Supplementary Material for
Large-Scale Land Cover Mapping with Fine-Grained Classes via Class-Aware Semi-Supervised Semantic Segmentation

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1. Visual Comparison Results

We give visual comparison examples of two typical minority classes, *i.e.*, *fish pond* and *garden land*. Figure 1 shows the visual comparison results of the fish pond area. Our method exhibits superior discriminative capability between fish ponds and paddy fields compared to the competing methods. Figure 2 shows the visual comparison results of the garden land area. Our method alleviates the confusion between garden land and arbor forest compared to the competing methods.

Baseline and competing methods (c)-(h) misclassify fish ponds to paddy fields and confuse garden land and arbor forest, while our method alleviates these issues. Compared to the baseline, Pseudo-labeling [2], Advent [4], and DPA [3] aggravate the confusion because these methods tend to predict majority classes and neglect the learning of minority classes. Since CADR [1] uses a sample re-weighting method and dynamically decreases the pseudo-label assignment threshold for minority classes, it can partly alleviate the misclassification. However, it does not consider the class imbalance issue on the entire training dataset. Our method exhibits the superior discriminative capability of minority classes compared to the competing methods.

References

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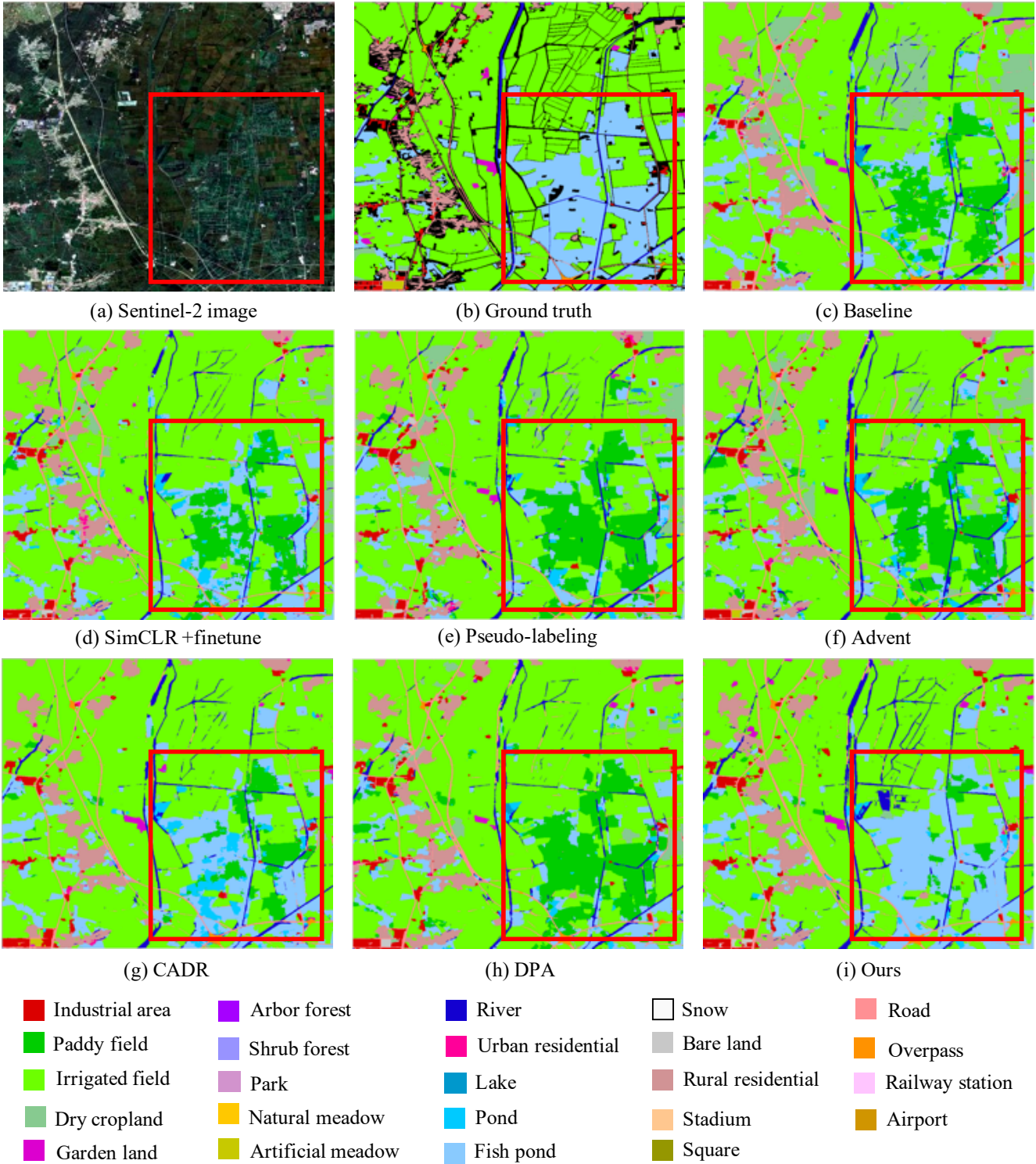|				
■ Industrial area	■ Arbor forest	■ River	☐ Snow	■ Road
■ Paddy field	■ Shrub forest	■ Urban residential	■ Bare land	■ Overpass
■ Irrigated field	■ Park	■ Lake	■ Rural residential	■ Railway station
■ Dry cropland	■ Natural meadow	■ Pond	■ Stadium	■ Airport
■ Garden land	■ Artificial meadow	■ Fish pond	■ Square	

Figure 1. Visual comparison results of the area encompassing fish ponds. Baseline and competing methods (c)-(h) misclassify fish ponds into paddy fields. Our method exhibits superior discriminative capability between fish ponds and paddy fields compared to the competing methods.

(a) Sentinel-2 image   (b) Ground truth   (c) Baseline

(d) SimCLR +finetune   (e) Pseudo-labeling   (f) Advent

(g) CADR   (h) DPA   (i) Ours

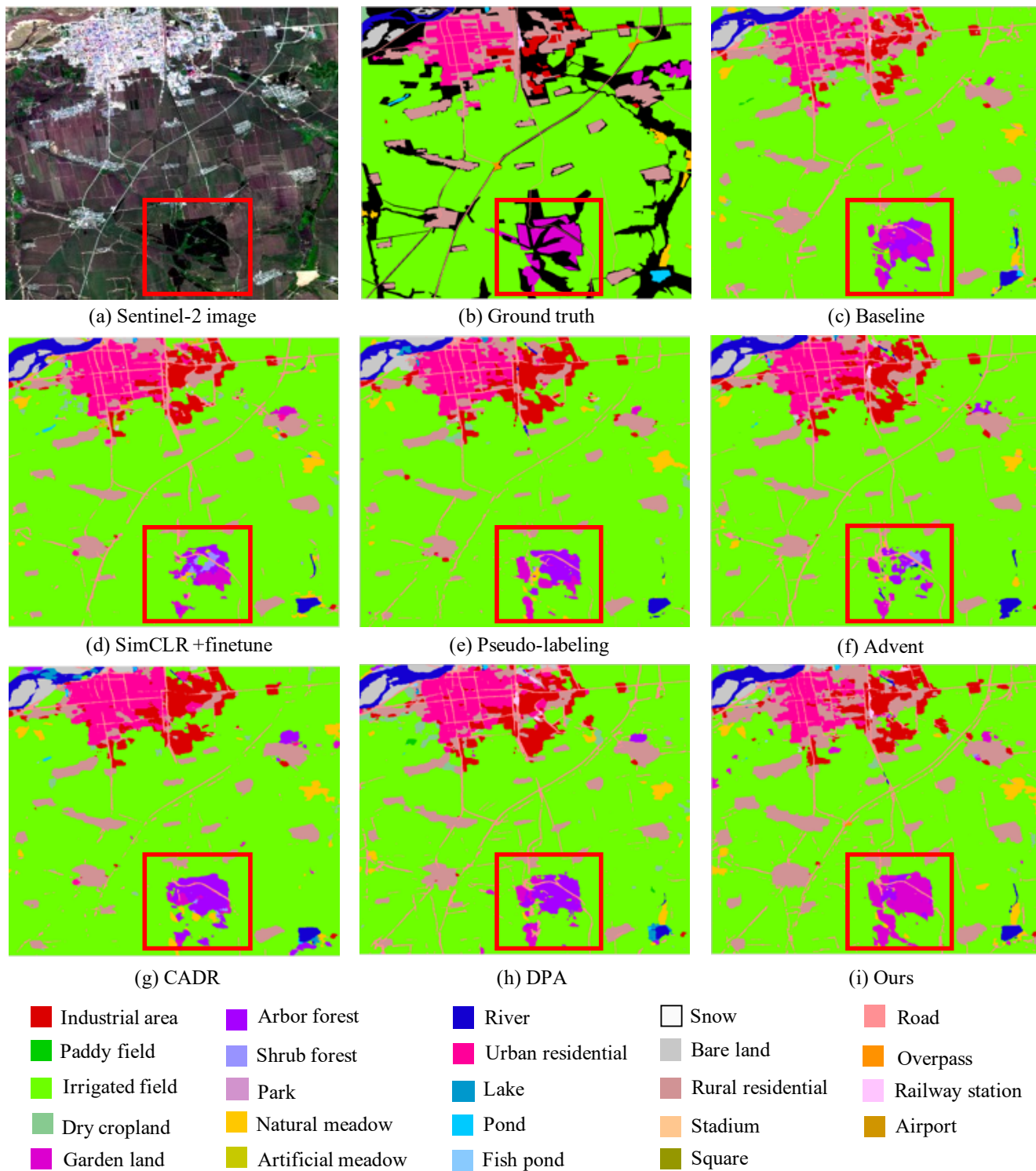|				
■ Industrial area	■ Arbor forest	■ River	☐ Snow	■ Road
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■ Garden land	■ Artificial meadow	■ Fish pond	■ Square	

Figure 2. Visual comparison results of the area encompassing garden land. Baseline and competing methods (c)-(h) confuse garden land and arbor forest. Our method alleviates the confusion between garden land and arbor forest compared to the competing methods.