Towards Weakly-Supervised Domain Adaptation for Lane Detection

Supplementary Material

A. Preliminary Study

As a preliminary study, we evaluate the performance of five frequently used models dealing with domain shifts in the initial experiments, in which the models are first trained only on the source dataset $\mathcal{D}_s$ and directly run inference on the target dataset $\mathcal{D}_T$ without any adaptation and inference configuration changes. The evaluation results can be found in Tab. 6, where we observe significant performance degradation across all the models. It is especially challenging for the setup where the model is previously trained on a less challenging setup, *e.g.*, on *TuSimple* dataset, where we can observe a performance disparity of about 50% even with the best performing model measured by F1 score.

B. Implementation Details

We conduct the experiment based on the LaneDet framework [60]. We utilize the ImageNet pre-trained weights from Hugging Face and TorchVision. For all the experiments with EMA, we choose the smoothing coefficient hyperparameter $\alpha = 0.99$. During the experiments, we first train the base networks on the source datasets according to the implementations from LaneDet. We always apply an identical set of hyperparameters for all network architectures for each domain adaptation task, *e.g.*, from *CULane* to *TuSimple*. When evaluating the domain generalization performance, we run experiments with evenly spaced test confidence threshold over an interval of 0.1 up to 0.9 and select the best threshold measured by the F1-score. We also follow this principle to determine the pseudo label thresholds δ, avoiding unfair comparison between unsupervised and weakly-supervised domain adaptation. For the weights ω for the different loss terms, we refer to the training configs from LaneATT and CLRNet on respective datasets with $\omega_{\text{num.}} = 1.0$. It is worth noting that we also strictly follow the evaluation scheme from [55] for the results of the *CurveLanes* dataset, which is similar to the *CULane* evaluation. For simplicity and fairness, we do not employ any handcrafted crop size for the images from the *CurveLanes* dataset as source dataset during training and evaluation. During training of the models, we apply heavy data augmentation for the student model with the setup shown in Tab. 7.

C. Ablation Segmentation Task

From Tab. 8, it is apparent that the inclusion of the lane segmentation task provides only marginal improvement in the source domain *CULane* for both CLRNet and LaneATT. There is no notable distinction between binary segmentation and instance segmentation. Tab. 9 shows the results of models on the target domain *TuSimple*: The enhancement in the adaptability of detectors through the lane segmentation task becomes evident. Binary segmentation consistently outperforms instance segmentation in DG and WSDAL setup. With the effect of the lane segmentation task on the performance of the model on both source and target domains, we conclude that incorporating a suitable auxiliary task during lane detector training in the source domain is an effective strategy to enhance adaptability.

D. Ablation Teacher-Student Network

In order to obtain more accurate pseudo labels, we refer to the method proposed in [36] and introduce the teacher–student network in the WSDAL framework. Following the method in Sec. 3, the unaugmented images are fed into the teacher network to obtain more accurate pseudo lane labels, which are then used to supervise the lane predictions generated in the student network. The results of the ablation experiment are shown in Tab. 10. Without teacher-student network, performance improvement on the target domain *TuSimple* can still be achieved through the weak label NoL and the lane segmentation task. This further demonstrates the rationale for adding these two domain adaptation tasks. Upon integrating the teacher–student network, CLRNet achieves an even stronger performance gain on the target domain by utilizing more accurate pseudo-labels generated by the teacher network. Training with the teacher–student network does not increase the model's size at deployment, so adopting this training strategy for performance enhancement is entirely desirable.

E. Complete WSDAL Results

As mentioned in Sec. 4 and Sec. 5.1, we also validate the proposed WSDAL framework utilizing three different backbones including DLA34 [57], ConvNext-atto [54] and the ERFNet [32] encoder besides the ResNet-18 backbone. In this section, we show the complete comparison table including the results from all four backbones and two network architectures. We report the performance of the models that are adapted to *TuSimple* dataset in Tab. 11. The results correspond to the analysis in the Sec. 4.3, as all backbones, despite their difference in the architecture and training setup, improve their performance on the target domain data. The backbones with higher learning capacity demonstrate their advantage in reusing the feature representations learned from the source domain. For instance,

Table 6. Domain generalization evaluation on two datasets. Models that trained directly on target domain in **(bold)**

Model	$\mathcal{D}_s$ CULane $\rightarrow$ $\mathcal{D}_T$ TuSimple				$\mathcal{D}_s$ TuSimple $\rightarrow$ $\mathcal{D}_T$ CULane		
	F1 ↑	FPR ↓	FNR ↓	Accuracy ↑	F1 ↑	Precision ↑	Recall ↑
CondLaneNet [21]	70.2 **(97.0)**	17.4 **(2.2)**	52.6 **(3.8)**	58.7 **(95.5)**	12.7 **(77.7)**	22.8 **(83.1)**	8.8 **(73.1)**
CLRNet [62]	70.3 **(95.3)**	32.6 **(5.5)**	26.3 **(3.8)**	85.9 **(95.1)**	23.0 **(78.8)**	50.9 **(84.5)**	14.8 **(73.8)**
LaneATT [41]	54.9 **(95.1)**	49.6 **(5.9)**	39.4 **(3.7)**	81.3 **(94.9)**	23.4 **(76.0)**	67.3 **(82.7)**	14.1 **(70.4)**
GANet [49]	74.0 **(97.8)**	24.0 **(1.6)**	29.4 **(2.9)**	82.0 **(95.8)**	21.9 **(78.5)**	54.3 **(85.4)**	13.7 **(72.6)**
CLRerNet [9]	69.9 **(97.6)**	24.7 **(1.7)**	40.2 **(3.1)**	73.2 **(96.5)**	31.1 **(81.1)**	38.0 **(88.1)**	26.4 **(75.2)**

Table 7. Data augmentation setup for training

Method	p	parameters
HorizontalFlip	0.5	
ChannelShuffle	0.1	
MultiplyAndAddToBrightness	0.6	mul=(0.85, 1.15), add=(-10, 10)
AddToHueAndSaturation	0.5	value=(-10, 10)
GammaContrast	0.5	gamma=(0.5, 2.0)
MotionBlur or MedianBlur	0.5	k=(3, 5)
Affine	0.7	translate=(x=(-0.1, 0.1), y=(-0.1, 0.1)), rotate=(-10, 10), scale=(0.8, 1.2))

Table 8. The LaneATT and CLRNet models with segmentation tasks in the source domain *CULane*. All values in %.

Model	Segmentation	F1	Precision	Recall
CLRNet		77.8	84.6	72.0
CLRNet	Instance	78.5	85.9	72.3
CLRNet	Binary	78.8	84.5	73.8
LaneATT		75.5	82.2	69.8
LaneATT	Instance	76.3	82.8	70.7
LaneATT	Binary	76.0	82.7	70.4

Table 9. The CLRNet and LaneATT models with segmentation tasks are trained on *CULane* and adapted to the target domain *TuSimple*. All values in %.

Model	Segmentation	Method	F1	FPR	FNR	Accuracy
CLRNet		DG	70.4	32.6	26.3	85.9
CLRNet	Instance	DG	71.0	33.1	24.3	87.6
CLRNet	Binary	DG	73.4	28.3	24.7	86.9
CLRNet		WSDAL	80.2	16.5	22.8	85.1
CLRNet	Instance	WSDAL	83.2	14.5	19.0	86.5
CLRNet	Binary	WSDAL	86.9	11.5	15.2	89.0
LaneATT		DG	55.0	49.7	39.4	81.3
LaneATT	Instance	DG	58.9	42.8	39.2	80.5
LaneATT	Binary	DG	60.0	43.0	36.7	81.2
LaneATT		WSDAL	76.0	25.5	22.5	87.3
LaneATT	Instance	WSDAL	79.8	20.4	19.9	87.7
LaneATT	Binary	WSDAL	81.7	18.8	17.5	88.8

the ResNet-18 backbone and DLA34 backbone, independent from the source dataset, show a significant advantage after domain adaptation as the difference between the oracle and adaptation model is much smaller than those with fewer parameters. When trained with a dataset that consists

Table 10. Effects of adding a teacher–student network (TS) in the task *CULane* $\rightarrow$ *Tusimple* when CLRNet has different segmentation tasks. All values in %.

Model	Method	Segmentation	NoL	TS	F1	FPR	FNR	Accuracy
CLRNet	DG				70.4	32.6	26.4	85.9
CLRNet	WSDAL		✓		69.1	29.4	32.3	82.4
CLRNet	WSDAL		✓	✓	80.2	16.5	22.8	85.1
CLRNet	DG	Instance			71.0	33.1	24.3	87.6
CLRNet	WSDAL	Instance	✓		77.1	20.6	25.1	84.5
CLRNet	WSDAL	Instance	✓	✓	83.2	14.5	19.0	86.5
CLRNet	DG	Binary			73.4	28.3	24.7	86.9
CLRNet	WSDAL	Binary	✓		82.7	15.1	19.4	90.2
CLRNet	WSDAL	Binary	✓	✓	86.9	11.5	15.2	89.0

of complex driving scenarios, *e.g.*, with the *CurveLanes* dataset, all backbones show an advantage in their target domain after domain adaptation. In Tab. 12 the comparison of the lane detection performance on the target dataset *CULane* is shown, which is also corresponding to the results and analyses from Sec. 4.4, where we see in addition to the disparity of unsupervised domain adaptation methods and our weakly-supervised method caused by the quality–quantity dilemma of the generated pseudo-labels. The proposed WSDAL reduces the gap to oracle models by an average of around 5 % absolute value with the *CurveLanes* dataset. Tab. 13 depicts the comparison of four different backbones adapting from *CULane* to *CurveLanes*, where the label distribution shifts significantly as the lane curvature and lane structure are noticeably different. We observe a similar trend as mentioned in Sec. 4.5 where unsupervised methods only bring performance improvements to a limited extent while WSDAL boosts the performance substantially by significantly increased recall, especially when a higher tolerance of positional shift is granted due to divergent labeling policies in the two datasets.

F. Unreliable Labels

In this section, we further discuss the impact of utilizing unreliable NoL labels during the adaptation process mentioned in Sec. 5.3. In Fig. 4 we compare the difference of adapting a model which is previously trained with *CULane* dataset to the same architecture that was trained on *CurveLanes* before. We observe that the network that was previously trained on *CULane* dataset suffers more from the un-

Table 11. Comparison of the LaneATT and CLRNet models which are trained on *CULane* and *CurveLanes* datasets and adapt to *TuSimple*. We report average score in % according to three runs.

$\mathcal{D}_s$	Model	Backbone	Method	F1	FPR	FNR	Accuracy
CULane	LaneATT	ResNet-18	DG	54.9	49.6	39.4	81.29
CULane	LaneATT	ResNet-18	TSUDA	$69.9_{\pm0.7}$	$32.6_{\pm0.7}$	$25.4_{\pm0.6}$	$84.7_{\pm0.2}$
CULane	LaneATT	ResNet-18	WSDAL	$81.7_{\pm0.3}$	$18.8_{\pm1.0}$	$17.5_{\pm0.7}$	$88.8_{\pm0.4}$
CULane	CLRNet	ResNet-18	DG	70.3	32.6	26.35	85.89
CULane	CLRNet	ResNet-18	TSUDA	$84.8_{\pm0.3}$	$12.6_{\pm0.1}$	$18.9_{\pm0.9}$	$85.5_{\pm0.7}$
CULane	CLRNet	ResNet-18	WSDAL	$86.9_{\pm0.3}$	$11.5_{\pm0.2}$	$15.2_{\pm0.5}$	$89.0_{\pm0.4}$
CULane	CLRNet	ERFNet	DG	67.7	14.2	67.9	41.8
CULane	CLRNet	ERFNet	TSUDA	$79.7_{\pm0.4}$	$22.8_{\pm0.3}$	$16.5_{\pm0.6}$	$89.2_{\pm0.4}$
CULane	CLRNet	ERFNet	WSDAL	$81.5_{\pm0.6}$	$19.4_{\pm0.7}$	$17.1_{\pm0.4}$	$89.5_{\pm0.2}$
CULane	CLRNet	ConvNext	DG	69.1	22.8	46.0	66.7
CULane	CLRNet	ConvNext	TSUDA	$77.7_{\pm0.9}$	$26.0_{\pm0.9}$	$16.5_{\pm1.0}$	$88.9_{\pm0.5}$
CULane	CLRNet	ConvNext	WSDAL	$81.6_{\pm1.0}$	$19.7_{\pm1.5}$	$16.6_{\pm0.9}$	$89.5_{\pm0.5}$
CULane	CLRNet	DLA34	DG	70.4	12.9	60.4	49.1
CULane	CLRNet	DLA34	TSUDA	$81.7_{\pm0.3}$	$20.3_{\pm0.4}$	$15.4_{\pm0.4}$	$89.4_{\pm0.2}$
CULane	CLRNet	DLA34	WSDAL	$86.3_{\pm0.3}$	$13.4_{\pm0.3}$	$14.0_{\pm0.4}$	$90.8_{\pm0.2}$
CurveLanes	CLRNet	ResNet-18	DG	80.7	8.1	35.8	72.9
CurveLanes	CLRNet	ResNet-18	TSUDA	$84.5_{\pm0.2}$	$15.7_{\pm0.5}$	$15.3_{\pm0.6}$	$86.5_{\pm0.4}$
CurveLanes	CLRNet	ResNet-18	WSDAL	$91.2_{\pm0.5}$	$8.1_{\pm0.5}$	$9.7_{\pm0.5}$	$91.2_{\pm0.3}$
CurveLanes	CLRNet	ERFNet	DG	81.8	17.1	19.7	86.4
CurveLanes	CLRNet	ERFNet	TSUDA	$82.2_{\pm0.0}$	$18.0_{\pm0.0}$	$17.5_{\pm0.0}$	$86.0_{\pm0.0}$
CurveLanes	CLRNet	ERFNet	WSDAL	$87.2_{\pm0.9}$	$12.4_{\pm1.0}$	$13.2_{\pm0.9}$	$90.5_{\pm0.2}$
CurveLanes	CLRNet	ConvNeXt	DG	82.4	10.7	27.1	80.0
CurveLanes	CLRNet	ConvNeXt	TSUDA	$78.0_{\pm2.1}$	$23.1_{\pm1.9}$	$15.5_{\pm1.9}$	$84.2_{\pm0.6}$
CurveLanes	CLRNet	ConvNeXt	WSDAL	$88.9_{\pm0.7}$	$10.7_{\pm0.8}$	$11.6_{\pm0.7}$	$90.4_{\pm0.4}$
CurveLanes	CLRNet	DLA34	DG	86.6	10.7	17.0	87.2
CurveLanes	CLRNet	DLA34	TSUDA	$84.0_{\pm0.0}$	$18.1_{\pm0.0}$	$13.2_{\pm0.0}$	$88.3_{\pm0.0}$
CurveLanes	CLRNet	DLA34	WSDAL	$91.0_{\pm0.1}$	$8.4_{\pm0.1}$	$9.7_{\pm0.2}$	$90.4_{\pm0.2}$
$\mathcal{D}_T$	CLRNet	ResNet-18		95.3	5.5	3.8	95.1
$\mathcal{D}_T$	CLRNet	ERFNet		95.2	6.0	3.4	95.5
$\mathcal{D}_T$	CLRNet	ConvNext		95.8	5.6	2.8	95.6
$\mathcal{D}_T$	CLRNet	DLA34		96.3	4.1	3.2	95.6
$\mathcal{D}_T$	LaneATT	ResNet-18		95.1	5.9	3.7	94.9

reliable labels than the one trained on *CurveLanes* dataset, which is another indication that sophisticated source dataset helps the network to learn more robust and generalized features. However, as the proportion of the incorrect number of lane labels increases, the one with *CurveLanes* pretraining suffers more from the supervision signal that the unreliable labels provide.

In addition, we compare two detector architectures that have the same task from *TuSimple* to *CULane* in Fig. 5. Compared with the transition point that we observe in the *CurveLanes* → *TuSimple* task, the transition point where the unsupervised adaptation method performs better than the weakly supervised one shifts to the right, which is an indication that in this setup the tolerance against unreliable labels improves. However, as the evaluations show in Sec. 4 and Appendix E, the LaneATT models perform poorly in comparison with the CLRNet models, which is an indication of limited generalization ability from the detection head.

G. Qualitative Results

In Figs. 6 and 7 we show the qualitative results adapting from *CurveLanes* to *TuSimple*, which shifts from highly complex urban driving scenario to normal highway driving in clear weather. In general, WSDAL shows its advantage in this task by diminishing false positive predictions, which are caused by road boundaries, road material shifts, and similar lane marking structures on the road, such as tyre marks. In those cases, where the lane markings are visible, knowledge distillation from the models helps the model to identify the blurry markings. At the same time, it also increases the possibility that structures on the road which share visual properties with lane markings are more frequently detected as a false positive. Besides that, the network learns to prioritize detection in case more lanes are detected with high confidence than they should have.

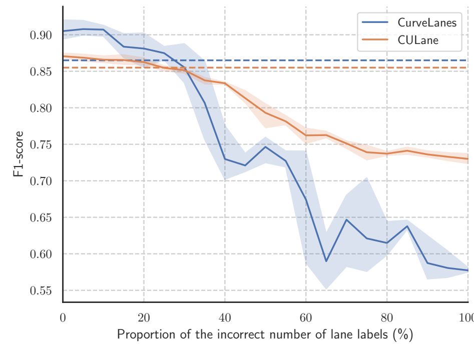

Figure 4. Comparison of using different datasets *CurveLanes* and *CULane* for the adaptation to *TuSimple* with incorrect NoL labels based on CLRNet with ResNet 18 backbone. The dashed lines show the results from TSUDA.

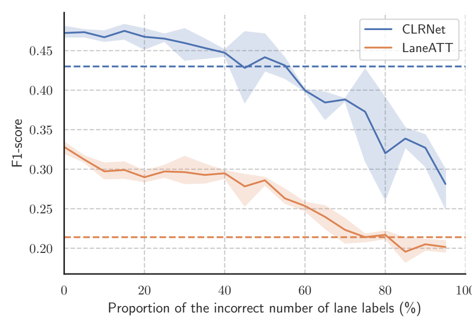

Figure 5. Results of two detector architectures adpating from *TuSimple* to *CULane* with incorrect NoL labels. The dashed lines show the results from TSUDA.

In addition, we see similar improvement of the networks adapting from *CULane* to *CurveLanes*, which is considered as domain adaptation to a more challenging driving situation compared with the source dataset. Figs. 8 to 11 depict the qualitative results from the domain adaptation result. We employ a more error tolerant IoU threshold of 0.3 for the visualization. We see that, after WSDAL, the models are outputting more predictions with higher confidence scores compared to the unsupervised model and the model without

Table 12. Comparison of the LaneATT and CLRNet models which are trained on the *TuSimple* and *CurveLanes* dataset and adapt to *CULane*. We report the average score in % according to three runs.

$\mathcal{D}_s$	Model	Backbone	Method	Normal	Crowd	Dazzle	Shadow	Noline	Arrow	Curve	Cross	Night	Total
TuSimple	CLRNet	ResNet-18	DG	42.0	20.4	11.6	5.6	8.2	28.1	22.3	1950	2.9	23.0
			TSUDA	$59.9_{\pm0.7}$	$40.2_{\pm0.5}$	$32.3_{\pm1.4}$	$24.9_{\pm0.8}$	$26.3_{\pm0.8}$	$54.1_{\pm0.5}$	$44.6_{\pm0.7}$	$4510_{\pm388}$	$30.2_{\pm1.5}$	$43.0_{\pm0.9}$
			WSDAL	$65.2_{\pm0.4}$	$43.4_{\pm0.7}$	$35.6_{\pm1.4}$	$28.2_{\pm1.5}$	$29.3_{\pm0.5}$	$57.5_{\pm0.7}$	$48.7_{\pm0.2}$	$1975_{\pm178}$	$33.4_{\pm0.8}$	$47.2_{\pm0.6}$
	LaneATT		DG	38.9	18.1	10.9	3.9	6.5	26.1	21.4	569	2.6	21.5
			TSUDA	$33.6_{\pm0.8}$	$19.8_{\pm0.4}$	$19.9_{\pm0.7}$	$10.8_{\pm0.2}$	$13.5_{\pm0.3}$	$25.6_{\pm0.3}$	$21.3_{\pm0.8}$	$7378_{\pm250}$	$9.0_{\pm0.3}$	$21.4_{\pm0.5}$
			WSDAL	$49.0_{\pm0.9}$	$28.0_{\pm0.7}$	$25.2_{\pm1.4}$	$15.6_{\pm0.9}$	$22.0_{\pm0.2}$	$37.3_{\pm0.8}$	$36.6_{\pm0.3}$	$2560_{\pm90}$	$21.6_{\pm0.7}$	$32.8_{\pm0.6}$
CurveLanes	CLRNet	ResNet-18	DG	82.2	66.0	60.2	70.1	48.0	76.8	72.0	6730	62.9	66.7
			TSUDA	$68.5_{\pm0.5}$	$50.1_{\pm0.6}$	$42.4_{\pm0.4}$	$48.5_{\pm0.7}$	$30.8_{\pm0.4}$	$63.6_{\pm0.7}$	$56.5_{\pm0.3}$	$889_{\pm21}$	$51.7_{\pm0.5}$	$55.0_{\pm0.5}$
			WSDAL	$86.2_{\pm0.0}$	$68.5_{\pm0.2}$	$60.1_{\pm0.2}$	$72.7_{\pm0.1}$	$47.3_{\pm0.1}$	$80.5_{\pm0.2}$	$73.0_{\pm0.4}$	$2370_{\pm15}$	$66.6_{\pm0.1}$	$70.9_{\pm0.1}$
		ERFNet	DG	80.1	65.2	56.6	63.6	44.5	74.0	68.0	4070	61.7	65.9
			TSUDA	$71.5_{\pm0.2}$	$54.6_{\pm0.2}$	$44.1_{\pm0.3}$	$54.5_{\pm0.2}$	$34.2_{\pm0.2}$	$67.3_{\pm0.0}$	$59.3_{\pm0.3}$	$5190_{\pm156}$	$53.6_{\pm0.2}$	$56.4_{\pm0.2}$
			WSDAL	$85.8_{\pm0.1}$	$68.3_{\pm0.1}$	$60.9_{\pm0.3}$	$69.5_{\pm0.0}$	$46.0_{\pm0.2}$	$80.8_{\pm0.2}$	$68.5_{\pm0.5}$	$2642_{\pm59}$	$66.6_{\pm0.2}$	$70.4_{\pm0.2}$
		ConvNext	DG	78.5	63.6	54.6	66.3	42.4	72.7	69.0	3208	59.3	64.7
			TSUDA	$49.9_{\pm0.4}$	$27.5_{\pm0.2}$	$26.1_{\pm0.4}$	$40.4_{\pm0.8}$	$20.8_{\pm0.2}$	$39.6_{\pm0.5}$	$47.4_{\pm0.2}$	$5803_{\pm144}$	$34.5_{\pm0.2}$	$35.5_{\pm0.2}$
			WSDAL	$86.7_{\pm0.2}$	$68.2_{\pm0.2}$	$62.8_{\pm0.3}$	$71.1_{\pm0.2}$	$46.7_{\pm0.2}$	$81.5_{\pm0.3}$	$70.8_{\pm0.2}$	$2311_{\pm12}$	$67.2_{\pm0.3}$	$71.0_{\pm0.2}$
		DLA34	DG	83.2	67.8	62.1	71.8	48.7	78.9	73.9	5973	64.8	68.4
			TSUDA	$67.1_{\pm0.4}$	$51.8_{\pm0.6}$	$41.5_{\pm0.6}$	$58.0_{\pm0.2}$	$34.0_{\pm0.5}$	$63.9_{\pm0.5}$	$58.0_{\pm0.1}$	$5142_{\pm41}$	$50.8_{\pm0.5}$	$53.8_{\pm0.4}$
			WSDAL	$87.9_{\pm0.2}$	$70.9_{\pm0.1}$	$64.9_{\pm0.3}$	$74.2_{\pm0.4}$	$48.6_{\pm0.3}$	$84.0_{\pm0.2}$	$72.2_{\pm0.2}$	$2448_{\pm33}$	$68.6_{\pm0.3}$	$72.8_{\pm0.1}$
$\mathcal{D}_T$	CLRNet	ResNet-18		93.0	77.5	70.1	77.4	52.7	89.3	68.2	1239	77.5	78.5
$\mathcal{D}_T$	CLRNet	ERFNet		92.0	75.6	69.2	77.4	48.3	88.1	63.4	1030	72.0	77.3
$\mathcal{D}_T$	CLRNet	ConvNext		91.1	73.6	67.9	72.5	48.3	85.5	66.1	1025	71.1	76.1
$\mathcal{D}_T$	CLRNet	DLA34		93.1	77.8	71.4	81.9	52.5	89.6	69.9	1127	74.0	79.1
$\mathcal{D}_T$	LaneATT	ResNet-18		91.0	73.0	65.6	76.7	48.8	86.7	65.1	1173	70.1	75.5

Table 13. Comparison of task *CUlane* → *CurveLanes* of CLRNet architectures based on various IoU thresholds. We report the average score in % according to three runs.

			$\text{IoU}_{0.2}$			$\text{IoU}_{0.3}$			$\text{IoU}_{0.5}$		
$\mathcal{D}_s$	Backbone	Method	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall
CULane	ResNet 18	DG	69.5	90.1	52.3	67.6	92.0	53.5	61.4	82.5	48.5
		TSUDA	$70.6_{\pm0.1}$	$94.9_{\pm0.1}$	$56.2_{\pm0.1}$	$68.8_{\pm0.1}$	$92.5_{\pm0.1}$	$54.8_{\pm0.1}$	$62.4_{\pm0.0}$	$83.9_{\pm0.1}$	$49.7_{\pm0.1}$
		WSDAL	$77.4_{\pm0.1}$	$86.8_{\pm0.1}$	$69.8_{\pm0.2}$	$74.2_{\pm0.1}$	$83.2_{\pm0.2}$	$66.9_{\pm0.2}$	$64.1_{\pm0.1}$	$71.9_{\pm0.1}$	$57.8_{\pm0.2}$
	ConvNext	DG	67.4	93.8	52.6	65.4	91.1	51.1	58.9	82.0	46.0
		TSUDA	$66.1_{\pm0.2}$	$83.1_{\pm1.0}$	$54.9_{\pm0.7}$	$63.7_{\pm0.1}$	$80.1_{\pm1.1}$	$52.9_{\pm0.5}$	$53.6_{\pm0.4}$	$67.4_{\pm1.3}$	$44.5_{\pm0.3}$
		WSDAL	$74.5_{\pm0.1}$	$86.3_{\pm0.3}$	$65.5_{\pm0.2}$	$70.9_{\pm0.0}$	$82.2_{\pm0.3}$	$62.4_{\pm0.2}$	$59.6_{\pm0.1}$	$69.1_{\pm0.3}$	$52.5_{\pm0.1}$
	ERFNet	DG	70.8	91.6	57.8	68.5	88.5	55.9	61.7	79.7	50.3
		TSUDA	$69.9_{\pm0.0}$	$91.5_{\pm0.2}$	$56.5_{\pm0.1}$	$67.9_{\pm0.0}$	$88.9_{\pm0.2}$	$54.9_{\pm0.1}$	$61.5_{\pm0.0}$	$80.5_{\pm0.2}$	$49.7_{\pm0.1}$
		WSDAL	$76.6_{\pm0.0}$	$85.8_{\pm0.1}$	$69.1_{\pm0.1}$	$73.4_{\pm0.0}$	$82.3_{\pm0.2}$	$66.3_{\pm0.1}$	$63.8_{\pm0.1}$	$71.5_{\pm0.2}$	$57.6_{\pm0.0}$
	DLA34	DG	67.5	95.3	52.3	65.9	93.0	51.1	60.4	85.2	46.8
		TSUDA	$70.9_{\pm0.2}$	$91.7_{\pm0.3}$	$57.8_{\pm0.4}$	$68.8_{\pm0.1}$	$89.0_{\pm0.4}$	$56.1_{\pm0.3}$	$61.8_{\pm0.1}$	$80.0_{\pm0.5}$	$50.4_{\pm0.2}$
		WSDAL	$78.0_{\pm0.1}$	$88.7_{\pm0.2}$	$69.6_{\pm0.0}$	$74.9_{\pm0.1}$	$85.2_{\pm0.2}$	$66.8_{\pm0.0}$	$65.2_{\pm0.3}$	$74.1_{\pm0.4}$	$58.2_{\pm0.2}$
$\mathcal{D}_T$	ResNet-18		86.0	92.8	80.2	83.3	89.8	77.7	75.2	81.1	70.1
$\mathcal{D}_T$	ConvNext		85.5	93.0	79.1	83.0	90.3	76.8	75.4	82.0	69.7
$\mathcal{D}_T$	ERFNet		85.4	91.6	80.0	82.8	88.7	77.5	74.9	80.3	70.1
$\mathcal{D}_T$	DLA34		86.0	93.6	79.6	83.6	90.9	77.4	76.1	82.8	70.5

domain adaptation from Fig. 8. Furthermore, Fig. 9 shows the performance of WSDAL by eliminating false positive predictions using only the weak supervision signals compared to the baseline. However, we also observe the limitation of utilizing weak labels due to the missing regression regularization during the adaptation process, which is shown in Fig. 10. If there is a shift in the annotation policy, for instance, the width of the ego lane shifts between the dataset, simple NoL loss does not show advantages during the adaptation. During the experiment, we notice that in the target dataset *CurveLanes*, sometimes the annotation policy is not consistent concerning the lanes in the ramps and curbstone, as shown in Fig. 11. An essential prerequisite for the WSDAL is that the label policy should be consistent throughout the target dataset. Otherwise, the performance of the proposed WSDAL may be negatively affected.

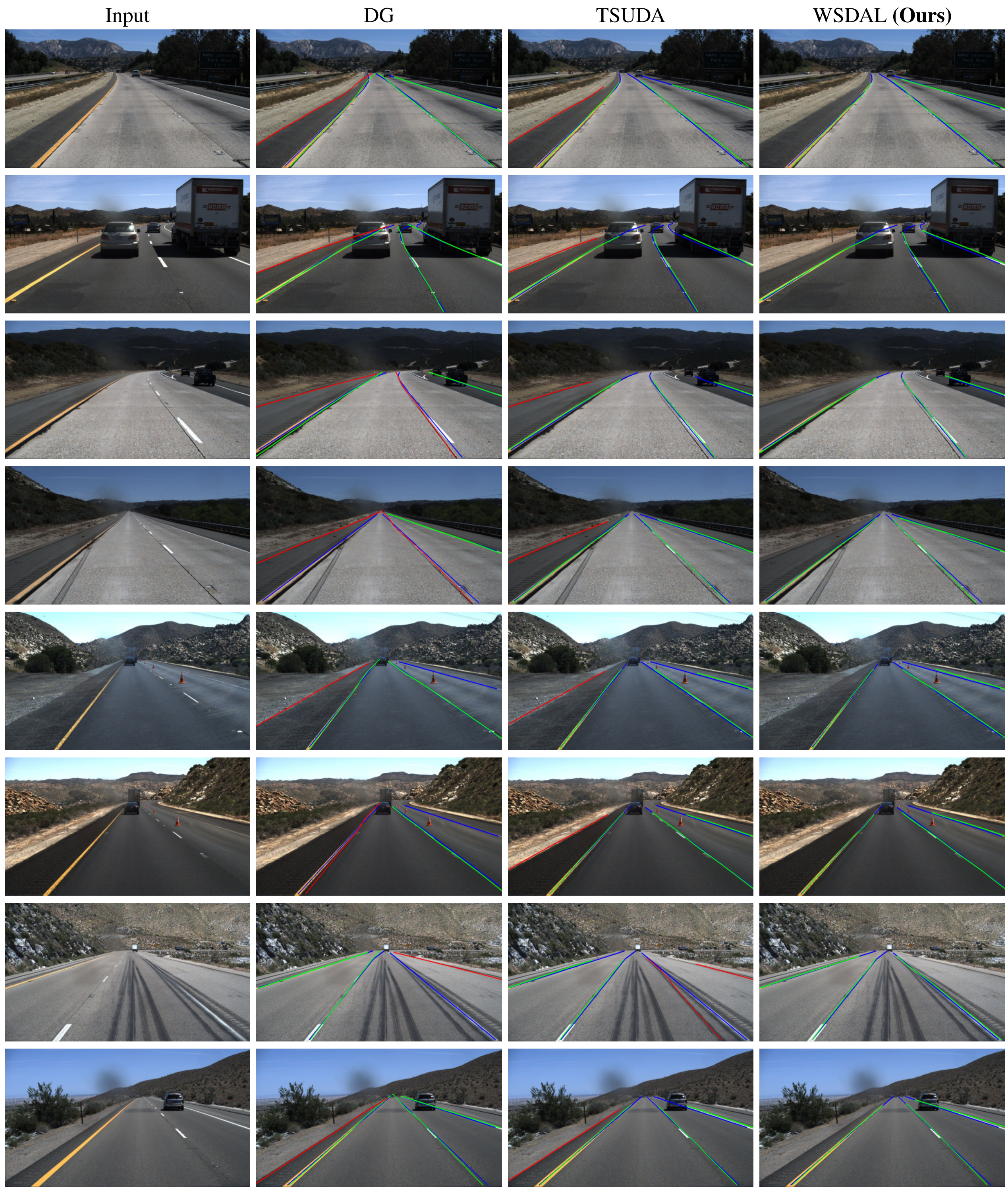

Figure 6. Qualitative results on the task *CurveLanes* → *TuSimple* from CLRNet with ResNet-18 backbone. We show the true positive predictions in green, false positive predictions in red, and ground truth in blue.

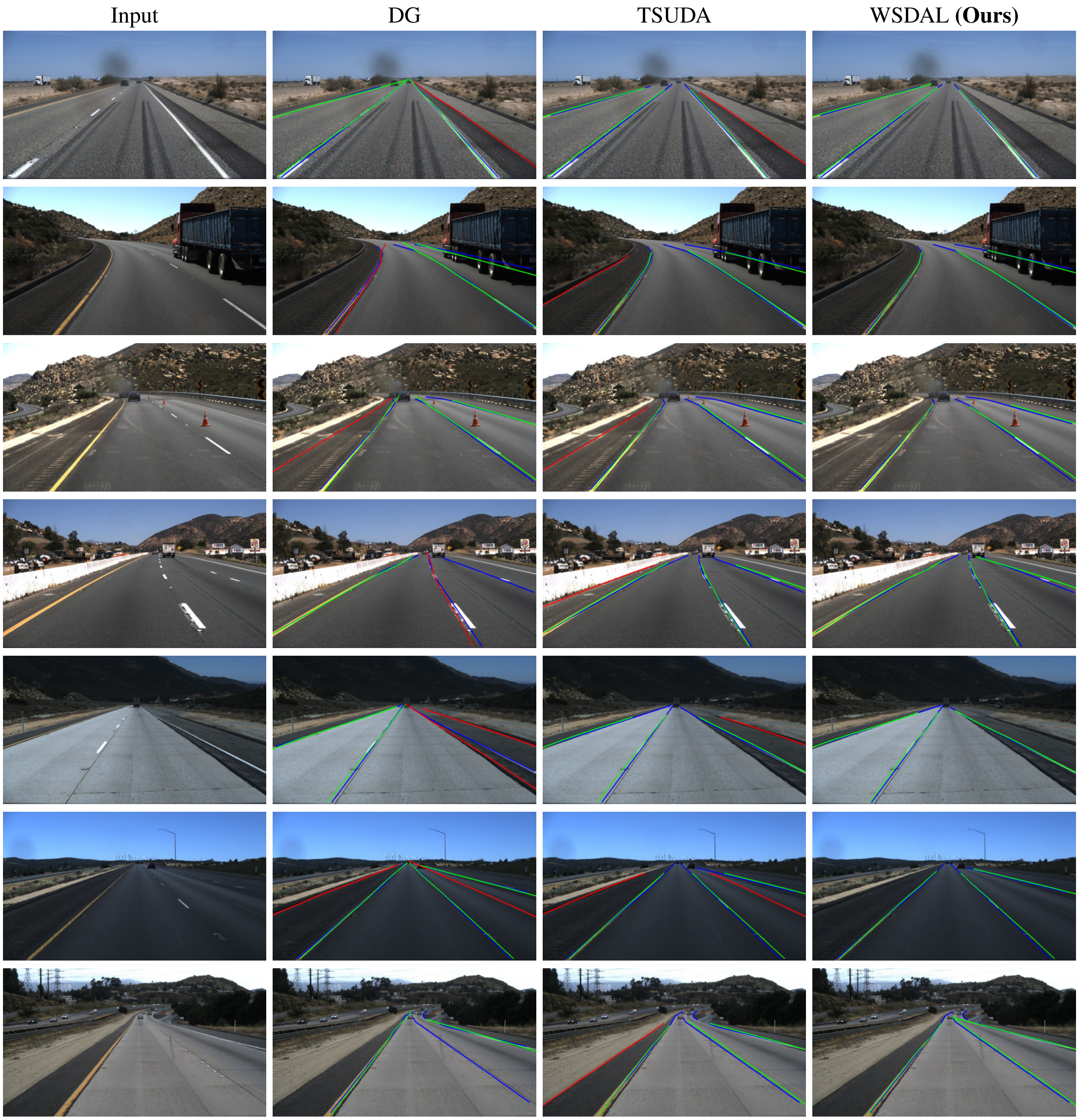

Figure 7. Qualitative results on the task *CurveLanes* → *TuSimple* from CLRNet with ResNet-18 backbone. We show the true positive predictions in green, false positive predictions in red, and ground truth in blue.

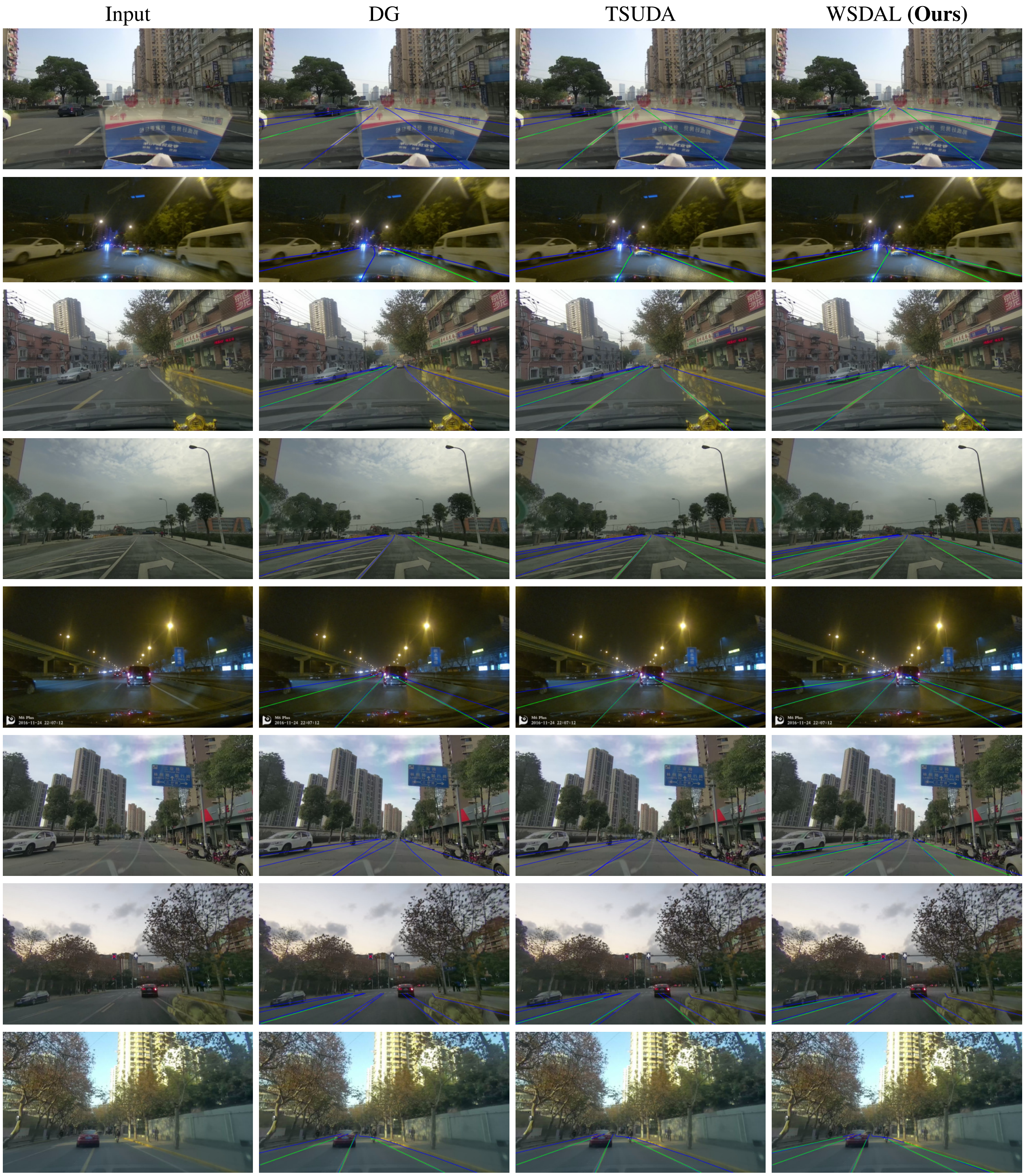

Figure 8. Qualitative results on the task *CULane* → *CurveLanes* from CLRNet with ResNet-18 backbone. After WSDAL, the models are outputting more predictions compared to the baseline. We show the true positive predictions in green, false positive predictions in red, and ground truth in blue.

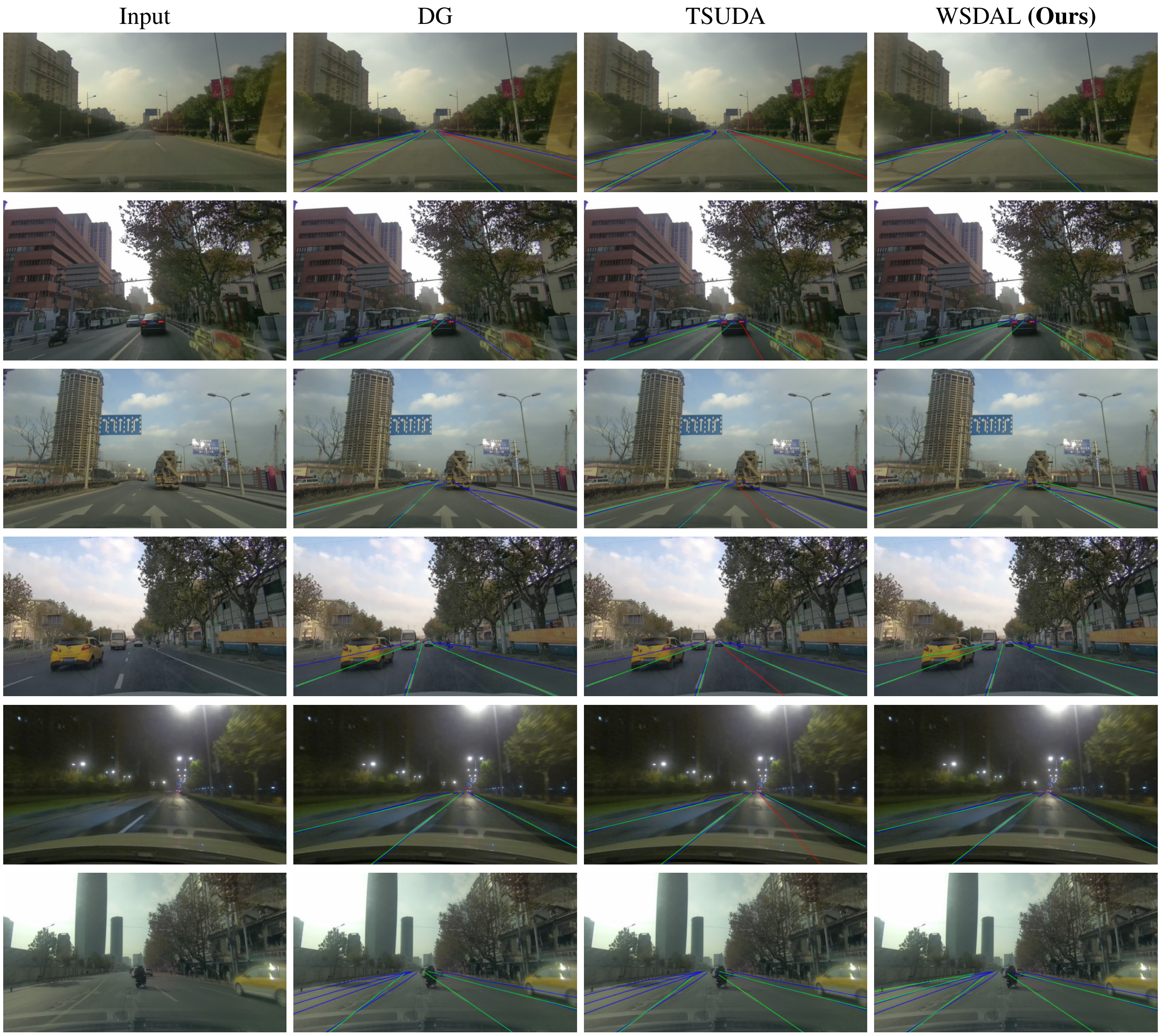

Figure 9. Qualitative results on the task *CULane* → *CurveLanes* from CLRNet with ResNet-18 backbone. We demonstrate the ability to eliminate the false positive predictions driven by WSDAL. We show the true positive predictions in green, false positive predictions in red, and ground truth in blue.

Figure 10. Qualitative results on the task *CULane* → *CurveLanes* from CLRNet with ResNet-18 backbone. These examples demonstrate the limitations of weakly supervised domain adaptation due to the missing regression constraint during training. We show the true positive predictions in green, false positive predictions in red, and ground truth in blue.

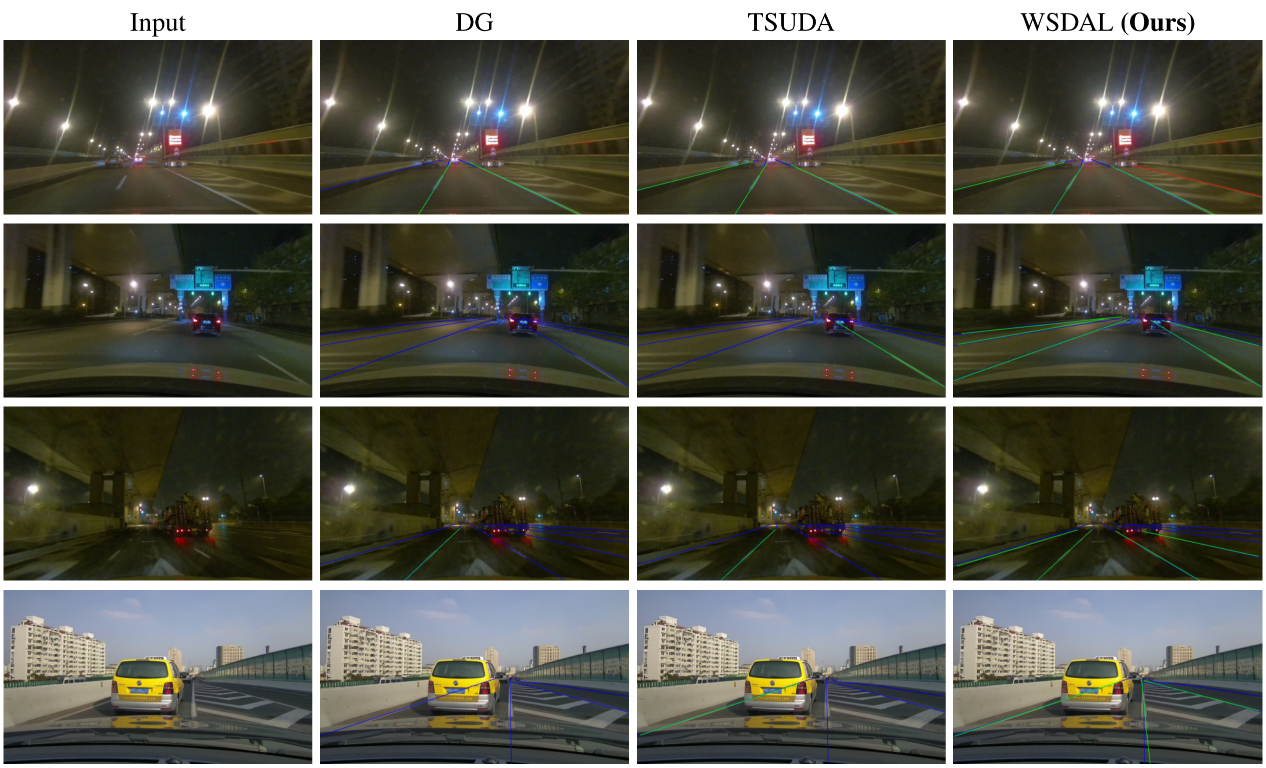

Figure 11. Qualitative results on the task *CULane* $\rightarrow$ *CurveLanes*. We observe that there are also inconsistent annotation policies that may affect the NoL-based adaptation process. We show the true positive predictions in green, false positive predictions in red, and ground truth in blue.