

# Supplementary Material for LiDAR2Map: In Defense of LiDAR-Based Semantic Map Construction Using Online Camera Distillation

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## A. Training for Vehicle Segmentation

The training details for vehicle segmentation in Setting 1 and Setting 2 are slightly different from map segmentation. Also, we adopt Swin-Tiny [5] and PointPillars [3] as the feature extractors for image and LiDAR point cloud, respectively. The BEV feature pyramid decoder (BEV-FPD) uses a three-layer model with a trade-off between the accuracy and inference speed. We train the whole network for 15 epochs with 2 NVIDIA RTX 2080Ti GPUs. The learning rate is  $1.5e^{-3}$ , which decreases by a factor of 10 at the 10th epoch. The image size is set to  $352 \times 128$  during training.

## B. Additional Results

### B.1. Map Segmentation

**More Visual Results for BEV-FPD.** We provide more visual results from the output of LiDAR2Map with different BEV-FPDs. In Fig. A1, the predicted semantic maps are gradually refined and become more accurate with the deepening of the number of layers, which further indicates the effectiveness of BEV-FPD on promoting our LiDAR2Map.

**Comparison Under Different Weather and Light Conditions.** As illustrated in Tab. A1, we compare LiDAR2Map with the state-of-the-art methods including HDMapNet-Fusion [4] and BEVerse [6] in different conditions. We employ PointPillars [3] as LiDAR backbone and 6-layer BEV-FPD for LiDAR2Map. Our method achieves the stable segmentation accuracy and outperforms other methods under different weather and light conditions. Fig. A2 provides the qualitative comparison in several typical scenarios. LiDAR2Map presents the superior capability in sunny, rainy and nighttime compared to HDMapNet-Fusion [4] and BEVerse [6]. Fig. A3 further reports more map predictions of our LiDAR2Map.

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Method	Modality	Rainy	Night	All
HDMapNet-Fusion [4]	Camera & LiDAR	38.7	39.3	44.5
BEVerse* [6]	Camera	48.8	44.4	51.7
LiDAR2Map (Ours)	LiDAR	49.6	49.2	57.4

Table A1. Map segmentation results under different weather and light conditions on the nuScenes dataset. “\*” means the results are obtained from its official public model.

### B.2. Vehicle Segmentation

For vehicle segmentation, we provide the qualitative results on the nuScenes dataset with Setting 2 in Fig. A4. It obviously indicates that our method obtains the accurate vehicle predictions in different scenes.

## C. Limitations and Future Work

The online Camera-to-LiDAR distillation scheme in our method incurs a certain amount of computation during the training, which increases the overall training time. Besides, the semantic map construction task relies on high-definition map annotations for the network training, which are only available in few datasets [1]. This limits the application of semantic map to more general autonomous driving scenarios. In the future, we will try to speed up the training process and explore the potential of LiDAR2Map with weakly-supervised forms, such as open street map [2].

## References

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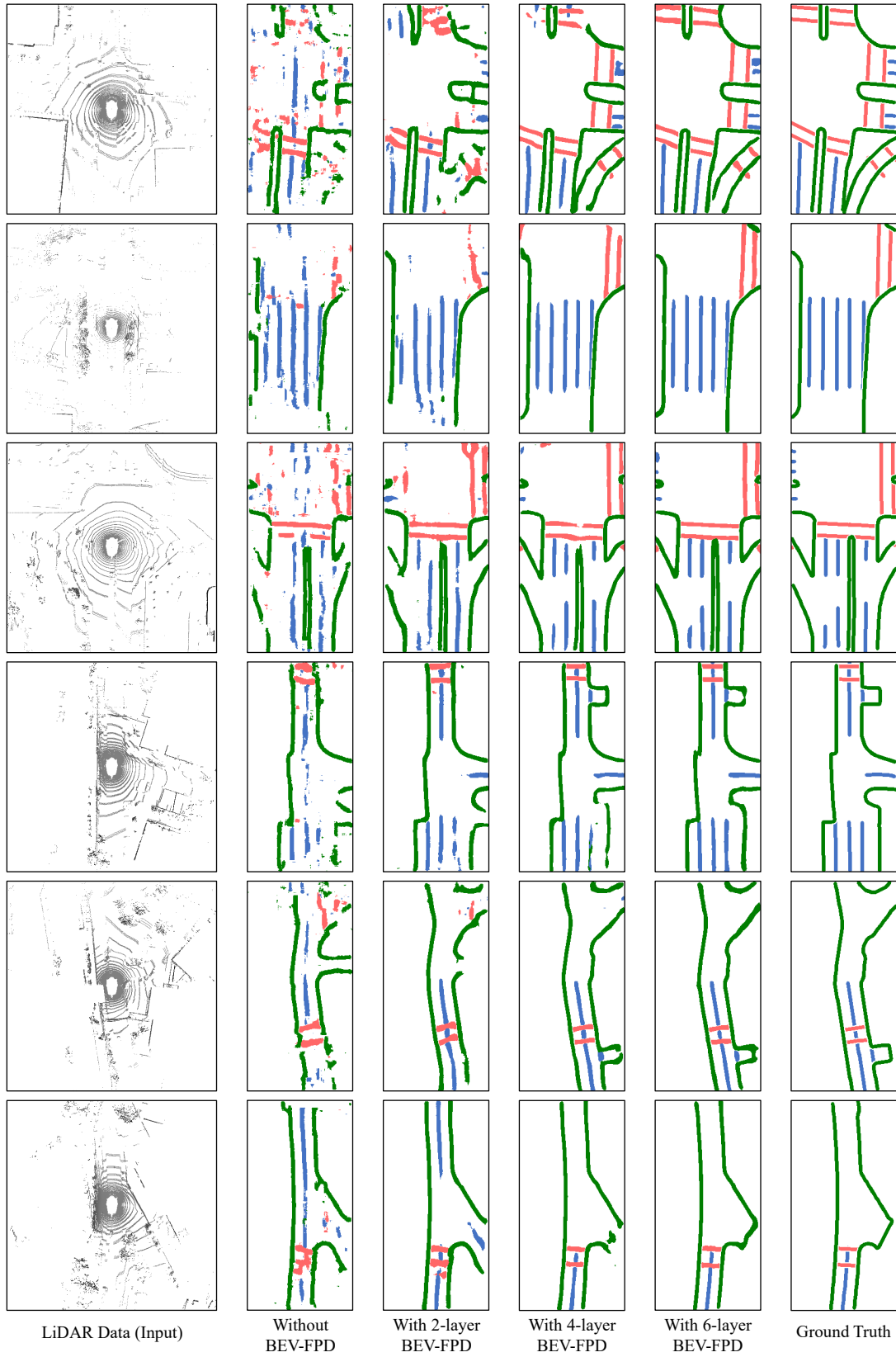
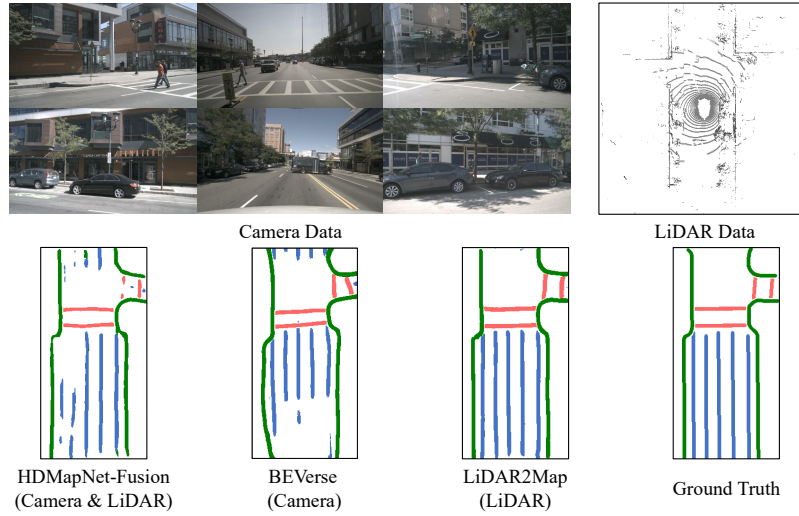
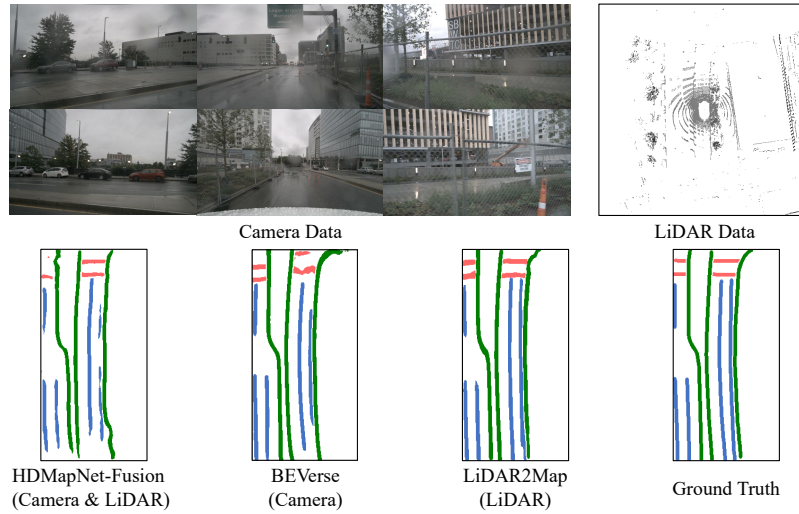


Figure A1. Additional visualization comparisons of LiDAR2Map with different BEV-FPDs on the nuScenes dataset.

**(a) Sunny Condition**



**(b) Rainy Condition**



**(c) Night Condition**

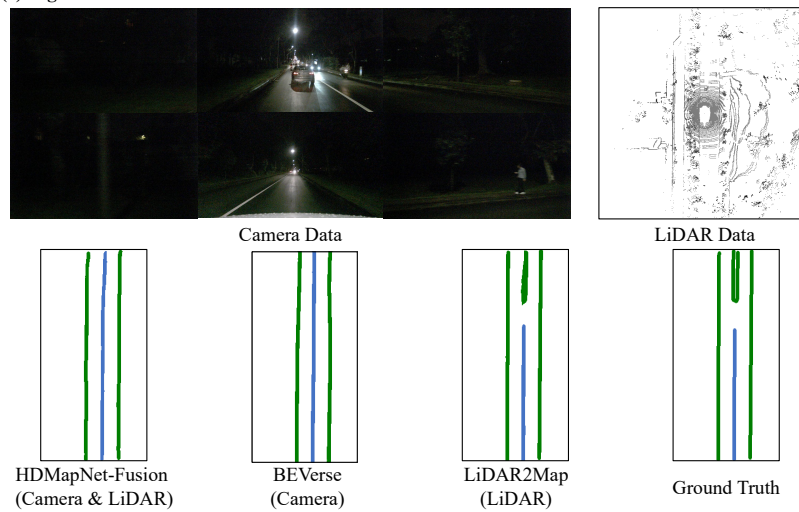
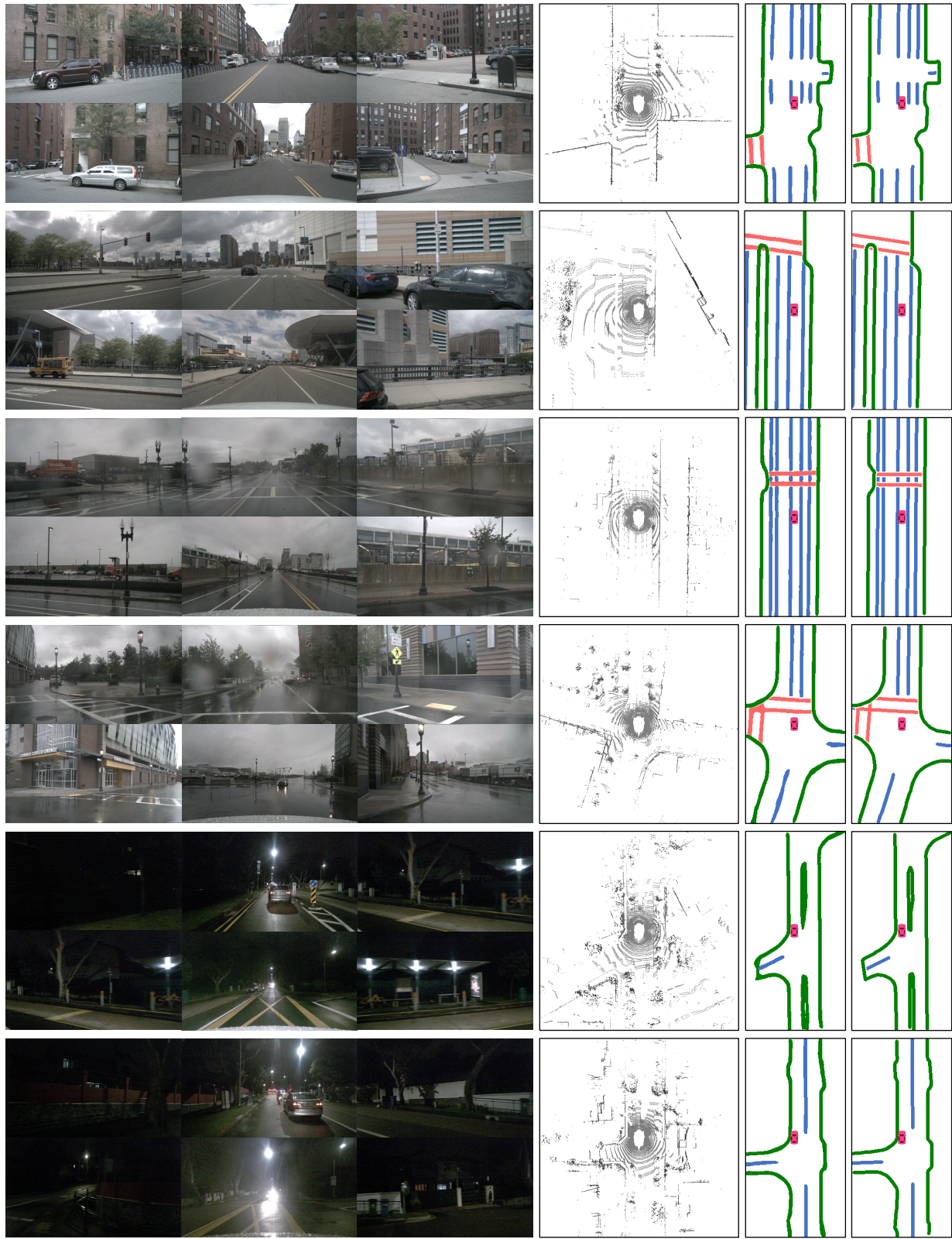


Figure A2. Qualitative results under various conditions. We compare our LiDAR2Map with other advanced approaches, including HDMaPNet-Fusion [4] and BEVerse [6].



Camera Data (Visualization Only)

LiDAR Data (Input)

Pred. (Output) Ground Truth

Figure A3. Additional visualization on map segmentation of LiDAR2Map with cloudy/rainy and day/night condition scenes.

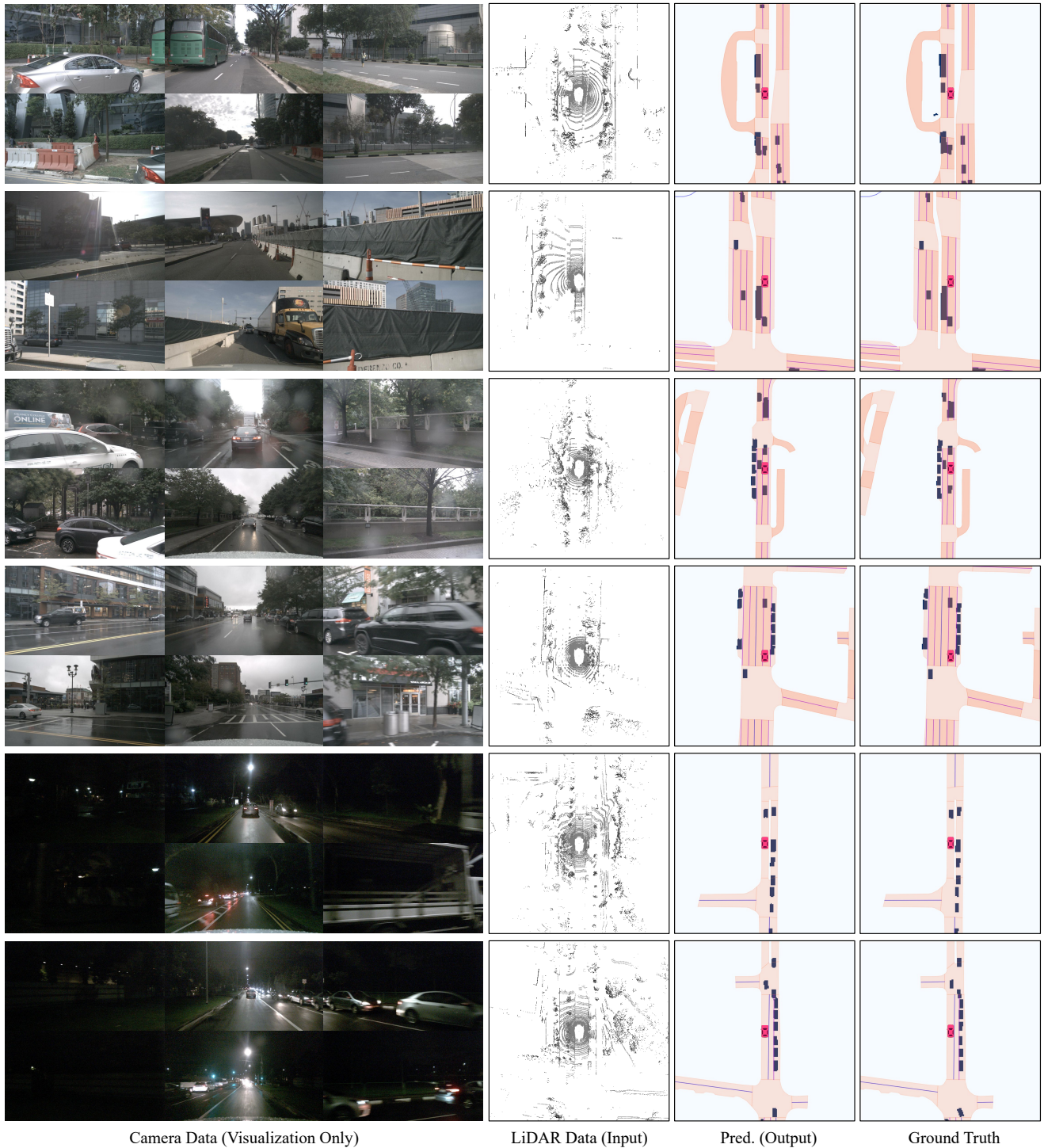


Figure A4. Visual vehicle segmentation of LiDAR2Map with cloudy/rainy and day/night condition scenes.

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