MODEM: A Morton-Order Degradation Estimation Mechanism for Adverse Weather Image Recovery

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Motivation

➢ Bridging Image Degradation Estimation and State Space Modeling

The relationship between an observed degraded image x and its clean version y can be modeled as:

$$x = \text{Degrade}(y, \theta := \{\theta_G, \theta_L\}) \quad \Leftrightarrow \quad y = \text{Restore}(x, \theta := \{\theta_G, \theta_L\})$$

Recall the core recurrence of a discrete-time SSM:

$$h_k = Ah_{k-1} + Bx_k, \quad y_k = Ch_k + Dx_k$$

Residual term

$$y_k = Ch_k$$

$$y_k = CAh_{k-1} + CBx_k$$

We interpret SSM components as degradation estimators.

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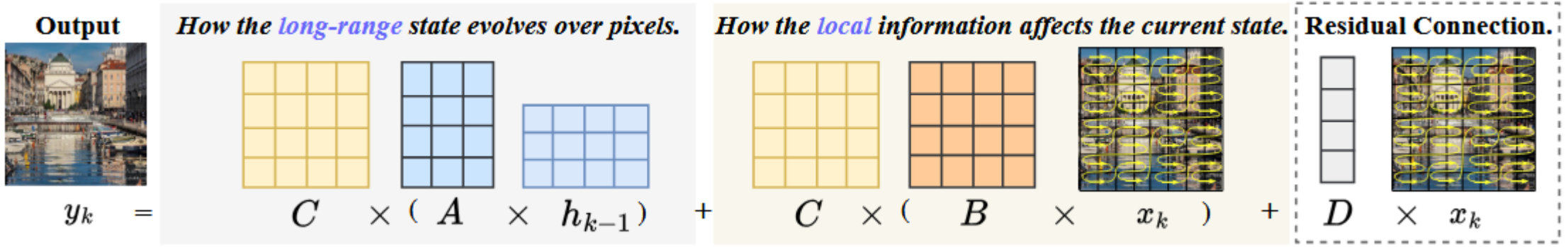
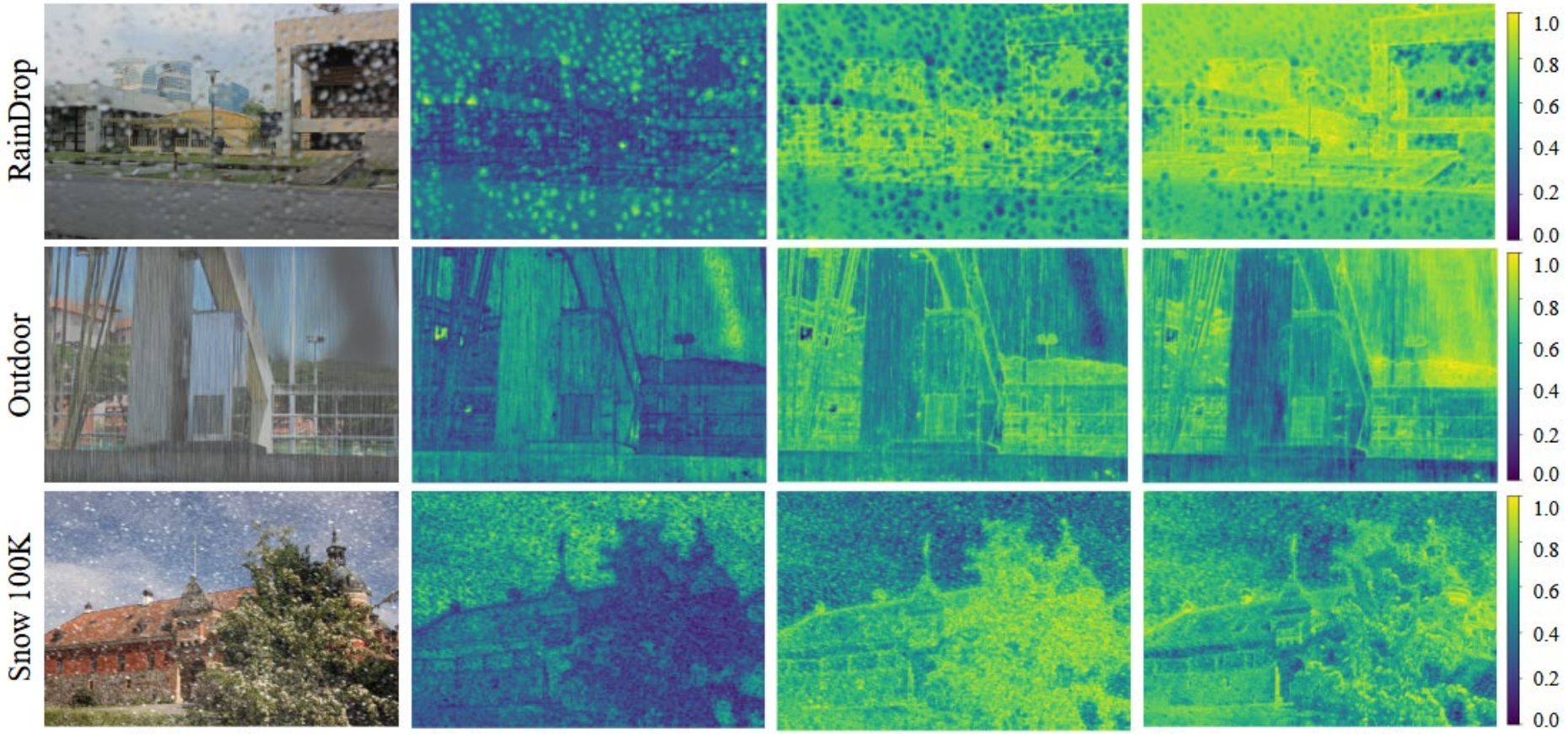
$$y_k = CAh_{k-1} + CBx_k$$



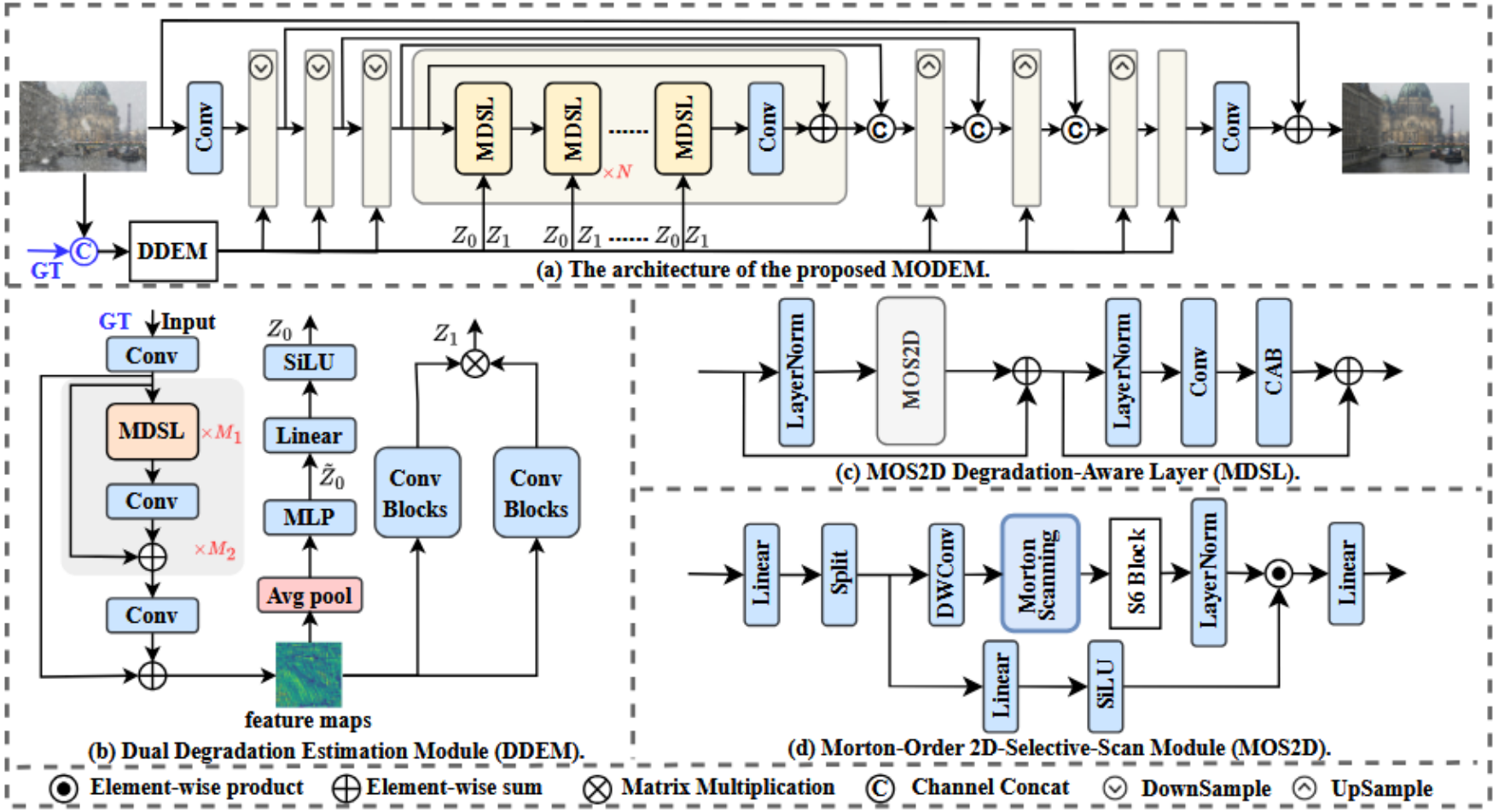
Motivation

➢ Bridging Image Degradation Estimation and State Space Modeling



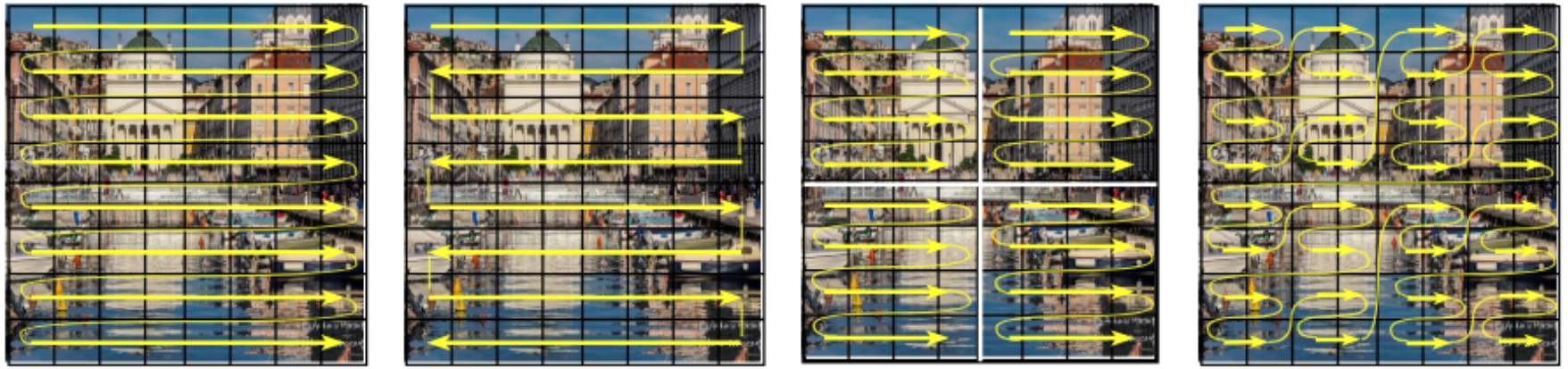
Method

➢ Overall architecture of MODEM



Method

➢ Morton-coded Spatial Scanning



(a) Raster Scanning (b) Continuous Scanning (c) Local Scanning (d) Morton Scanning

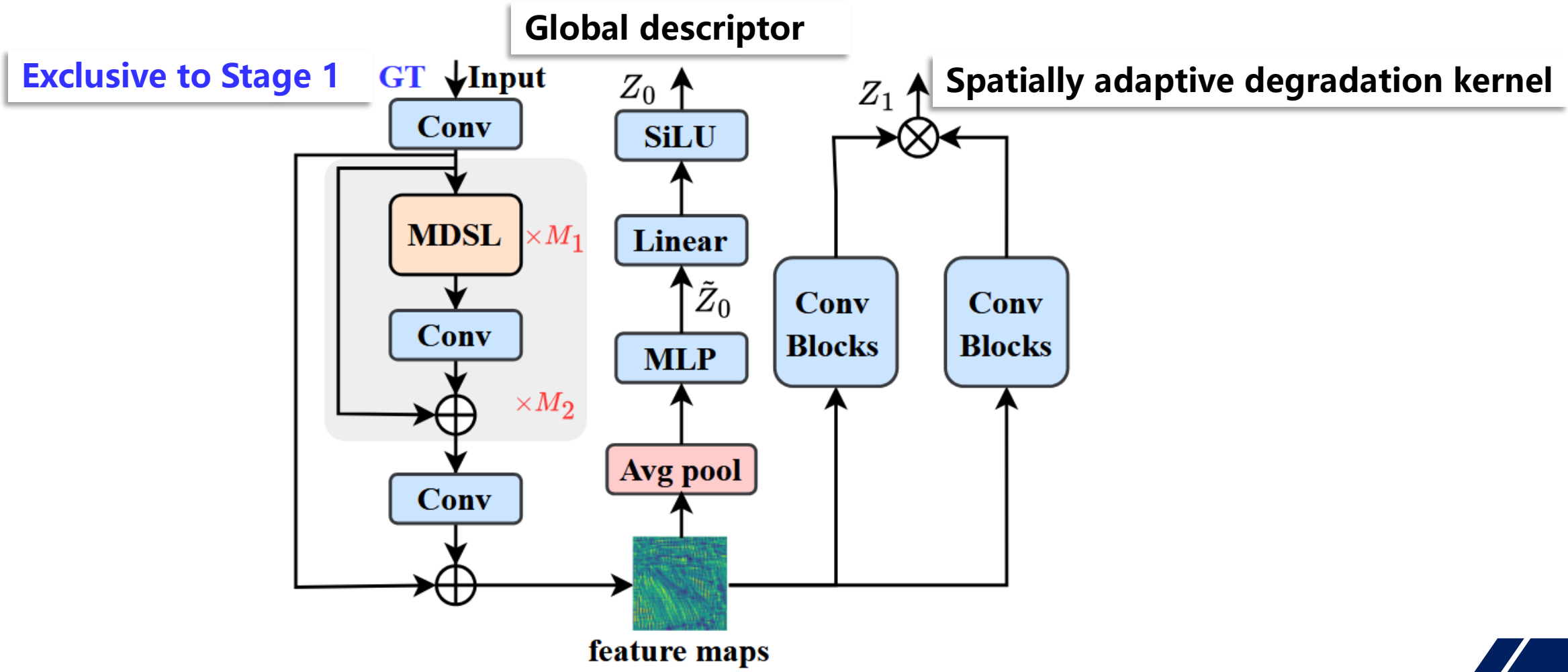
$$z = \text{interleave}(i, j) = (j_n, i_n, j_{n-1}, i_{n-1}, \ldots, j_1, i_1, j_0, i_0)_2$$

Table 12: Ablation study of diffrent scanning scheme.

Methods	Snow100K-L		Snow100K-S		Outdoor		RainDrop	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Raster (MambaIR [20])	32.33	0.9283	38.03	0.9672	32.89	0.9399	32.69	0.9423
Continuous (Zigzag [74])	32.17	0.9266	37.74	0.9662	32.35	0.9385	32.59	0.9422
OSS (VmambaIR [63])	32.14	0.9262	37.39	0.9651	32.61	0.9387	32.11	0.9413
Local (LocalMamba [25])	32.23	0.9266	37.75	0.9661	32.60	0.9382	32.53	0.9418
Hilbert (LC-Mamba [28])	32.46	0.9287	37.96	0.9671	32.99	**0.9414**	32.82	0.9433
Morton (Ours)	**32.52**	**0.9292**	**38.08**	**0.9673**	**33.10**	0.9410	**33.01**	**0.9434**

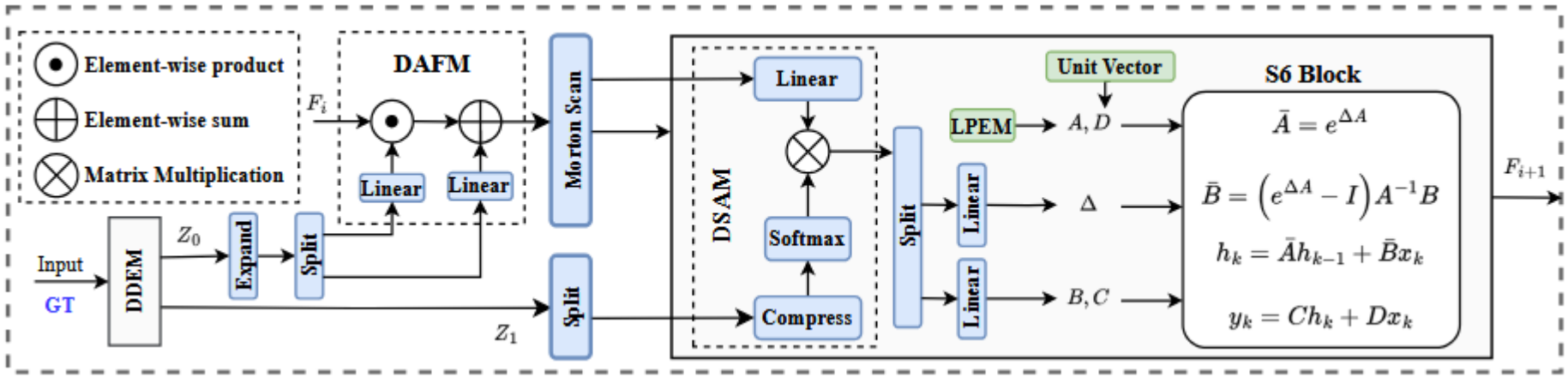
Method

➢ Dual Degradation Estimation Module (DDEM)



Method

➢ Morton-Order 2D-Selective-Scan Module (MOS2D)



DAFM: $F_{\text{DAFM}} = (Z_0^w \odot F_i) + Z_0^b, \quad Z_0^w, Z_0^b = \text{Split}(\text{Linear}(Z_0))$

DSAM: $F_{\text{DSAM}} = W_F F_{\text{DAFM}} \times \text{Softmax}(W_Z Z_1)$

$$F_\Delta, F_B, F_C = \text{Split}(F_{\text{DSAM}}), \quad \Delta = W_\Delta F_\Delta, \quad B = W_B F_B, \quad C = W_C F_C$$

$$y_k = C h_k + D x_k, \quad h_k = \bar{A} h_{k-1} + \bar{B} x_k, \quad x_k = F_{\text{DAFM}}[z]$$

Morton-ordered scanning

Method

➢ Loss Function

$$\mathcal{L}_{\text{stage1}} = \mathcal{L}_1(I_{\text{HQ}}, I_{\text{GT}}) + \mathcal{L}_{\text{cor}}(I_{\text{HQ}}, I_{\text{GT}})$$

Pixel Loss **Correlation Loss**

$$\mathcal{L}_{\text{cor}}(I_{\text{HQ}}, I_{\text{GT}}) = \frac{1}{2}\left(1 - \rho(I_{\text{HQ}}, I_{\text{GT}})\right), \quad \rho(I_{\text{HQ}}, I_{\text{GT}}) = \frac{\sum_{i=1}^{N}(I_{i,\text{HQ}} - \bar{I}_{\text{HQ}})(I_{i,\text{GT}} - \bar{I}_{\text{GT}})}{N \cdot \sigma(I_{\text{HQ}}) \cdot \sigma(I_{\text{GT}})}$$

$$\mathcal{L}_{\text{stage2}} = \mathcal{L}_1(I_{\text{HQ}}, I_{\text{GT}}) + \mathcal{L}_{\text{cor}}(I_{\text{HQ}}, I_{\text{GT}}) + \mathcal{L}_{\text{KL}}(\tilde{Z}_{0,\text{st1}}, \tilde{Z}_{0,\text{st2}})$$

Pixel Loss **Correlation Loss** **KL Divergence Loss**

$$\mathcal{L}_{\text{KL}} = D_{\text{KL}}\left(\phi(\tilde{Z}_{0,\text{st1}}) \parallel \phi(\tilde{Z}_{0,\text{st2}})\right) = \sum_{j=1}^{4C_d} \phi(\tilde{Z}_{0,\text{st1}}(j)) \log\left(\frac{\phi(\tilde{Z}_{0,\text{st1}}(j))}{\phi(\tilde{Z}_{0,\text{st2}}(j))}\right)$$

Experimental Validation

➢ Quantitative Comparison

Table 1: Quantitative comparison with recent state-of-the-art unified methods [40, 67, 11, 95, 55, 79, 65] across various datasets. The best and second-best results are in **bold** and underlined, respectively.

Methods	Snow100K-S		Snow100K-L		Outdoor		RainDrop		Average	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
All-in-One [40]	-	-	28.33	0.8820	24.71	0.8980	31.12	0.9268	28.05	0.9023
TransWeather [67]	32.51	0.9341	29.31	0.8879	28.83	0.9000	30.17	0.9157	30.21	0.9094
Chen *et al.* [11]	34.42	0.9469	30.22	0.9071	29.27	0.9147	31.81	0.9309	31.43	0.9249
WGWSNet [95]	34.31	0.9460	30.16	0.9007	29.32	0.9207	32.38	0.9378	31.54	0.9263
WeatherDiff$_{64}$ [55]	35.83	0.9566	30.09	0.9041	29.64	0.9312	30.71	0.9312	31.57	0.9308
WeatherDiff$_{128}$ [55]	35.02	0.9516	29.58	0.8941	29.72	0.9216	29.66	0.9225	31.00	0.9225
AWRCP [79]	36.92	0.9652	31.92	**0.9341**	31.39	0.9329	31.93	0.9314	33.04	0.9409
Histoformer [65]	37.41	0.9656	32.16	0.9261	32.08	0.9389	**33.06**	**0.9441**	33.68	0.9437
MODEM (Ours)	**38.08**	**0.9673**	**32.52**	0.9292	**33.10**	**0.9410**	33.01	0.9434	**34.18**	**0.9452**

Experimental Validation

➢ Quantitative Comparison

Table 2: Desnowing Task

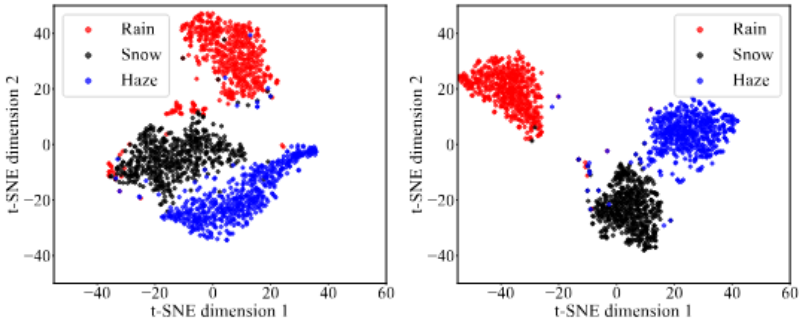
Methods	Snow100K-S		Snow100K-L	
	PSNR	SSIM	PSNR	SSIM
SPANet [69]	29.92	0.8260	23.70	0.7930
JSTASR [10]	31.40	0.9012	25.32	0.8076
RESCAN [41]	31.51	0.9032	26.08	0.8108
DesnowNet [45]	32.33	0.9500	27.17	0.8983
DDMSNet [87]	34.34	0.9445	28.85	0.8772
Restormer [82]	36.01	0.9579	30.36	0.9068
ConvIR [13]	<u>37.98</u>	<u>0.9686</u>	<u>32.11</u>	**0.9300**
FSNet [12]	37.42	0.9654	31.62	0.9246
MODEM (Ours)	**38.08**	**0.9673**	**32.52**	<u>0.9292</u>

Table 3: Raindrop Removal Task

Methods	RainDrop	
	PSNR	SSIM
pix2pix [27]	28.02	0.8547
DuRN [43]	31.24	0.9259
RaindropAttn [58]	31.44	0.9263
AttentiveGAN [57]	31.59	0.9170
IDT [73]	31.87	0.9313
MAXIM [66]	31.87	0.9352
Restormer [82]	<u>32.18</u>	<u>0.9408</u>
AST [92]	30.57	0.9333
MODEM (Ours)	**33.01**	**0.9434**

Table 4: Deraining & Dehazing Task

Methods	Outdoor-Rain	
	PSNR	SSIM
CycleGAN [93]	17.62	0.6560
pix2pix [27]	19.09	0.7100
HRGAN [39]	21.56	0.8550
PCNet [29]	26.19	0.9015
MPRNet [81]	28.03	0.9192
NAFNett [9]	29.59	0.9027
Restormer [82]	<u>30.03</u>	<u>0.9215</u>
MODEM (Ours)	**33.10**	**0.9410**



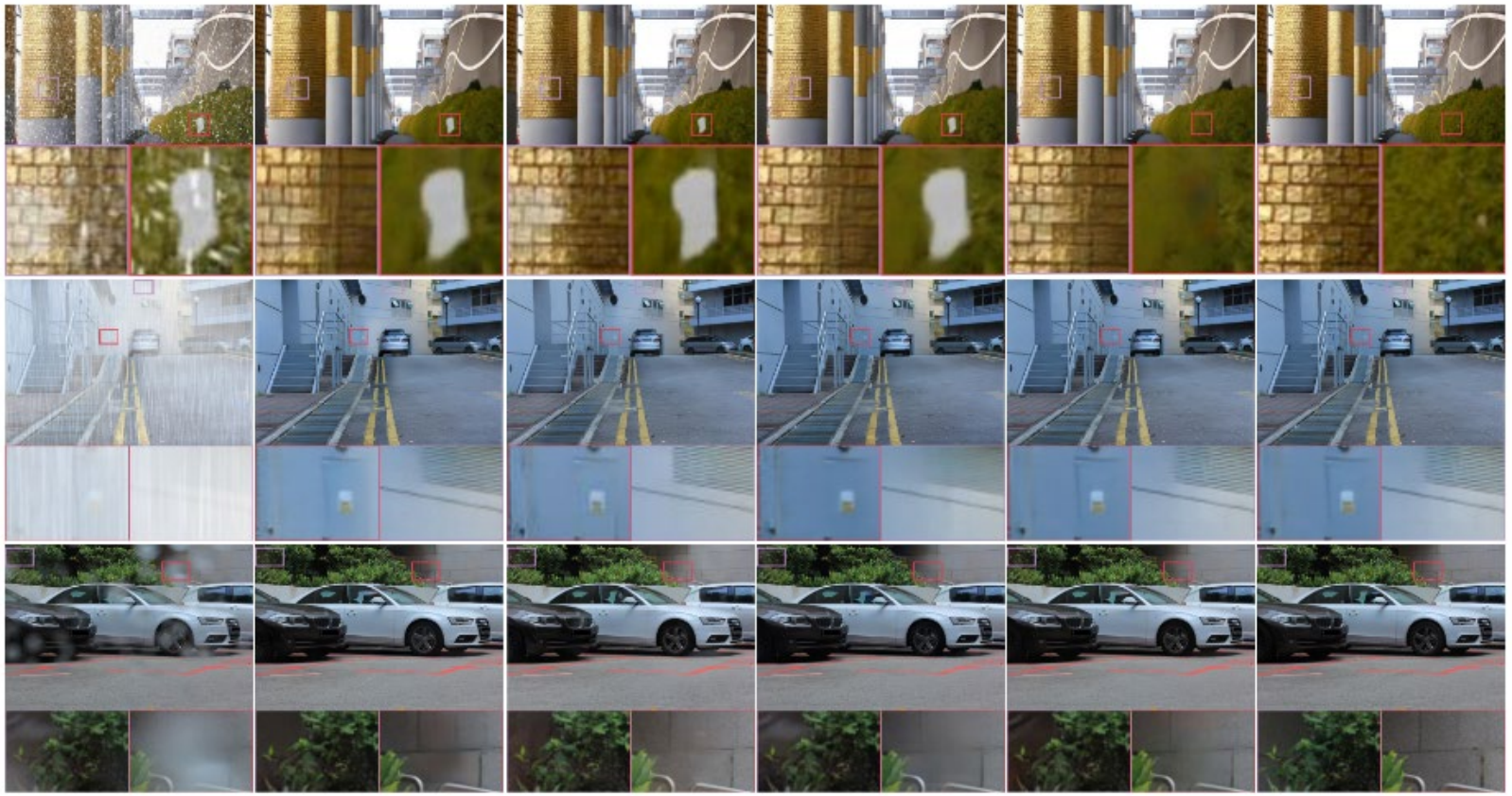
(g) T-SNE of Histoformer [65]

(h) T-SNE of MODEM

Figure 7: T-SNE results of Histoformer [65] and MODEM, which reflect that MODEM exhibits better clustering of features corresponding to different weather types than Histoformer [65].

Experimental Validation

➢ Qualitative comparison



(a) Input (b) WGWSNet (c) WeatherDiff (d) Histoformer (e) Ours (f) GT

Figure 8: Visual comparisons of MODEM against state-of-the-art unified methods across diverse adverse weather restoration tasks. **Top Row**: Image desnowing. **Middle Row**: Joint deraining and dehazing. **Bottom Row**: Raindrop removal.

Experimental Validation

➢ Perceptual Quality and Real-World Performance

Table 5: Comparison of perceptual metrics, including referenced (LPIPS↓) and non-referenced (Q-Align↑, MUSIQ↑) scores. Best results are **bolded**; second-best are underlined.

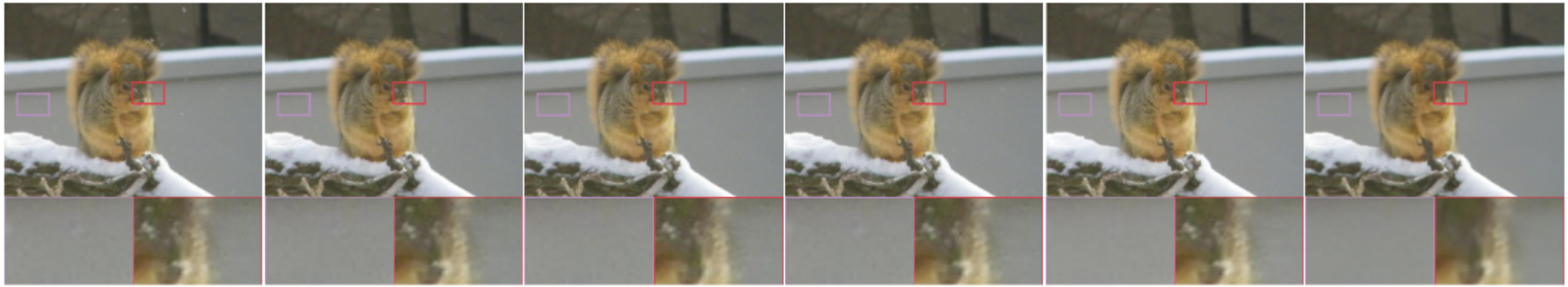
	Method	Snow100K-L	Snow100K-S	Outdoor	Raindrop	Snow100K-Real
LPIPS	Histoformer [65]	0.0919	0.0445	0.0778	0.0672	–
	WeatherDiff [55]	0.0982	0.0541	0.0887	**0.0615**	–
	MODEM (Ours)	**0.0880**	**0.0407**	**0.0699**	0.0650	–
Q-Align	Histoformer [65]	3.7207	3.7598	4.1445	4.0156	3.5449
	WeatherDiff [55]	3.4531	3.5293	3.8691	4.0000	3.4512
	MODEM (Ours)	**3.7324**	**3.7695**	**4.1875**	**4.0664**	**3.5586**
MUSIQ	Histoformer [65]	**64.2526**	64.2581	67.7461	68.4852	59.4040
	WeatherDiff [55]	62.6267	63.1278	67.4814	69.3608	59.4493
	MODEM (Ours)	64.2438	**64.2853**	**68.2926**	**69.7925**	**59.6042**

Experimental Validation

➢ Perceptual Quality and Real-World Performance

Table 6: Comparison of different methods on various real-world datasets using the Q-Align metric.

Method	Snow100K-Real	RainDrop	NTURain	RESIDE	WeatherStream
WeatherDiff [55]	3.4531	4.0000	3.2031	**3.4219**	1.9561
Histoformer [65]	3.7207	4.0156	3.2266	3.2891	1.9434
MODEM (Ours)	**3.7324**	**4.0664**	**3.2891**	3.3164	**1.9863**



(a) Input (b) WGWSNet (c) WeatherDiff (d) Histoformer (e) Histoformer† (f) Ours

Figure 6: Visual comparison on the real world snow dataset [45]. Compared to the prior methods [95, 55, 65], where "†" denotes the Histoformer [65] for real snow from their official repository, our MODEM achieves superior results without additional training.

Experimental Validation

➢ Complexity Analysis

Table 8: Comparison of parameters and inference time, along with average PSNR.

Methods	WGWSNet [95]	WeatherDiff [55]	Histoformer [65]	MODEM (Ours)
Time (ms)	24.83	1.67×10^6	109.07	92.86
Parameters (M)	2.65	82.96	16.62	19.96
Average PSNR	31.54	31.57	33.68	34.18

Table 9: Comparison of inference time (ms) for different input sizes and average PSNR.

Input Size	WGWSNet [95]	WeatherDiff [55]	Histoformer [65]	MODEM (Ours)
256×256	24.83	1.67×10^6	109.07	92.86
512×512	110.34	5.37×10^6	576.15	443.02
1024×1024	439.13	1.35×10^7	3056.29	1946.34
Average PSNR	31.54	31.57	33.68	34.18

Thank you!

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