ACDC: The Adverse Conditions Dataset with Correspondences for Robust Semantic Driving Scene Perception — Supplementary Material

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TABLE 1
Training details for UDA semantic segmentation methods in Cityscapes→ACDC adaptation. "SSL rounds": number of training rounds that include supervision from pseudo-labels; if not relevant for a method, – is reported. "Training iterations": number of SGD iterations for each training round (number of epochs for each training round is alternatively reported).

Method	SSL rounds	Training iterations
AdaptSegNet	–	95k
ADVENT	–	80k
BDL	0	80k
CLAN	–	90k
CRST	3	2 epochs
FDA	1	80k
SIM	1	80k
MRNet	1	50k

TABLE 2
Training details for UDA semantic segmentation methods in Cityscapes→ACDC adaptation for individual conditions. "SSL rounds": number of training rounds that include supervision from pseudo-labels; if not relevant for a method, – is reported. "Training iterations": number of SGD iterations for each training round.

Method	SSL rounds	Training iterations
AdaptSegNet	–	40k
ADVENT	–	40k
BDL	0	40k
CLAN	–	40k
FDA	1	40k
SIM	1	40k
MRNet	1	40k

Appendix A Training Details

We provide the detailed training configurations for the various methods for semantic segmentation that have been used in Sec. 4 of the paper and for the method in [1] for uncertainty-aware semantic segmentation that has been used in Sec. 5 of the paper.

TABLE 3
Training details for supervised semantic segmentation methods on ACDC.

Method	Base LR	Training epochs
RefineNet	5×10^{-5}	60
DeepLabv2	2.5×10^{-4}	60
DeepLabv3+	10^{-4}	60
HRNet	10^{-4}	60

A.1 Normal-to-Adverse Adaptation

A.1.1 *Domain adaptive semantic segmentation*

For the comparison in Table 2, we use as source-domain model the DeepLabv2 [5] model that is used as the Cityscapes oracle in AdaptSegNet [43], with a performance of 65.1% mIoU on the Cityscapes validation set. For all eight unsupervised domain adaptation (UDA) methods that are compared, we use their default training configurations, including the learning rate schedule and the weights of the various losses. The number of training iterations run for each method as well as the number of self-supervised learning rounds that are used by some of the methods are reported in Table 1. For FDA, SIM and MRNet, we run a first training round without self-training followed by a second training round with self-training, as per default implementation of these methods. For FDA, we train three separate models in each training round, one for each different value of the β parameter from the set $\{0.01, 0.05, 0.09\}$, and use the average prediction of the three models at test time. In all cases, we use the model weights corresponding to the final training iteration for testing.

The same source-domain model is also used for the experiment on adaptation to individual conditions presented in Table 3. Again, we use the default training configurations for all examined methods and across all four conditions. The number of training iterations run for each method to adapt to each condition as well as the number of self-supervised learning rounds that are used by some of the methods are reported in Table 2. For MRNet and fog, the self-supervised training round includes 35k iterations instead of 40k. In addition, for MRNet and rain, the first training round

TABLE 4
Comparison of state-of-the-art unsupervised domain adaptive semantic segmentation methods on Cityscapes→ACDC adaptation for fog. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
Source model	66.4	31.2	26.8	22.9	18.6	8.2	32.3	10.7	70.7	39.0	31.3	17.6	41.1	65.0	30.0	34.3	18.3	42.3	29.0	33.5
AdaptSegNet	35.4	45.9	35.4	25.6	17.5	9.0	32.5	23.1	70.5	47.4	11.6	22.3	28.2	44.4	43.9	35.0	46.0	15.6	15.0	31.8
ADVENT	44.2	38.9	26.4	20.7	20.1	7.9	34.4	23.6	70.7	35.6	8.3	17.3	43.5	60.0	48.6	46.8	40.5	19.9	17.6	32.9
BDL	36.9	37.8	47.0	28.2	21.6	13.7	37.2	34.5	67.2	49.4	27.6	29.1	51.3	58.5	49.4	51.8	30.3	21.4	22.5	37.7
CLAN	48.8	41.3	29.6	27.2	21.0	16.1	41.1	39.6	67.7	50.2	15.4	36.2	30.8	72.2	52.2	54.4	47.2	27.1	22.6	39.0
FDA	68.8	37.3	27.1	27.6	19.8	21.6	37.5	43.3	74.9	43.7	33.1	35.0	21.5	65.7	44.6	45.3	47.1	41.5	15.8	39.5
SIM	76.7	43.1	23.5	23.6	17.9	10.9	32.1	15.3	70.4	50.5	21.4	34.8	44.3	58.4	50.5	55.2	34.7	23.0	8.8	36.6
MRNet	78.6	26.1	19.6	29.0	13.5	12.0	41.9	49.0	78.2	59.0	6.6	39.8	26.1	72.5	44.8	37.9	59.6	19.1	24.1	38.8
Oracle	89.9	65.6	81.2	39.1	25.9	28.1	45.9	47.7	83.0	67.4	96.7	35.2	38.4	73.5	46.1	29.8	37.9	28.4	31.6	52.2

TABLE 5
Comparison of state-of-the-art unsupervised domain adaptive semantic segmentation methods on Cityscapes→ACDC adaptation for nighttime. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
Source model	77.0	22.9	56.3	13.5	9.2	23.8	22.9	25.6	41.4	16.1	2.9	44.1	17.5	64.1	11.9	34.5	42.4	22.6	22.7	30.1
AdaptSegNet	84.9	39.9	66.8	17.2	17.7	13.4	17.6	16.4	39.6	16.1	5.7	42.8	21.4	44.8	11.9	13.0	39.1	27.5	28.4	29.7
ADVENT	86.5	45.3	60.8	23.2	12.5	15.4	18.0	19.4	41.2	18.3	2.7	43.8	21.3	61.6	12.6	19.1	43.0	30.2	27.6	31.7
BDL	87.1	49.6	68.8	20.2	17.5	16.7	19.9	24.1	39.1	23.7	0.2	42.0	20.4	63.7	18.0	27.0	45.6	27.8	31.3	33.8
CLAN	82.3	28.8	65.9	15.1	9.3	22.1	16.1	26.5	39.2	23.4	0.4	45.9	25.4	63.6	9.5	24.2	39.8	31.5	31.1	31.6
FDA	82.7	39.4	57.0	14.7	7.6	26.1	37.8	30.5	53.2	14.0	15.3	48.0	28.8	62.6	26.6	47.5	51.5	27.0	35.0	37.1
SIM	87.0	48.4	42.1	6.3	8.3	15.8	8.4	17.6	21.7	22.8	0.1	39.3	22.1	60.3	8.7	18.2	42.3	30.1	32.9	28.0
MRNet	83.6	36.3	65.6	8.1	8.2	21.5	30.0	23.7	39.4	24.2	0.0	44.1	26.0	64.9	0.8	3.6	7.6	10.3	31.8	27.9
Oracle	90.5	63.7	78.0	30.0	29.6	32.9	37.0	41.2	61.9	25.2	75.3	47.9	23.4	69.5	2.7	15.4	60.3	39.7	37.9	45.4

TABLE 6
Comparison of state-of-the-art unsupervised domain adaptive semantic segmentation methods on Cityscapes→ACDC adaptation for rain. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
Source model	71.2	26.7	73.8	20.8	27.1	29.9	39.3	44.4	87.3	25.2	82.0	42.0	14.3	76.2	36.3	26.6	49.8	30.3	42.2	44.5
AdaptSegNet	81.2	43.2	83.3	27.3	31.4	23.0	41.4	40.5	87.2	35.0	93.1	40.2	15.5	73.9	45.7	34.9	57.0	27.1	49.1	49.0
ADVENT	77.0	31.0	52.5	35.0	34.2	23.4	42.1	41.0	85.3	34.2	26.7	41.3	14.1	75.6	47.3	40.4	64.3	29.6	46.2	44.3
BDL	79.1	39.0	82.8	30.0	34.5	28.1	40.1	47.3	87.0	28.7	91.8	40.6	17.8	74.6	46.3	36.7	60.4	33.2	46.3	49.7
CLAN	77.5	40.0	46.8	24.9	30.3	28.1	37.7	48.3	83.8	37.0	6.6	45.7	17.4	79.7	43.7	42.9	63.7	35.0	46.1	44.0
FDA	76.6	45.0	82.9	37.0	35.6	34.8	49.8	52.0	88.7	37.8	88.8	43.6	17.4	76.8	46.5	53.6	64.8	34.5	45.5	53.3
SIM	76.6	29.6	85.7	20.4	28.7	21.3	37.4	34.2	87.3	34.8	94.0	29.4	16.6	73.2	46.1	22.3	46.2	21.8	39.3	44.5
MRNet	70.5	9.9	46.5	35.6	36.1	36.5	56.4	56.2	90.2	41.3	4.3	53.0	23.5	81.6	39.3	26.7	57.8	43.6	54.5	45.4
Oracle	87.3	63.9	89.0	50.3	40.6	38.4	52.2	53.4	89.2	42.2	96.7	51.5	13.0	81.9	47.9	47.2	72.2	29.1	48.8	57.6

without self-supervised training includes 25k iterations instead of 40k.

A.1.2 Domain adaptive object detection

For the comparison in Table 5, we use the representative FCOS and Faster R-CNN as the source-domain models for object detection. For a fair and consistent comparison, each model is trained with a ResNet-50 backbone. For all compared UDA obejct detection methods, we use their default training configurations for Cityscapes to Foggy Cityscapes adaptation task as it is a common normal-to-adverse setting in existing UDA object detection works. All hyperparameters including the learning rate scheduling, the loss weights and the training iterations are consistent with the original configurations. Following SIGMA [33], we use the ACDC

TABLE 7
Comparison of state-of-the-art unsupervised domain adaptive semantic segmentation methods on Cityscapes→ACDC adaptation for snow. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
Source model	68.5	26.6	52.7	18.8	26.9	22.2	35.7	40.7	76.5	3.6	49.9	50.4	27.1	73.7	27.6	39.1	60.9	21.1	42.5	40.2
AdaptSegNet	51.3	32.5	47.3	21.5	31.5	13.2	37.8	23.2	76.0	2.6	4.5	49.9	23.1	68.7	38.3	31.8	51.5	21.7	45.0	35.3
ADVENT	50.8	24.8	46.2	15.5	26.0	15.5	27.9	23.0	70.0	2.1	9.5	44.2	25.3	68.5	22.9	24.9	50.1	23.9	38.9	32.1
BDL	42.3	36.4	60.2	15.7	30.4	15.1	41.4	30.4	71.3	1.7	11.2	46.8	27.8	57.7	38.6	34.1	59.2	28.1	43.7	36.4
CLAN	71.8	26.0	37.3	12.5	27.0	21.1	32.0	41.1	78.5	1.9	0.9	50.9	23.9	82.4	43.2	39.5	61.6	25.2	39.4	37.7
FDA	74.6	30.9	56.1	20.5	34.8	28.7	53.9	47.8	80.5	1.1	55.9	53.1	37.9	79.7	40.5	51.9	67.4	34.3	41.8	46.9
SIM	72.1	26.7	39.4	13.3	29.5	15.3	26.4	17.9	76.4	4.8	5.1	45.9	32.0	76.2	29.8	26.6	48.3	23.2	24.2	33.3
MRNet	67.7	3.5	36.8	8.3	24.8	18.0	52.6	55.4	82.4	0.5	0.1	62.2	30.2	79.2	32.1	59.3	58.4	29.1	35.8	38.7
Oracle	89.1	61.7	82.7	26.4	40.9	35.5	56.5	54.1	85.2	39.0	95.1	55.0	25.7	84.3	38.6	53.8	77.6	29.0	49.5	56.8

TABLE 8
Comparison of state-of-the-art unsupervised domain-adaptive object detection methods on Cityscapes→ACDC for fog. The first and second groups of rows present two-stage domain-adaptive detection and one-stage domain-adaptive detection methods, respectively. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP_{50}^{box}	AP^{box}
Source model (Faster R-CNN)	18.2	10.7	46.2	16.8	30.3	12.3	15.6	7.1	19.7	10.8
DA-Faster	8.1	8.9	51.5	13.0	24.6	12.3	12.5	7.3	17.3	9.0
SADA	23.3	3.9	60.8	11.7	24.9	8.2	16.6	6.7	19.5	10.0
MIC (SADA)	31.3	19.2	64.8	10.3	16.1	16.7	27.3	12.6	24.8	12.4
FRCNN-SIGMA++	19.1	14.4	54.8	16.7	33.1	22.6	16.6	8.4	23.2	12.2
Oracle	27.5	13.1	58.5	29.8	41.0	26.6	22.7	12.1	28.9	16.4
Source model (FCOS)	29.9	12.4	53.0	18.8	33.9	11.7	12.7	3.2	22.0	12.9
EPM	28.4	9.7	56.3	16.7	33.8	11.1	14.1	8.6	22.3	12.3
SIGMA	32.1	16.7	59.2	17.9	25.1	17.7	27.3	7.0	25.4	14.2
Oracle	30.4	12.2	64.8	26.7	32.0	23.6	29.4	9.5	28.6	16.9

TABLE 9
Comparison of state-of-the-art unsupervised domain-adaptive object detection methods on Cityscapes→ACDC for nighttime. The first and second groups of rows present two-stage domain-adaptive detection and one-stage domain-adaptive detection methods, respectively. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP_{50}^{box}	AP^{box}
Source model (Faster R-CNN)	19.0	17.0	27.3	3.2	28.3	8.1	3.4	8.8	14.4	7.2
DA-Faster	15.1	14.5	20.1	2.1	13.3	8.4	3.8	15.2	11.6	5.3
SADA	34.7	23.7	37.0	2.8	15.2	6.3	6.5	17.1	17.9	7.8
MIC (SADA)	26.6	21.1	34.0	5.3	27.8	5.3	7.5	19.1	18.4	8.9
FRCNN-SIGMA++	24.5	24.0	41.7	10.1	40.4	16.9	6.6	21.4	23.2	11.1
Oracle	28.7	28.9	51.0	11.1	31.5	32.9	14.6	24.3	27.9	14.1
Source model (FCOS)	23.5	15.9	25.9	2.5	26.8	6.7	5.5	8.8	14.4	7.2
EPM	25.1	15.4	29.8	1.9	30.5	9.5	3.9	9.2	15.7	7.8
SIGMA	29.9	18.8	38.2	1.5	33.2	5.2	8.2	13.2	18.5	9.3
Oracle	39.0	30.2	54.2	3.6	39.4	28.9	15.2	19.1	28.7	15.1

validation set for each condition to select the model weights for testing.

A.2 Supervised Learning on Adverse Conditions

A.2.1 Supervised Semantic Segmentation

For training the four semantic segmentation methods that are compared in Tables 9 and 10, we have generally used the default configuration for each method both in the case of condition experts and uber models. For DeepLabv2 [5], we use the architecture employed in AdaptSegNet [43] in the context of domain adaptation and not the original architecture. We have used the default learning rate schedule for each method, with the base learning rates that are reported in Table 3. We generally use 60 training epochs for all four methods, which yields 96k training iterations for uber models

TABLE 10
Comparison of state-of-the-art unsupervised domain-adaptive object detection methods on Cityscapes→ACDC for rain. The first and second groups of rows present two-stage domain-adaptive detection and one-stage domain-adaptive detection methods, respectively. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP^{box}_{50}	AP^{box}
Source model (Faster R-CNN)	23.1	8.1	66.2	29.6	2.9	20.4	25.1	15.5	23.9	11.2
DA-Faster	19.5	8.3	64.1	24.5	4.2	16.7	22.1	14.0	21.7	9.7
SADA	34.8	11.4	78.0	20.3	0.4	7.4	22.6	17.0	24.0	11.3
MIC (SADA)	38.7	13.4	76.7	19.9	0.2	15.3	26.0	18.4	26.1	12.5
FRCNN-SIGMA++	30.3	7.9	69.0	36.2	1.0	29.3	28.5	17.2	27.4	12.7
Oracle	36.7	12.5	73.8	49.0	12.6	37.4	37.1	28.1	35.9	17.8
Source model (FCOS)	27.3	6.2	68.2	20.3	2.8	18.6	20.8	16.5	22.6	11.2
EPM	29.3	9.3	65.8	17.1	1.5	16.6	19.6	15.8	21.9	10.6
SIGMA	28.0	5.3	72.3	25.1	1.7	26.2	16.5	20.1	24.4	12.1
Oracle	44.4	15.0	79.0	38.8	13.3	40.1	31.8	26.9	36.2	18.9

TABLE 11
Comparison of state-of-the-art unsupervised domain-adaptive object detection methods on Cityscapes→ACDC for snow. The first and second groups of rows present two-stage domain-adaptive detection and one-stage domain-adaptive detection methods, respectively. Performance of the model trained only on the source domain (Source model) and of the oracle with access to the target domain labels (Oracle) is also reported.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP^{box}_{50}	AP^{box}
Source model (Faster R-CNN)	33.4	17.6	66.8	25.5	29.7	23.2	21.6	15.7	29.2	14.7
DA-Faster	37.3	12.3	67.5	21.4	31.2	23.4	21.4	24.8	29.9	14.3
SADA	48.1	20.2	74.6	7.2	7.2	11.5	23.8	32.6	28.2	12.3
MIC (SADA)	46.3	30.1	76.4	8.1	19.3	19.9	23.9	28.3	31.5	15.9
FRCNN-SIGMA++	41.5	19.1	69.3	19.4	33.4	28.4	33.9	25.1	33.8	16.4
Oracle	49.4	19.2	73.2	32.0	37.0	48.5	41.7	33.7	41.9	20.8
Source model (FCOS)	40.9	18.3	68.1	23.3	24.4	18.6	19.3	14.3	28.4	15.2
EPM	41.8	22.2	70.9	13.4	18.6	15.7	13.5	10.5	25.8	14.3
SIGMA	40.6	8.1	57.6	0.5	14.9	15.8	17.4	4.8	19.9	10.1
Oracle	56.6	22.8	76.2	36.4	30.5	38.6	26.0	26.2	39.2	21.5

TABLE 12
Comparison of state-of-the-art supervised semantic segmentation methods on ACDC for fog. The first group of rows presents condition-specific expert models trained only on fog, while the second group presents uber models trained on all conditions.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	93.2	75.5	86.1	44.1	37.6	46.0	64.2	64.8	85.5	70.8	97.9	46.1	34.8	79.3	59.4	64.8	82.4	36.6	38.8	63.6
DeepLabv2	89.9	65.6	81.2	39.1	25.9	28.1	45.9	47.7	83.0	67.4	96.7	35.2	38.4	73.5	46.1	29.8	37.9	28.4	31.6	52.2
DeepLabv3+	93.8	77.4	88.8	51.0	43.3	54.2	68.2	71.7	87.7	74.6	98.2	53.5	32.1	83.8	69.3	84.4	85.3	47.2	40.1	68.7
HRNet	94.6	79.6	89.9	53.6	44.9	59.4	74.3	76.1	88.9	77.6	98.3	61.5	53.3	86.0	66.6	80.0	88.5	41.1	30.2	70.8
RefineNet	93.5	75.6	87.2	42.3	39.2	49.8	68.5	67.2	85.6	70.1	97.9	52.6	48.2	81.0	62.6	62.0	69.1	57.7	37.4	65.7
DeepLabv2	90.9	67.2	81.6	38.7	29.5	29.7	51.2	50.7	81.4	61.9	96.0	34.8	40.5	74.1	53.4	53.1	59.9	8.3	32.5	54.5
DeepLabv3+	93.6	77.6	89.2	54.0	44.8	55.8	67.6	72.0	88.0	73.5	98.2	49.5	24.4	83.9	72.2	84.2	89.2	52.8	42.4	69.1
HRNet	94.9	81.0	90.5	58.9	53.7	61.9	79.0	78.7	89.3	78.7	98.3	63.2	54.6	87.2	72.3	87.8	90.6	58.7	38.9	74.7

and 24k training iterations for condition experts. Exceptions to this rule are RefineNet and fog where we use 30 epochs, DeepLabv2 and fog where we use 45 epochs, DeepLabv2 and night where we use 240 epochs, and the DeepLabv3+ uber model for which we use 30 epochs. For HRNet, we use the snapshot with the best mIoU performance on the respective validation set of ACDC for predicting on the test set, while for the rest of the methods we use the final training snapshot for the same purpose.

A.2.2 Supervised Instance Segmentation

For training the four instance segmentation methods that are compared in Tables 13 and 14, we have generally used the default configuration for each method both in the case of condition experts and uber models. We use the consistent ResNet-50 backbone for each model and train each model on data of each condition for 60 epoches. We use the model weights corresponding to the final training iteration for testing.

TABLE 13
Comparison of state-of-the-art supervised semantic segmentation methods on ACDC for nighttime. The first group of rows presents condition-specific expert models trained only on nighttime, while the second group presents uber models trained on all conditions.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	93.4	70.3	78.6	34.3	34.1	46.9	52.2	54.2	66.3	18.7	78.1	60.3	35.5	76.2	4.7	47.8	59.4	36.0	45.3	52.2
DeepLabv2	90.5	63.7	78.0	30.0	29.6	32.9	37.0	41.2	61.9	25.2	75.3	47.9	23.4	69.5	2.7	15.4	60.3	39.7	37.9	45.4
DeepLabv3+	94.7	75.9	85.0	48.4	38.6	52.2	55.8	54.4	76.1	30.3	84.2	67.4	41.1	85.0	8.3	62.3	80.6	35.6	49.8	59.2
HRNet	95.5	78.8	86.5	49.2	44.1	58.0	64.5	63.2	75.6	41.0	83.9	71.7	48.8	84.6	15.5	76.9	81.2	25.9	55.9	63.2
RefineNet	93.5	70.9	80.3	32.0	32.0	46.0	53.9	54.1	69.2	31.9	78.0	61.0	35.4	80.2	11.6	60.0	69.4	48.9	46.8	55.5
DeepLabv2	86.6	57.8	71.7	30.3	23.6	31.8	37.4	38.9	60.0	26.8	72.8	47.6	25.1	71.1	16.9	27.8	65.1	30.6	38.5	45.3
DeepLabv3+	94.7	75.3	84.9	46.9	37.8	53.8	57.3	52.1	75.7	41.2	82.9	66.6	40.2	83.6	24.7	67.9	80.8	41.7	49.4	60.9
HRNet	95.7	79.0	86.2	46.8	43.5	59.2	64.9	64.5	75.3	40.3	82.7	72.1	52.6	86.9	18.8	78.8	83.6	52.5	57.3	65.3

TABLE 14
Comparison of state-of-the-art supervised semantic segmentation methods on ACDC for rain. The first group of rows presents condition-specific expert models trained only on rain, while the second group presents uber models trained on all conditions.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	89.2	69.8	91.7	52.2	51.3	57.9	71.0	69.9	93.6	50.5	98.4	65.8	25.1	88.1	49.4	55.4	74.8	47.0	60.2	66.4
DeepLabv2	87.3	63.9	89.0	50.3	40.6	38.4	52.2	53.4	89.2	42.2	96.7	51.5	13.0	81.9	47.9	47.2	72.2	29.1	48.8	57.6
DeepLabv3+	92.8	77.4	93.9	67.3	58.1	64.1	74.4	75.9	94.2	50.8	98.6	70.8	33.4	90.4	67.7	79.2	86.8	54.6	66.1	73.5
HRNet	94.8	81.8	94.9	69.6	63.7	69.5	79.6	80.7	94.8	51.2	98.7	73.5	27.0	93.1	75.4	40.9	61.4	59.6	70.8	72.7
RefineNet	91.5	73.5	91.1	51.0	51.6	58.3	72.5	73.7	92.9	51.2	97.9	65.5	29.5	89.2	59.8	68.2	80.3	48.0	59.5	68.7
DeepLabv2	87.4	64.8	88.1	48.2	40.4	38.4	52.0	56.9	89.3	40.2	96.5	52.3	17.4	83.9	55.5	63.0	75.8	28.9	47.2	59.3
DeepLabv3+	92.7	76.5	93.5	64.8	58.0	63.8	75.8	77.3	94.1	50.0	98.0	70.5	33.1	91.2	75.9	85.1	86.2	55.8	65.0	74.1
HRNet	95.6	83.1	94.2	60.1	66.3	71.2	82.3	82.4	94.6	55.1	98.6	75.2	39.7	93.4	73.8	86.2	85.9	66.4	71.3	77.7

TABLE 15
Comparison of state-of-the-art supervised semantic segmentation methods on ACDC for snow. The first group of rows presents condition-specific expert models trained only on snow, while the second group presents uber models trained on all conditions.

Method	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	90.1	65.7	86.4	31.2	48.1	58.0	76.7	70.3	89.7	45.7	97.3	70.8	15.4	87.1	35.0	43.1	79.1	38.7	59.9	62.5
DeepLabv2	89.1	61.7	82.7	26.4	40.9	35.5	56.5	54.1	85.2	39.0	95.1	55.0	25.7	84.3	38.6	53.8	77.6	29.0	49.5	56.8
DeepLabv3+	91.9	70.9	90.1	48.9	52.0	62.2	79.2	74.5	92.0	47.0	97.6	78.2	35.9	90.4	61.7	64.3	89.2	43.9	69.4	70.5
HRNet	93.6	75.2	89.0	42.0	55.6	67.7	83.3	78.9	93.0	48.9	97.8	78.1	16.4	92.6	54.8	61.6	87.0	50.0	68.9	70.2
RefineNet	90.2	65.7	86.5	33.7	50.6	57.8	78.0	71.5	89.2	44.5	97.0	73.8	46.0	88.4	50.0	48.0	79.9	40.6	60.3	65.9
DeepLabv2	88.7	62.5	82.5	35.3	41.7	35.0	59.0	52.8	84.4	36.0	95.2	58.1	29.8	84.8	48.9	30.9	77.9	32.9	48.4	57.1
DeepLabv3+	91.4	69.6	88.8	48.8	53.9	60.6	79.5	72.9	90.5	44.7	97.4	77.4	37.2	90.0	64.3	55.0	87.8	41.7	70.0	69.6
HRNet	94.4	77.3	91.5	53.1	63.6	70.2	85.1	81.4	92.1	57.7	97.7	83.3	69.6	93.6	71.8	54.5	86.3	52.7	73.1	76.3

TABLE 16
Comparison of state-of-the-art supervised instance segmentation methods on ACDC for fog. The first group of rows presents condition-specific expert models trained only on fog, while the second group presents uber models trained on all conditions. For each condition we report the performance in AP^{mask}.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP^{mask}
Mask R-CNN	14.7	1.5	41.3	17.5	21.3	17.3	8.5	2.8	15.6
Cascaded Mask R-CNN	15.5	0.8	42.3	21.7	23.6	13.2	10.3	2.4	16.2
HTC	17.4	1.3	43.9	21.8	28.1	14.7	8.0	3.1	17.3
Detectors	16.2	1.4	44.0	22.0	25.9	20.0	6.8	2.6	17.4
Mask R-CNN	22.7	9.8	46.8	23.8	31.3	33.5	20.6	7.1	24.4
Cascaded Mask R-CNN	22.6	9.7	47.7	25.1	33.9	31.9	15.5	8.0	24.3
HTC	26.6	9.3	49.4	27.3	35.8	33.9	18.4	7.1	26.0
Detectors	23.8	8.0	49.3	26.8	35.1	37.6	15.4	6.3	25.3

TABLE 17
Comparison of state-of-the-art supervised instance segmentation methods on ACDC for nighttime. The first group of rows presents condition-specific expert models trained only on nighttime, while the second group presents uber models trained on all conditions. For each condition we report the performance in AP^{mask}.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP^{mask}
Mask R-CNN	13.7	3.4	36.6	2.2	8.1	14.4	2.9	3.9	10.7
Cascaded Mask R-CNN	13.8	3.4	36.9	2.2	8.7	17.8	4.8	4.2	11.5
HTC	14.9	4.7	39.1	2.5	10.6	17.5	5.3	4.5	12.4
Detectors	15.1	3.8	39.4	5.5	12.6	18.3	5.9	4.3	13.1
Mask R-CNN	16.9	4.9	40.7	8.3	9.5	21.1	5.8	6.3	14.2
Cascaded Mask R-CNN	17.1	4.8	41.6	3.5	9.4	22.7	5.6	6.3	13.9
HTC	18.6	6.8	43.0	2.2	15.7	23.3	6.6	7.3	15.4
Detectors	19.3	6.7	42.5	5.7	15.9	27.6	6.0	8.0	16.5

TABLE 18
Comparison of state-of-the-art supervised instance segmentation methods on ACDC for rain. The first group of rows presents condition-specific expert models trained only on rain, while the second group presents uber models trained on all conditions. For each condition we report the performance in AP^{mask}.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP^{mask}
Mask R-CNN	20.7	1.4	56.1	26.1	20.9	27.9	9.8	7.7	21.3
Cascaded Mask R-CNN	20.1	1.0	56.6	24.3	21.0	28.0	11.2	7.0	21.2
HTC	22.2	1.0	58.9	25.2	19.7	30.5	11.1	9.3	22.3
Detectors	21.0	3.4	59.1	26.4	25.4	31.5	10.5	9.0	23.3
Mask R-CNN	20.2	1.4	57.1	27.1	20.7	27.1	10.7	8.4	21.6
Cascaded Mask R-CNN	20.4	1.4	58.0	26.9	24.5	29.3	11.4	8.2	22.5
HTC	22.6	2.5	60.3	25.0	22.7	32.1	11.0	9.7	23.2
Detectors	23.2	3.0	60.6	30.5	26.1	32.7	12.7	10.7	24.9

TABLE 19
Comparison of state-of-the-art supervised instance segmentation methods on ACDC for snow. The first group of rows presents condition-specific expert models trained only on snow, while the second group presents uber models trained on all conditions. For each condition we report the performance in AP^{mask}.

Method	person	rider	car	truck	bus	train	motorc.	bicycle	AP^{mask}
Mask R-CNN	28.6	5.1	52.9	17.7	19.0	21.5	17.1	4.5	20.8
Cascaded Mask R-CNN	28.8	5.9	52.6	21.3	28.3	26.5	9.0	5.8	22.3
HTC	29.8	5.3	55.0	21.2	28.5	28.0	13.0	6.2	23.4
Detectors	29.2	5.7	55.5	23.1	29.3	26.7	12.2	5.8	23.4
Mask R-CNN	30.0	7.3	58.4	27.2	37.3	30.4	18.2	10.1	27.4
Cascaded Mask R-CNN	30.5	10.3	59.5	27.2	40.1	30.8	17.0	10.1	28.2
HTC	33.0	10.1	61.9	32.2	40.1	35.5	17.9	11.2	30.2
Detectors	33.8	11.7	61.2	28.9	37.3	37.9	17.9	9.5	29.8

A.2.3 Supervised Panoptic Segmentation

For training the four panoptic segmentation methods that are compared in Tables 15 and 16, we have generally used the default configuration for each method both in the case of condition experts and uber models. We also use the consistent ResNet-50 backbone for each model and train each model on data of each condition for 60 epoches. The model weights corresponding to the final training iteration are reported for testing.

A.3 Uncertainty-Aware Semantic Segmentation

We have used the two-head model designed in [1] and trained it on the entire training set of ACDC for 60 epochs. We use the default learning rate schedule of [1], with a base learning rate of 4×10^{-4}, which is equal to the default. For predicting on the test set, we use the final training snapshot.

Appendix B Detailed Class-level Results

We provide class-level performance for the experiments for which only mean performance over all classes is reported in the paper due to space limitations.

B.1 Normal-to-Adverse Adaptation

In Tables 4–7, we present the class-level IoU performance of the UDA semantic segmentation methods that are examined in the

TABLE 20
Comparison of state-of-the-art supervised panoptic segmentation methods on ACDC for fog. The first group of rows presents condition-specific expert models trained only on fog, while the second group presents uber models trained on all conditions.

Method	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	38.4	25.2	48.0	72.8	47.3
K-Net	37.9	16.1	53.8	68.8	47.1
Panoptic-Deeplab	42.4	23.9	55.8	79.9	51.2
Mask2Former	44.9	23.8	60.3	79.0	54.5
PanopticFPN	43.9	33.3	51.6	79.0	53.4
K-Net	47.8	32.3	59.1	78.9	59.1
Panoptic-Deeplab	49.1	33.8	60.1	80.1	58.9
Mask2Former	52.9	37.0	64.5	82.0	63.2

TABLE 21
Comparison of state-of-the-art supervised panoptic segmentation methods on ACDC for nighttime. The first group of rows presents condition-specific expert models trained only on nighttime, while the second group presents uber models trained on all conditions.

Method	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	29.8	22.0	35.4	67.4	39.5
K-Net	30.7	15.6	41.7	67.3	41.0
Panoptic-Deeplab	34.1	20.2	44.3	68.9	44.3
Mask2Former	34.0	18.0	45.7	69.5	44.1
PanopticFPN	32.6	26.6	37.0	73.4	42.9
K-Net	33.4	18.3	44.4	70.6	44.7
Panoptic-Deeplab	37.2	22.9	47.7	74.9	47.9
Mask2Former	39.4	26.5	48.8	74.9	50.6

TABLE 22
Comparison of state-of-the-art supervised panoptic segmentation methods on ACDC for rain. The first group of rows presents condition-specific expert models trained only on rain, while the second group presents uber models trained on all conditions.

Method	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	46.7	37.9	53.0	77.9	57.5
K-Net	48.5	29.6	62.2	78.0	60.1
Panoptic-Deeplab	52.7	37.9	63.5	80.0	63.6
Mask2Former	53.0	34.7	66.4	80.8	64.0
PanopticFPN	43.9	33.3	51.6	79.0	53.4
K-Net	47.1	28.8	60.4	76.4	59.3
Panoptic-Deeplab	53.1	38.2	63.9	79.9	63.9
Mask2Former	54.2	36.3	67.3	81.2	65.2

setting of adaptation to individual conditions in Table 3 of the paper.

In Tables 8–11, the class-wise AP_{50}^{box} for each UDA object detection methods are reported, which corresponds to the results in Table 5 of the paper.

B.2 Supervised Learning on Adverse Conditions

In Tables 12–15, we present the class-level IoU performance of the supervised semantic segmentation methods that are examined in Table 10 of the paper. In particular, we consider the individual conditions of ACDC separately for evaluation, and evaluate on each condition both the respective condition experts that have been trained only on that condition and uber models trained on all conditions.

TABLE 23
Comparison of state-of-the-art supervised panoptic segmentation methods on ACDC for snow. The first group of rows presents condition-specific expert models trained only on snow, while the second group presents uber models trained on all conditions.

Method	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	44.8	36.3	51.0	74.1	55.1
K-Net	48.0	32.4	59.4	74.2	59.4
Panoptic-Deeplab	51.6	38.4	61.2	81.6	61.9
Mask2Former	52.5	37.0	63.8	80.6	63.4
PanopticFPN	49.1	44.2	52.7	79.0	59.9
K-Net	53.2	40.7	62.3	78.9	65.6
Panoptic-Deeplab	55.1	43.2	63.8	81.6	65.7
Mask2Former	58.6	46.0	67.7	82.2	69.8

In Tables 16–19, we present the class-level AP^{mask} performance of the supervised instance segmentation methods that are examined in Table 14 of the paper. The performance of condition experts and uber models are reported for each condition respectively.

In Tables 20–23, we present the detailed performance of the supervised panoptic segmentation methods that are examined in Table 16 of the paper. The performance of condition experts and uber models are reported for each condition respectively.

B.3 Evaluation of Pre-trained Models on ACDC

In Tables 24–28, we present the class-level IoU performance of the externally pre-trained semantic segmentation models that are evaluated in Table 17 of the paper.

In Tables 29–33, we present the class-level AP^{box} and AP^{mask} performance of the externally pre-trained instance segmentation models that are evaluated in Table 18 of the paper.

In Tables 34–38, we present the detailed performance of the externally pre-trained panoptic segmentation models that are evaluated in Table 19 of the paper.

B.4 Uncertainty-aware Semantic Segmentation

In Tables 39–43, we present the class-level average uncertainty-aware IoU (AUIoU) performance of the baselines and oracles that are examined in Table 9 of the paper. More specifically, Table 39 considers methods trained jointly on all conditions of ACDC and also evaluated jointly on all conditions, while Tables 40–43 present methods trained and evaluated on individual conditions. The results corresponding to the baseline that uses constant confidence equal to 1 are omitted, as they are identical by definition to IoU results and are thus already included in Table 5 of the paper and Tables 12–15.

Appendix C
Additional Details on ACDC Dataset

We provide additional details on the construction and the characteristics of ACDC.

TABLE 24
Comparison of externally pre-trained semantic segmentation models on the complete test set of ACDC including all conditions. The three groups of rows present models pre-trained on normal, foggy, and nighttime conditions respectively. CS: Cityscapes, FC: Foggy Cityscapes, FC-DBF: Foggy Cityscapes-DBF, FZ: Foggy Zurich, ND: Nighttime Driving, DZ: Dark Zurich.

Method	Trained on	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	CS	66.3	28.9	67.6	19.2	25.9	36.7	50.0	47.5	69.4	28.8	83.0	42.1	17.7	72.6	30.9	31.6	48.9	26.1	36.7	43.7
DeepLabv2	CS	71.9	26.2	51.1	18.8	22.5	19.7	33.0	27.7	67.9	28.6	44.2	43.1	22.1	71.2	29.8	33.3	48.4	26.2	35.8	38.0
DeepLabv3+	CS	75.1	32.8	65.9	17.5	20.2	32.2	46.7	45.2	70.5	33.5	80.9	23.9	14.7	71.5	40.1	20.3	51.2	20.2	28.8	41.6
DANet	CS	58.0	6.0	57.3	6.8	22.3	27.7	41.3	42.1	66.4	19.9	69.2	32.2	10.2	46.5	22.4	19.1	43.1	13.2	25.5	33.1
HRNet	CS	55.6	10.9	55.4	7.7	15.9	21.7	37.8	42.5	67.4	13.3	59.0	38.7	14.0	68.3	23.8	48.0	48.3	17.9	23.6	35.3
SFSU	FC	72.9	28.8	68.3	19.6	23.9	37.3	49.3	47.0	60.4	33.4	72.3	43.1	14.8	72.7	31.7	31.2	47.0	25.4	35.5	42.9
CMAda	FC-DBF+FZ	79.9	32.5	69.5	14.7	24.7	41.1	53.6	51.3	67.4	34.8	83.8	49.0	19.9	77.0	34.1	38.5	51.1	29.6	42.7	47.1
DMAda	ND	75.3	35.5	67.4	19.2	27.1	40.0	53.7	50.9	74.6	30.9	84.9	48.8	23.1	76.6	39.7	37.4	52.5	29.1	42.1	47.9
GCMA	CS+DZ	79.7	48.7	71.5	21.6	29.9	42.5	56.7	57.7	75.8	39.5	87.2	57.4	29.7	80.6	44.9	46.2	62.0	37.2	46.5	53.4
MGCDA	CS+DZ	76.0	49.4	72.0	11.3	21.7	39.5	52.0	54.9	73.7	24.7	88.6	54.1	27.2	78.2	30.9	41.9	58.2	31.1	44.4	48.9

TABLE 25
Comparison of externally pre-trained semantic segmentation models on ACDC for fog. The three groups of rows present models pre-trained on normal, foggy, and nighttime conditions respectively. CS: Cityscapes, FC: Foggy Cityscapes, FC-DBF: Foggy Cityscapes-DBF, FZ: Foggy Zurich, ND: Nighttime Driving, DZ: Dark Zurich.

Method	Trained on	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	CS	64.4	40.0	69.6	24.2	19.7	36.5	52.7	55.2	71.1	35.4	93.9	27.4	19.2	72.7	42.0	42.1	69.3	30.3	15.8	46.4
DeepLabv2	CS	66.4	31.2	26.8	22.9	18.6	8.2	32.3	10.7	70.7	39.0	31.3	17.6	41.1	65.0	30.0	34.3	18.3	42.3	29.0	33.5
DeepLabv3+	CS	82.3	57.6	61.5	18.1	16.4	33.3	49.6	54.5	76.0	44.1	90.0	9.6	28.7	69.0	35.1	34.5	28.9	41.7	37.5	45.7
DANet	CS	52.1	14.5	49.7	5.5	16.9	30.0	47.9	51.5	72.2	23.3	80.1	24.2	3.0	44.7	32.4	27.5	65.1	10.8	7.7	34.7
HRNet	CS	57.3	19.3	49.1	12.8	17.8	27.3	44.0	54.7	72.8	15.5	81.7	28.3	3.9	66.6	28.4	52.0	72.7	7.2	18.1	38.4
SFSU	FC	72.3	37.9	74.4	28.9	19.3	37.5	49.4	54.6	58.0	43.7	77.9	28.6	5.3	73.6	42.4	44.0	72.7	31.4	14.9	45.6
CMAda	FC-DBF+FZ	81.7	43.5	72.8	25.6	19.5	39.8	51.0	58.9	80.5	51.3	95.3	36.9	12.7	76.5	45.2	51.2	77.1	33.2	19.9	51.2
DMAda	ND	75.5	44.7	72.6	26.4	20.8	38.3	52.9	57.8	75.9	38.6	96.3	35.5	26.8	75.8	47.7	50.7	73.9	35.8	17.3	50.7
GCMA	CS+DZ	80.8	53.5	70.1	29.2	20.7	38.4	53.0	60.9	70.2	46.5	95.4	44.2	38.0	76.6	52.4	49.7	56.8	41.0	17.6	52.4
MGCDA	CS+DZ	71.7	47.3	65.7	18.2	15.3	34.4	48.6	59.9	64.9	24.7	95.4	44.8	23.8	73.3	36.1	45.4	63.9	23.9	15.4	45.9

TABLE 26
Comparison of externally pre-trained semantic segmentation models on ACDC for nighttime. The three groups of rows present models pre-trained on normal, foggy, and nighttime conditions respectively. CS: Cityscapes, FC: Foggy Cityscapes, FC-DBF: Foggy Cityscapes-DBF, FZ: Foggy Zurich, ND: Nighttime Driving, DZ: Dark Zurich.

Method	Trained on	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	CS	66.5	24.0	50.3	16.9	11.6	26.4	34.2	25.5	44.2	21.6	0.1	40.8	24.8	57.4	6.8	37.3	20.5	23.9	19.1	29.0
DeepLabv2	CS	77.0	22.9	56.3	13.5	9.2	23.8	22.9	25.6	41.4	16.1	2.9	44.1	17.5	64.1	11.9	34.5	42.4	22.6	22.7	30.1
DeepLabv3+	CS	73.0	20.8	50.4	22.2	5.4	22.6	31.8	23.0	42.9	16.1	6.6	19.2	11.7	48.9	0.9	13.9	42.4	10.5	13.7	25.0
DANet	CS	67.1	4.5	46.7	5.5	5.1	13.1	29.3	19.6	36.6	15.6	0.1	29.3	12.4	29.1	4.5	12.3	9.0	10.3	13.3	19.1
HRNet	CS	50.0	10.1	59.9	0.7	6.0	14.2	25.6	22.3	19.1	3.4	0.1	37.6	7.9	49.4	6.9	45.9	13.9	7.8	11.3	20.6
SFSU	FC	76.9	26.2	50.4	18.1	9.6	27.4	33.3	25.3	41.0	21.5	0.0	41.5	25.3	58.7	7.3	40.7	17.9	22.0	17.9	29.5
CMAda	FC-DBF+FZ	82.6	25.4	53.9	10.1	11.2	30.5	36.7	30.0	38.7	16.5	0.1	46.0	26.2	65.8	13.9	50.9	20.4	24.8	23.8	32.0
DMAda	ND	74.7	29.5	49.4	17.1	12.6	31.0	38.2	30.0	48.0	22.8	0.2	47.0	25.4	63.8	12.8	46.1	23.1	24.7	24.6	32.7
GCMA	CS+DZ	78.6	45.9	58.5	17.7	18.6	37.5	43.6	43.5	58.7	39.2	22.4	57.9	29.9	72.1	21.5	56.2	41.8	35.7	35.4	42.9
MGCDA	CS+DZ	74.5	52.5	69.4	7.7	10.8	38.4	40.2	43.3	61.5	36.3	37.6	55.3	25.6	71.2	10.9	46.4	32.6	27.3	33.8	40.8
DANNet	CS+DZ	90.7	61.1	75.5	35.9	28.8	26.6	31.4	30.6	70.8	39.4	78.7	49.9	28.8	65.9	24.7	44.1	61.1	25.9	34.5	47.6

C.1 Collection

Our recordings were performed in Switzerland. Therefore, the geographic distribution of ACDC is similar to Cityscapes, which was also recorded in central Europe. This eliminates geographic location from the set of factors that introduce a domain shift between Cityscapes and ACDC and allows to study in isolation the effect of visual conditions at time of capture on the performance of semantic segmentation methods, both in the supervised setting and the unsupervised domain adaptation setting.

C.2 Correspondence Establishment

We present in Algorithm 1 the dynamic programming algorithm that we use for matching the GPS sequences of adverse-condition recordings and normal-condition recordings of ACDC. The algo-

TABLE 27
Comparison of externally pre-trained semantic segmentation models on ACDC for rain. The three groups of rows present models pre-trained on normal, foggy, and nighttime conditions respectively. CS: Cityscapes, FC: Foggy Cityscapes, FC-DBF: Foggy Cityscapes-DBF, FZ: Foggy Zurich, ND: Nighttime Driving, DZ: Dark Zurich.

Method	Trained on	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	CS	73.9	29.9	82.9	26.3	37.2	46.3	61.8	57.9	89.4	42.5	96.6	44.2	13.2	80.5	40.7	22.9	66.8	32.0	53.5	52.6
DeepLabv2	CS	71.2	26.7	73.8	20.8	27.1	29.9	39.3	44.4	87.3	25.2	82.0	42.0	14.3	76.2	36.3	26.6	49.8	30.3	42.2	44.5
DeepLabv3+	CS	74.4	29.8	82.3	18.1	28.8	41.7	54.3	55.6	88.7	32.8	97.2	36.7	8.5	84.7	51.7	34.0	61.5	29.7	40.0	50.0
DANet	CS	59.9	2.4	75.9	12.9	31.5	37.7	49.5	53.3	85.5	35.5	91.1	35.4	8.4	53.5	26.0	16.4	57.8	17.9	38.9	41.5
HRNet	CS	65.0	6.7	70.3	16.1	20.2	29.5	48.5	54.7	87.5	36.1	80.1	40.6	8.6	78.2	34.1	44.6	67.3	29.4	34.6	44.8
SFSU	FC	74.6	29.9	81.4	24.1	33.8	46.2	59.9	56.7	86.8	40.8	93.4	46.4	15.1	80.5	40.5	18.6	65.7	33.6	52.5	51.6
CMAda	FC-DBF+FZ	78.1	34.8	80.7	18.9	33.3	50.0	63.1	62.2	87.4	38.8	96.6	51.1	16.9	83.3	37.9	21.9	68.7	36.5	55.1	53.4
DMAda	ND	78.3	37.7	82.5	24.2	36.8	49.0	64.5	61.5	90.6	42.8	97.3	49.6	18.2	83.4	45.1	21.6	70.2	35.2	54.8	54.9
GCMA	CS+DZ	81.1	48.0	84.8	25.0	37.3	49.8	66.5	66.2	92.1	43.5	97.6	54.5	20.4	85.5	47.3	34.6	71.3	40.3	56.7	58.0
MGCDA	CS+DZ	80.5	46.5	79.9	16.0	28.8	44.9	60.0	61.5	90.3	44.8	97.1	51.1	23.1	82.3	33.4	30.2	69.1	36.5	53.8	54.2

TABLE 28
Comparison of externally pre-trained semnatic segmentation models on ACDC for snow. The three groups of rows present models pre-trained on normal, foggy, and nighttime conditions respectively. CS: Cityscapes, FC: Foggy Cityscapes, FC-DBF: Foggy Cityscapes-DBF, FZ: Foggy Zurich, ND: Nighttime Driving, DZ: Dark Zurich.

Method	Trained on	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mIoU
RefineNet	CS	61.0	25.5	73.7	11.7	31.1	37.2	53.1	57.7	71.3	0.9	92.7	44.1	14.7	77.0	30.3	26.9	57.2	18.4	38.5	43.3
DeepLabv2	CS	68.5	26.6	52.7	18.8	26.9	22.2	35.7	40.7	76.5	3.6	49.9	50.4	27.1	73.7	27.6	39.1	60.9	21.1	42.5	40.2
DeepLabv3+	CS	73.9	32.6	71.3	11.1	25.6	31.4	50.6	54.4	77.8	4.1	87.0	25.1	14.6	82.7	39.5	17.2	55.2	12.0	31.2	42.0
DANet	CS	47.6	5.4	57.5	2.9	29.1	29.3	41.4	51.2	71.1	0.5	64.8	32.7	11.7	56.5	14.5	27.9	53.7	8.1	25.9	33.3
HRNet	CS	59.6	9.3	43.9	4.0	17.8	17.6	35.6	47.0	77.0	0.0	32.5	39.4	39.2	74.2	13.4	54.0	61.1	15.9	26.1	35.1
SFSU	FC	64.5	24.0	72.6	10.9	28.8	37.8	54.9	58.1	62.4	0.8	78.4	44.2	9.5	76.0	29.5	25.6	55.2	16.7	37.3	41.4
CMAda	FC-DBF+FZ	74.6	31.6	73.6	9.4	30.3	43.1	61.9	61.7	75.7	0.7	93.5	53.1	19.1	79.6	29.7	31.6	61.9	22.9	50.3	47.6
DMAda	ND	73.6	34.4	74.9	12.3	33.4	41.1	58.4	60.1	79.9	0.6	95.4	53.1	23.0	80.4	40.3	34.5	62.9	22.7	48.6	48.9
GCMA	CS+DZ	79.7	49.5	75.3	17.5	37.9	43.2	59.0	61.9	78.8	2.2	95.5	62.5	33.6	83.2	42.5	43.4	72.1	32.2	51.1	53.7
MGCDA	CS+DZ	80.1	49.5	70.2	6.1	27.8	39.6	55.4	58.0	76.0	0.3	95.5	57.5	35.7	81.0	28.6	48.9	70.3	27.8	50.5	50.5

TABLE 29
Comparison of externally pre-trained instance segmentation models on ACDC including all conditions. The two groups of rows present performance in AP^{box} and AP^{mask} respectively. CS: Cityscapes.

Method	Trained on	person	rider	car	truck	bus	train	motorc.	bicycle	AP
Mask R-CNN	CS	12.8	6.3	29.9	8.2	8.2	5.2	6.5	4.5	10.2
Cascaded Mask R-CNN	CS	15.4	6.2	29.6	8.0	8.2	6.9	3.9	6.6	10.6
HTC	CS	8.6	1.7	21.8	5.3	5.5	4.6	1.6	2.9	6.5
Detectors	CS	12.5	4.6	28.3	6.4	8.8	4.3	4.8	5.2	9.4
Mask R-CNN	CS	9.9	3.4	27.5	8.1	8.8	5.7	4.7	2.4	8.8
Cascaded Mask R-CNN	CS	11.8	2.7	26.6	7.8	8.6	8.1	3.3	3.1	9.0
HTC	CS	6.8	1.2	20.7	5.3	5.7	4.7	0.9	1.8	5.9
Detectors	CS	8.3	2.1	24.8	6.2	9.0	5.5	3.8	2.5	7.8

rithm takes into account the sequential nature of the GPS measurements from the two recordings in computing the correspondence function A. In particular, we enforce $k < i \Rightarrow A(k) \leq A(i)$. That is, for a given sample i of the adverse-condition sequence P, its matched sample $A(i)$ of the normal-condition sequence R is restricted to not precede in time any sample of R that has been matched to a sample k of P that precedes i. This constraint is based on the fact that the routes of the two recordings are driven in the same direction and thus in the same order. Consequently, for routes that contain loops, our formulation prevents the matching of samples that are nearest neighbors but correspond to *different* passes from the same location and are thus potentially associated with different driving directions and 3D rotations of the camera.

C.3 Annotation

In Fig. 1, we show for the adverse-condition part of ACDC (4006 images) the percentage of the pixels of each semantic class that are marked as invalid in the ground-truth invalid mask J. For the majority of the classes, a notable percentage of more than 5% of the pixels are labeled as invalid, which demonstrates the ability

TABLE 30
Comparison of externally pre-trained instance segmentation models on ACDC for fog. The two groups of rows present performance in AP^{box} and AP^{mask} respectively. CS: Cityscapes.

Method	Trained on	person	rider	car	truck	bus	train	motorc.	bicycle	AP
Mask R-CNN	CS	13.1	7.5	27.5	8.4	21.4	1.6	5.8	3.5	11.1
Cascaded Mask R-CNN	CS	17.2	10.0	26.8	4.6	17.6	3.1	3.3	6.3	11.1
HTC	CS	8.9	5.3	21.8	3.1	11.8	2.9	2.4	4.9	7.6
Detectors	CS	15.7	7.5	31.1	5.4	22.5	4.0	5.9	4.4	12.1
Mask R-CNN	CS	9.9	2.5	26.4	8.2	21.0	1.1	5.8	3.2	9.8
Cascaded Mask R-CNN	CS	12.3	5.3	24.6	4.1	17.0	6.6	4.8	4.0	9.8
HTC	CS	6.8	4.0	20.6	3.2	12.9	2.1	2.4	3.7	7.0
Detectors	CS	11.5	4.4	29.0	5.5	20.3	4.0	3.1	2.8	10.1

TABLE 31
Comparison of externally pre-trained instance segmentation models on ACDC for nighttime. The two groups of rows present performance in AP^{box} and AP^{mask} respectively. CS: Cityscapes.

Method	Trained on	person	rider	car	truck	bus	train	motorc.	bicycle	AP
Mask R-CNN	CS	10.6	6.1	8.7	0.4	6.2	1.2	2.6	2.9	4.8
Cascaded Mask R-CNN	CS	12.1	7.1	8.6	0.1	6.9	1.5	1.1	5.2	5.3
HTC	CS	6.3	2.0	3.0	0.1	6.1	0.5	1.5	1.6	2.6
Detectors	CS	8.6	3.6	6.1	3.5	3.4	0.2	2.4	2.4	3.8
Mask R-CNN	CS	7.4	2.7	7.6	0.1	6.7	0.8	1.6	1.7	3.6
Cascaded Mask R-CNN	CS	8.3	2.7	7.7	0.0	7.3	1.5	1.3	2.3	3.9
HTC	CS	4.6	1.3	2.7	0.1	7.7	0.2	1.3	0.9	2.3
Detectors	CS	5.2	1.3	5.3	1.5	3.5	0.2	2.4	1.2	2.6

TABLE 32
Comparison of externally pre-trained instance segmentation models on ACDC for rain. The two groups of rows present performance in AP^{box} and AP^{mask} respectively. CS: Cityscapes.

Method	Trained on	person	rider	car	truck	bus	train	motorc.	bicycle	AP
Mask R-CNN	CS	12.7	4.5	43.9	12.9	2.7	8.8	10.2	6.4	12.8
Cascaded Mask R-CNN	CS	14.3	2.5	44.9	13.5	2.6	13.4	7.9	7.5	13.3
HTC	CS	9.6	0.5	34.8	8.1	4.9	9.6	1.6	4.7	9.2
Detectors	CS	14.1	5.5	41.6	11.0	2.8	10.2	8.1	10.0	12.9
Mask R-CNN	CS	10.5	1.9	39.9	13.1	3.4	9.9	6.6	2.9	11.0
Cascaded Mask R-CNN	CS	12.3	0.5	40.2	13.8	3.8	13.5	6.2	3.7	11.8
HTC	CS	8.0	0.2	33.4	8.2	4.5	9.4	0.7	2.8	8.4
Detectors	CS	10.0	2.5	35.7	11.1	4.6	13.7	6.1	3.9	10.9

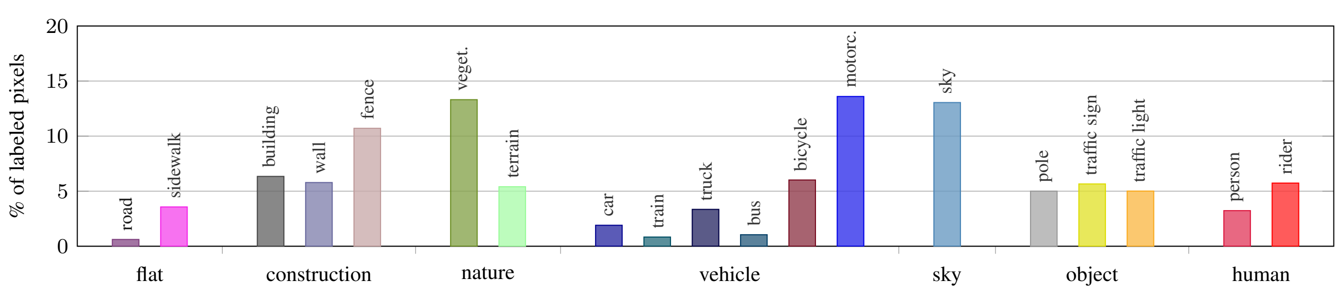


Fig. 1. Per-class percentages of labeled pixels that are marked as invalid in the adverse-condition part ACDC.

of our specialized annotation protocol with privileged information to assign a legitimate semantic label even to invalid regions with ambiguous semantic content.

The total number of annotated pixels in ACDC is presented

TABLE 33
Comparison of externally pre-trained instance segmentation models on ACDC for snow. The two groups of rows present performance in AP^{box} and AP^{mask} respectively. CS: Cityscapes.

Method	Trained on	person	rider	car	truck	bus	train	motorc.	bicycle	AP
Mask R-CNN	CS	18.6	18.5	38.9	7.7	9.6	6.8	7.3	6.8	14.3
Cascaded Mask R-CNN	CS	25.0	16.4	37.3	9.3	12.4	7.5	5.7	10.2	15.5
HTC	CS	13.9	4.9	28.4	6.0	8.7	4.1	3.3	4.6	9.2
Detectors	CS	18.8	13.6	35.0	4.2	14.7	2.5	5.8	7.1	12.7
Mask R-CNN	CS	15.6	13.4	35.8	7.1	10.8	7.9	8.0	4.3	12.9
Cascaded Mask R-CNN	CS	19.2	9.4	33.4	8.4	12.0	10.0	3.2	4.6	12.5
HTC	CS	11.7	3.3	27.2	5.9	8.0	5.6	1.3	3.3	8.3
Detectors	CS	12.4	7.7	29.8	3.2	16.0	3.0	4.5	4.0	10.1

Algorithm 1 Dynamic programming algorithm for GPS sequence matching

Input: Adverse-condition GPS sequence $P = (\mathbf{p}_1, \ldots, \mathbf{p}_n)$, normal-condition GPS sequence $R = (\mathbf{r}_1, \ldots, \mathbf{r}_m)$
Output: Correspondence function $A : \{1, \ldots, n\} \to \{1, \ldots, m\}$

▷ Compute pairwise Euclidean distances of GPS samples
$d_{ij} \leftarrow \|\mathbf{p}_i - \mathbf{r}_j\|,\ 1 \leq i \leq n,\ 1 \leq j \leq m$
▷ Compute cost matrix C $(n \times m)$
$C_{1j} \leftarrow d_{1j},\ 1 \leq j \leq m$
$C_{ij} \leftarrow \min\limits_{k \leq j}\{C_{i-1,k}\} + d_{ij},\ 2 \leq i \leq n,\ 1 \leq j \leq m$
▷ Compute backtracking indices matrix α
$\alpha_{ij} \leftarrow \arg\min\limits_{k \leq j}\{C_{i-1,k}\},\ 2 \leq i \leq n,\ 1 \leq j \leq m$
▷ Backtracking
$A(n) \leftarrow \arg\min\limits_{j}\{C_{nj}\}$
$A(i) \leftarrow \alpha_{i+1,A(i+1)},\ 1 \leq i \leq n-1$

TABLE 34
Comparison of externally pre-trained panoptic segmentation models on ACDC including all conditions. CS: Cityscapes.

Method	Trained on	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	CS	13.0	11.1	14.5	69.3	17.6
K-Net	CS	16.7	14.6	18.3	70.2	23.3
Panoptic-Deeplab	CS	4.7	0.7	7.7	47.2	6.8
Mask2Former	CS	37.7	29.0	44.1	77.5	47.4

TABLE 35
Comparison of externally pre-trained panoptic segmentation models on ACDC for fog. CS: Cityscapes.

Method	Trained on	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	CS	15.9	17.1	15.0	70.2	21.5
K-Net	CS	17.3	17.0	17.6	65.7	24.2
Panoptic-Deeplab	CS	6.5	1.9	9.9	40.4	9.1
Mask2Former	CS	42.7	30.8	51.4	79.1	52.7

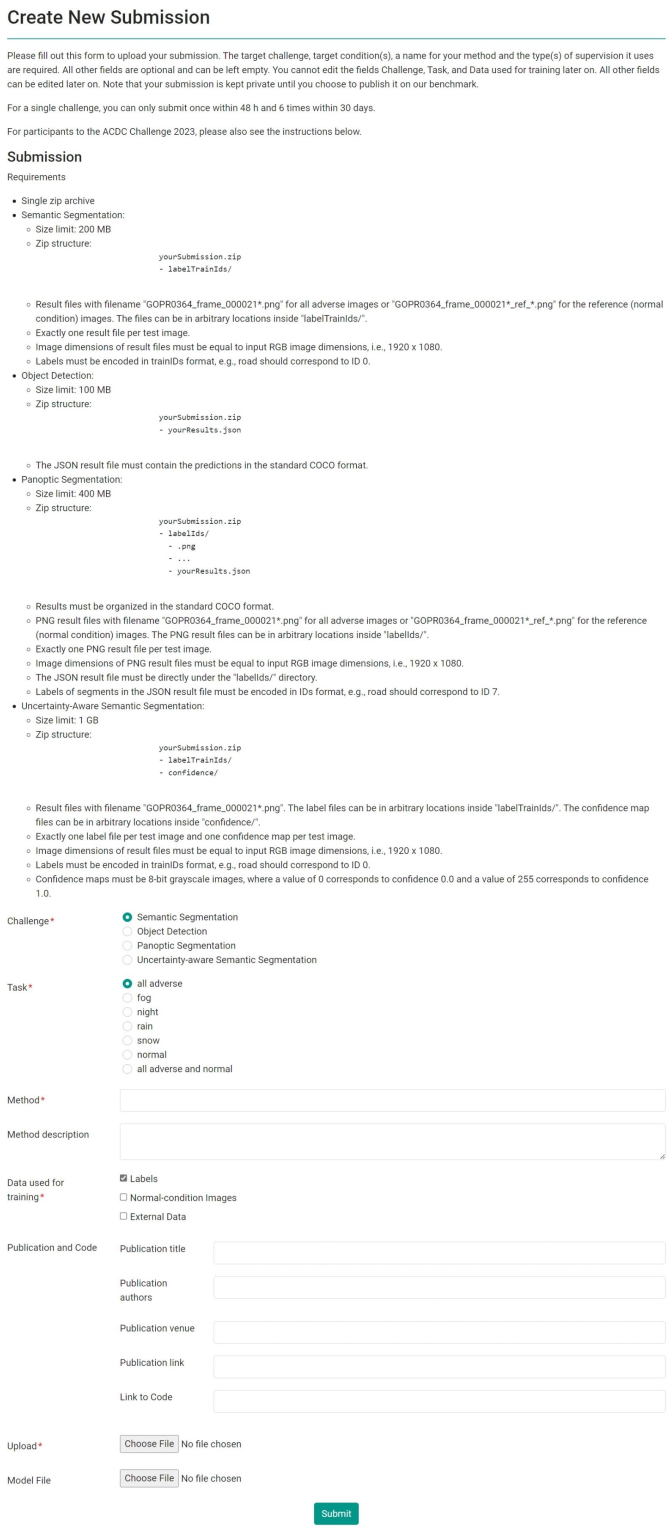
TABLE 36
Comparison of externally pre-trained panoptic segmentation models on ACDC for nighttime. CS: Cityscapes.

Method	Trained on	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	CS	4.0	3.2	4.8	49.4	6.0
K-Net	CS	6.0	3.8	7.6	48.9	9.0
Panoptic-Deeplab	CS	1.6	0.4	2.5	29.7	2.6
Mask2Former	CS	19.9	17.2	22.0	71.7	26.5

TABLE 37
Comparison of externally pre-trained panoptic segmentation models on ACDC for rain. CS: Cityscapes.

Method	Trained on	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	CS	18.6	14.2	21.9	67.7	25.2
K-Net	CS	23.0	18.7	26.1	69.4	31.7
Panoptic-Deeplab	CS	8.3	0.5	13.9	44.6	11.7
Mask2Former	CS	41.4	30.8	49.2	77.0	52.1

in Table 44. Note that labeled pixels that are marked as valid in the ground-truth invalid masks J constitute ca. 85% of the pixels in the adverse-condition part of the dataset. From the remaining 15% of pixels in the adverse-condition part that did not receive a legitimate semantic label in stage 1 of the annotation because of their ambiguity, it was possible to label *half* of them (7.5%) with a legitimate semantic label in stage 2 of the annotation, by making use of the additional privileged information in the form of corresponding normal-condition images and original adverse-condition videos. Note that for stage 2 of the annotation, we explicitly set the time budget (excluding quality control) to 20 minutes and asked the annotators to prioritize labeling of (i) traffic participants and (ii) distant and/or unclear objects that were affected the most by the adverse conditions at the time of capture. The normal-condition part of the dataset was annotated with the standard semantic segmentation protocol, so none of the labeled



Create New Submission

Please fill out this form to upload your submission. The target challenge, target condition(s), a name for your method and the type(s) of supervision it uses are required. All other fields are optional and can be left empty. You cannot edit the fields Challenge, Task, and Data used for training later on. All other fields can be edited later on. Note that your submission is kept private until you choose to publish it on our benchmark.

For a single challenge, you can only submit once within 48 h and 6 times within 30 days.

For participants to the ACDC Challenge 2023, please also see the instructions below.

Submission

Requirements

- Single zip archive
- Semantic Segmentation:
  - Size limit: 200 MB
  - Zip structure:

```
yourSubmission.zip
- labelTrainIds/
```

  - Result files with filename "GOPR0364_frame_000021*.png" for all adverse images or "GOPR0364_frame_000021*_ref_*.png" for the reference (normal condition) images. The files can be in arbitrary locations inside "labelTrainIds/".
  - Exactly one result file per test image.
  - Image dimensions of result files must be equal to input RGB image dimensions, i.e., 1920 x 1080.
  - Labels must be encoded in trainIDs format, e.g., road should correspond to ID 0.
- Object Detection:
  - Size limit: 100 MB
  - Zip structure:

```
yourSubmission.zip
- yourResults.json
```

  - The JSON result file must contain the predictions in the standard COCO format.
- Panoptic Segmentation:
  - Size limit: 400 MB
  - Zip structure:

```
yourSubmission.zip
- labelIds/
  - .png
  - ...
  - yourResults.json
```

  - Results must be organized in the standard COCO format.
  - PNG result files with filename "GOPR0364_frame_000021*.png" for all adverse images or "GOPR0364_frame_000021*_ref_*.png" for the reference (normal condition) images. The PNG result files can be in arbitrary locations inside "labelIds/".
  - Exactly one PNG result file per test image.
  - Image dimensions of PNG result files must be equal to input RGB image dimensions, i.e., 1920 x 1080.
  - The JSON result file must be directly under the "labelIds/" directory.
  - Labels of segments in the JSON result file must be encoded in IDs format, e.g., road should correspond to ID 7.
- Uncertainty-Aware Semantic Segmentation:
  - Size limit: 1 GB
  - Zip structure:

```
yourSubmission.zip
- labelTrainIds/
- confidence/
```

  - Result files with filename "GOPR0364_frame_000021*.png". The label files can be in arbitrary locations inside "labelTrainIds/". The confidence map files can be in arbitrary locations inside "confidence/".
  - Exactly one label file per test image and one confidence map per test image.
  - Image dimensions of result files must be equal to input RGB image dimensions, i.e., 1920 x 1080.
  - Labels must be encoded in trainIDs format, e.g., road should correspond to ID 0.
  - Confidence maps must be 8-bit grayscale images, where a value of 0 corresponds to confidence 0.0 and a value of 255 corresponds to confidence 1.0.

Challenge*
Semantic Segmentation
Object Detection
Panoptic Segmentation
Uncertainty-aware Semantic Segmentation

Task*
all adverse
fog
night
rain
snow
normal
all adverse and normal

Method*

Method description

Data used for training*
Labels
Normal-condition Images
External Data

Publication and Code
Publication title
Publication authors
Publication venue
Publication link
Link to Code

Upload*
Choose File No file chosen

Model File
Choose File No file chosen

Submit

Fig. 2. **The submission page of our benchmark website.** Our evaluation server supports four tasks, i.e. semantic segmentation, object detection, panoptic segmentation, and uncertainty-aware semantic segmentation, and seven condition configurations of ACDC, accepting submissions for each of the four individual adverse conditions, for normal conditions, all adverse conditions, and all adverse and normal conditions. Best viewed on a screen.

TABLE 38
Comparison of externally pre-trained panoptic segmentation models on ACDC for snow. CS: Cityscapes.

Method	Trained on	PQ	PQ^{things}	PQ^{stuff}	SQ	RQ
PanopticFPN	CS	13.1	12.5	13.6	62.0	17.4
K-Net	CS	18.7	19.8	18.0	66.6	25.8
Panoptic-Deeplab	CS	1.6	0.1	2.7	27.0	2.5
Mask2Former	CS	42.0	36.9	45.8	77.9	52.6

pixels is invalid. It is worth noting that, probably due to the normality of the conditions in this part of the dataset, a slightly larger percentage of pixels (96.8%) was possible to label compared to the adverse-condition part. Overall, more than 10 billion pixels in ACDC have received panoptic labels.

C.4 Evaluation Server

We have implemented a website and evaluation server for the ACDC benchmark and have made it publicly available at https://acdc.vision.ee.ethz.ch. An indicative screenshot from the submission page of the website is provided in Fig. 2.

TABLE 39
Uncertainty-aware semantic segmentation baseline results on the complete test set of ACDC including all conditions. Supervised methods for standard semantic segmentation are trained and evaluated jointly on all conditions for semantic label prediction. Confidence prediction baselines: max-softmax network outputs (Max-Softmax) and ground-truth invalid masks (GT).

Method	Confidence	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mAUIoU
RefineNet	Max-Softmax	91.3	67.6	84.4	34.3	42.1	49.9	64.7	64.2	85.8	54.6	95.3	59.6	34.4	84.6	51.9	60.6	70.6	43.3	48.9	62.5
RefineNet	GT	92.9	73.1	89.1	43.1	50.7	57.0	72.9	70.7	90.1	63.4	97.7	67.6	43.1	87.3	57.3	61.4	77.1	54.1	58.3	68.8
DeepLabv2	Max-Softmax	87.1	60.4	79.7	36.1	35.7	32.6	47.3	48.7	80.2	49.2	92.2	49.0	24.7	79.0	51.1	43.3	72.3	26.3	45.1	54.7
DeepLabv2	GT	88.5	64.4	84.2	40.9	41.8	37.8	54.0	54.2	86.4	54.9	96.0	53.6	30.3	81.8	52.5	42.7	73.6	33.3	47.6	58.9
DeepLabv3+	Max-Softmax	92.1	71.3	88.2	49.0	47.3	54.9	68.7	65.6	88.0	60.7	96.0	65.0	33.9	87.5	66.7	72.6	81.3	43.8	55.0	67.8
DeepLabv3+	GT	93.8	76.5	91.4	56.6	55.4	62.3	75.0	72.3	91.8	66.5	98.0	72.0	41.0	89.5	71.1	74.0	86.5	55.4	63.7	73.3

TABLE 40
Uncertainty-aware semantic segmentation baseline results on ACDC for fog. Supervised methods for standard semantic segmentation are trained and evaluated on fog for semantic label prediction. Confidence prediction baselines: max-softmax network outputs (Max-Softmax) and ground-truth invalid masks (GT).

Method	Confidence	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mAUIoU
RefineNet	Max-Softmax	92.6	71.9	82.9	40.7	35.8	42.7	62.1	62.6	84.1	64.1	97.5	45.0	26.8	77.1	57.8	59.9	79.8	35.2	33.4	60.6
RefineNet	GT	93.4	76.5	87.6	48.7	45.5	49.4	68.2	68.9	87.3	73.0	98.1	55.6	40.3	80.9	61.3	65.4	83.7	53.6	51.7	67.9
DeepLabv2	Max-Softmax	89.7	63.0	79.2	39.4	25.9	25.0	41.4	46.6	82.5	66.7	95.6	36.4	35.6	72.7	49.5	29.6	44.5	29.2	33.3	51.9
DeepLabv2	GT	90.2	66.7	82.8	44.2	35.3	31.5	49.5	52.2	84.8	69.4	96.9	44.2	44.5	76.0	48.3	30.1	39.0	48.0	42.7	56.7
DeepLabv3+	Max-Softmax	92.9	74.8	87.2	51.3	41.7	49.9	65.6	69.8	87.1	72.3	97.6	51.9	27.1	82.8	67.4	79.1	84.1	42.6	36.4	66.4
DeepLabv3+	GT	93.9	78.3	90.0	55.5	52.0	57.9	72.3	75.9	89.2	76.6	98.4	63.2	38.5	85.0	71.7	85.1	86.7	66.0	53.3	73.1

TABLE 41
Uncertainty-aware semantic segmentation baseline results on ACDC for nighttime. Supervised methods for standard semantic segmentation are trained and evaluated on nighttime for semantic label prediction. Confidence prediction baselines: max-softmax network outputs (Max-Softmax) and ground-truth invalid masks (GT).

Method	Confidence	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mAUIoU
RefineNet	Max-Softmax	92.3	66.4	78.6	31.8	37.2	46.2	48.3	53.3	73.5	16.9	83.6	54.9	34.6	77.4	8.5	43.1	53.6	35.2	41.6	51.4
RefineNet	GT	93.6	72.4	88.2	42.0	53.0	55.5	61.6	61.7	89.0	31.3	97.1	63.3	41.9	80.0	18.2	50.3	60.8	49.5	51.9	61.1
DeepLabv2	Max-Softmax	90.2	62.2	78.6	29.9	32.9	33.7	36.5	40.3	65.6	25.2	77.9	45.2	23.2	70.2	5.0	14.6	62.1	40.3	38.8	45.9
DeepLabv2	GT	90.8	65.8	87.2	37.8	45.3	43.3	48.1	49.6	87.8	37.5	97.0	51.1	29.8	74.3	17.3	17.3	63.0	51.8	43.8	54.7
DeepLabv3+	Max-Softmax	93.8	73.3	85.2	47.0	43.4	51.3	53.7	54.3	80.7	28.7	87.9	62.1	40.9	84.8	10.4	65.2	78.8	34.7	47.2	59.1
DeepLabv3+	GT	94.9	77.5	91.5	54.7	53.4	60.2	64.8	62.5	92.7	41.3	98.5	70.2	49.3	88.3	22.4	65.5	82.4	50.5	55.0	67.1

TABLE 42
Uncertainty-aware semantic segmentation baseline results on ACDC for rain. Supervised methods for standard semantic segmentation are trained and evaluated on rain for semantic label prediction. Confidence prediction baselines: max-softmax network outputs (Max-Softmax) and ground-truth invalid masks (GT).

Method	Confidence	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mAUIoU
RefineNet	Max-Softmax	86.0	67.8	89.9	44.9	45.7	53.2	65.1	67.3	92.1	48.4	97.8	58.6	23.6	86.6	44.1	53.1	65.6	40.3	56.6	62.5
RefineNet	GT	89.5	70.8	92.1	54.1	53.2	59.9	72.6	72.3	93.9	52.1	98.4	67.4	26.6	88.7	52.4	56.4	75.5	51.4	62.9	67.9
DeepLabv2	Max-Softmax	85.9	62.3	87.2	48.3	38.9	35.8	48.6	51.5	87.3	41.8	95.9	47.2	13.5	80.8	46.2	50.2	69.3	23.9	50.0	56.0
DeepLabv2	GT	87.8	65.1	89.4	52.1	42.5	40.2	53.7	56.1	89.6	43.6	96.8	53.4	13.8	82.7	50.2	48.1	72.9	33.3	51.4	59.1
DeepLabv3+	Max-Softmax	91.2	75.3	92.8	62.2	53.7	60.0	71.3	72.2	93.2	50.0	98.0	65.4	30.8	90.0	63.5	77.0	83.1	48.0	63.9	70.6
DeepLabv3+	GT	93.2	78.4	94.2	68.8	60.0	66.0	75.8	78.2	94.5	52.5	98.6	72.4	35.0	91.0	70.4	80.4	87.4	58.8	69.0	75.0

TABLE 43

Uncertainty-aware semantic segmentation baseline results on ACDC for snow. Supervised methods for standard semantic segmentation are trained and evaluated on snow for semantic label prediction. Confidence prediction baselines: max-softmax network outputs (Max-Softmax) and ground-truth invalid masks (GT).

Method	Confidence	road	sidew.	build.	wall	fence	pole	light	sign	veget.	terrain	sky	person	rider	car	truck	bus	train	motorc.	bicycle	mAUIoU
RefineNet	Max-Softmax	89.1	59.9	83.8	25.8	43.8	53.1	72.6	69.2	88.6	43.5	96.8	65.9	11.7	85.8	39.5	48.4	74.1	36.9	48.8	59.9
RefineNet	GT	91.3	69.1	86.8	32.4	49.9	59.0	78.2	72.8	90.0	52.5	97.3	71.8	16.1	87.6	37.6	44.7	79.5	39.8	60.1	64.0
DeepLabv2	Max-Softmax	89.1	61.7	82.7	26.4	40.9	35.5	56.5	54.1	85.2	39.0	95.1	55.0	25.7	84.3	38.6	53.8	77.6	29.0	49.5	56.8
DeepLabv2	GT	90.3	65.1	83.1	27.6	42.7	36.5	57.9	56.7	85.5	46.3	95.1	56.4	26.4	85.0	41.1	55.0	78.2	30.2	49.8	58.4
DeepLabv3+	Max-Softmax	90.6	67.0	88.8	45.1	48.9	57.8	76.6	72.9	90.8	45.7	97.0	74.8	28.4	89.2	63.3	67.8	87.8	36.7	61.1	67.9
DeepLabv3+	GT	92.9	74.0	90.4	50.3	53.9	63.4	80.5	77.4	92.2	53.6	97.6	79.2	36.6	90.9	64.4	65.9	90.0	45.2	69.8	72.0

TABLE 44

Overall annotation statistics for ACDC. We report the total number of pixels assigned to a legitimate semantic label (Labeled) and of pixels not assigned to any semantic label (Unlabeled) as well as the respective percentages for the adverse-condition part of the dataset with 4006 images (Adverse), the normal-condition part of the dataset with 1503 images (Normal), and their union (Full).

	Adverse		Normal		Full	
	#pixels	% of pixels	#pixels	% of pixels	#pixels	% of pixels
Labeled	7.682×10^9	92.47	3.015×10^9	96.77	10.697×10^9	93.64
-out of which Valid	7.055×10^9	84.93	3.015×10^9	96.77	10.071×10^9	88.16
-out of which Invalid	0.627×10^9	7.54	0	0	0.627×10^9	5.48
Unlabeled	0.625×10^9	7.53	0.101×10^9	3.23	0.726×10^9	6.36
Total	8.307×10^9	100.00	3.117×10^9	100.00	11.423×10^9	100.00