A Comparative Analysis of Pansharpening Techniques for Very High Resolution Satellite Imagery

Arunima Sen

Analysis and Modeling (Remote Sensing)
SS25

July 30, 2025

Abstract

This seminar paper evaluates four classical Component Substitution (CS) pansharpening methods–Brovey, PCA, IHS, and Gram-Schmidt–using urban satellite imagery of Naples and New York from the PAirMAx dataset. The goal is to assess their ability to enhance spatial detail while preserving spectral information. Quantitative metrics (PSNR, SSIM, correlation, spectral distortion, runtime) and visual inspection were used for comparison. Results show that Gram-Schmidt consistently achieves the best spectral and structural performance, while Brovey offers high visual quality and speed. PCA excels at edge preservation, and IHS performs the weakest overall. Findings underscore the trade-offs in pansharpening and highlight the importance of method selection based on application needs. Future work may explore deep learning approaches.

Contents

1 Introduction **3**

2 Theory **3**
2.1 Component Substitution (CS) Methods 4
2.1.1 Brovey Transform 4
2.1.2 Principal Component Analysis (PCA) 4
2.1.3 Intensity-Hue-Saturation (IHS) 5
2.1.4 Gram-Schmidt (GS) 5

3 Methods and Data **6**
3.1 Dataset 6
3.2 Evaluation criteria 6
3.3 Implementation 7

4 Results **7**
4.1 Visual results 8
4.2 Quantitative results 9

5 Discussion **9**

6 Conclusion **11**

References **14**

1 Introduction

Satellites and remote sensing have become increasingly popular in the last few decades. With evolving technological sophistication, we are now able to monitor the Earth better and at finer scales, both in terms of detail and frequency. This has opened up new possibilities for tracking environmental changes, managing resources, and responding to natural disasters, all with a level of spatial and temporal resolution that was previously not possible.

In remote sensing, high-resolution (HR) or very high-resolution (VHR) satellite imagery often lacks detailed spectral information, while data with rich spectral detail may have lower spatial resolution. Pansharpening aims to bridge this gap by creating an HR image that combines the best of both worlds: the detailed spatial information from an HR panchromatic (PAN) image and the rich spectral information from a lower-resolution (LR) multispectral (MS) image. The resulting fused image, an HR MS image, enhances the ability to analyze and interpret the observed scene.

Pansharpening is an important pre-processing step in remote sensing, with diverse applications in areas like change detection (Bovolo et al. 2009), urban mapping (Xu et al. 2017), environmental monitoring (Wang et al. 2019), anomaly detection (Qu et al. 2017), and more. By improving the visual quality and spatial detail of MS images, pansharpening enhances feature recognition and supports more accurate classification, interpretation, and decision-making across various domains.

With so many pansharpening algorithms in the literature and practice, and more advancements in the recent past, we come to the question: which ones work best? This is also important when it comes to answering scientific questions or implementing strategies based on the applications we are interested in. For the scope of this class, I focus on a subset of these methods, specifically Component Substitution (CS) techniques. In my seminar paper, I carry out a comparative analysis of some commonly used CS-based pansharpening approaches: the Brovey Transform, Principal Component Analysis (PCA), Intensity Hue Saturation (IHS), and Gram-Schmidt (GS). How these methods work and how they perform will be discussed in the sections that follow. The rest of this paper is structured as follows: Section 2 covers the basics of CS-based pansharpening methods like Brovey, PCA, IHS, and Gram-Schmidt. Section 3 describes the datasets, evaluation criteria, and implementation details. Section 4 shows the visual and numerical results. Section 5 discusses the main findings, trade-offs, and which methods work best. Finally, Section 6 wraps up with a conclusion.

2 Theory

Pansharpening, short for panchromatic sharpening, is a technique used to fuse an HR PAN image with an LR MS image to generate an output that maintains both high spatial detail and rich spectral information. Typically, PAN images offer finer spatial resolution, whereas MS images provide greater spectral richness across several wavelength bands.

In many remote sensing applications, accurate spatial co-registration is a critical prerequisite to ensure proper pixel alignment across datasets; without it, analyses like change detection or image fusion may produce misleading results due to spatial mismatches (Townshend et al. 1992; Cinquini 2020). However, in pansharpening, this step is often unnecessary, as PAN and MS images are usually captured simultaneously by sensors on the same platform, resulting in inherently aligned data (Vivone et al. 2014).

While pansharpening is most commonly associated with fusing PAN and MS data, its applications have expanded into the hyperspectral domain. Research has shown that methods developed for MS pansharpening can be extended to hyperspectral data, enabling similar enhancement of spatial resolution while preserving detailed spectral characteristics (Loncan et al. 2015).

There have been several groupings or classifications of pansharpening methods (Meng et al. 2019), but these authors more or less categorize them into component substitution (CS), multiresolution analysis (MRA), and variational optimization (VO) based methods. There have also been hybrid or machine learning, specifically deep learning based pansharpening techniques, and these are considered as a new generation of methods by the authors. CS methods replace specific bands in the LR MS image with information from the HR PAN image. MRA methods decompose the MS and PAN images into different spatial frequency components and then merge the most informative components from each image to create the final HR product. VO methods use mathematical optimization techniques to create an HR image that best satisfies certain criteria, such as matching the statistical properties of the original MS image.

Since this seminar paper focuses on comparing different CS methods, the next subsection will introduce and detail the individual algorithms under this category.

2.1 Component Substitution (CS) Methods

2.1.1 Brovey Transform

The Brovey Transform method combines MS and PAN bands using a ratio-based approach: each MS band is scaled by the PAN image and normalized by the sum of the MS bands. This helps preserve spectral balance while injecting spatial resolution (Vrabel 1996; Sarp 2014). The method is simple but best suited for RGB images, as it assumes spectral overlap between PAN and MS bands (Bovolo et al. 2009).

2.1.2 Principal Component Analysis (PCA)

PCA is a statistical method that transforms correlated MS bands into uncorrelated components. For pansharpening, the first principal component PC_1 (this holds most of the spatial variance) is replaced by the PAN image. After histogram matching, an inverse PCA is applied to reconstruct an HR MS image

Algorithm 1 Brovey Transform for Pansharpening

Require: Multispectral bands $MS_1, MS_2, ..., MS_n$, Panchromatic image PAN

```
for each pixel (i, j) do
    Compute total intensity: T = \sum_{k=1}^{n} MS_k(i, j)
    for k = 1 to n do
        MS_k^{HR}(i, j) = MS_k(i, j)T · PAN(i, j)
    end for
end for
return Fused high-resolution multispectral image MS^{HR}
```

(Chavez et al. 1991; Shettigara 1992; Vivone et al. 2014). While it works with any number of bands and generally preserves spectral information, performance depends on the correlation between MS and PAN data.

Algorithm 2 PCA-based Pansharpening

Require: Multispectral image MS, Panchromatic image PAN

```
Apply PCA to MS to get components PC_1, PC_2, ..., PC_n
Match histogram of PAN to PC_1
Replace PC_1 with histogram-matched PAN
Apply inverse PCA to get fused image MS^{HR}
return MS^{HR}
```

2.1.3 Intensity-Hue-Saturation (IHS)

The IHS method converts RGB bands into intensity, hue, and saturation. The PAN image replaces the intensity component, and then an inverse transform is applied. This enhances spatial resolution while preserving color information (Carper et al. 1990; Sarp 2014). However, IHS is limited to three bands and may not work well for datasets with more than three spectral bands or when NIR is included (Vivone et al. 2014).

Algorithm 3 IHS-based Pansharpening

Require: RGB bands R, G, B, Panchromatic image PAN

```
Convert (R, G, B) to (I, H, S)
Match histogram of PAN to intensity I
Replace I with matched PAN
Convert (I, H, S) back to (R, G, B) to get fused image
return Pansharpened RGB image
```

2.1.4 Gram-Schmidt (GS)

The GS approach begins by simulating an LR PAN image from the MS data, often by averaging. A GS transformation is applied, and the simulated PAN is replaced with the real PAN image. After histogram matching, the inverse GS transform yields the pansharpened output (Laben & Brower 2000; Sarp 2014).

This method performs well due to its mathematical rigor and is widely used in software such as ENVI (Vivone et al. 2014).

Algorithm 4 GS-based Pansharpening

Require: Multispectral image MS, Panchromatic image PAN

1: Simulate low-res PAN image: $PAN_{sim} = f(MS)$
2: Apply Gram-Schmidt transform using PAN_{sim} to get components
3: Match histogram of PAN to PAN_{sim}
4: Replace PAN_{sim} with matched PAN
5: Apply inverse Gram-Schmidt transform
6: **return** Fused high-resolution multispectral image MS^{HR}

3 Methods and Data

3.1 Dataset

For this implementation, I use the PAirMAx dataset introduced by Vivone et al. (2021), which is meant for evaluating and comparing pansharpening algorithms. It includes 14 pairs of PAN and MS images, collected by different HR satellites over a variety of landscapes. The dataset provides both original full-resolution images and reduced-resolution versions that follow Wald's protocol. Some of the scenes are from cities like Naples, Stockholm, New York, and Houston, offering a good mix of environments to test algorithm performance.

3.2 Evaluation criteria

To evaluate the quality of the pansharpened outputs, I use five metrics: PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), correlation, spectral distortion, and execution time (in seconds).

Following Vivone et al. (2021), two important concepts in evaluating pansharpened products are consistency and synthesis.

- Consistency refers to how well a pansharpened image, when degraded back to the original MS resolution, matches the original MS image. This is usually done using a Modulation Transfer Function (MTF) filter to simulate the sensor characteristics. Though traditionally considered a necessary check, more recent studies suggest it may also be sufficient for assessing quality at the MS scale.
- Synthesis, on the other hand, refers to how similar the pansharpened image is to what we would get if there were an ideal MS sensor operating at PAN resolution. This is typically evaluated via a reduced-resolution (RR) framework by degrading both MS and PAN, fusing them, and then comparing the result to the original MS. However, the assumption of scale invariance in the RR approach doesn't always hold, and the choice of how to degrade images can influence the outcome.

Alternatively, the full-resolution (FR) approach assesses quality directly at the PAN scale, by comparing the spectral fidelity (against the original MS image) and spatial details (against PAN). One well-established FR metric is the QNR (Quality with No Reference) index, which combines spectral and spatial distortion into a single score (Vivone et al. 2021).

Among the metrics I compute, SSIM is particularly useful for gauging structural similarity. It works by comparing local patterns of luminance, contrast, and structure between two images (Sarp 2014). Meanwhile, PSNR and correlation are more traditional pixel-level measures of error and similarity, and spectral distortion helps quantify how much the fusion process alters the spectral content.

3.3 Implementation

All pansharpening algorithms were implemented in a Jupyter Notebook using Python. Core libraries include NumPy for numerical operations, Rasterio for handling satellite image files, scikit-image and scikit-learn for image processing and PCA, and Matplotlib for visualizations.

Images from PAirMAx are loaded using Rasterio, converted to float32, and normalized using 1st–99th percentile stretching to reduce the impact of outliers. The MS image is upsampled to PAN resolution using bicubic interpolation with anti-aliasing.

As has been discussed, the following CS algorithms were implemented:

- **Brovey:** Computes intensity as the sum of MS bands, then adjusts each band using the ratio of PAN to intensity, enhancing spatial detail.
- **PCA:** Applies PCA to the MS image, replaces the first principal component with a histogram-matched PAN, and reconstructs via inverse PCA.
- **HSV:** Converts the RGB bands of MS to HSV, swaps the V (intensity) with histogram-matched PAN, and converts back to RGB.
- **Gram-Schmidt:** Simulates a low-res PAN from MS, creates orthogonal vectors via the Gram-Schmidt process, then replaces the first vector with PAN before reconstructing.

All outputs are normalized to [0,1]. Evaluation includes average PSNR, SSIM (for the first 3 bands), correlation with PAN, spectral distortion (mean absolute difference from reference), and execution time. Results are visualized through side-by-side comparisons, difference maps, and bar charts.

4 Results

Visual comparisons are shown for two urban scenes: Naples, Italy and New York City, United States. Each set includes the original LR RGB composite (simulated from MS), the pansharpened output, the reference HR MS image (used as ground truth), and a difference map (absolute difference) between the pansharpened result and the reference, highlighting residual spatial and spectral errors.

4.1 Visual results

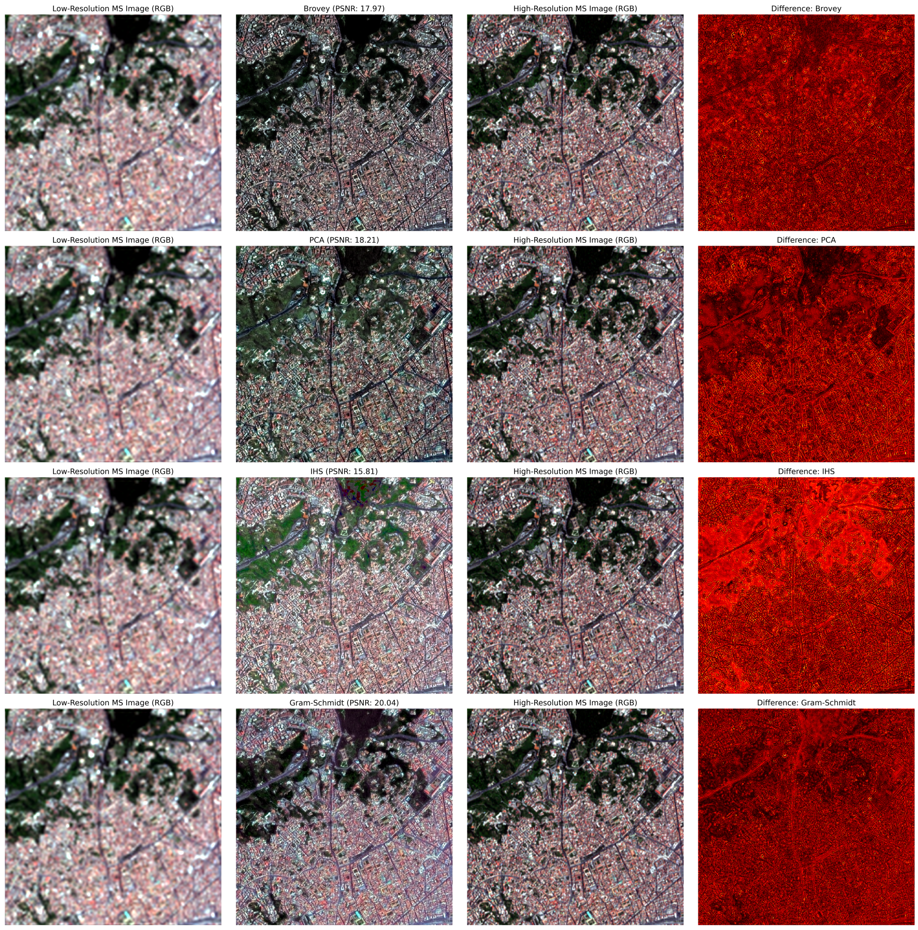

Figure 1: Pansharpened outputs of Naples, Italy

Looking at the visual results for both the Naples and New York test cases, all four pansharpening methods enhance spatial detail relative to the original LR MS image. In terms of spectral preservation, Gram-Schmidt and PCA maintain the most natural color reproduction, especially in Naples, aligning with their relatively high PSNR values. Gram-Schmidt stands out in Naples for its good balance between spatial sharpness and spectral fidelity. In New York, Brovey performs particularly well visually; it produces crisp details and vivid contrast while preserving edges, consistent with its high SSIM and correlation values, although, it tends to introduce slightly oversaturated tones in some regions. IHS consistently shows the weakest visual performance across both scenes, with noticeable spectral distortions–such as greenish tints and unnatural hues–corresponding with its lower PSNR and higher spectral distortion scores. The difference maps support these observations. IHS exhibits the most pronounced error regions, while Gram-Schmidt shows minimal differences. Brovey

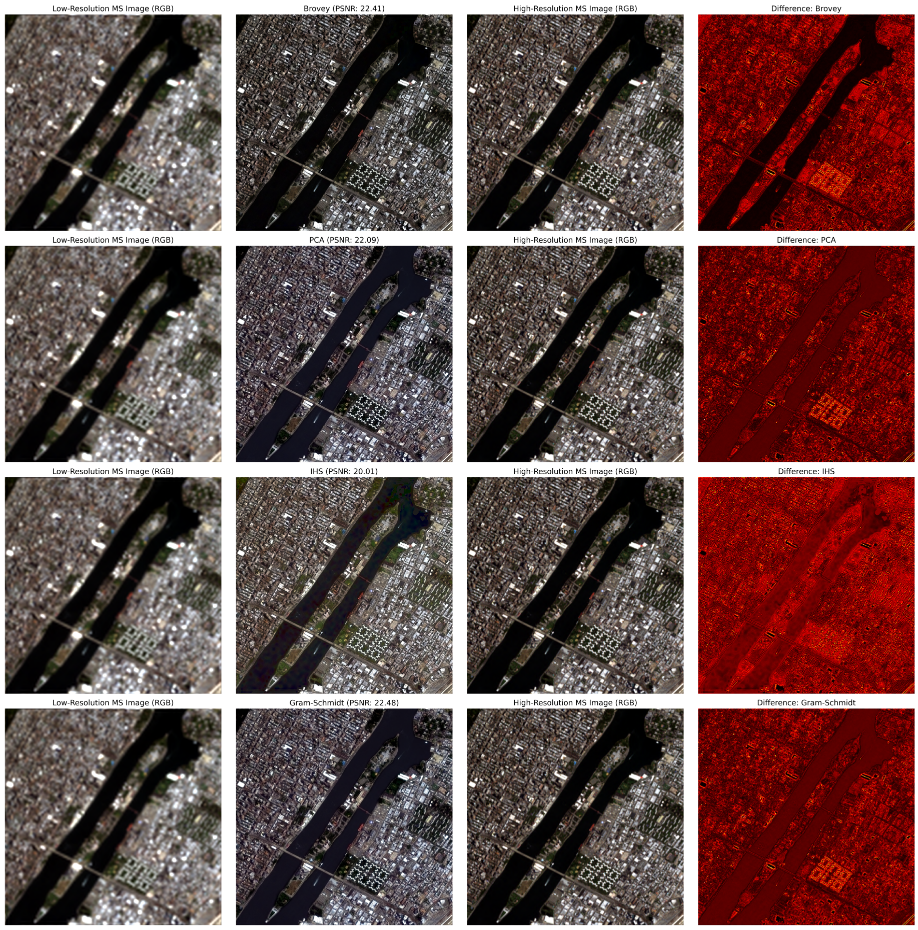

Figure 2: Pansharpened outputs of New York City, United States

and PCA show moderate, spatially uniform errors across both locations.

4.2 Quantitative results

Best methods summary:

- **Naples:** GS leads in PSNR, SSIM, and spectral distortion; PCA best in correlation; Brovey fastest.
- **New York:** Brovey best in SSIM, correlation, spectral distortion, and speed; GS has highest PSNR.

5 Discussion

The results show a trade-off between spatial detail and spectral fidelity across the tested pansharpening methods. While all methods enhanced spatial reso-

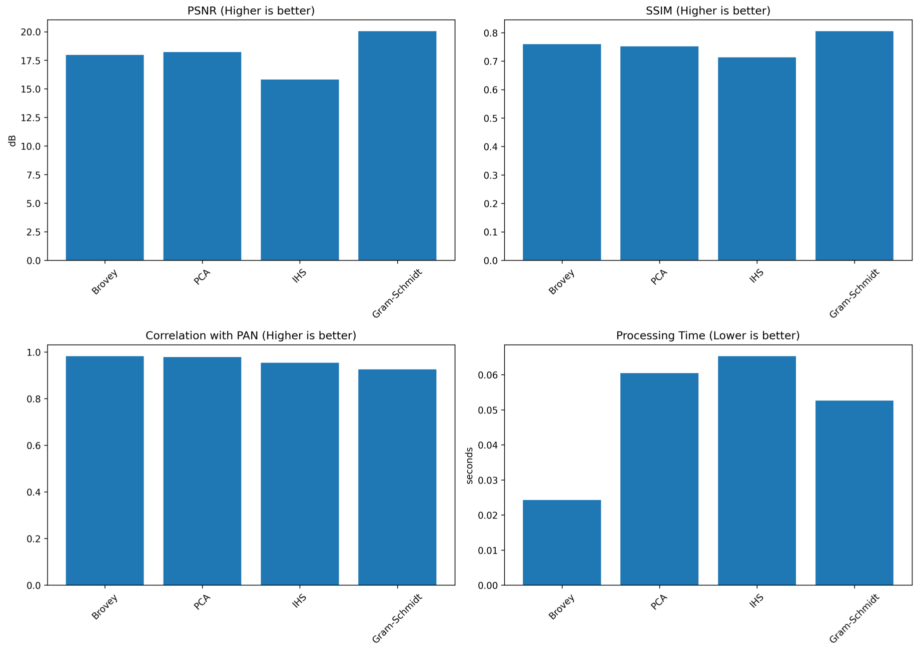

Figure 3: Metrics of the pansharpened outputs of Naples, Italy

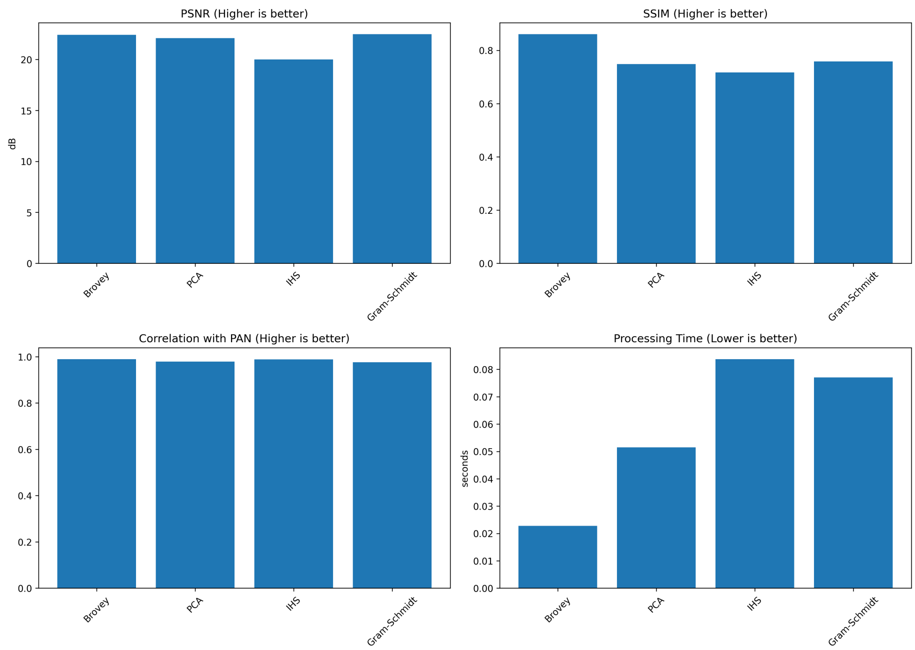

Figure 4: Metrics of the pansharpened outputs of New York City, United States

Table 1: Performance metrics for pansharpening methods

Method	PSNR	SSIM	Corr.	Spectral Dist.	Time (s)
			Naples		
Brovey	15.70	0.4358	0.9770	0.1218	0.5822
PCA	15.80	0.3850	**0.9781**	0.1298	0.6302
IHS	14.52	0.3618	0.9431	0.1571	1.3542
Gram-Schmidt	**18.07**	**0.4443**	0.9164	**0.0950**	1.3426
			New York		
Brovey	22.41	**0.8607**	**0.9897**	**0.0523**	**0.0228**
PCA	22.09	0.7486	0.9793	0.0616	0.0515
IHS	20.01	0.7175	0.9884	0.0830	0.0838
Gram-Schmidt	**22.48**	0.7584	0.9762	0.0597	0.0771

lution compared to the LR input, their ability to preserve spectral characteristics varied. Performance-wise, Gram-Schmidt consistently achieved the highest PSNR and lowest spectral distortion in both test scenes, indicating strong spectral fidelity. PCA excelled in spatial structure preservation (high correlation) in Naples, whereas Brovey performed best overall in New York, especially in SSIM, correlation, and speed. IHS underperformed across most metrics.

These outcomes suggest method suitability varies by application:

- Gram-Schmidt is ideal where spectral accuracy is critical (e.g., vegetation, urban mapping).
- PCA suits edge-sensitive tasks like road detection.
- Brovey may be preferred for quick-look visualizations or applications with limited resources.

In terms of computational efficiency, Brovey was the fastest method by far, especially on the larger New York image. Limitations include the small number of test scenes, which may affect generalizability. Some methods (e.g., IHS) are sensitive to sensor type and color distortion (Qiu et al. 2009). Further, traditional methods don't adapt well to varying scene content. Future improvements could include adaptive or learning-based methods, such as Convolutional Neural Networks (CNNs) (Masi et al. 2016; Scarpa et al. 2018), which have shown results in preserving both spatial and spectral qualities. However, they require more data and computational resources.

6 Conclusion

The goal of this seminar paper was to explore and compare classical Component Substitution (CS) methods for pansharpening, assessing both their visual performance and quantitative accuracy across different urban scenes. The analysis showed that Gram-Schmidt performed best overall with a good balance between spatial enhancement and spectral fidelity. Brovey stood out for its visual clarity and computational speed, especially in the New York case. PCA offered effective edge preservation, while IHS showed weaker performance due to color distortions. These findings highlight that method selection should depend on the application: Gram-Schmidt is preferable when spectral accuracy is key, Brovey suits fast or visually oriented tasks, and PCA can be useful for structure-focused analysis. IHS may be less reliable when spectral integrity matters. That said, pansharpening remains a trade-off: while it enhances resolution, it can also introduce noise and spectral artifacts that degrade data quality. As emphasized in prior work (Vivone et al. 2014), CS methods are generally more robust than MRA approaches in handling aliasing and misregistration issues. For future work, integrating deep learning techniques (Deng et al. 2022; Wei et al. 2017; Yang et al. 2017) may offer more adaptive and accurate fusion results. Testing on more varied scenes and including modern methods could further strengthen our understanding of pansharpening's role in remote sensing workflows.

AI Use Disclaimer

I used AI tools to proofread my work, generate algorithms for the techniques used, polish my writing, and come up with a title.

References

Bovolo et al. 2009
Bovolo, Francesca; Bruzzone, Lorenzo; Capobianco, Luca; Garzelli, Andrea; Marchesi, Silvia; Nencini, Filippo: Analysis of the effects of pansharpening in change detection on VHR images. In: *IEEE Geoscience and Remote Sensing Letters* 7 (2009), Nr. 1, pages 53–57

Carper et al. 1990
Carper, Wjoseph; Lillesand, Thomasm; Kiefer, Ralphw et al.: The use of intensity-hue-saturation transformations for merging SPOT panchromatic and multispectral image data. In: *Photogrammetric Engineering and remote sensing* 56 (1990), Nr. 4, pages 459–467

Chavez et al. 1991
Chavez, Pats; Sides, Stuart C.; Anderson, Jeffrey A. et al.: Comparison of three different methods to merge multiresolution and multispectral data-Landsat TM and SPOT panchromatic. In: *Photogrammetric Engineering and remote sensing* 57 (1991), Nr. 3, pages 295–303

Cinquini 2020
Cinquini, Jonas: *GIS and co-registration: an overview - GeoDataLab - Sistemi Informativi Territoriali*. `https://www.geodatalab.it/gis-tecnologie/gis-and-co-registration-an-overview/#fonti`. Version: Aug 2020

Deng et al. 2022
Deng, Liang-Jian; Vivone, Gemine; Paoletti, Mercedes E.; Scarpa, Giuseppe; He, Jiang; Zhang, Yongjun; Chanussot, Jocelyn; Plaza, Antonio: Machine learning in pansharpening: A benchmark, from shallow

to deep networks. In: *IEEE Geoscience and Remote Sensing Magazine* 10 (2022), Nr. 3, pages 279–315

Laben & Brower 2000
Laben, Craig A.; Brower, Bernard V.: *Process for enhancing the spatial resolution of multispectral imagery using pan-sharpening.* Januar 4 2000. – US Patent 6,011,875

Loncan et al. 2015
Loncan, Laetitia; De Almeida, Luis B.; Bioucas-Dias, José M; Briottet, Xavier; Chanussot, Jocelyn; Dobigeon, Nicolas; Fabre, Sophie; Liao, Wenzhi; Licciardi, Giorgio A.; Simoes, Miguel et al.: Hyperspectral pansharpening: A review. In: *IEEE Geoscience and remote sensing magazine* 3 (2015), Nr. 3, pages 27–46

Masi et al. 2016
Masi, Giuseppe; Cozzolino, Davide; Verdoliva, Luisa; Scarpa, Giuseppe: Pansharpening by convolutional neural networks. In: *Remote Sensing* 8 (2016), Nr. 7, pages 594

Meng et al. 2019
Meng, Xiangchao; Shen, Huanfeng; Li, Huifang; Zhang, Liangpei; Fu, Randi: Review of the pansharpening methods for remote sensing images based on the idea of meta-analysis: Practical discussion and challenges. In: *Information Fusion* 46 (2019), pages 102–113

Qiu et al. 2009
Qiu, Renyuan; Zhang, Xiaoling; Wei, Baoguo: *An improved spatial/spectral-resolution image fusion method based on IHS-MC for IKONOS imagery.* In: *2009 2nd International Congress on Image and Signal Processing* IEEE, 2009, pages 1–4

Qu et al. 2017
Qu, Ying; Qi, Hairong; Ayhan, Bulent; Kwan, Chiman; Kidd, Richard: *DOES multispectral/hyperspectral pansharpening improve the performance of anomaly detection?* In: *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* IEEE, 2017, pages 6130–6133

Sarp 2014
Sarp, Gulcan: Spectral and spatial quality analysis of pan-sharpening algorithms: A case study in Istanbul. In: *European Journal of Remote Sensing* 47 (2014), Nr. 1, pages 19–28

Scarpa et al. 2018
Scarpa, Giuseppe; Vitale, Sergio; Cozzolino, Davide: Target-adaptive CNN-based pansharpening. In: *IEEE Transactions on Geoscience and Remote Sensing* 56 (2018), Nr. 9, pages 5443–5457

Shettigara 1992
Shettigara, Vittala K.: A generalized component substitution technique for spatial enhancement of multispectral images using a higher resolution data set. In: *Photogrammetric Engineering and remote sensing* 58 (1992), Nr. 5, pages 561–567

Townshend et al. 1992
Townshend, John R.; Justice, Christopher O.; Gurney, Charlotte; McManus, James: The impact of misregistration on change detection. In: *IEEE Transactions on Geoscience and remote sensing* 30 (1992), Nr. 5, pages 1054–1060

Vivone et al. 2014
Vivone, Gemine; Alparone, Luciano; Chanussot, Jocelyn; Dalla Mura, Mauro; Garzelli, Andrea; Licciardi, Giorgio A.; Restaino, Rocco; Wald, Lucien: A critical comparison among pansharpening algorithms. In: *IEEE Transactions on Geoscience and Remote Sensing* 53 (2014), Nr. 5, pages 2565–2586

Vivone et al. 2021
Vivone, Gemine; Dalla Mura, Mauro; Garzelli, Andrea; Pacifici, Fabio: A benchmarking protocol for pansharpening: Dataset, preprocessing, and quality assessment. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14 (2021), pages 6102–6118

Vrabel 1996
Vrabel, Jim: Multispectral imagery band sharpening study. In: *Photogrammetric engineering and remote sensing* 62 (1996), Nr. 9, pages 1075–1084

Wang et al. 2019
Wang, Shengke; Liu, Lu; Qu, Liang; Yu, Changyin; Sun, Yujuan; Gao, Feng; Dong, Junyu: Accurate Ulva prolifera regions extraction of UAV images with superpixel and CNNs for ocean environment monitoring. In: *Neurocomputing* 348 (2019), pages 158–168

Wei et al. 2017
Wei, Yancong; Yuan, Qiangqiang; Shen, Huanfeng; Zhang, Liangpei: Boosting the accuracy of multispectral image pansharpening by learning a deep residual network. In: *IEEE Geoscience and Remote Sensing Letters* 14 (2017), Nr. 10, pages 1795–1799

Xu et al. 2017
Xu, Ru; Zhang, Hongsheng; Wang, Ting; Lin, Hui: Using pan-sharpened high resolution satellite data to improve impervious surfaces estimation. In: *International journal of applied earth observation and geoinformation* 57 (2017), pages 177–189

Yang et al. 2017
Yang, Junfeng; Fu, Xueyang; Hu, Yuwen; Huang, Yue; Ding, Xinghao; Paisley, John: *PanNet: A deep network architecture for pan-sharpening.* In: *Proceedings of the IEEE international conference on computer vision*, 2017, pages 5449–5457