitless) | 0.9982  | 0.9998  | 0.9943  | 0.9983  | 0.9996  | 0.9996  |
| SSIM (Unitless) | 0.9638  | 0.9877  | 0.8268  | 0.8697  | 0.9811  | 0.9329  |
| NIF (Unitless)  | 0.1560  | 0.0856  | 0.0496  | 0.1850  | 0.0458  | 0.2334  |
| NDF (Unitless)  | 0.8516  | 0.9153  | 0.9527  | 0.8213  | 0.9543  | 0.7661  |

(Figs. 15 (e) to 15(h)). Notice that the destriped $L_t$ values correlate well with the original $L_t$ values regardless of the higher dynamic range (Fig. 15(d)).

D. IMAGE QUALITY ASSESSMENT

The destriped image quality is evaluated using ten metrics, namely, Mean Relative Error (MRE), Normalized Root Mean
Squared Error (NRMSE), Normalized Mean Absolute Error (NMAE), Universal Image Quality Index (UIQI), Structural Similarity Index Measure (SSIM), Normalized Improvement Factor (NIF), Normalized Distortion Factor (NDF), \( R^2 \), Slope, Intercept. Table 4 shows the values of these metrics for different cases (Figs. 10-15). Note that the values of MRE, NRMSE, and NMAE are close to zero for all the images, except Figs. 10, 12, and 13 because of the significant impulse noise (salt and pepper noise) contributions near the New Moon or the first quarter of the Lunar phase. The UIQI values for these cases are close to 1.0, which indicates that the destriped image quality is not degraded. Similarly, the values of SSIM are close to unity (except for Figs. 12-13 due to the higher impulse noise contributions).

The NIF and NDF values are generally close to 0 and 1.0, respectively, for all the images except Figure 15, which indicates that the proposed destriping technique can correct the horizontal stripes and vertical banding effectively from the day and nighttime images. The relatively higher variation of the twilight image, Figure 15, is mainly due to the stripping noise pattern mismatch at HGS-MGS and MGS-LGS transition boundaries.

The \( R^2 \) values for all the images are close to 1.0, indicating that the original and destriped images are highly correlated. Slopes and Intercepts for all the figures are close to 1.0 and 0, respectively, which shows the linear relationship between the input and output images. The intercept values for daytime (Fig. 14) and twilight (Fig. 15) scenes may look deviated from zero; however, a division of \( 10^6 \) with the intercept will make these values closer to 0 as the daytime radiance unit (\( \text{mW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1} \)) is different than the nighttime radiance unit (\( \text{nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1} \)) (mentioned in Table 4).

E. DETECTOR GAIN VARIATION

The VIIRS DNB noise pattern showed substantial variations across the rows and columns of the scene. The noise contribution at the center of the scene (near nadir) was mainly uniform and degraded by horizontal stripe lines only. However, the noise contribution increased drastically on two sides of the scene due to the horizontal stripes and banding effect. The proposed destriping method mimics these noise patterns and estimates detector gain factors to correct the images.

Figure 16 shows the estimated gain factors for 16 detectors across the image columns during the daytime and nighttime scenes captured over the Sahara Desert on 14 August 2021 and the Bay of Bengal/South China Sea on 2 January 2020, respectively. The detailed image analysis of these two cases is already covered in section III(C) (see Figs. 12 and 14). The Sahara Desert image was destriped after classifying the image pixels into two categories: land/cloud and water pixels, and the gain factors were calculated separately for each category. Figures 16(a) and 16(b) show the results for land/cloud pixels. The detector gain amplitude is not uniform across the image columns and reaches the maximum values at the scene edge and minimum values at the scene center (Figs. 16(a) and 16(c)). The detector gain amplitude also differs between the daytime and nighttime scenes. For example, the daytime scenes usually have a lower amplitude range (0.95 ≤ amplitude ≤ 1.06) than the nighttime scenes (0.75 ≤ amplitude ≤ 1.50) due to better signal strength. The detector gain variation from the scene center to the edges shows multiple distinct peaks corresponding to the different aggregation zones in the daytime scene (Fig. 16(b)). In contrast, the detector gain amplitude changes gradually in the nighttime scene (Fig. 16(d)). These discrepancies occur due to the two different calibration methods used for the day (LGS calibration) and nighttime (HGS calibration) scenes.

F. STRIPING ISSUES OVER MOSAICKED VIIRS NIGHT TIME LIGHT (NTL) DATA PRODUCT

The VIIRS DNB \( L_r \) data used in the present study are Level 1 SDR products which were downloaded from the NASA LAADS DAAC website. Apart from these data products, the nighttime VIIRS DNB data are also available as the nightly mosaicked data products from the Earth Observation Group (EOG), Colorado School of Mines (https://eogdata.mines.edu/products/vnl/), and the NASA LAADS DAAC as the Black marble product (product name: VNP46A1 and VNP46A2). The data products accessible from the EOG website and VNP46A1 are created from mosaicking the nighttime Level 1 SDR data at a spatial resolution of 500 m without applying any radiometric or atmospheric correction method. However, the VNP46A2 is the atmospherically corrected product produced from the nighttime VNP46A1 data available only over the land region. The striping noise visible in the Level 1 SDR data is also transferred to these mosaicked data products and significantly...
degrades the image quality, as no destriping techniques are applied on these data products.

Figure 17 shows a nighttime VIIRS DNB scene captured over the Sahara Desert on 16 March 2022. The Level 1 SDR L1 image (Fig. 17(a)) is reprojected and resampled to 500 m spatial resolution for comparison with the mosaicked data products. The actual SDR data were affected by horizontal stripe lines; however, after the reprojection, these stripe lines became oblique in shape (Fig. 17(c)). The oblique stripings are also shifted to mosaicked data (Figs. 17(d) to 17(f)), hampering the quality of the images. In general, removing the oblique striping effect from the scene is more
complex than the horizontal/vertical stripe correction problems. Hence, to reduce the complexity, it is recommended to apply a destriping correction directly over the unprojected Level 1 image rather than correcting the oblique stripe-affected mosaicked image. The destriped image shown in Figure 17(b) is reprojected later only to compare its quality with the mosaicked image.

IV. CONCLUSION
An improved destriping technique for correcting the VIIRS DNB scenes has been developed and evaluated for a range of environmental and light conditions. This technique treated the periodic striping noise as multiplicative so that the destriped image has a linear relationship with the original image. The noise amplitude also changes depending on the pixel type as the radiiances over the water, land, and cloud top are not equal. Consequently, the day and nighttime images were separated into different image classes based on the Otsu’s threshold value for each histogram mode. In contrast, the twilight images were classified into 20 or more categories using the solar zenith angles instead of the Otsu’s threshold method due to the significant variation of radiance values. The gain factor was then estimated from the ratio of the original noise image to the median filter smoothened image for each class across the image columns. The left and right edges of the scene were further smoothened by multiplying an error factor with each column. Overall, the proposed destriping method works well for a wide range of lighting and environmental conditions. It even corrected the nonuniform stripings along the different gain stage boundaries in twilight scenes.

This technique also rectified most of the nonuniformities produced due to the detector-to-detector response issues, including horizontal striping and banding effect at the scene edges. However, this method is inappropriate for intense stripings caused by stray light and the electronic hysteresis effect, which requires additional stray light corrections [20], [42]. The quality of the destriped image was analyzed based on ten different error metrics. In most cases, the destriped image quality was ensured within an error of less than a few percent. It should be noted that the destriping error analysis shown in this paper is more qualitative, as it shows the overall changes that occurred over the entire scene and does not demonstrate the variation between the individual pixels. The destriped images produced by the present technique are highly desired for various research and operational applications related to the global ocean, land, and atmosphere.

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S. Banerjee, P. Shanmugam: Improved Method for Destriping of VIIRS Day/Night Band Images

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