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Exploring Dehazing Methods For Remote Sensing Imagery: A Review

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Abstract

Remote sensing imagery plays a pivotal role in numerous applications, from environmental monitoring to disaster management. However, the occurrence of haze which is atmospheric often reduces the quality and interpretability of these images. Atmospheric Haze reduces visibility of remote sensed images by reducing contrast and causing colour distortions. Dehazing techniques are employed to improve the perceptibility and clarity affected images by haze. In this review, we delve into the realm of dehazing methods specifically tailored for remote sensing imagery, aiming to shed light on their efficacy and applicability. We focus on a comprehensive comparison of four prominent dehazing techniques: Histogram Equalization (HE), Light Channel Prior (LCP), Contrast Enhancement Filters (CEF), and Dark Channel Prior (DCP). These methods, representing a spectrum of approaches, are evaluated based on key quality metrics of images, including PSNR, MSE and SSIM.

***Keywords**: Remote Sensing, Image Dehazing, Histogram Equalization, Channel Prior, Contrast Enhancement, Dark Channel Priors*

1. Introduction

Remote sensing image [1] [2] retrieval involves the efficient and accurate search of specific areas in a large-scale database. Achieving accuracy, efficiency, and robustness is crucial in implementing such retrieval systems. The quality and clarity of remote sensing images are important, but they often suffer from degradation due to atmospheric conditions during the acquisition process. Haze is a meteorological phenomenon characterized by the presence of fine particles, smoke, dust, or moisture droplets in the atmosphere, which reduces visibility and causes the air to appear hazy or foggy [3] [4] [5]. Haze often results from the suspension of tiny solid or liquid particles in the air. These particles can include dust, smoke, pollutants, and even tiny water droplets. Certain weather conditions can promote the formation of haze. Geographical features such as valleys and basins can trap air and pollutants, leading to localized haze, often referred to as smog. Human activities, particularly the burning of fossil fuels, industrial processes, and agricultural practices, can release pollutants into the atmosphere and contribute to haze formation. This is often seen in urban areas with high levels of pollution [6].

Figure 1: Example of Atmospheric Haze present in remote sensed data [7]

Reducing contrast and visibility due to hazy or foggy settings might provide a challenge in meeting the fundamental requirements for remote sensing image retrieval. In addition to impeding the recovery of remote sensing images, fog, haze, and mist also affect aerial photography. Haze reduction is therefore crucial for applications involving aerial photography and pictures from remote sensing. On the other hand, if there is just one fuzzy image provided as input, haze reduction becomes more difficult. Haze in nature and remote sensing images arises from similar physical principles, such as suspended aerosol particles in the air. Additionally, the varying distances of imaging sensors lead to different estimations of scene depth in remote sensing images. Consequently, training for accurate estimation becomes necessary for effective haze removal in the images [8]. To mitigate the negative effects of haze on images, various dehazing techniques and algorithms have been developed. These techniques aim to estimate the haze. They work by estimating the atmospheric conditions and using this information to reverse the effects of haze subsequent in richer and more pleasing images. Dehazing methods are commonly used in applications like remote sensing, computer vision, and photography to improve the quality and interpretability of images captured in hazy or foggy conditions.

Image dehazing techniques are widely used in various applications, including remote sensing, computer vision, and photography to improve perception of images taken in challenging weather or environmental conditions [9]. The technique of picture dehazing is applied to improve the visibility and clarity of photographs impacted by fog, atmospheric haze, or other airborne particles. Due to light being scattered and absorbed by particles and moisture in the environment, photos taken outside or in remote locations frequently have diminished contrast, colour distortion, and detail loss. By reducing or eliminating these ambient effects, dehazing techniques help to improve the visual appeal and readability of the photos.

This paper focus on a comprehensive comparison of four prominent dehazing techniques: Histogram Equalization (HE) [10], Light Channel Prior (LCP) [7], Contrast Enhancement Filters (CEF) [11], and Dark Channel Prior (DCP) [12]. These methods, representing a spectrum of approaches, are evaluated based on key image quality metrics. Our investigation extends beyond a mere assessment of dehazing performance; we unravel the intricacies of each method, uncovering their strengths and limitations. From the simplicity of Histogram Equalization to the robustness of Dark Channel Prior, each technique brings its unique contribution to the realm of remote sensing image enhancement. Through rigorous experimentation and analysis, this review aims to equip practitioners and researchers with valuable insights into the selection and utilization of dehazing methods, ultimately enhancing the clarity and utility of remote sensing imagery in diverse applications.

2. Related works

Different dehazing algorithms have been developed over the years, and they vary in complexity and performance depending on the specific use case and requirements [13]. These techniques aim to enhance visibility, restore contrast, and reduce the impact of haze on image interpretation. Here are some common types of dehazing techniques for remote sensing images This method estimates the haze thickness and removes haze by analysing the dark channel [14], a low-intensity channel in the image. It enhances image contrast by equalizing the histogram of the haze-affected image. Various image filters and enhancement algorithms are applied to improve local contrast and reduce haze effects. Stereo pairs of images, captured from different viewpoints, are used to estimate depth and then remove haze effects by combining information from both images [15]. Images at different wavelengths are fused for creating a haze-free composite image. These methods use atmospheric models to estimate the haze parameters (e.g., atmospheric light, transmission map) and remove haze accordingly. They consider the physics to simulate haze-free images. CNNs and other deep learning architectures are trained [16]. GANs networks are used to remove haze while being adversarial trained by a discriminator network [17]. Identify objects or regions in the image and apply dehazing techniques selectively to enhance specific areas of interest. Utilize semantic segmentation to separate objects from the background and apply dehazing selectively [18]. Apply wavelet transform to the image and process different frequency components to remove haze and enhance contrast [19]. This method utilizes non-local similarities in the image to estimate and remove haze. It often produces good results in textured regions. Combine images with lidar data to improve the accuracy of dehazing, especially in complex terrain [20]. The choice of dehazing technique depends on factors such as the specific characteristics of the remote sensing data, computational resources, and the level of haze present in the images. In practice, a combination of techniques may be used to achieve the best results in dehazing remote sensing imagery.

3. Dehazing Methods for Remote Imaging

As this work focus on a comprehensive comparison of four prominent dehazing techniques: Histogram Equalization (HE), Light Channel Prior (LCP), Contrast Enhancement Filters (CEF), and Dark Channel Prior (DCP). These methods, representing a spectrum of approaches, are evaluated based on key image quality metrics, The methods are details as:

3.1 Histogram Equalization (HE)

HE is a technique used to improve the visibility and contrast by redistributing the intensity values in the image histogram. It works by equalizing the histogram, making the pixel intensity values more evenly distributed across the entire range [21]. This process can be applied to various types of images, including remote sensing images, to enhance their visual quality and interpretability. HE is typically used as the first step is to compute the histogram of the input remote sensing image. The histogram represents the frequency of occurrence of each pixel intensity value in the image. Cumulative Distribution Function (CDF) Calculation: Next, the CDF is calculated from the histogram. The CDF represents the cumulative sum of histogram values. To equalize the histogram, the CDF values are mapped to new intensity values such that the resulting histogram becomes approximately uniform. This mapping is applied to each pixel in the image. The output of histogram equalization is an enhanced image with improved contrast and better visibility of details and features. HE effectively enhances image contrast, making it particularly useful for remote sensing images with poor contrast due to factors like haze or low lighting conditions. It is a straightforward and computationally efficient technique that is easy to implement [22].

HE operates on the entire image, providing a global enhancement that can be beneficial for various types of remote sensing data. Histogram Equalization does not consider the spatial relationships between pixels, potentially leading to over-enhancement of noise in certain regions of the image. In some cases, HE can result in the loss of fine details and subtle features, especially if the image has a well-balanced contrast to begin with. It may not be appropriate for all types of remote sensing images, especially those with specific characteristics or requirements, such as multispectral or hyperspectral data. While HE can be a valuable tool for enhancing the contrast and visibility of remote sensing images, it should be applied judiciously and in consideration of the specific characteristics of the imagery and the goals of the analysis. In some cases, alternative contrast enhancement methods that consider spatial information or spectral characteristics may be more suitable for remote sensing applications.

3.2 Contrast Enhancement Filters (CEF)

CEF, also known as contrast enhancement techniques or filters, are image processing methods can be utilized visual quality of images, including remote sensing images. These filters work by enhancing the differences in intensity between adjacent pixels, which leads to more pronounced features and improved image interpretability [23]. There are various types of CEF, each with its own characteristics and applications. The choice of a contrast enhancement filter is dependent on the specific characteristics of image and objectives of the image analysis. Commonly used filters include histogram-based methods, spatial domain filters, and frequency domain filters. The selected filter is applied to the remote sensing image. The filter operation varies depending on the chosen technique. Histogram-based methods may adjust the pixel intensity values directly, while spatial and frequency domain filters may convolve the image with a filter kernel or apply mathematical transformations. The result of applying the contrast enhancement filter is an enhanced image with improved contrast, sharper features, and better visibility of details, which can aid in image analysis and interpretation. CEF can make it easier to discern features and details in remote sensing images, which is crucial for accurate analysis and interpretation.

Different filters can be applied depending on the specific requirements of the remote sensing task, making these techniques versatile. Many CEF can be applied in real-time or near-real-time, making them suitable for applications that require quick decision-making [24]. Depending on the filter and the image characteristics, In some cases, aggressive contrast enhancement can lead to a loss of subtle details and may alter the original appearance of the image. Choosing the appropriate filter for a specific remote sensing task can be challenging, as the effectiveness of a filter may vary depending on the image content and noise levels. The choice of a contrast enhancement filter should consider the specific needs of the remote sensing application and the trade-offs between enhancing contrast and preserving image fidelity. It is often advisable to apply filters conservatively to avoid noise amplification and excessive manipulation of the original image. Additionally, combining contrast enhancement techniques with other image processing and analysis methods can lead to more robust and accurate results in remote sensing applications.

3.3 Light Channel Priors (LCP)

LCP involve considering the characteristics, statistics, or information gamma channels within an image [25]. LCP can be used to guide various image processing tasks, including enhancement, restoration, segmentation, and analysis. By analysing or leveraging the properties of different channels, it's possible to improve the accuracy and quality of image processing results. LCP can guide contrast enhancement or colour balancing to improve the visual quality of remote sensing images. Gamma channel information is used for feature extraction and object detection in multispectral or hyperspectral remote sensing data [26]. In remote sensing, channel priors can be used for atmospheric correction, where different spectral bands provide information about atmospheric conditions. Leveraging channel-specific information can lead to more accurate and visually pleasing image processing results. Channel priors can be adapted to specific tasks and image characteristics.

In remote sensing, LCP can aid in extracting valuable information about land cover, vegetation health, and more. LCP models can add complexity to image processing pipelines, especially when dealing with multispectral or hyperspectral data. Effective use of channel priors often requires access to high-quality, well-calibrated sensor data. The application of channel priors may be task-specific and may not be universally applicable to all image processing challenges. The specific application of channel priors in remote sensing may vary depending on the task and data at hand. Researchers and practitioners often employ domain-specific knowledge and techniques to exploit channel priors effectively for improving the quality and accuracy of remote sensing image analysis.

3.4 Dark Channel Priors (DCP)

The DCP is a widely used and effective dehazing technique for improving the visibility and clarity of hazy or foggy images [27]. It was originally introduced for natural images and has since been adapted for remote sensing applications. The DCP is based on a key observation as in most natural images, even in the presence of haze or fog, there exist small, dark regions where the intensity values of certain color channels are very low. These dark regions typically correspond to non-haze or clear areas in the scene, such as shadows, dark objects, or background sky regions. The DCP leverages this observation to estimate and remove haze from images. DCP is used to estimate the thickness or extent of haze in the image. It identifies the dark channel, which is a local minimum in the minimum channel (usually the blue channel) of the image. DCP also estimates the atmospheric light or airlight, which is the light scattered by the haze in the scene. This is typically done by finding the brightest pixels in the dark channel. Using the estimated dark channel and airlight, a transmission map is calculated to represent the fraction of light that has been scattered or absorbed by the haze at each pixel. The transmission map is then used to remove or reduce the haze effects by enhancing the contrast and visibility in the image. This is achieved by inversely applying the estimated transmission map to the hazy image.

DCP is a relatively simple and computationally efficient dehazing technique, making it suitable for real-time or near-real-time applications [28] [29]. It often produces visually pleasing results by effectively enhancing image contrast and removing haze. DCP makes minimal assumptions about the scene and the haze model, making it versatile and applicable to various types of imagery. DCP may not perform well in scenes where the dark channel assumption does not hold, such as scenes with uniformly bright backgrounds. In some cases, DCP can introduce color artifacts or unrealistic color shifts in dehazed images. DCP can be sensitive to noise in the input image, which may lead to artifacts in the dehazed output. It may not be the best choice for highly complex or extreme haze conditions, where more sophisticated methods may be needed. Despite its limitations, the DCP remains a valuable and widely used dehazing tool, especially in cases where its assumptions align well with the characteristics of the remote sensing images being processed. Table 1 provides a comparison of the Dark Channel Prior, Light Channel Prior, Histogram Equalization and Contrast Enhancement Filters haze removal techniques for Remote Sensing Imaging.

Table 1: Comparison of the Dark Channel Prior, Light Channel Prior, Histogram Equalization and Contrast Enhancement Filters methods in various aspects

Aspects	Dark Channel Prior	Light Channel Prior	Histogram Equalization	Contrast Enhancement Filters
Effectively Removes Haze	Yes	Yes	No	Yes
Computational Complexity	High	Moderate	Low	Moderate
Preserves Image Details	No	No	Yes	Yes
Applicability	Outdoor Scenes	Outdoor Scenes	General	Specific
Sensitivity to Scene Variations	Yes	Yes	No	Yes
Artefacts Introduced	Yes	Yes	Yes	Yes
Additional Image Enhancement	Limited	Limited	Yes	Yes

4. Results

The experiments are performed on the remote sensing images in MATLAB 2019a using windows 10 Intel i5 processor with 8GB ram. The results of the evaluation are presented in table 2, when comparing Histogram Equalization (HE), Light Channel Prior (LCP), Contrast Enhancement Filters (CEF) and Dark Channel Prior (DCP) dehazing methods for remote sensing imaging. The results of dehazing of remote sensing image using DCP method are shown in figure 2.

Figure 2: Original Image (left) image with atmospheric haze (middle) and the result from the DCP method (right)

The metrics used to evaluate the performance of these methods are PSNR, SSIM, and MSE. In the context of dehazing methods for remote sensing imaging, the chart data represents the performance of different methods HE, CEF, LCP, and DCP, in terms of three metrics: PSNR, SSIM, and MSE.

Table 2: Evaluation Results of HE, CEF, LCP, and DCP methods

Metric	HE	LCP	CEF	DCP
PSNR	40.98	46.26	43.54	49.15
SSIM	0.9418	0.9713	0.9554	0.9845
MSE	2.68	1.097	1.892	0.457

The mean squared error (MSE) between the original and reconstructed pictures is calculated. Improved picture quality is shown by lower MSE values.

$$MSE = \frac{1}{[M \times N]} \sum_{M,N} [(I_1(m,n) - I_2(m,n)]^2$$

where, I_1 and I_2 represents the ground truth images and processed image respectively, M×N is the size of the image and m, n signifies the x, y location of the image pixel. PSNR (Peak Signal-to-Noise Ratio) measures the quality of the reconstructed image compared to the original image. Higher values indicate better image quality.

$$\text{PSNR} = 10 * \text{log10(MAX\^{}2 / MSE)}$$

The structural similarity between the original and reconstructed pictures is measured using SSIM. It considers contrast, structure, and brightness. Higher values indicate more similarity between pictures in the SSIM value range of -1 to 1.

As shown in the figure 3 the CEF Method shows a percentage improvement of (1.892-2.68)/2.68 * 100 = -29.37% in MSE compared to HE. - LCP shows a percentage improvement of (1.097-1.892)/1.892 * 100 = -41.90% in MSE compared to CEF. DCP shows a percentage improvement of (0.457-1.097)/1.097 * 100 = -58.45% in MSE compared to LCP. For MSE, we observe that the MSE values decrease as we move from the HE to CEF

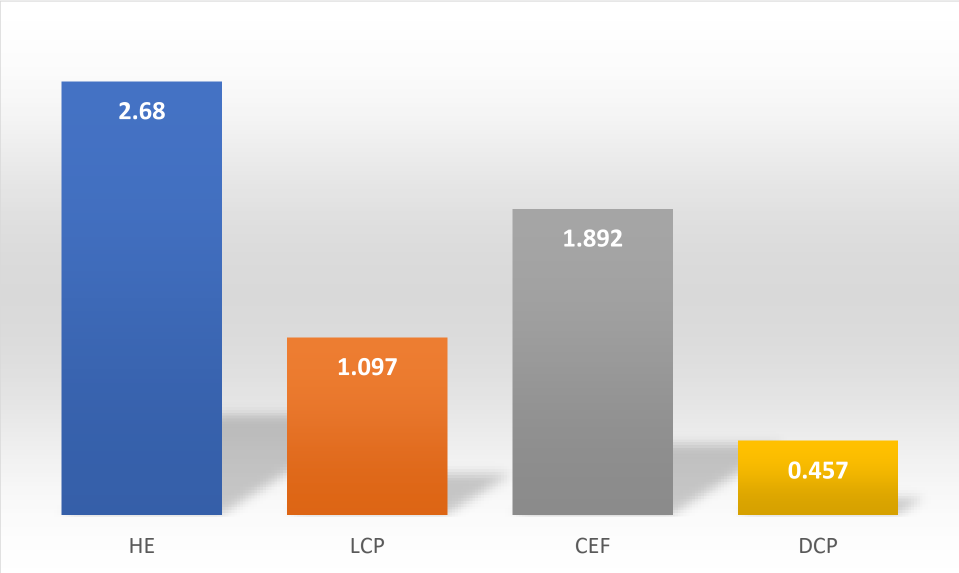

Figure 3: Comparison of the HE, LCP, CEF and DCP algorithms in terms of MSE

In PSNR case, we observe that the PSNR values increase as we move from, HE to CEF to LCP to DCP methods. This suggests that the DCP method provides the highest image quality in terms of PSNR as shown in figure below. From the figure 4, we can see that the DCP method has the highest PSNR value of 49.15, followed by LCP with 46.26, and CEF with 43.54. HE has the lowest PSNR value of 40.98. CEF Method shows a percentage improvement of (43.54-40.98)/40.98 * 100 = 6.25% in PSNR compared to HE. LCP shows a percentage improvement of (46.26-43.54)/43.54 * 100 = 6.26% in PSNR compared to CEF. Whereas, the DCP shows a percentage improvement of (49.15-46.26)/46.26 * 100 = 6.25% in PSNR compared to LCP.

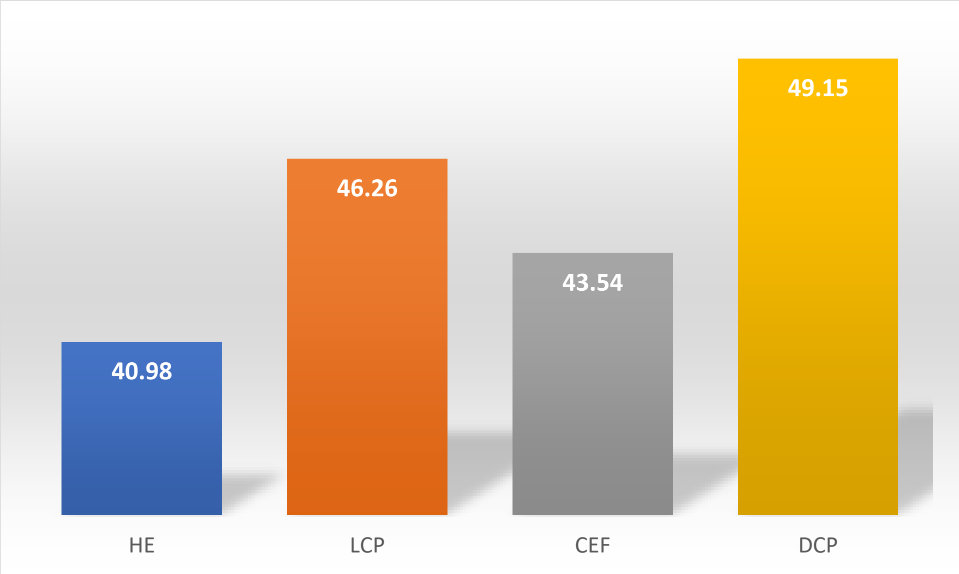

Figure 4: Comparison of the HE, LCP, CEF and DCP algorithms in terms of PSNR

For SSIM, we can see that the SSIM values also increase as we move from, HE to CEF to LCP to DCP methods. This suggests that the DCP method provides the highest similarity to the original image. CEF shows a percentage improvement of (0.9554-0.9418)/0.9418 * 100 = 1.44% in SSIM compared to HE. LCP shows a percentage improvement of (0.9713-0.9554)/0.9554 * 100 = 1.66% in SSIM compared to CEF. DCP shows a percentage improvement of (0.9845-0.9713)/0.9713 * 100 = 1.36% in SSIM compared to LCP.

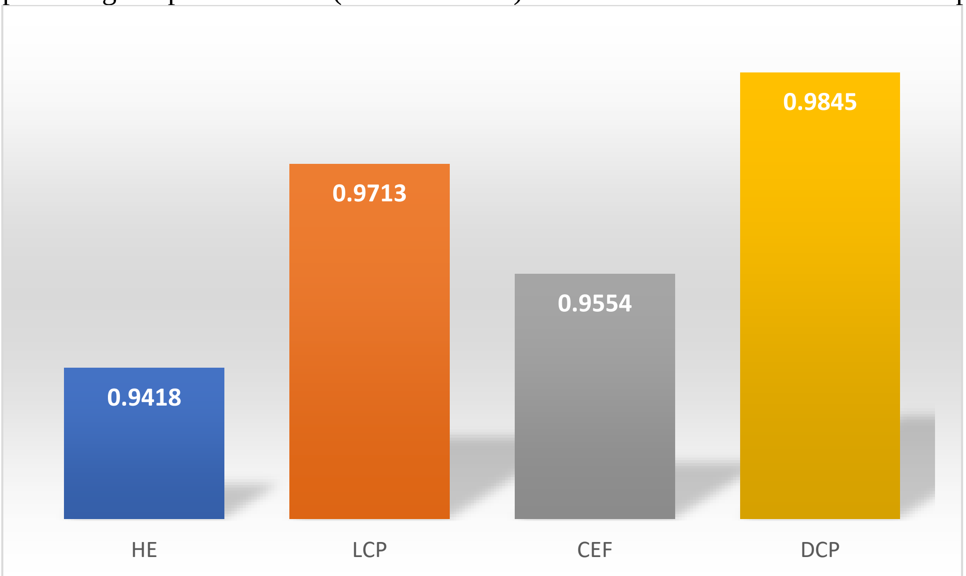

Figure 5: Comparison of the HE, LCP, CEF and DCP algorithms in terms of SSIM

The reasons for these improvements can be attributed to the specific algorithms and techniques utilized in each method. As, Histogram Equalization (HE) is a simple method that redistributes the pixel intensities of an image to improve contrast. However, it may not effectively enhance hazy images due to the lack of consideration for haze-specific features. The Contrast Enhancement Filtering (CEF) applies local contrast enhancement to remove haze from the image. This technique can result in improved image quality by enhancing the contrast and suppressing the haze. The Local Contrast Preservation (LCP) is a method that aims to preserve local contrast information while reducing haze. It achieves this by locally adjusting the image's contrast and brightness. This approach helps in achieving better visualization of the image details. Dark Channel Prior (DCP) is a widely used dehazing algorithm that leverages the dark channel information in hazy images. It estimates the transmission map and removes the haze accordingly. DCP often produces superior results by effectively estimating and removing haze from the image. The results shows that the Dark Channel Prior (DCP) method outperforms the other three methods in terms of PSNR, SSIM, and MSE. It demonstrates the highest image quality, best preservation of structural information, and lowest error in the dehazed images. The improvements in DCP can be attributed to its ability to accurately estimate the transmission map and effectively remove haze from the image.

4.1 Results

In this comprehensive review, we have explored and compared four prominent dehazing methods Histogram Equalization (HE), Light Channel Prior (LCP), Contrast Enhancement Filters (CEF), and Dark Channel Prior (DCP) in the context of remote sensing imagery enhancement. Our evaluation, based on crucial image quality metrics including Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM), has provided valuable insights into the effectiveness of these techniques. Notably, our findings highlight the exceptional performance of the Dark Channel Prior (DCP) algorithm across all evaluated metrics. DCP consistently achieved superior results in terms of reduced MSE, higher PSNR, and enhanced SSIM when compared to its counterparts. This underscores the robustness and reliability of DCP as a dehazing method tailored for remote sensing images. While DCP's prowess in mitigating atmospheric haze is evident, it is essential to acknowledge the multifaceted nature of remote sensing applications. Future work should continue to explore the broader implications and intricacies of dehazing methods, considering factors such as computational efficiency, adaptability to varying atmospheric conditions, and applicability to diverse remote sensing data sources.

References

1. Cheng, G., Xie, X., Han, J., Guo, L., & Xia, G. S. (2020). Remote sensing image scene classification meets deep learning: Challenges, methods, benchmarks, and opportunities. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 3735-3756.
2. Zhong, Y., Ma, A., soon Ong, Y., Zhu, Z., & Zhang, L. (2018). Computational intelligence in optical remote sensing image processing. Applied Soft Computing, 64, 75-93.
3. Liu, J., Wang, S., Wang, X., Ju, M., & Zhang, D. (2021). A review of remote sensing image dehazing. Sensors, 21(11), 3926.
4. Parihar, A. S., Gupta, Y. K., Singodia, Y., Singh, V., & Singh, K. (2020, June). A comparative study of image dehazing algorithms. In 2020 5th International Conference on Communication and Electronics Systems (ICCES) (pp. 766-771). IEEE.
5. Li, B., Ren, W., Fu, D., Tao, D., Feng, D., Zeng, W., & Wang, Z. (2018). Benchmarking single-image dehazing and beyond. IEEE Transactions on Image Processing, 28(1), 492-505.
6. Wen, H., Dai, F., & Wang, D. (2020, November). A survey of image dehazing algorithm based on retinex theory. In 2020 5th International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS) (pp. 38-41). IEEE.
7. Ning, J., Zhou, Y., Liao, X., & Duo, B. (2023). Single Remote Sensing Image Dehazing Using Robust Light-Dark Prior. Remote Sensing, 15(4), 938.
8. Singh, D., & Kumar, V. (2018). Comprehensive survey on haze removal techniques. Multimedia Tools and Applications, 77, 9595-9620.
9. Sahu, G., Seal, A., Krejcar, O., & Yazidi, A. (2021). Single image dehazing using a new color channel. Journal of Visual Communication and Image Representation, 74, 103008.
10. Dawar, J., Raheja, P., Vashisth, U., Cheng, I., & Basu, A. (2020, July). Color balanced histogram equalization for image enhancement. In 2020 IEEE International Conference on Multimedia & Expo Workshops (ICMEW) (pp. 1-4). IEEE.
11. Soni, B., & Mathur, P. (2020, February). An improved image dehazing technique using CLAHE and guided filter. In 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN) (pp. 902-907). IEEE.
12. Singh, D., & Kumar, V. (2017). Dehazing of remote sensing images using improved restoration model based dark channel prior. The Imaging Science Journal, 65(5), 282-292.
13. Han, M., Lyu, Z., Qiu, T., & Xu, M. (2018). A review on intelligence dehazing and color restoration for underwater images. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50(5), 1820-1832.
14. Peng, Y. T., Cao, K., & Cosman, P. C. (2018). Generalization of the dark channel prior for single image restoration. IEEE Transactions on Image Processing, 27(6), 2856-2868.
15. Gibson, K. B., Vo, D. T., & Nguyen, T. Q. (2011). An investigation of dehazing effects on image and video coding. IEEE transactions on image processing, 21(2), 662-673.

16. Ren, W., Pan, J., Zhang, H., Cao, X., & Yang, M. H. (2020). Single image dehazing via multi-scale convolutional neural networks with holistic edges. International Journal of Computer Vision, 128, 240-259.
17. Dong, Y., Liu, Y., Zhang, H., Chen, S., & Qiao, Y. (2020, April). FD-GAN: Generative adversarial networks with fusion-discriminator for single image dehazing. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 34, No. 07, pp. 10729-10736).
18. Hassan, H., Bashir, A. K., Ahmad, M., Menon, V. G., Afridi, I. U., Nawaz, R., & Luo, B. (2021). Real-time image dehazing by superpixels segmentation and guidance filter. Journal of Real-Time Image Processing, 18, 1555-1575.
19. Dharejo, F. A., Zhou, Y., Deeba, F., Jatoi, M. A., Khan, M. A., Mallah, G. A., ... & Wang, X. (2021). A deep hybrid neural network for single image dehazing via wavelet transform. Optik, 231, 166462.
20. Chung, W. Y., Kim, S. Y., & Kang, C. H. (2022). Image dehazing using LiDAR generated grayscale depth prior. Sensors, 22(3), 1199.
21. Dhal, K. G., Das, A., Ray, S., Gálvez, J., & Das, S. (2021). Histogram equalization variants as optimization problems: a review. Archives of Computational Methods in Engineering, 28, 1471-1496.
22. Mondal, K., Rabidas, R., & Dasgupta, R. (2022). Single image haze removal using contrast limited adaptive histogram equalization based multiscale fusion technique. Multimedia Tools and Applications, 1-26.
23. Sahu, S., Singh, A. K., Ghrera, S. P., & Elhoseny, M. (2019). An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE. Optics & Laser Technology, 110, 87-98.
24. Liu, X., Li, H., & Zhu, C. (2021). Joint contrast enhancement and exposure fusion for real-world image dehazing. IEEE transactions on multimedia, 24, 3934-3946.
25. Wang, J. B., He, N., Zhang, L. L., & Lu, K. (2015). Single image dehazing with a physical model and dark channel prior. Neurocomputing, 149, 718-728.
26. Ju, M., Ding, C., Guo, Y. J., & Zhang, D. (2019). IDGCP: Image dehazing based on gamma correction prior. IEEE Transactions on Image Processing, 29, 3104-3118.
27. Cai, J., Zuo, W., & Zhang, L. (2020). Dark and bright channel prior embedded network for dynamic scene deblurring. IEEE Transactions on Image Processing, 29, 6885-6897.
28. Singh, D., Kumar, V., & Kaur, M. (2019). Single image dehazing using gradient channel prior. Applied Intelligence, 49(12), 4276-4293.
29. Kapoor, R., Gupta, R., Son, L. H., Kumar, R., & Jha, S. (2019). Fog removal in images using improved dark channel prior and contrast limited adaptive histogram equalization. Multimedia Tools and Applications, 78, 23281-23307.