

# Clear Nights Ahead: Towards Multi-Weather Nighttime Image Restoration

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## Abstract

Restoring nighttime images affected by multiple adverse weather conditions is a practical yet under-explored research problem, as multiple weather degradations usually coexist in the real world alongside various lighting effects at night. This paper first explores the challenging multi-weather nighttime image restoration task, where various types of weather degradations are intertwined with flare effects. To support the research, we contribute the AllWeatherNight dataset, featuring large-scale nighttime images with diverse compositional degradations. By employing illumination-aware degradation generation, our dataset significantly enhances the realism of synthetic degradations in nighttime scenes, providing a more reliable benchmark for model training and evaluation. Additionally, we propose ClearNight, a unified nighttime image restoration framework, which effectively removes complex degradations in one go. Specifically, ClearNight extracts Retinex-based dual priors and explicitly guides the network to focus on uneven illumination regions and intrinsic texture contents respectively, thereby enhancing restoration effectiveness in nighttime scenarios. Moreover, to more effectively model the common and unique characteristics of multiple weather degradations, ClearNight performs weather-aware dynamic specificity and commonality collaboration that adaptively allocates optimal sub-networks associated with specific weather types. Comprehensive experiments on both synthetic and real-world images demonstrate the necessity of the AllWeatherNight dataset and the superior performance of ClearNight.

**Project Page:** — <https://henlyta.github.io/ClearNight/>

## Introduction

Image restoration under adverse weather conditions is a vital preprocessing step in many computer vision applications, such as autonomous driving (Yu et al. 2020; Quan et al. 2021b; Wang et al. 2024; Xu, Zhu, and Yang 2025; Xu et al. 2022) and video surveillance (Liu et al. 2023c; Li et al. 2024, 2025; Wu et al. 2026, 2025b). Although significant efforts have been made to tackle the issues posed by adverse weather images, prior works (Sun et al. 2024a; Yang et al. 2024; Yue et al. 2024) often neglect the complexities of

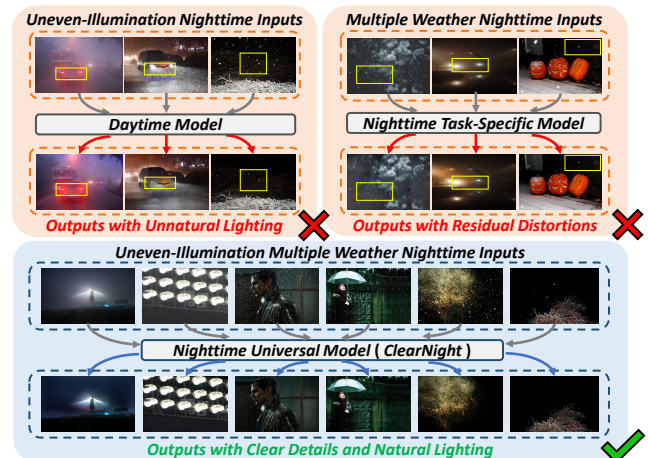


Figure 1: ClearNight is the first multi-weather nighttime image restoration framework, which effectively removes complex and coupled weather and flare degradations in one go.

lighting conditions (*e.g.*, flare effects) and their intricate interplay with weather degradations, limiting the effectiveness in real-world applications.

In particular, nighttime scenes exacerbate such problem, where adverse weather degradations and uneven illumination are tightly coupled, severely obscuring background contents. Although a few works (Zhang et al. 2020; Liu et al. 2023a; Zhang et al. 2023a) have explored nighttime adverse weather image restoration, they seldom take into account these unique characteristics. More critically, existing methods are limited to handling a single type of degradations, which leads to unsatisfactory performance in complex real-world scenarios where multiple adverse weather conditions frequently co-occur (see Fig. 1). To better meet the demands of real-world applications, this paper first explores a highly practical yet remains largely under-explored task: multi-weather nighttime image restoration. In this context, two critical challenges must be addressed: ① **the scarcity of realistic multi-weather training samples** and ② **the insufficient ability of existing models to effectively address entangled degradations in nighttime scenes**.

To the best of our knowledge, there is no existing dataset

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Datasets	H	RS	RD	S	F	Syn	Real	Night
Outdoor-Rain	✓	✓	✗	✗	✗	✓	✗	✗
RainDS	✗	✓	✓	✗	✗	✓	✓	✗
BID-II	✓	✓	✓	✓	✗	✓	✗	✗
WeatherStream	✓	✓	✓	✓	✗	✗	✓	✗
CDD-11	✓	✓	✗	✓	✗	✓	✗	✗
Raindrop Clarity	✗	✗	✓	✗	✗	✗	✗	✓
Night/YellowHaze	✓	✗	✗	✗	✗	✓	✓	✓
NHC/NHM/NHR	✓	✗	✗	✗	✗	✓	✓	✓
GTA5	✓	✗	✗	✗	✗	✓	✗	✓
UNREAL-NH	✓	✗	✗	✗	✓	✓	✓	✓
GTAV-NightRain	✗	✓	✗	✗	✗	✓	✗	✓
RVSD	✗	✗	✗	✓	✗	✓	✗	✓
AllWeatherNight	✓	✓	✓	✓	✓	✓	✓	✓

Table 1: Comparison to related adverse weather datasets. **H**, **RS**, **RD** and **S** indicate haze, rain streak, raindrop and snow, respectively. **F** denotes the presence of synthesized flare images. **Syn** denotes synthesized images. **Night** denotes the presence of nighttime data.

that is applicable to multi-weather nighttime image restoration. As summarized in Tab. 1, all previous datasets (Guo et al. 2024; Jin et al. 2024; Liu et al. 2023a; Zhang et al. 2023a; Chen et al. 2023) overlook nighttime scenarios with multiple weather degradations under non-uniform illumination. To facilitate the research, we construct AllWeatherNight, a dataset for restoring nighttime images affected by multiple adverse weather effects and flares (see Fig. 2). Specifically, we collect diverse nighttime images from multiple sources and design an illumination-aware degradation generation method to faithfully emulate degradations in real-world nighttime photos, yielding images characterized by the realistic intertwined effects of uneven illumination and multiple adverse weather degradations. Consequently, training with our synthesized images enables models to generalize better in real-world nighttime scenarios.

To effectively handle the intertwined degradations caused by artificial lighting and multiple adverse weather effects at night, we present ClearNight, the first unified framework tailored for multi-weather nighttime image restoration. We first leverage Retinex-based dual prior guidance to explicit disentangle the lighting and texture information within degraded images. Specifically, the decoupled illumination prior guides the model to focus on the uneven lit regions for effective restoration in nighttime scenes, while the reflectance prior enhances texture representations to mitigate weather-induced degradations and recover clear background details.

In order to better represent complex degradations consisting of multiple adverse weather conditions, ClearNight employs a specificity-commonality dual-branched architecture, where the specificity branch is dynamically constructed and synergizes with the commonality branch. The dynamic specificity branch contains diverse sub-networks, formed by selecting different combinations of candidate units (Shazeer et al. 2017; Zhong et al. 2024; Jia et al. 2024; Luo and Yang 2024). To further enhance the capabilities of handling multi-weather degradations, we associate these candidate units with specific weather types using an auxiliary weather in-

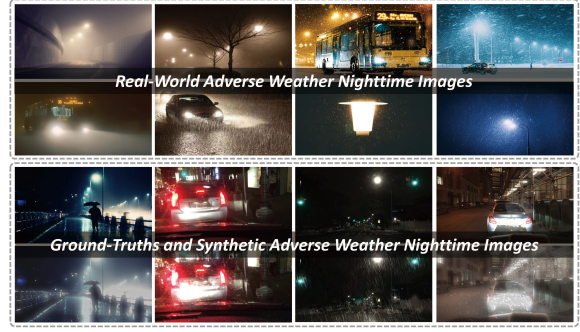


Figure 2: Real-world and synthetic samples in our AllWeatherNight dataset. The synthetic images effectively simulate real-world nighttime scenes with various degradations.

structor, which identifies weather degradations and implicitly guides their dynamic allocation. Thus, the dynamic allocator becomes weather-aware and is encouraged to consistently select appropriate units for the same types of weather conditions.

Extensive experiments and analysis demonstrate the superiority of our ClearNight on both synthetic and real-world images. The main contributions are summarized as follows:

- This work pioneers multi-weather image restoration in nighttime conditions. We contribute a new dataset featuring 10K realistic illumination-aware synthetic images with multi-degradation alongside real-world samples.
- We propose ClearNight, the first unified framework for multi-weather nighttime image restoration, which integrates Retinex-based dual prior guidance and weather-aware dynamic specificity-commonality collaboration, tailored to address challenging uneven lighting and diverse weather effects entangled in nighttime scenes.
- Our ClearNight effectively removes various degradations and outperforms state-of-the-art approaches on both synthetic and real-world adverse weather nighttime images.

## Related Work

**Adverse Weather Nighttime Image Restoration.** Early works (Zhang, Cao, and Wang 2014; Zhang et al. 2017) typically relied on physical priors and statistical assumptions, limiting their effectiveness and robustness in handling real-world scenarios. To address the limitations, several data-driven methods have been developed, achieving impressive results in restoring nighttime images degraded by haze (Pei and Lee 2012; Liu et al. 2023a; Cong et al. 2024; Wang, Wang, and Liu 2022; Liu et al. 2023b, 2022; Lin et al. 2025), rain (Zhang et al. 2023a; Lin et al. 2024) and snow (Chen et al. 2023). However, existing works focus on single-type degradations and overlook the fact that real-world nighttime scenes often involve multiple simultaneous degradations caused by adverse weather and uneven lighting.

**Multi-Weather Image Restoration.** Multi-weather image restoration aims to restore various weather-degraded scenes using a single model (Kulkarni, Phutke, and Murala 2023; Kim et al. 2024; Yang et al. 2024; Ai et al. 2024; Wu



Figure 3: Visualization of four synthesized variants of complex rain scene, where **Weather Only** and **Flare Only** denote synthesis with illumination-aware weather degradation and flare, respectively. Ours involves both degradations.

et al. 2024; Liu et al. 2024; Wu et al. 2025a; Hu et al. 2025; Dong et al. 2025). Recently, numerous Transformer-based approaches are developed, which investigate weather queries (Valanarasu, Yasarla, and Patel 2022), adverse weather pixel categorization (Sun et al. 2024b), texture-guided appearance flow (Wang et al. 2023), codebook prior fusion (Ye et al. 2023), and *etc.* Moreover, several recent works (Özdenizci and Legenstein 2023; Chen et al. 2024; Zheng et al. 2024) leverage remarkable generative capabilities of diffusion models for restoration performance boosting. To the best of our knowledge, all the previous methods focus on daytime scenes and ignore the entanglement of multiple weather conditions with non-uniform lighting in nighttime scenes.

**Adverse Weather Datasets.** Most previous datasets, like Outdoor-Rain (Li, Cheong, and Tan 2019), RainDS (Quan et al. 2021a), BID-II (Han et al. 2022), CDD-11 (Guo et al. 2024) and WeatherStream (Zhang et al. 2023b), only focus on adverse weather image restoration in daytime scenarios. A few recent studies explore this task in nighttime scenes and build datasets for haze (*e.g.* Night/YellowHaze (Liao et al. 2018), NHC/NHM/NHR (Zhang et al. 2020), UNREAL-NH (Liu et al. 2023a)), rain (*e.g.* GTA5 (Yan, Tan, and Dai 2020), GTAV-NightRain (Zhang et al. 2022, 2023a), Raindrop Clarity (Jin et al. 2024)) and snow (*e.g.* RVSD (Chen et al. 2023)). However, each existing nighttime dataset only considers a single type of weather condition, ignoring the challenge of mixed weather conditions commonly found in the real world.

### AllWeatherNight Dataset

Real-world nighttime scenes are often degraded by a complex interplay of co-occurring weather and flares, challenging models for faithful restoration and visibility enhancement. To address this gap, we introduce AllWeatherNight, a new large-scale dataset featuring nighttime images with coupled degradations from mixed weather and uneven lighting.

**Data Collection and Filtering.** We repurpose images from BDD100K (Yu et al. 2020) and ExDark (Loh and Chan 2019) as ground truths. These candidate images undergo a two-step process: selecting high-quality nighttime samples

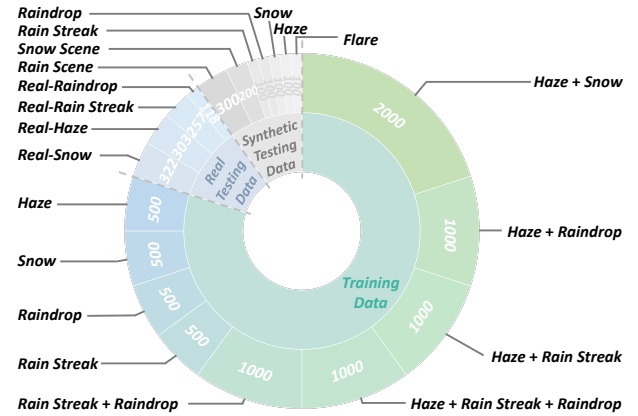


Figure 4: Distribution of the our AllWeatherNight dataset.

using average brightness, average gradient and grayscale variance; and manually selecting the 1,000 diverse images from each dataset. We also collect 1,000 real-world nighttime images with various weather conditions from the Internet and existing datasets (Li et al. 2019; Wang et al. 2019; Liu et al. 2018; Zhang, Sindagi, and Patel 2020; Fu et al. 2017; Jin et al. 2023; Yang et al. 2020).

**Illumination-Aware Degradation Generation.** We observe that uneven lighting conditions in real-world nighttime scenes often interact with adverse weather degradations, yet this phenomenon is largely overlooked by prior works (Zhang et al. 2020, 2023a). To synthesize more realistic nighttime images with weather effects, we introduce an illumination-aware degradation generation approach that first modulates the lighting effects and then superimposes an illumination-aware combination of weather degradations.

Given a clean nighttime image  $X$ , we generate flare-degraded image  $X^{\text{flare}}$  based on light regions:

$$X^{\text{flare}} = \alpha \cdot X + \beta \cdot (L * K^{\text{APSF}}), \quad (1)$$

where  $\alpha$  controls clean image preservation.  $\beta$  regulates flare blending and is adaptively set by the light source pixel ratio.  $L$  is a light source map devised via thresholding and alpha matting refinement (Levin, Lischinski, and Weiss 2008).  $K^{\text{APSF}}$  is a 2D kernel from the atmospheric point spread function (Jin et al. 2023), and  $*$  is the convolution operator.

Subsequently, building upon  $X^{\text{flare}}$ , the illumination-aware weather-degraded image  $X^{\text{d}}$  is synthesized by:

$$X^{\text{d}} = X^{\text{flare}} + \sum_{e \in \mathcal{E}} \omega_e \cdot \mathcal{F}_e^{\text{G}}(X^{\text{flare}}), \quad (2)$$

where  $\mathcal{E}$  is the set of selected weather effects for generating a specific degraded image, which is a subset of the universal set of all possible effects, *i.e.*,  $\mathcal{E} \subseteq \{\text{H, RS, RD, S}\}$  (Haze, Rain Streak, Raindrop, and Snow). We devise a weight map  $\omega_e$  to better simulate weather degradations under uneven lighting, where  $\omega_{e \neq \text{RD}}$  is set to the Retinex decomposed illumination map, while  $\omega_{e = \text{RD}}$  is empirically set to 1, as raindrops are primarily affected by local background rather than distant lighting.  $\mathcal{F}_e^{\text{G}}(\cdot)$  represents corresponding weather generation functions. We simulate adverse weather

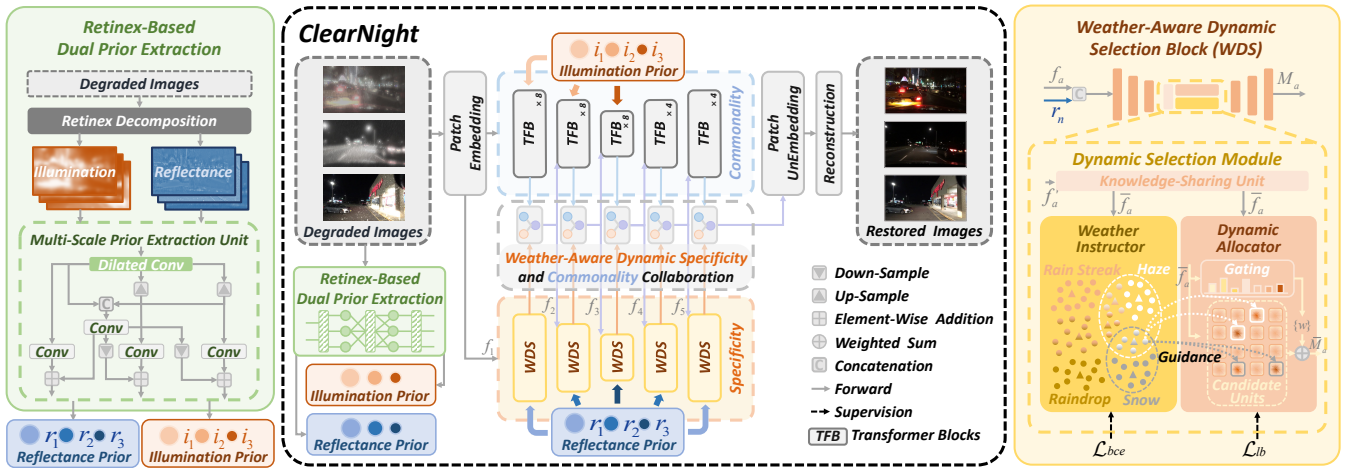


Figure 5: Overview of our ClearNight framework. ClearNight primarily comprises Retinex-based dual prior guidance as well as weather-aware dynamic specificity and commonality branches. The Retinex-based dual priors explicitly guide the network to focus on illumination regions and intrinsic textures. The weather-aware dynamic specificity branch adaptively accommodates various weather effects and collaborates with the commonality branch to effectively handle complex multi-weather scenes.

using established models (Li, Cheong, and Tan 2019; Soboleva and Shipitko 2021; Liu et al. 2018; Chen et al. 2021). As shown in Fig. 3, unlike simplistic, spatially uniform synthesis, illumination-aware method generates more natural degradations.

**Dataset Statistics.** Overall, we synthesize 8,000 nighttime training images, covering multiple weather with varying scales, directions, patterns and intensities. As summarized in Fig. 4, the test dataset comprises synthetic and real-world subsets, each containing 1,000 images for model evaluation.

## ClearNight

ClearNight is a unified nighttime image restoration framework designed to simultaneously remove multiple weather degradations. As depicted in Fig. 5, ClearNight integrates Retinex-based dual prior guidance and weather-aware dynamic specificity-commonality collaboration. The former explicitly decouples uneven lighting and textures to guide the network in recovering clear images with natural lighting and rich background details. The latter effectively captures the unique and shared characteristics of diverse weather conditions, enabling powerful multi-weather image restoration.

### Retinex-Based Dual Prior Guidance

Decoupling illumination and texture information is critical for nighttime image restoration, as it allows the model to separately handle non-uniform lighting and adverse weather degradations. Retinex theory (Edwin 1977) provides a classic physical model for this decomposition, formulating the input degraded image  $X^d$  as:

$$X^d = R^d \cdot I^d, \quad (3)$$

where  $R^d$  and  $I^d$  are the reflectance and illumination components, respectively. The decomposed components  $p^{\text{rtx}} \in \{I^d, R^d\}$  are then fed into shared-weight multi-scale prior

extraction units (MPE):

$$p_1, p_2, p_3 = \mathcal{F}^{\text{MPE}}(p^{\text{rtx}}) \quad \text{with} \quad p_n \in \{i_n, r_n\}, \quad (4)$$

where  $p_n$  denotes the illumination or reflectance prior at the  $n$ -th scale, with  $n \in \{1, 2, 3\}$ . Within each MPE unit, a dilated convolution first projects the  $p^{\text{rtx}}$  into three scales. Then, resulting multi-scale features are interactively fused to produce the final illumination/reflectance priors  $p_n$ .

More specifically, the illumination priors  $i_n$  are successively injected into the Transformer blocks (TFBs) of the first three stages, which guide the network to focus on the uneven lighting regions in nighttime images, thereby facilitating the handling of lighting-influenced weather degradations. As the reflectance priors  $r_n$  contain rich intrinsic textures that not only capture background details but also reveal degradation types, we incorporate them into each weather-aware dynamic selection block (WDS) to enhance weather type discrimination and improve multi-weather restoration.

### Weather-Aware Dynamic Specificity-Commonality Collaboration

**Dynamic Specificity and Commonality Synergy.** As different weather degradations (e.g., snow and rain streaks) exhibit both shared and unique patterns, we introduce a synergistic design of dynamic specificity and commonality to effectively model complex multi-weather degradations. The commonality branch consists of sequential Transformer blocks (TFBs), while the specificity branch incorporates multiple weather-aware dynamic selection blocks (WDS) as residuals for each stage of TFBs.

As shown in the right of Fig. 5, each WDS consists of an encoder-decoder structure and a dynamic selection module, which jointly process the merged features from two branches and the reflectance prior. The encoder-decoder structure, inspired by (Zhong et al. 2024), learns compact representations, while the dynamic selection module constructs input-

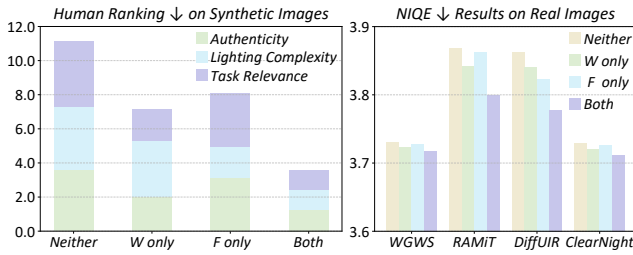


Figure 6: Comparison of 4 synthesized variants of nighttime images, where **W** and **F** indicate synthesis with illumination-aware weather degradation and flare effects respectively.

tailored sub-networks by sparsely selecting candidate units ( $\mathcal{F}_k^U(\cdot)$ ), where  $k$  is the unit index.

Besides the candidate units, the dynamic selection module includes a gating ( $\mathcal{F}^W(\cdot)$ ) that computes the importance weights assigned to each candidate unit, and a router ( $\mathcal{F}^R(\cdot)$ ) that estimates the probability of each unit being selected. Given the input feature  $\bar{f}_a$ , the output of the  $a$ -th dynamic selection module can be calculated by

$$\bar{M}_a = \sum_{k \in \mathcal{T}} \mathcal{F}^W(\bar{f}_a)_k \cdot \mathcal{F}_k^U(\bar{f}_a), \quad (5)$$

where  $\mathcal{T} = \text{TopK}(\mathcal{F}^R(\bar{f}_a))$  denotes the set of selected top- $K$  candidate unit indices, and  $\mathcal{F}^W(\bar{f}_a)_k$  is the importance weight for the  $k$ -th unit.

**Dynamic Weather Degradation Modeling.** Relying solely on visual content would limit the ability to capture the correlations and distinctive characteristics of different weather types, thereby hindering the module’s effectiveness in complex multi-weather scenarios. To better associate distinct weather types with designated candidate units, we reorganize the dynamic selection module and introduce a new component, the weather instructor ( $\mathcal{F}^{\text{WI}}(\cdot)$ ).

In the new design, features first pass through a knowledge-sharing unit ( $\mathcal{F}^{\text{KSU}}(\cdot)$ ), which is composed of shared linear layers preceding the dynamic allocator. The output of the knowledge-sharing unit is then utilized by the weather instructor, which classifies degradations and learns weather-specific prototypes to aggregate features from the same weather conditions:

$$y_a = \mathcal{F}^{\text{WI}}(\bar{f}_a) \quad \text{with} \quad \bar{f}_a = \mathcal{F}^{\text{KSU}}(f'_a), \quad (6)$$

where  $f'_a$  is the output of the encoder, and  $y_a$  is the weather type predicted by the  $a$ -th dynamic selection module.

The weather instructor performs multi-label classification using binary cross-entropy loss  $\mathcal{L}_{\text{bce}}$ , guiding the prototypes to attract features of the corresponding weather.

## Network Optimization

Multiple losses are utilized to jointly optimize ClearNight, where L1 loss  $\mathcal{L}_1$  and perceptual loss  $\mathcal{L}_p$  (Johnson, Alahi, and Li 2016) are used to ensure that restored results resemble ground-truths closely. To enhance the structure and details of outputs, depth loss  $\mathcal{L}_d$  is exploited via minimizing the differences between ground-truths and predictions of a

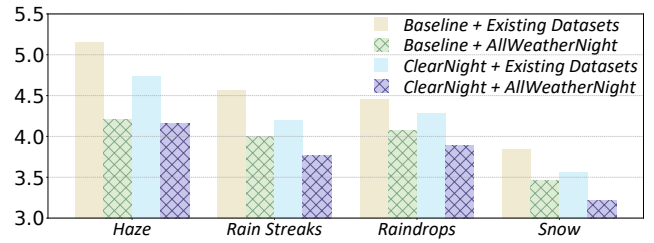


Figure 7: Models trained on AllWeatherNight achieve superior NIQE $\downarrow$  results on real-world images compared to those trained on the combination of existing nighttime datasets.

pre-trained depth estimation model (Liu et al. 2021). In addition, we use a load balancing loss  $\mathcal{L}_{\text{lb}}$  (Shazeer et al. 2017) to balance the utilization of the candidate units. We jointly optimize the network using the total loss function:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_1 + \lambda_p \mathcal{L}_p + \lambda_{\text{bce}} \mathcal{L}_{\text{bce}} + \lambda_{\text{lb}} \mathcal{L}_{\text{lb}} + \lambda_d \mathcal{L}_d, \quad (7)$$

where  $\lambda_p$ ,  $\lambda_{\text{bce}}$ ,  $\lambda_{\text{lb}}$  and  $\lambda_d$  are the loss weights.

## Experiments

### Implementation Details

The synthetic image size is  $640 \times 360$ . During training, the input image is randomly cropped to  $256 \times 256$ . We adopt DehazeFormer (Song et al. 2023) as our baseline for its advanced spatial aggregation, allowing effective natural lighting restoration. We use Adam as optimizer and the initial learning rate is set to  $2 \times 10^{-4}$  for 100 epochs. The learning rate is adjusted using the cosine annealing scheme. The loss weight  $\lambda_p$ ,  $\lambda_{\text{bce}}$ ,  $\lambda_{\text{lb}}$  and  $\lambda_d$  are empirically set to 0.1, 0.001, 0.01 and 0.02, respectively.  $\alpha$  is set to 0.995.

### Dataset Analysis

To demonstrate the effectiveness of illumination-aware degradation generation, we analyze four different synthetic variants of nighttime images (showcased in Fig. 3). Ten volunteers are recruited to rank image quality on authenticity, lighting complexity and task relevance. As shown in the left of Fig. 6, we can observe that the combination of illumination-aware weather and flare achieves the best human preference. Furthermore, the right part of Fig. 6 demonstrates that training with our illumination-aware data improves performance in real-world scenes, with four representation models (Zhu et al. 2023; Choi et al. 2024; Zheng et al. 2024) exhibiting consistent improvements.

To further validate the proposed dataset, we compare the performance of models trained on our AllWeatherNight dataset with those trained on a composite dataset constructed from existing nighttime datasets, as shown in Tab. 1. As shown in Fig. 7, models trained on AllWeatherNight exhibit superior performance on real-world samples, which is attributable to our illumination-aware synthetic images simulating degradations more realistically.

### Comparison with the State-of-the-Art

**Results on Synthetic Data.** We compare ClearNight with state-of-the-art adverse weather image restoration methods

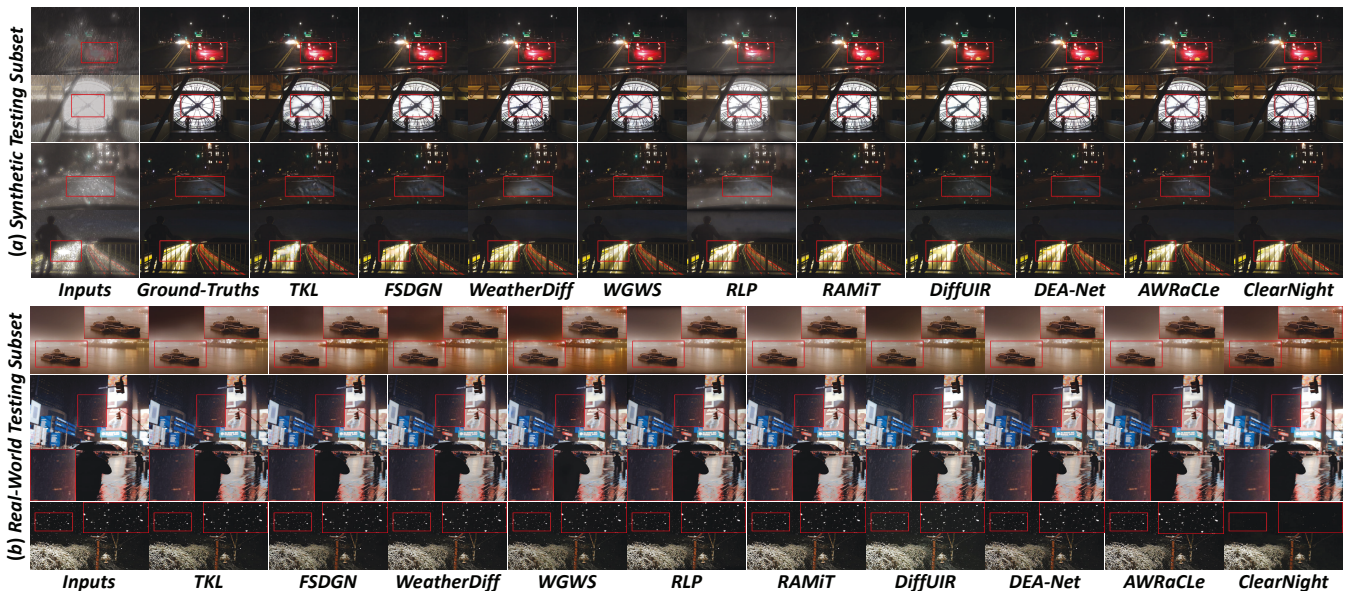


Figure 8: Qualitative results on AllWeatherNight synthetic and real-world testing subset. Please zoom in for more details.

Method	Multi-Degradation				Single-Degradation				
	Rain Scene		Snow Scene		Haze	Rain Streak	Raindrop	Snow	Flare
	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$	PSNR $\uparrow$ / SSIM $\uparrow$
TKL	29.0919 / 0.8769	26.2657 / 0.8456	31.6136 / 0.9401	30.4227 / 0.8844	32.5573 / 0.9561	31.0471 / 0.9247	36.7239 / 0.9741		
FSDGN	29.9850 / 0.8730	28.0147 / 0.8474	34.1807 / 0.9378	31.3309 / 0.8851	33.9535 / 0.9638	31.9022 / 0.9288	38.7223 / 0.9798		
WeatherDiff	29.7631 / 0.8936	27.1109 / 0.8537	30.5020 / 0.9256	<u>33.3630</u> / <b>0.9352</b>	<b>35.9385</b> / <b>0.9726</b>	33.6573 / 0.9488	<u>40.2057</u> / 0.9826		
WGWS	30.5811 / 0.8961	27.9023 / 0.8658	31.6132 / 0.9181	32.8077 / 0.9221	34.3616 / 0.9554	32.1325 / 0.9196	32.1085 / 0.9017		
RLP	21.2180 / 0.6641	19.3059 / 0.6124	18.6348 / 0.6379	31.1586 / 0.8867	32.4204 / 0.9322	31.5645 / 0.9101	34.7658 / 0.9451		
RAMiT	30.4565 / 0.9106	29.1169 / 0.8889	<u>36.4414</u> / <b>0.9738</b>	31.9433 / 0.9204	33.8452 / 0.9632	32.8934 / 0.9491	<b>43.0080</b> / <b>0.9934</b>		
DiffUIR	27.6676 / 0.8040	25.8151 / 0.7892	28.4763 / 0.8341	30.2547 / 0.8624	29.6778 / 0.8740	26.9833 / 0.8055	31.2789 / 0.8816		
DEA-Net	31.4244 / 0.9202	29.2500 / <u>0.8956</u>	35.8174 / 0.9612	32.7631 / 0.9285	34.8406 / 0.9704	33.5811 / 0.9493	38.6533 / 0.9807		
AWRaCle	<u>31.5392</u> / <u>0.9210</u>	<u>29.4270</u> / 0.8738	36.4315 / 0.9599	33.1078 / 0.9317	35.2985 / 0.9686	<u>33.6716</u> / <u>0.9532</u>	40.1014 / 0.9836		
Baseline	28.7976 / 0.8825	27.1337 / 0.8452	30.2905 / 0.9257	30.5615 / 0.8994	33.0758 / 0.9598	31.3318 / 0.9182	36.0821 / 0.9738		
ClearNight	<b>32.5937</b> / <b>0.9223</b>	<b>30.6464</b> / <b>0.9041</b>	<b>36.4655</b> / <u>0.9621</u>	<b>33.6238</b> / <u>0.9331</u>	<u>35.4282</u> / <u>0.9723</u>	<b>33.9747</b> / <b>0.9539</b>	38.7707 / <u>0.9838</u>		

Table 2: Quantitative results on AllWeatherNight synthetic testing subset. The **best** and second-best results are highlighted.

on AllWeatherNight, including TKL (Chen et al. 2022), FSDGN (Yu et al. 2022), RLP (Zhang et al. 2023a), WeatherDiff (Özdenizci and Legenstein 2023), WGWS (Zhu et al. 2023), RAMiT (Choi et al. 2024), DiffUIR (Zheng et al. 2024), DEA-Net (Chen, He, and Lu 2024) and AWRaCle (Rajagopalan and Patel 2025). As shown in Fig. 8a, TKL (Chen et al. 2022), FSDGN (Yu et al. 2022) and DiffUIR (Zheng et al. 2024) produce overly smooth results such as the clock and railing regions, while other approaches often lose structural details or leave residual artifacts. In contrast, ClearNight preserves rich background details and restores natural lighting, illustrating robust performance across diverse and complex nighttime scenarios.

Tab. 2 reports quantitative results on multi-degradation and single-degradation scenes, evaluated using PSNR (Horé and Ziou 2010) and SSIM (Zhou et al. 2004) for synthetic samples. Among these methods, FSDGN, RLP and DEA-Net are tailored for daytime/nighttime task-specific restoration, but struggle in other task scenes due to limited weather

feature extraction. In contrast, our method targets robust nighttime weather effects removal. As the training data lack dedicated flare samples, its performance in flare removal remains moderate. Nevertheless, ClearNight achieves the best results on the multi-degradation subset and delivers competitive performance on single-degradation samples.

**Results on Real-World Data.** As shown in Fig. 8b, ClearNight effectively removes most weather effects on real images and mitigates flares, producing more natural results compared to state-of-the-art methods. Furthermore, we use NIQE (Mittal, Soundararajan, and Bovik 2013) to assess the restored images in Tab. 3. The experimental results demonstrate that ClearNight can predict highly realistic images under various adverse weather conditions.

**Comparison with Cascade Solutions.** As demonstrated in Fig. 9, we compare ClearNight against two pre-trained task-specific models (Lin et al. 2025; Zhang et al. 2023a) on real-world nighttime rain streak images from AllWeatherNight. ClearNight not only achieves superior results visually and

Method	Haze	Rain Streak	Raindrop	Snow
TKL	4.1872	3.7765	3.9238	3.2680
FSDGN	4.2780	4.4694	4.9149	4.1528
WeatherDiff	4.1964	3.7842	3.9254	3.3451
WGWS	4.1879	3.7732	3.9635	3.2769
RLP	4.9699	4.1882	5.6240	4.7669
RAMiT	4.1655	3.9298	4.0808	3.2497
DiffUIR	<b>4.1063</b>	3.8728	4.0471	3.3547
DEA-Net	4.1665	3.9826	4.0889	3.4201
AWRaCLe	4.1681	3.9516	4.0936	3.3398
Baseline	4.2054	3.9983	4.0778	3.4605
ClearNight	4.1623	<b>3.7653</b>	<b>3.8882</b>	<b>3.2191</b>

Table 3: Quantitative results on AllWeatherNight real-world testing subset, evaluated using the commonly used NIQE $\downarrow$ .

#	IP	DA	RP	WI	PSNR $\uparrow$ / SSIM $\uparrow$
1	✗	✗	✗	✗	28.7976 / 0.8825
2	✓	✗	✗	✗	32.1304 / 0.9176
3	✗	✓	✗	✗	31.7075 / 0.9113
4	✓	✓	✗	✗	32.2393 / 0.9179
5	✗	✓	✓	✓	32.4430 / 0.9214
6	✓	✓	✓	✗	32.2528 / 0.9184
7	✓	✓	✓	✓	<b>32.5937 / 0.9223</b>

Table 4: Ablation study of key component. **IP** and **RP** denote illumination and reflectance priors. **DA** and **WI** indicate dynamic allocator and weather instructor in WDS.

quantitatively, but requires significantly less inference time.

## Ablation Studies

**Ablation on Model Components.** We evaluate the effectiveness of the illumination prior, reflectance prior, dynamic allocator and weather instructor on the Rain Scene testing subset. As shown in Tab. 4, dual priors significantly enhance the restoration performance over the baseline, while the dynamic allocator, guided by the weather instructor, optimizes candidate unit selection to handle multi-weather scenes. Quantitative results demonstrate that the integration of all components achieves the best performance.

**Effectiveness of WDS.** Fig. 10 illustrates the relationships between various degradations and selected units, demonstrating the effectiveness of WDS in capturing the specificity of different degradations. The WDS differentiates weather features, selecting similar unit combinations for degraded scenes with the same weather, enabling the network to efficiently eliminate diverse distortions. We visualize the feature  $\bar{f}^a$  of different weather types in Fig. 11. Despite the visual similarity between rain and snow, ClearNight still differentiates them. Notably, the features of “H + S” lie between haze and snow features, indicating that our model learns the correlations among multiple weather effects in complex nighttime scenarios.

## Conclusion

This paper explores a practical yet under-explored task, *i.e.*, multi-weather nighttime image restoration. To facilitate this task, we introduce an illumination-aware degradation gener-

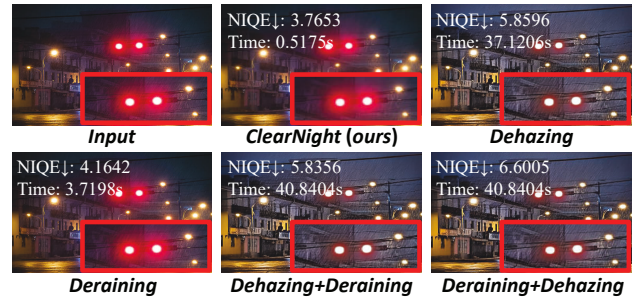


Figure 9: ClearNight outperforms a cascade of two latest task-specific nighttime restoration methods. Quantitative results are averaged over all the real-world rain streak images.

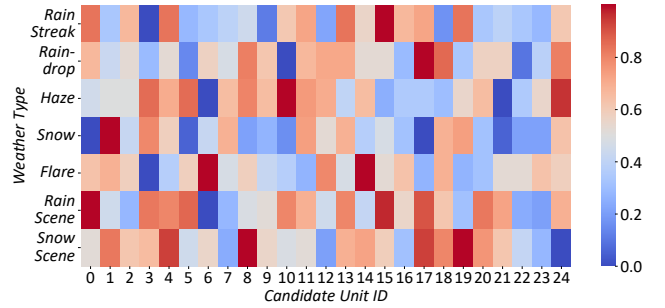


Figure 10: Correlation of selected units and diverse degradations. WDS associates various distortions with candidate units.

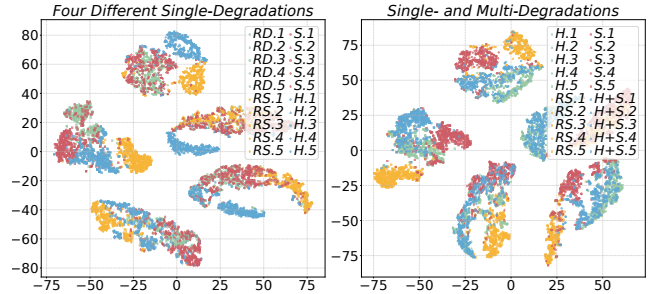


Figure 11: T-SNE visualization of feature distributions across distinct weather. **H**, **RS**, **RD** and **S** indicate haze, rain streak, raindrop and snow. The number is the index of WDS.

ation approach and construct a new dataset featuring 10K high-quality nighttime images with various compositional adverse weather and lighting conditions. In addition, we propose ClearNight, a unified framework, tailored for the new task, capable of removing multiple degradations in one go. ClearNight leverages Retinex-based dual priors to explicitly guide the network to focus on illumination regions and intrinsic textures respectively. Moreover, ClearNight incorporates weather-aware dynamic specific-commonality collaboration to better capture the characteristics of diverse weather, enabling effective multi-weather degradation removal. Comprehensive experiments on both synthetic and real-world images demonstrate the superiority of our ClearNight.

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## References

- Ai, Y.; Huang, H.; Zhou, X.; et al. 2024. Multimodal prompt perceiver: Empower adaptiveness, generalizability and fidelity for all-in-One image restoration. In *CVPR*.
- Chen, H.; Ren, J.; Gu, J.; et al. 2023. Snow removal in video: A new dataset and a novel method. In *ICCV*.
- Chen, S.; Ye, T.; Zhang, K.; et al. 2024. Teaching tailored to talent: Adverse weather restoration via prompt pool and depth-anything constraint. In *ECCV*.
- Chen, W.-T.; Fang, H.-Y.; Hsieh, C.-L.; et al. 2021. All snow removed: Single image desnowing algorithm using hierarchical dual-tree complex wavelet representation and contradict channel loss. In *ICCV*.
- Chen, W.-T.; Huang, Z.-K.; Tsai, C.-C.; et al. 2022. Learning multiple adverse weather removal via two-stage knowledge learning and multi-contrastive regularization: Toward a unified model. In *CVPR*.
- Chen, Z.; He, Z.; and Lu, Z.-M. 2024. DEA-Net: Single image dehazing based on detail-enhanced convolution and content-guided attention. *IEEE TIP*.
- Choi, H.; Na, C.; Oh, J.; et al. 2024. Reciprocal attention mixing transformer for lightweight image restoration. In *CVPRW*.
- Cong, X.; Gui, J.; Zhang, J.; et al. 2024. A semi-supervised nighttime dehazing baseline with spatial-frequency aware and realistic brightness constraint. In *CVPR*.
- Dong, L.; Fan, Q.; Guo, Y.; et al. 2025. TSD-SR: One-step diffusion with target score distillation for real-world image super-resolution. In *CVPR*.
- Edwin, H. L. 1977. The Retinex theory of color vision. *Scientific American*.
- Fu, X.; Huang, J.; Zeng, D.; et al. 2017. Removing rain from single images via a deep detail network. In *CVPR*.
- Guo, Y.; Gao, Y.; Lu, Y.; et al. 2024. OneRestore: A universal restoration framework for composite degradation. In *ECCV*.
- Han, J.; Li, W.; Fang, P.; et al. 2022. Blind image decomposition. In *ECCV*.
- Horé, A.; and Ziou, D. 2010. Image quality metrics: Psnr vs. ssim. In *ICPR*.
- Hu, J.; Jin, L.; Yao, Z.; et al. 2025. Universal image restoration pre-training via degradation classification. In *ICLR*.
- Jia, H.; Xu, Y.; Zhu, L.; et al. 2024. MoS2: Mixture of Scale and Shift Experts for Text-Only Video Captioning. In *ACM MM*.
- Jin, Y.; Li, X.; Wang, J.; et al. 2024. Raindrop clarity: A dual-focused dataset for day and night raindrop removal. In *ECCV*.
- Jin, Y.; Lin, B.; Yan, W.; et al. 2023. Enhancing visibility in nighttime haze images using guided APSF and gradient adaptive convolution. In *ACM MM*.
- Johnson, J.; Alahi, A.; and Li, F.-F. 2016. Perceptual losses for real-time style transfer and super-resolution. In *ECCV*.
- Kim, Y.; Cho, Y.; Nguyen, T.-T.; et al. 2024. MetaWeather: Few-shot weather-degraded image restoration. In *ECCV*.
- Kulkarni, A.; Phutke, S. S.; and Murala, S. 2023. Unified transformer network for multi-weather image restoration. In *ECCV*.
- Levin, A.; Lischinski, D.; and Weiss, Y. 2008. A closed-form solution to natural image matting. *IEEE TPAMI*.
- Li, B.; Ren, W.; Fu, D.; et al. 2019. Benchmarking single-image dehazing and beyond. *IEEE TIP*.
- Li, R.; Cheong, L.-F.; and Tan, R. T. 2019. Heavy rain image restoration: Integrating physics model and conditional adversarial learning. In *CVPR*.
- Li, X.; Liu, J.; Chen, Z.; et al. 2024. Contourlet residual for prompt learning enhanced infrared image super-resolution. In *ECCV*.
- Li, X.; Wang, Z.; Zou, Y.; et al. 2025. Difiisr: A diffusion model with gradient guidance for infrared image super-resolution. In *CVPR*.
- Liao, Y.; Su, Z.; Liang, X.; et al. 2018. HDP-net: Haze density prediction network for nighttime dehazing. In *Advances in Multimedia Information Processing-PCM*.
- Lin, B.; Jin, Y.; Yan, W.; et al. 2024. Nightrain: Nighttime video deraining via adaptive-rain-removal and adaptive-correction. In *AAAI*.
- Lin, B.; Jin, Y.; Yan, W.; et al. 2025. Nighthaze: Nighttime image dehazing via self-prior learning. In *AAAI*.
- Liu, L.; Song, X.; Wang, M.; et al. 2021. Self-supervised Monocular Depth Estimation for All Day Images using Domain Separation. In *ICCV*.
- Liu, X.; Zhang, Z.; Wu, X.; et al. 2024. Learning real-world image de-weathering with imperfect supervision. In *AAAI*.
- Liu, Y.; Yan, Z.; Chen, S.; et al. 2023a. NightHazeFormer: Single nighttime haze removal using prior query transformer. In *ACM MM*.
- Liu, Y.; Yan, Z.; Tan, J.; et al. 2023b. Multi-purpose oriented single nighttime image haze removal based on unified variational Retinex model. *IEEE TCSVT*.
- Liu, Y.; Yan, Z.; Wu, A.; et al. 2022. Nighttime image dehazing based on variational decomposition model. In *CVPRW*.
- Liu, Y.-F.; Jaw, D.-W.; Huang, S.-C.; et al. 2018. DesnowNet: Context-aware deep network for snow removal. *IEEE TIP*.
- Liu, Z.; Wu, X.-M.; Zheng, D.; et al. 2023c. Generating anomalies for video anomaly detection with prompt-based feature mapping. In *CVPR*.
- Loh, Y. P.; and Chan, C. S. 2019. Getting to know low-light images with the exclusively dark dataset. *CVIU*.
- Luo, Y.; and Yang, Y. 2024. Large language model and domain-specific model collaboration for smart education. *Front Inform Technol Electron Eng*.

- Mittal, A.; Soundararajan, R.; and Bovik, A. C. 2013. Making a “completely blind” image quality analyzer. *IEEE SPL*.
- Pei, S.-C.; and Lee, T.-Y. 2012. Nighttime haze removal using color transfer pre-processing and Dark Channel Prior. In *ICIP*.
- Quan, R.; Yu, X.; Liang, Y.; et al. 2021a. Removing raindrops and rain streaks in one go. In *CVPR*.
- Quan, R.; Zhu, L.; Wu, Y.; et al. 2021b. Holistic LSTM for pedestrian trajectory prediction. *IEEE TIP*.
- Rajagopalan, S.; and Patel, V. M. 2025. AWRaCLE: All-weather image restoration using visual in-context learning. In *AAAI*.
- Shazeer, N.; Mirhoseini, A.; Maziarz, K.; et al. 2017. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. In *ICLR*.
- Soboleva, V.; and Shipitko, O. 2021. Raindrops on windshield: Dataset and lightweight gradient-based detection algorithm. In *SSCI*.
- Song, Y.; He, Z.; Qian, H.; et al. 2023. Vision transformers for single image dehazing. *IEEE TIP*.
- Sun, S.; Ren, W.; Gao, X.; et al. 2024a. Restoring images in adverse weather conditions via histogram transformer. In *ECCV*.
- Sun, S.; Ren, W.; Gao, X.; et al. 2024b. Restoring images in adverse weather conditions via histogram transformer. In *ECCV*.
- Valanarasu, J. M. J.; Yasarla, R.; and Patel, V. M. 2022. TransWeather: Transformer-based restoration of images degraded by adverse weather conditions. In *CVPR*.
- Wang, C.; Zheng, Z.; Quan, R.; et al. 2023. Context-aware pretraining for efficient blind image decomposition. In *CVPR*.
- Wang, T.; Yang, X.; Xu, K.; et al. 2019. Spatial attentive single-image deraining with a high quality real rain dataset. In *CVPR*.
- Wang, W.; Wang, A.; and Liu, C. 2022. Variational single nighttime image haze removal with a gray haze-line prior. *IEEE TIP*.
- Wang, X.; Zhu, Z.; Huang, G.; et al. 2024. DriveDreamer: Towards Real-World-Drive World Models for Autonomous Driving. In *ECCV*.
- Wu, G.; Jiang, J.; Jiang, K.; et al. 2024. Learning from history: Task-agnostic model contrastive learning for image restoration. In *AAAI*.
- Wu, G.; Jiang, J.; Wang, Y.; et al. 2025a. Debaised all-in-one image restoration with task uncertainty regularization. In *AAAI*.
- Wu, Z.; Chen, K.; Li, K.; et al. 2025b. BVINet: Unlocking blind video inpainting with zero annotations. In *ICCV*.
- Wu, Z.; Li, K.; Xu, Y.; et al. 2026. DLVINet: Advancing dual-lens video inpainting beyond parallax constraints. In *AAAI*.
- Xu, Y.; Sun, Y.; Yang, Z.; et al. 2022. H2FA R-CNN: Holistic and hierarchical feature alignment for cross-domain weakly supervised object detection. In *CVPR*.
- Xu, Y.; Zhu, L.; and Yang, Y. 2025. Mc-bench: A benchmark for multi-context visual grounding in the era of mllms. In *ICCV*.
- Yan, W.; Tan, R. T.; and Dai, D. 2020. Nighttime defogging using high-low frequency decomposition and grayscale-color networks. In *ECCV*.
- Yang, H.; Pan, L.; Yang, Y.; et al. 2024. Language-driven all-in-one adverse weather removal. In *CVPR*.
- Yang, W.; Tan, R. T.; Feng, J.; et al. 2020. Joint rain detection and removal from a single image with contextualized deep networks. *IEEE TPAMI*.
- Ye, T.; Chen, S.; Bai, J.; et al. 2023. Adverse weather removal with codebook priors. In *ICCV*.
- Yu, F.; Chen, H.; Wang, X.; et al. 2020. BDD100K: A diverse driving dataset for heterogeneous multitask learning. In *CVPR*.
- Yu, H.; Zheng, N.; Zhou, M.; et al. 2022. Frequency and spatial dual guidance for image dehazing. In *ECCV*.
- Yue, C.; Peng, Z.; Ma, J.; et al. 2024. Image restoration through generalized Ornstein-Uhlenbeck bridge. In *ICML*.
- Zhang, F.; You, S.; Li, Y.; et al. 2022. Gtav-nightrain: Photometric realistic large-scale dataset for night-time rain streak removal. *arXiv:2210.04708*.
- Zhang, F.; You, S.; Li, Y.; et al. 2023a. Learning rain location prior for nighttime deraining. In *ICCV*.
- Zhang, H.; Ba, Y.; Yang, E.; et al. 2023b. WeatherStream: Light transport automation of single image deweathering. In *CVPR*.
- Zhang, H.; Sindagi, V.; and Patel, V. M. 2020. Image deraining using a conditional generative adversarial network. *IEEE TCSVT*.
- Zhang, J.; Cao, Y.; Fang, S.; et al. 2017. Fast haze removal for nighttime image using maximum reflectance prior. In *CVPR*.
- Zhang, J.; Cao, Y.; and Wang, Z. 2014. Nighttime haze removal based on a new imaging model. In *ICIP*.
- Zhang, J.; Cao, Y.; Zha, Z.-J.; et al. 2020. Nighttime dehazing with a synthetic benchmark. In *ACM MM*.
- Zheng, D.; Wu, X.-M.; Yang, S.; et al. 2024. Selective hourglass mapping for universal image restoration based on diffusion model. In *CVPR*.
- Zhong, Z.; Tang, Z.; He, T.; et al. 2024. Convolution meets LoRA: Parameter efficient finetuning for segment anything model. In *ICLR*.
- Zhou, W.; Bovik, A.; Sheikh, H.; et al. 2004. Image quality assessment: from error visibility to structural similarity. *IEEE TIP*.
- Zhu, Y.; Wang, T.; Fu, X.; et al. 2023. Learning weather-general and weather-specific features for image restoration under multiple adverse weather conditions. In *CVPR*.
- Özdenizci, O.; and Legenstein, R. 2023. Restoring vision in adverse weather conditions with patch-based denoising diffusion models. *IEEE TPAMI*.