

Correcting Blue-Shift in Single-Image Dehazing via Haze-Compensated Von Kries Adaptation

Asniyani Nur Haidar Abdullah¹, Mohd Shafry Mohd Rahim², Sim Hiew Moi³,
Azah Kamilah Draman⁴, Ahmad Hoirul Basori⁵, Novanto Yudistira⁶

Pervasive Computing & Educational Technology, Center for Advanced Computing Technology (C-ACT), Department of Media
Interactive-Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia¹

Department of Emergent Computing-Faculty of Computing, Universiti Teknologi Malaysia,
81310 UTM Johor Bahru, Johor, Malaysia²

Department of Software Engineering-Faculty of Computing, Universiti Teknologi Malaysia,
81310 UTM Johor Bahru, Johor, Malaysia³

Department of Software Engineering, Faculty of Information and Communication Technology,
Universiti Teknikal Malaysia Melaka, Melaka, Malaysia⁴

Department of Information Technology-Faculty of Computing and Information Technology in Rabigh King Abdulaziz University,
Rabigh, Saudi Arabia⁵

Departemen Teknik Informatika-Fakultas Ilmu Komputer, Universitas Brawijaya, Jl. Veteran, Ketawanggede, Lowokwaru, Kota
Malang, Jawa Timur, Indonesia – 65145⁶

Abstract—Haze severely degrades image quality by reducing contrast, obscuring details, and introducing a blue-shift color cast caused by atmospheric scattering. Traditional dehazing methods, including prior-based approaches (e.g., DCP, CAP, LPMinVP) and preprocessing techniques (e.g., ICAP WB, Dynamic Gamma), improve visibility but fail to correct haze-induced color imbalance, resulting in unstable RGB distributions and unnatural tone reproduction. This study proposes the Haze-Compensated Color Von Kries (HCCVK) method, a lightweight and training-free preprocessing strategy that performs color compensation before transmission estimation in single-image dehazing. HCCVK integrates a novel red-channel compensation mechanism with Von Kries chromatic adaptation to mitigate wavelength-dependent haze suppression and stabilize chromatic consistency under varying illumination. Unlike learning-based color correction approaches, HCCVK does not require training data, is computationally efficient, and maintains algorithmic interpretability, making it suitable for practical deployment. The method was evaluated on six benchmark datasets: CHIC, Dense-Haze, I-Haze, O-Haze, SOT, and NH-Haze, covering indoor, outdoor, dense, and non-homogeneous haze scenarios. Experimental results based on the RGB color balance metric (σ_{RGB}) show that HCCVK reduces color deviation by approximately 75–92% on CHIC, 80–90% on Dense-Haze, and 82–90% on NH-Haze compared to the widely used DCP, and also outperforms CAP, ICAP WB, Dynamic Gamma, and LPMinVP by producing more compact and stable RGB distributions. These findings demonstrate that HCCVK effectively corrects blue-shift imbalance, preserves luminance consistency, and enhances the color stability of dehazing pipelines.

Keywords—Image dehazing; blue-shift correction; color compensation; Von Kries adaptation; preprocessing

I. INTRODUCTION

Haze is an atmospheric phenomenon that degrades image quality due to the scattering and absorption of light by particles such as water droplets, dust, and smoke suspended in the air [1]. This degradation reduces contrast, obscures fine details,

and introduces a characteristic blue-shift color cast caused by wavelength-dependent scattering, where shorter wavelengths (blue) are scattered more strongly than longer wavelengths (red) [2][3]. Such distortions negatively affect human perception and degrade the performance of computer vision applications, including autonomous driving, UAV imaging, security surveillance, and remote sensing [4][5].

Similarly, studies in other computer vision domains have shown that poor quality input data leads to degraded feature extraction and reduced system performance. For example, Waheed et al. [6] demonstrated that melanoma classification accuracy declines when dermoscopic images are not properly preprocessed before CNN analysis, while Awan et al. [7] emphasized that preprocessing significantly reduces execution time and improves classification stability in MRI-based diagnosis. Furthermore, Jabal et al. [8] showed that structural errors in raw CAD drawings lead to error propagation during feature extraction, reinforcing the importance of early corrective processing. Therefore, haze removal is essential for both visual enhancement and robust scene understanding under real-world outdoor conditions [9-10].

Single-image dehazing techniques are commonly categorized into prior-based, preprocessing-based, and learning-based methods. Prior-based methods rely on physical or statistical assumptions to estimate scene transmission and atmospheric light. Examples include the Dark Channel Prior (DCP) [11] and the Color Attenuation Prior (CAP) [12], including their enhanced variants ICAP [13], Extremum Value prior-based Local Patch Wise Minimal Values (LPMinVP) [14] and Dynamic Gamma [15]. These methods can enhance structural visibility but often introduce color distortions, halo artifacts, and inconsistent illumination recovery in dense haze regions due to inaccurate atmospheric light estimation [13]. Preprocessing-based techniques such as white balancing, histogram equalization, and gamma correction improve global illumination but do not explicitly correct haze-induced color

bias, leading to unstable RGB distributions [14][16]. Recently, deep learning methods such as CCD-Net [17] and attention-guided restoration models [18] have achieved significant improvements, yet they depend on large-scale training datasets, high computational cost, and lack interpretability, limiting their deployment in resource-constrained or real-time applications.

A major limitation across existing dehazing methods is that color imbalance caused by atmospheric scattering is not explicitly corrected before transmission estimation. Due to wavelength-dependent scattering, the red channel experiences greater attenuation than the blue channel, resulting in a dominant blue-shift color cast in hazy images [3][19]. When dehazing is applied directly to such chromatically unbalanced inputs, error propagation occurs during transmission estimation, leading to unnatural tone reproduction and unstable RGB restoration [13][14][17]. This type of error propagation from unbalanced inputs has also been highlighted in medical image analysis and CAD extraction research, indicating that effective preprocessing is necessary before advanced processing [8].

Therefore, this study addresses the lack of a lightweight, training-free preprocessing mechanism that compensates red-channel attenuation and stabilizes RGB color channels before dehazing. To solve this problem, we propose the Haze-Compensated Color Von Kries (HCCVK) method, a preprocessing strategy that integrates red-channel compensation with Von Kries chromatic adaptation to correct haze-induced spectral imbalance. Unlike deep learning-based enhancement approaches that require GPU training resources, HCCVK requires no training data [7], offers full interpretability, and maintains low computational cost, making it suitable for real-time deployment.

II. RELATED WORKS

Single-image dehazing techniques have been widely explored in computer vision and can be categorized into three main groups: prior-based methods, preprocessing-based methods, and learning-based methods. Prior-based dehazing methods estimate scene transmission based on statistical assumptions about haze-free images. The DCP [11] assumes that at least one color channel in a local image patch has low intensity, enabling effective haze removal. However, it frequently generates halo artifacts and color distortion, especially in bright regions and sky areas where the prior is invalid. The CAP [112] utilizes the relationship between depth and brightness to estimate scene depth but often suffers from over-saturation and instability under varying illumination. Improved variants such as ICAP [13] and LPMinVP [14] enhance transmission estimation using adaptive priors but still struggle with chromatic inconsistency and residual color bias, particularly in dense haze conditions. Overall, prior-based methods enhance visibility but inherently lack a mechanism to correct haze-induced color imbalance.

Preprocessing-based approaches aim to enhance visibility before dehazing by normalizing illumination or contrast. White balance correction is commonly used to suppress color cast but does not correct wavelength-dependent red-channel suppression in haze [16]. Similarly, gamma correction and histogram equalization improve brightness and contrast but

often amplify noise and cause over-enhancement [14]. Methods such as Dynamic Gamma (DD-Gamma) [15] improve global tone distribution but still fail to address blue-shift caused by atmospheric scattering, resulting in unstable RGB distributions. These approaches improve perceptual quality but do not provide physically meaningful color correction.

Learning-based dehazing methods have recently gained popularity by leveraging convolutional neural networks to learn end-to-end haze removal. Models such as AOD-Net and DCPDN incorporate physical priors into CNN architectures, while CCD-Net [17] introduces a dual-branch fusion network in RGB and Lab color space to reduce perceptual distortions. Other studies employ transformer-based attention or adversarial learning to improve scene restoration [18]. However, these methods generally require large training datasets, lack interpretability, and perform poorly in real-world atmospheric variations due to training bias and overfitting. Additionally, most learning-based models do not explicitly solve the color imbalance problem and often rely on post-processing color correction.

The importance of early-stage preprocessing to prevent feature distortion has also been emphasized across other computer vision fields. For example, Waheed et al. demonstrated that CNN-based melanoma classification can only achieve high accuracy when color distortion and illumination are corrected during preprocessing [6]. Similarly, Awan et al. showed that preprocessing improves both diagnostic stability and computational efficiency in MRI image analysis [7]. Additionally, Jabal et al. reported that failure to correct noisy or inconsistent CAD input data leads to error propagation in feature extraction systems [8]. These findings support the need for preprocessing strategies that stabilize input data before complex restoration or estimation steps.

Based on this review, it is evident that most dehazing research prioritizes visibility enhancement but neglects chromatic fidelity. Neither prior-based methods nor preprocessing and learning strategies provide a reliable solution to haze-induced blue-shift and red-channel attenuation, which leads to unnatural tone reproduction and unstable color restoration. Unlike these methods, the proposed HCCVK method focuses specifically on stabilizing RGB balance before dehazing, offering a lightweight and interpretable solution to mitigate color distortion caused by atmospheric scattering.

III. METHODOLOGY

This section outlines the experimental design, including the proposed HCCVK method, benchmark datasets, and evaluation metrics. The methodology is structured to ensure reproducibility and clarity for future implementations. It also demonstrates the effectiveness of the proposed approach under a variety of indoor and outdoor hazy conditions. Color balance is applied as a preprocessing step to mitigate blue-channel bias and preserve luminance consistency under hazy conditions.

Preprocessing plays a crucial role in preventing feature degradation during downstream processing, especially when the input data suffers from structural or spectral distortion. Similar to dehazing challenges, Waheed et al. reported that

classification accuracy in melanoma skin cancer detection drops significantly if illumination bias and color distortion are not corrected prior to CNN classification [6]. Likewise, Awan et al. demonstrated that MRI-based diagnostic performance improves when input instability is reduced through intensity normalization and contrast enhancement, especially in resource-constrained environments [7]. In another domain, Jabal et al. emphasized that uncorrected noise in CAD drawings propagates errors in feature extraction and interpretation, highlighting the importance of robust preprocessing before complex analysis [8]. Motivated by these findings, the HCCVK method introduces a lightweight preprocessing strategy to stabilize color distribution before dehazing, preventing chromatic error propagation during transmission estimation.

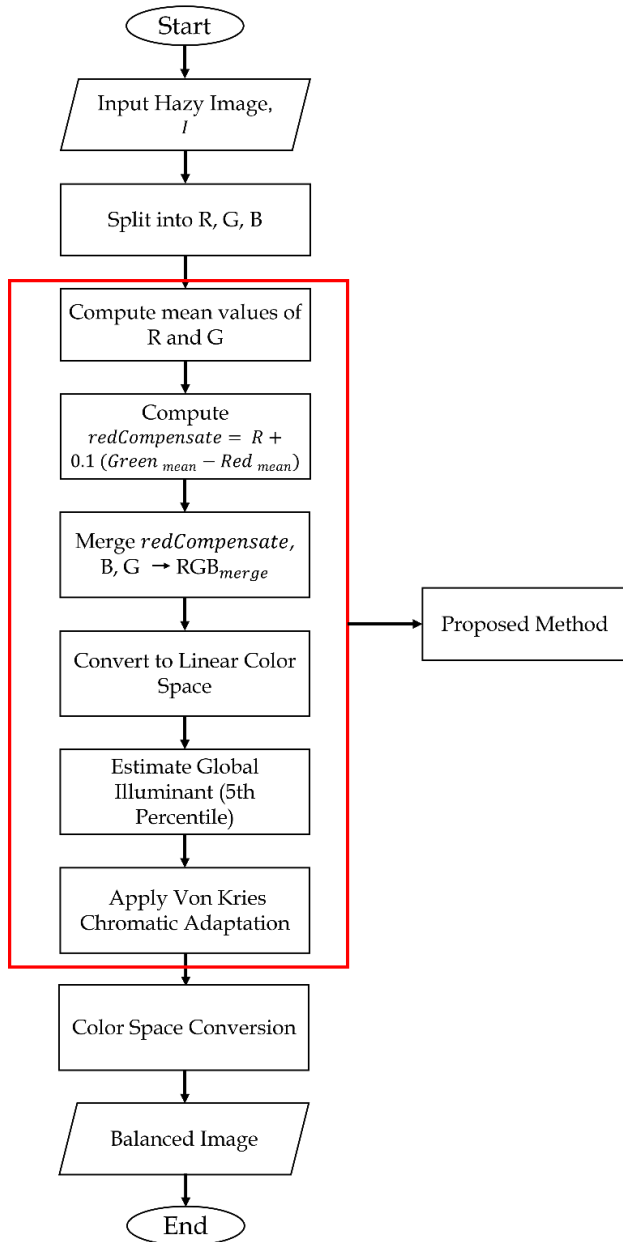


Fig. 1. Flowchart of the proposed Haze-Compensated Color Von Kries method for haze-compensated color balance.

A. Proposed Haze-Compensate Color Von Kries Method Acronyms

The HCCVK method is designed as a preprocessing stage prior to dehazing. It balances the RGB distribution by compensating the red channel and correcting the global illuminant through the Von Kries chromatic adaptation transformation. Unlike deep learning-based preprocessing techniques, which often require dedicated training resources and GPU acceleration [7], HCCVK is computationally efficient and entirely training-free. The overall workflow of the method is illustrated in Fig. 1.

As shown in the flowchart, the method proceeds through a sequence of operations from channel separation to illuminant correction. For clarity and reproducibility, the detailed steps are presented in Algorithm 1.

Algorithm 1 Haze-Compensated Color Von Kries (HCCVK) Method

Input: Hazy Image, I

Output: Haze-compensated balanced image, $I_{balance}$

Step:

1) Preprocessing:

- Split the input image into RGB channels: R, G, B .
- Compute mean intensities: $Red_{mean}, Green_{mean}$
- Apply red-channel compensation:
 $redCompensate = R + 0.1 (Green_{mean} - Red_{mean})$

2) Reconstruction

- Merge $redCompensate$, G , and B to obtain RGB_{merge}
- Convert RGB_{merge} into linear color space: RGB_{linear}

3) Illuminant Estimation:

- Define a 5% percentile threshold for robust estimation
- Estimate global illuminant using the gray-world assumption at the 5th percentile

4) Chromatic Adaptation:

- Apply the Von Kries transform using the estimated illuminant
- Generate corrected image $I_{balance}$

5) Finalization:

- Convert $I_{balance}$ back to RGB color space
- Output the haze-compensated balanced image

As shown in Table I, the weight of 0.1 achieved the highest average compensation and the lowest standard deviation among all tested parameters. This finding was further validated through entropy analysis, where entropy is defined as:

$$e = - \sum_{i=0}^{255} \sum_{j=0}^{255} \sum_{k=1}^{255} p_{i,j,k} \cdot \log_2(p_{i,j,k}) \quad (1)$$

Here, i, j, k denote the three dimensions of the probability distribution. The analysis was conducted over 390 images selected from the total dataset of 1,239, covering both controlled (indoor) and non-controlled (outdoor) illumination

conditions. Therefore, a fixed weighting factor of 0.1 was adopted in the proposed method to ensure stability and robustness across different haze conditions.

TABLE I. WEIGHTED RED AND BLUE CHANNEL COMPENSATION COMPARISON WITH ENTROPY INFORMATION

Weight	Entropy Information, e			
	Average		Standard Deviation	
	Channel			
	Red	Blue	Red	Blue
0.1	6.8503	6.8452	0.4738	0.4762
0.3	6.7879	6.7847	0.5229	0.5263
0.5	6.7873	6.7690	0.5248	0.5384
0.7	6.8288	6.7976	0.4852	0.5071
0.9	6.7739	6.7456	0.5355	0.5644

B. Dataset

To ensure a comprehensive evaluation and demonstrate the robustness of the proposed method, a total of 1,239 hazy images with corresponding ground-truth (GT) images were utilized. The dataset comprises 588 indoor images and 651 outdoor images, enabling performance assessment under different environmental conditions. These variations ensure that the evaluation covers both controlled scenarios and more challenging natural conditions.

Indoor datasets were captured under controlled illumination, which guarantees stable lighting and minimizes external variability. These include I-Haze with 30 images [20], SOT from the RESIDE dataset with 500 images [21], CHIC with 36 images [22], and Dense-Haze with 22 images [23]. Such conditions make them suitable for analyzing the performance of the method in consistent environments.

The outdoor datasets were collected under natural illumination, where changes in weather, solar position, and atmospheric scattering introduce greater complexity for dehazing. These include O-Haze with 45 images [20], SOT with 500 images [21], CHIC with 18 images [22], Dense-Haze with 33 images [23], and NH-Haze with 55 images [19]. The inclusion of these datasets ensures that the method is evaluated across both controlled and highly variable conditions.

C. Evaluation Matrix

The effectiveness of the proposed HCCVK method was evaluated using the RGB Color Balance metric (σ_{RGB}), which quantifies the degree of consistency among the three color channels. This metric is particularly suitable for haze removal tasks, as hazy conditions often suppress the red channel, leading to visible color imbalance. A lower σ_{RGB} value indicates better channel consistency and improved color fidelity, while higher values reflect imbalance and potential color casts. The metric is defined as:

$$\sigma_{RGB} = \sqrt{\frac{(R-\mu)^2 + (G-\mu)^2 + (B-\mu)^2}{3}}, \mu = \frac{R+G+B}{3} \quad (2)$$

where R , G , and B denote the average intensities of the red, green, and blue channels, and μ represents their mean intensity.

Unlike structural indices such as PSNR and SSIM, which emphasize pixel-level or textural similarity, σ_{RGB} directly measures the preservation of color balance, aligning more closely with the objectives of the proposed method.

D. Comparative Analysis

For benchmarking, the proposed method (PM OUT) was compared against several well-established dehazing algorithms, including DCP, CAP, ICAP WB, LPMInVP, DD GAMMA, PM CC and PM CM. These methods were chosen because they represent both prior-based and preprocessing-driven strategies, ensuring a fair and comprehensive evaluation. Since each approach directly affects brightness preservation and color balance, their inclusion enables a systematic comparison, highlighting not only overall dehazing performance but also the influence of distinct preprocessing modules on final image quality.

IV. RESULTS

This section evaluates the performance of the proposed HCCVK method using the σ_{RGB} , where lower values indicate better chromatic stability and reduced blue-shift distortion. HCCVK is compared against five baseline methods: DCP, CAP, ICAP WB, LPMInVP, and Dynamic Gamma. Results are reported across six benchmark datasets covering indoor, outdoor, dense, and non-homogeneous haze conditions.

A. CHIC Dataset (Indoor and Outdoor)

The results in Fig. 2 show that on the CHIC Indoor dataset, HCCVK consistently achieves the lowest σ_{RGB} values among all methods, demonstrating stable color restoration across varying illumination. While LPMInVP and ICAP WB partially improve color consistency, their σ_{RGB} ranges remain significantly wider than HCCVK, indicating lingering blue-shift imbalance. DCP exhibits the highest σ_{RGB} deviation due to its inaccurate atmospheric light estimation in bright regions.

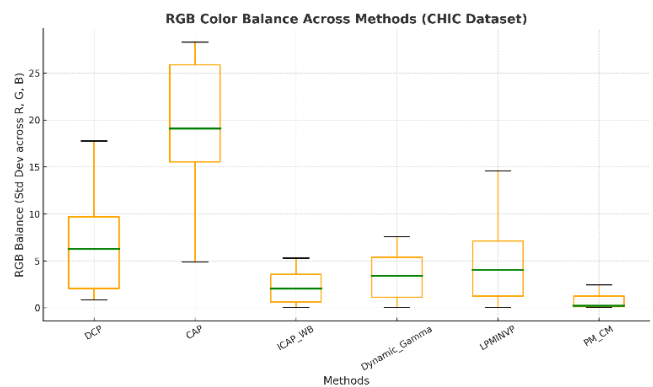


Fig. 2. RGB color balance comparison across dehazing methods on the CHIC indoor dataset.

For the CHIC Outdoor dataset (Fig. 3), similar behavior is observed. HCCVK maintains a compact σ_{RGB} distribution, confirming its effectiveness in both indoor and outdoor haze environments. Competing methods such as CAP and Dynamic Gamma struggle to stabilize the red and green channels, resulting in color shifts in scenes with strong sky illumination. In comparison, HCCVK corrects red-channel suppression, producing visually natural color tone balance.

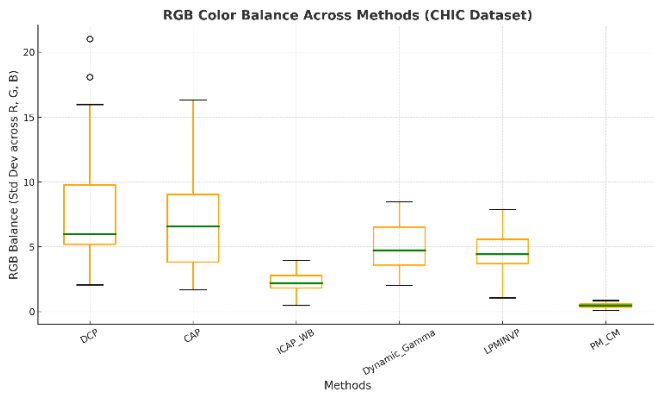


Fig. 3. RGB color balance comparison across dehazing methods on the CHIC outdoor dataset.

B. Dense Dataset (Indoor and Outdoor)

On the Dense-Haze dataset (Fig. 4, 5), haze density increases image color distortion. Despite this challenge, HCCVK maintains the most stable RGB balance with minimal variance. Competing methods such as LPMVP outperform DCP and CAP in high-density haze but still suffer chromatic instability, shown by higher σ_{RGB} interquartile ranges. This indicates that intensity equalization alone is insufficient without spectral compensation.

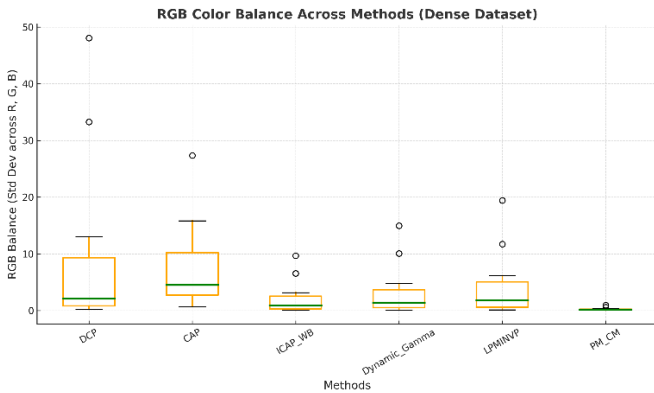


Fig. 4. RGB color balance comparison across dehazing methods on the dense indoor dataset.

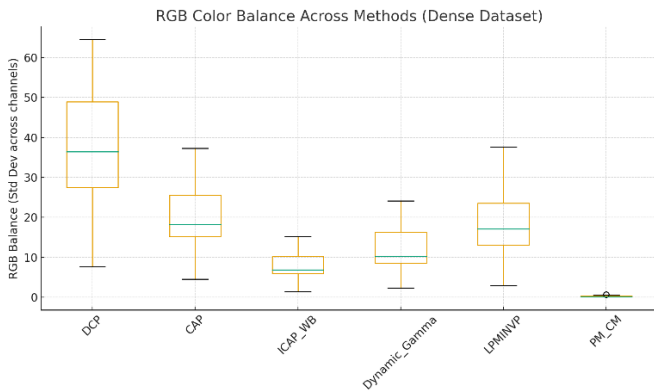


Fig. 5. RGB color balance comparison across dehazing methods on the dense outdoor dataset.

C. I-Haze and O-Haze Dataset

The I-Haze and O-Haze datasets (Fig. 6–7) evaluate haze removal in real historical scenes. HCCVK consistently produces lower σ_{RGB} compared to learning-free baselines, proving strong generalization to real-world atmospheric haze. ICAP WB improves luminance consistency but fails to correct haze-induced red-channel attenuation, leading to residual blue tint in several scenes. HCCVK effectively addresses this limitation.

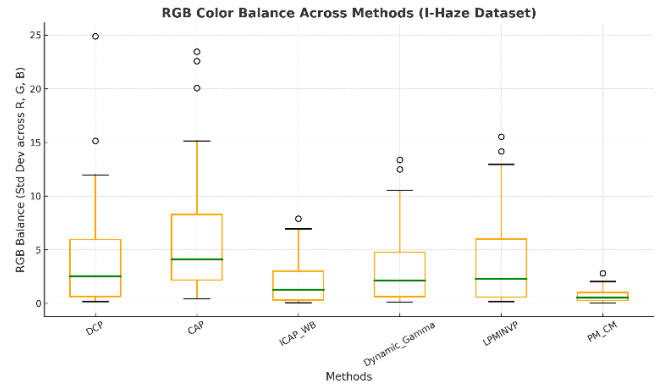


Fig. 6. RGB color balance comparison across dehazing methods on the I-Haze dataset.

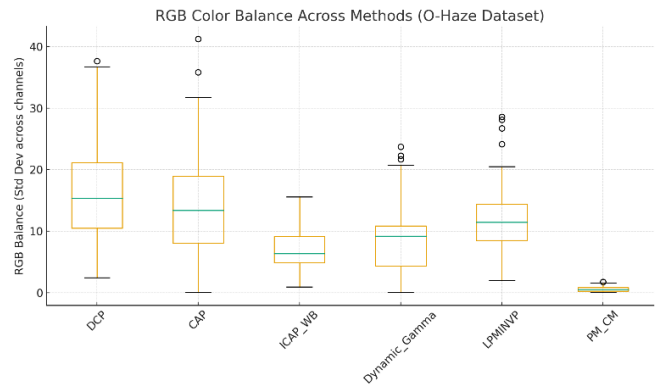


Fig. 7. RGB color balance comparison across dehazing methods on the O-Haze dataset.

D. SOT Dataset (Indoor and Outdoor)

On the SOT dataset (Fig. 8–9), which contains challenging texture transitions and depth variations, HCCVK provides the tightest σ_{RGB} dispersion, reflecting robust channel stability. CAP and Dynamic Gamma show inconsistent behavior, performing well in some scenes but failing in low-light regions due to over-enhancement artifacts.

E. NH Dataset

Finally, the NH-Haze dataset (Fig. 10), representing non-homogeneous haze, poses the greatest difficulty. HCCVK again achieves the lowest color imbalance and strongest robustness against haze variation. Prior-based methods degrade sharply in this dataset, demonstrating their limited adaptability to haze thickness variation. In contrast, HCCVK maintains consistent σ_{RGB} even under severe haze scattering.

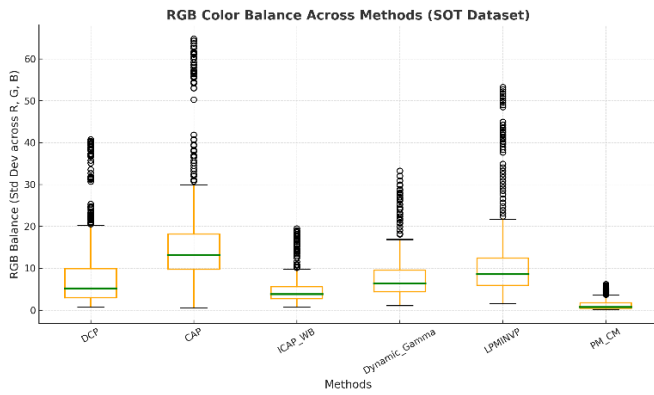


Fig. 8. RGB color balance comparison across dehazing methods on the SOT indoor dataset.

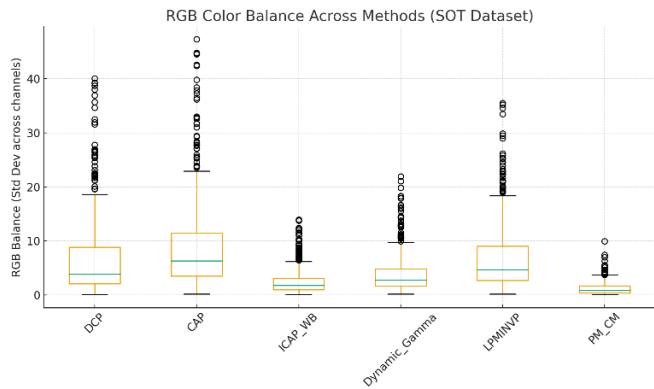


Fig. 9. RGB color balance comparison across dehazing methods on the SOT outdoor dataset.

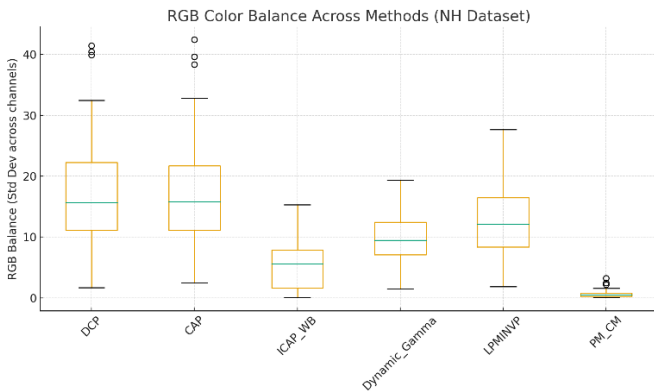


Fig. 10. RGB color balance comparison across dehazing methods on the NH dataset.

V. DISCUSSION

The experimental results across six benchmark datasets consistently demonstrate that the proposed HCCVK method outperforms both prior-based and preprocessing-driven dehazing techniques. The superiority of HCCVK can be attributed to two core design principles: 1) explicit compensation of the red channel to counteract haze-induced blue-shift imbalance, and 2) global illuminant correction through Von Kries chromatic adaptation. These steps stabilize RGB distributions before dehazing, yielding more compact box plots and lower σ_{RGB} values compared to competing methods.

Prior-based methods such as DCP and CAP exhibit high variability and frequent outliers in σ_{RGB} , indicating unstable color restoration, especially under severe haze. These observations are consistent with findings reported in previous studies. Guo et al. [24] showed that classical scattering-based priors are sensitive to atmospheric light estimation errors, often causing excessive color deviation and halo artifacts. Similarly, Ancuti et al. [19] emphasized in the NTIRE dehazing challenge that handcrafted priors struggle to preserve color fidelity, especially in outdoor haze scenarios. Our results reinforce these limitations, as DCP and CAP show wide σ_{RGB} dispersion across most datasets, demonstrating their inability to correct haze-induced color imbalance.

Preprocessing-driven methods such as ICAP WB, LPMVP, and Dynamic Gamma show moderate improvement in color consistency but remain inadequate for haze compensation. These methods apply intensity or gamma corrections without addressing wavelength-dependent scattering, resulting in incomplete chromatic recovery. Husain and Rahim [15] observed that gamma-based adjustments improve brightness but fail to eliminate residual blue-shift, while Huang et al. [25] found that simple color balancing lacks robustness in non-uniform haze conditions. This limitation is evident in our results, where ICAP WB and LPMVP produce higher median σ_{RGB} and broader channel variations compared to HCCVK.

Compared to recent learning-based approaches, HCCVK maintains strong generalization without requiring model training. Chen et al. [17] introduced CCD-Net to address color distortion in deep networks, while Jing et al. [18] implemented color correction modules to improve stability under changing illumination. Although effective, these methods rely on large annotated datasets and intensive computation, limiting real-time applicability. In contrast, HCCVK delivers competitive color correction without training, offering interpretability and low computational cost.

Overall, the consistently narrow σ_{RGB} range obtained by HCCVK across CHIC, Dense-Haze, I-Haze, O-Haze, SOT, and NH-Haze confirms its robust chromatic recovery and blue-shift mitigation capability. Unlike existing methods that treat color correction as a post-processing step, HCCVK stabilizes chromatic information before dehazing, preventing color error propagation. This makes HCCVK a generalizable and deployment-ready preprocessing module for haze removal, especially in real-world applications such as intelligent transportation, visual navigation, and UAV imaging.

VI. CONCLUSION AND FUTURE WORK

This study presented the HCCVK method, a lightweight preprocessing solution designed to correct haze-induced chromatic imbalance before dehazing. By integrating a red-channel compensation mechanism with Von Kries chromatic adaptation in linear RGB space, the method directly addresses the spectral attenuation that leads to blue-shift dominance in hazy images. Experimental validation on six heterogeneous benchmark datasets (CHIC, Dense-Haze, I-Haze, O-Haze, SOT, and NH-Haze) demonstrated that HCCVK consistently achieved the lowest σ_{RGB} values and the most compact channel distributions, indicating superior chromatic stability

compared to prior-based and preprocessing-driven baselines. These results confirm that addressing color imbalance at the preprocessing stage prevents chromatic error propagation during dehazing and provides a more reliable foundation for subsequent visibility restoration.

Beyond performance, the significance of HCCVK lies in its interpretability, generalizability, and low computational cost, making it suitable for deployment in real-time and resource-constrained computer vision systems. Unlike learning-based approaches, it does not require training or dataset-dependent tuning, yet maintains consistent robustness across varying haze densities and illumination conditions.

Future work will extend this research in three directions. First, HCCVK will be integrated with existing deep learning dehazing networks to explore hybrid learning-enhancement architectures. Second, additional evaluation metrics such as CIEDE2000, SSIM, and perceptual metrics like LPIPS will be incorporated to further quantify visual quality improvements. Finally, the method will be expanded to video dehazing and multimodal fusion scenarios to support safety-critical applications such as autonomous driving, UAV navigation, maritime vision, and intelligent surveillance.

ACKNOWLEDGMENT

This work was supported by Universiti Teknikal Malaysia Melaka (UTeM) under research grant PJP/2024/FTMK/PERINTIS/SA0043. The authors would also like to acknowledge the continuous support from the Center for Research and Innovation Management (CRIM), UTeM.

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