Appendix

A. Detailed Comparison with Other Works.

In Section 4.4 and Section 4.5 of our main paper, we provide comparison of the overall performance (mean IoU) of the models, specifically comparison with other domain generalization works from GTA to Cityscapes, and with other domain adaptation works from GTA to Cityscapes as well as from SYNTHIA to Cityscapes. Here, we provide more detailed comparison of the class-wise accuracies in Table 7, Table 8, and Table 9. From the detailed tables, we can see that our method provides better performance in many classes and outperforms the state-of-the-art methods in terms of *mIoU* under both domain generalization and domain adaptation, which shows the efficacy and superiority of our method.

B. Additional Experiments on auxiliary domains and color augmentation.

Two more experiments are conducted with FCN8s-VGG16 in this section. First, we re-run our approach with 15 real-world styles from the BDD dataset, including different weather conditions, time of day (TOD), *etc.* Then, we replace the style transfer step with 15 color augmentations [1], varying the hue, saturation, grayscale, contrast, etc. These changes preserve the semantics of the objects.

Table 6 shows the new results (last two rows) along with those reported in the main paper. "Random" stands for the styles randomly selected from ImageNet and Artworks, and "Semantics" are the styles of the Cityscapes classes (*e.g.*, Car, Road, etc.). The results are close to each other except that the color augmentation is a little worse than the others. The pyramid consistency is effective for all the test cases.

Table 6. Adaptation from GTA with different style sets. We report results (mIoU%) both without / with the pyramid consistency.

Style Set	Semantics Safe?	Cityscapes	Mapillary
Random	✗	34.64 / 36.11	31.64 / 32.25
Semantics	✗	34.84 / 35.62	31.29 / 32.18
Weather-TOD	✗	34.51 / 35.89	31.24 / 32.18
Color Change	✓	33.56 / 34.52	30.27 / 32.06

C. More Discussion.

Table 6 shows that the color augmentation performs a little worse than the style transfers probably for two reasons. One is that it does not bring to the synthetic images any appearances of the real images by design. The other is that it randomizes the images only by color (almost uniformly) and no texture. Learning an optimal non-uniform color shift policy is another future direction to explore.

[1] https://github.com/aleju/imgaug

Table 6 shows that different style sets, including the real styles (*i.e.* weather) suggested by R3, lead to similar results. Together with Figure 4 in the paper, we find that "how many domains" influences the results more than "what domains".

Table 7. Class-wise Performance comparison on Domain Generalization from GTA to Cityscapes with ResNet-50 base network.

Network	Method	Train w/ Tgt	Val on Tgt	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetion	terrain	sky	person	rider	car	truck	bus	train	motorbike	bicycle	mIoU
ResNet-50	NonAdapt [34]	✗	✗	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	22.17
	IBN-Net [34]			–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	29.64
	NonAdapt	✗	✗	84.5	12.3	75.4	19.2	9.1	18.7	19.2	7.5	81.6	30.9	73.8	42.7	8.9	76.4	17.2	27.8	1.8	8.6	1.2	32.45
	Ours			90.1	21.6	79.4	25.6	18.2	22.6	26.4	16.5	82.9	34.3	77.1	46.1	13.5	78.3	24.4	29.1	3.6	13.4	7.8	**37.42**

Table 8. Class-wise Performance comparison from GTA to Cityscapes with VGG base network. All the best accuracies with respect to VGG-16 base network are in bold.

Network	Method	Train w/ Tgt	Val on Tgt	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetation	terrain	sky	person	rider	car	truck	bus	train	motorbike	bicycle	mIoU
VGG19	NonAdapt [56]	✓	✓	18.1	6.8	64.1	7.3	8.7	21.0	14.9	16.8	45.9	2.4	64.4	41.6	17.5	55.3	8.4	5.0	6.9	4.3	13.8	22.3
	Curriculum [56]			74.9	22.0	71.7	6.0	11.9	8.4	16.3	11.1	75.7	13.3	66.5	38.0	9.3	55.2	18.8	18.9	0.0	16.8	16.6	28.9
	CGAN [20]	✓	✓	89.2	49.0	70.7	13.5	10.9	38.5	29.4	33.7	77.9	37.6	65.8	75.1	32.4	77.8	39.2	45.2	0.0	25.5	35.4	44.5
VGG16	NonAdapt [19]	✓	✓	31.9	18.9	47.7	7.4	3.1	16.0	10.4	1.0	76.5	13.0	58.9	36.0	1.0	67.1	9.5	3.7	0.0	0.0	0.0	21.1
	FCNs Wld [19]			70.4	32.4	62.1	14.9	5.4	10.9	14.2	2.7	79.2	21.3	64.6	44.1	4.2	70.4	8.0	7.3	0.0	3.5	0.0	27.1
	NonAdapt [41]	✓	✓	73.5	21.3	72.3	18.9	14.3	12.5	15.1	5.3	77.2	17.4	64.3	43.7	12.8	75.4	24.8	7.8	0.0	4.9	1.8	29.6
	LSD [41]			88.0	30.5	78.6	25.2	**23.5**	16.7	23.5	11.6	78.7	27.2	71.9	51.3	**19.5**	80.4	19.8	18.3	0.9	**20.8**	18.4	37.1
	NonAdapt [3]	✓	✓	29.8	16.0	56.6	9.2	17.3	13.5	13.6	9.8	74.9	6.7	54.3	41.9	2.9	45.0	3.3	13.1	1.3	6.8	0.0	21.9
	ROAD [3]			85.4	31.2	78.6	**27.9**	22.2	21.9	23.7	11.4	80.7	29.3	68.9	48.5	14.1	78.0	19.1	23.8	**9.4**	8.3	0.0	35.9
	NonAdapt [18]	✓	✓	26.0	14.9	65.1	5.5	12.9	8.9	6.0	2.5	70.0	2.9	47.0	24.5	0.0	40.0	12.1	1.5	0.0	0.0	0.0	17.9
	CyCADA [18]			85.2	37.2	76.5	21.8	15.0	23.8	22.9	**21.5**	80.5	31.3	60.7	50.5	9.0	76.9	17.1	**28.2**	4.5	9.8	0.0	35.4
	NonAdapt [40]	✓	✓	25.9	10.9	50.5	3.3	12.2	25.4	28.6	13	78.3	7.3	63.9	52.1	7.9	66.3	5.2	7.8	0.9	13.7	0.7	24.9
	MCD [40]			86.4	8.5	76.1	18.6	9.7	14.9	7.8	0.6	**82.8**	32.7	71.4	25.2	1.1	76.3	16.1	17.1	1.4	0.2	0.0	28.8
	I2I [32]	✓	✓	85.3	38.0	71.3	18.6	16	18.7	12	4.5	72	**43.4**	63.7	43.1	3.3	76.7	14.4	12.8	0.3	9.8	0.6	31.8
	NonAdapt [62]	✓	✓	64.0	22.1	68.6	13.3	8.7	19.9	15.5	5.9	74.9	13.4	37.0	37.7	10.3	48.2	6.1	1.2	1.8	10.8	2.9	24.3
	CBST-SP [62]			**90.4**	**50.8**	72.0	18.3	9.5	27.2	28.6	14.1	82.4	25.1	70.8	42.6	14.5	76.9	5.9	12.5	1.2	14.0	**28.6**	36.1
	NonAdapt [52]	✓	✓	72.5	25.1	71.2	6.6	13.4	12.3	11.0	4.7	76.1	16.4	67.7	43.1	8.0	70.4	11.3	4.8	0.0	13.9	0.4	27.8
	DCAN [52]			82.3	26.7	77.4	23.7	20.5	20.4	**30.3**	15.9	80.9	25.4	69.5	**52.6**	11.1	79.6	24.9	21.2	1.3	17.0	6.7	36.2
	NonAdapt [60]	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	30.0
	PTP [60]			–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	38.1
	AdaptSeg [50]	✓	✓	87.3	29.8	78.6	21.1	18.2	22.5	21.5	11.0	79.7	29.6	71.3	46.8	6.5	80.1	23.0	26.9	0.0	10.6	0.3	35.0
	NonAdapt [21]	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	18.8
	DAM [21]			–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	32.6
	NonAdapt	✗	✓	68.4	24.7	68.9	18.1	15.2	18.1	16.7	9.6	78.4	18.3	65.7	43.6	12.3	69.1	18.7	16.1	0.4	5.3	3.2	30.04
	Ours			86.6	38.4	**79.8**	26.4	18.1	**34.7**	21.3	16.3	81.2	28.7	**76.5**	50.1	16.6	**80.7**	**28.3**	21.4	2.3	14.3	10.9	**38.56**
	NonAdapt	✗	✗	66.4	23.9	69.1	16.3	15.8	19.6	15.8	8.6	77.7	19.5	66.1	43.2	12.1	68.9	17.3	17.2	0.3	4.8	2.9	29.76
	Ours			84.6	31.5	76.3	25.4	17.2	28.2	21.5	13.7	80.7	26.8	74.9	47.5	15.8	77.1	22.2	22.7	1.7	8.9	9.7	36.11

Table 9. Class-wise Performance comparison from SYNTHIA to Cityscapes with VGG base network. All the best accuracies with respect to VGG-16 base network are in bold.

Network	Method	Train w/ Tgt	Val on Tgt	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetation	sky	person	rider	car	bus	motorbike	bicycle	mIoU
VGG19	NonAdapt [56]	✓	✓	5.6	11.2	59.6	0.8	0.5	21.5	8.0	5.3	72.4	75.6	35.1	9.0	23.6	4.5	0.5	18.0	22.0
	Curriculum [56]			65.2	26.1	74.9	0.1	0.5	10.7	3.7	3.0	76.1	70.6	47.1	8.2	43.2	20.7	0.7	13.1	29.0
	CGAN [20]	✓	✓	85.0	25.8	73.5	3.4	3.0	31.5	19.5	21.3	67.4	69.4	68.5	25.0	76.5	41.6	17.9	29.5	41.2
VGG16	NonAdapt [19]	✓	✓	6.4	17.7	29.7	1.2	0.0	15.1	0.0	7.2	30.3	66.8	51.1	1.5	47.3	3.9	0.1	0.0	17.4
	FCNs Wld [19]			11.5	19.6	30.8	4.4	0.0	20.3	0.1	11.7	42.3	68.7	**51.2**	3.8	54.0	3.2	0.2	0.6	20.2
	NonAdapt [41]	✓	✓	30.1	17.5	70.2	5.9	0.1	16.7	9.1	12.6	74.5	76.3	43.9	13.2	35.7	14.3	3.7	5.6	26.8
	LSD [41]			**80.1**	29.1	77.5	2.8	0.4	26.8	11.1	18.0	78.1	76.7	48.2	15.2	**70.5**	**17.4**	8.7	16.7	36.1
	NonAdapt [3]	✓	✓	4.7	11.6	62.3	10.7	0.0	22.8	4.3	15.3	68.0	70.8	49.7	6.4	60.5	11.8	2.6	4.3	25.4
	ROAD [3]			77.7	30.0	77.5	9.6	0.3	25.8	10.3	15.6	77.6	79.8	44.5	16.6	67.8	14.5	7.0	23.8	36.2
	NonAdapt [62]	✓	✓	17.2	19.7	47.3	1.1	0.0	19.1	3.0	9.1	71.8	78.3	37.6	4.7	42.2	9.0	0.1	0.9	22.6
	CBST [62]			69.6	28.7	69.5	**12.1**	0.1	25.4	**11.9**	13.6	**82.0**	**81.9**	49.1	14.5	66.0	6.6	3.7	32.4	35.4
	NonAdapt [52]	✓	✓	10.8	11.4	66.6	1.6	0.1	16.9	5.5	14.1	74.2	76.2	46.0	11.5	45.4	15.1	6.0	13.4	25.9
	DCAN [52]			79.9	30.4	70.8	1.6	**0.6**	22.3	6.7	**23.0**	76.9	73.9	41.9	**16.7**	61.7	11.5	**10.3**	**38.6**	35.4
	DAM [21]	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	30.7
	NonAdapt [60]	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	24.9
	PTP [60]			–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	34.2
	NonAdapt	✗	✓	15.6	12.3	70.3	6.7	0.2	20.4	5.6	15.3	73.5	76.2	47.2	10.5	54.3	12.1	5.3	10.6	27.3
	Ours			78.9	**31.4**	**79.3**	9.6	0.2	**27.3**	10.1	15.6	76.2	78.5	45.1	16.4	69.8	13.6	8.3	22.7	**36.4**
	NonAdapt	✗	✗	14.7	11.8	68.5	7.3	0.1	19.6	4.6	14.4	71.8	73.2	48.5	9.1	56.1	11.7	4.9	11.7	26.8
	Ours			77.5	30.7	78.6	5.6	0.2	26.7	10.6	16.1	75.2	76.5	44.1	15.8	69.9	14.7	8.6	17.6	35.5