**Table 1.** Performances and limitations of the different fusion approaches

| Fusion approach | Performances | Limitations |
|---|---|---|
| Prior-level | -Direct use of semantic information from images<br>-Fast convergence<br>-Low loss function<br>-High classification accuracy. | -Problems of non-overlapping regions and uncertainties<br>-Bit long process |
| Point-level | -Fast drive<br>-Easy handling<br>-No prior information is required. | - High cost<br>- Not able to classify diversified urban contexts<br>- Relatively low classification accuracy |
| Feature-level | -Objective data compression<br>-Retaining enough important information | -Training loss higher<br>-Features may not reflect the real objects. |
| Decision-level | -Non-interference of the two semantic segmentation processes<br>-Good flexibility<br>-Low-complexity<br>-Learning the representation of independent features is allowed | -Impacted by the shortcomings of both classifiers.<br>- Additional parameters for layers are required<br>- More memory requirement |

**Table 2.** Quantitative results of the proposed scenarios and the reference approach obtained by KPConv

| urban scenes | Processes | F1-score | Recall | Precision | IoU |
|---|---|---|---|---|---|
| Scene 1 | Reference approach | 0.68 | 0.74 | 0.68 | 0.58 |
| | S1 | **0.81** | **0.84** | **0.81** | **0.72** |
| | S2 | 0.70 | 0.76 | 0.70 | 0.60 |
| Scene 2 | Reference approach | 0.76 | 0.81 | 0.78 | 0.67 |
| | S1 | **0.87** | **0.89** | **0.87** | **0.81** |
| | S2 | 0.80 | 0.84 | 0.82 | 0.73 |

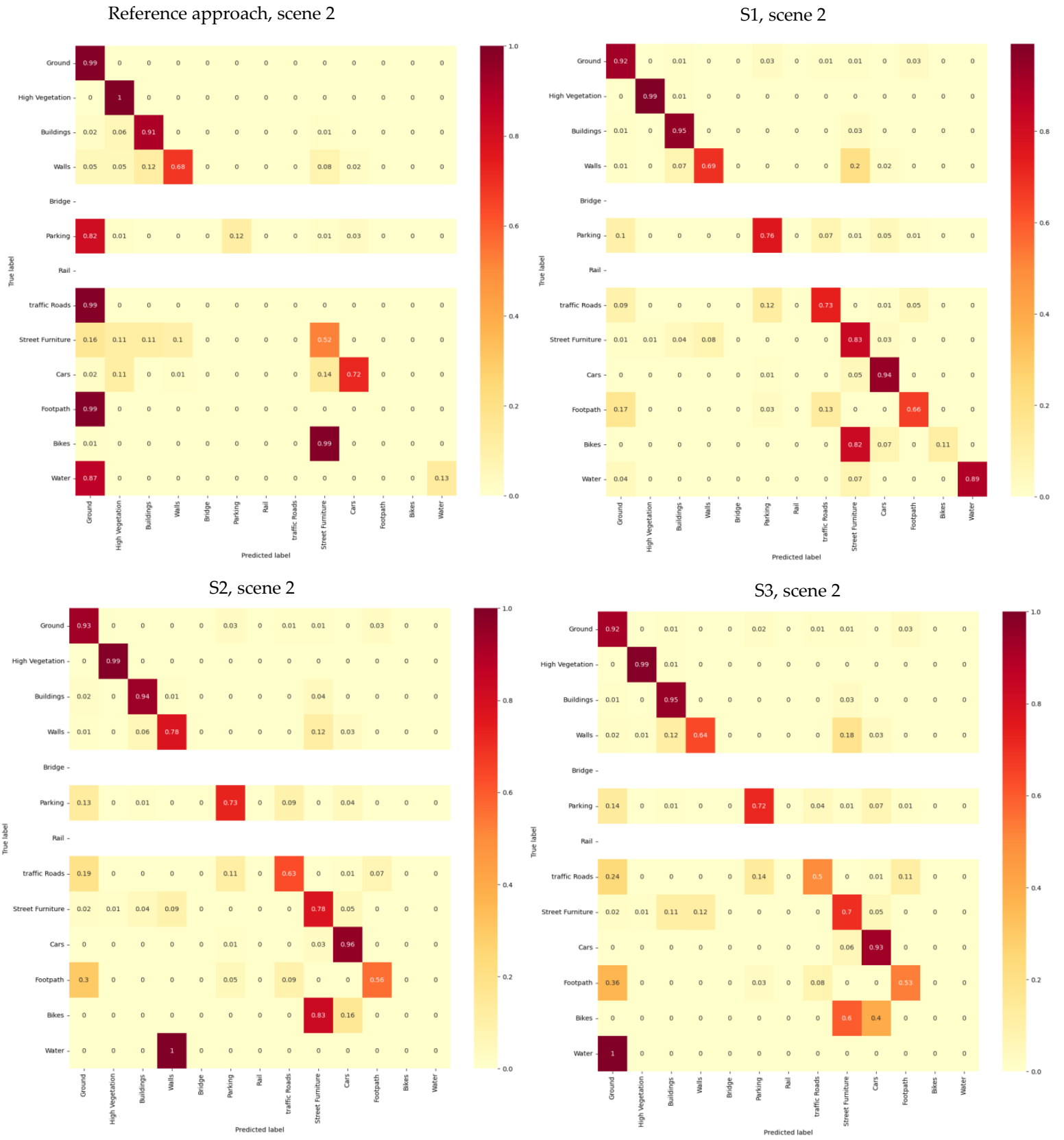


Figure 1. Normalized Confusion matrix of evaluated semantic segmentation approaches over the scene 2

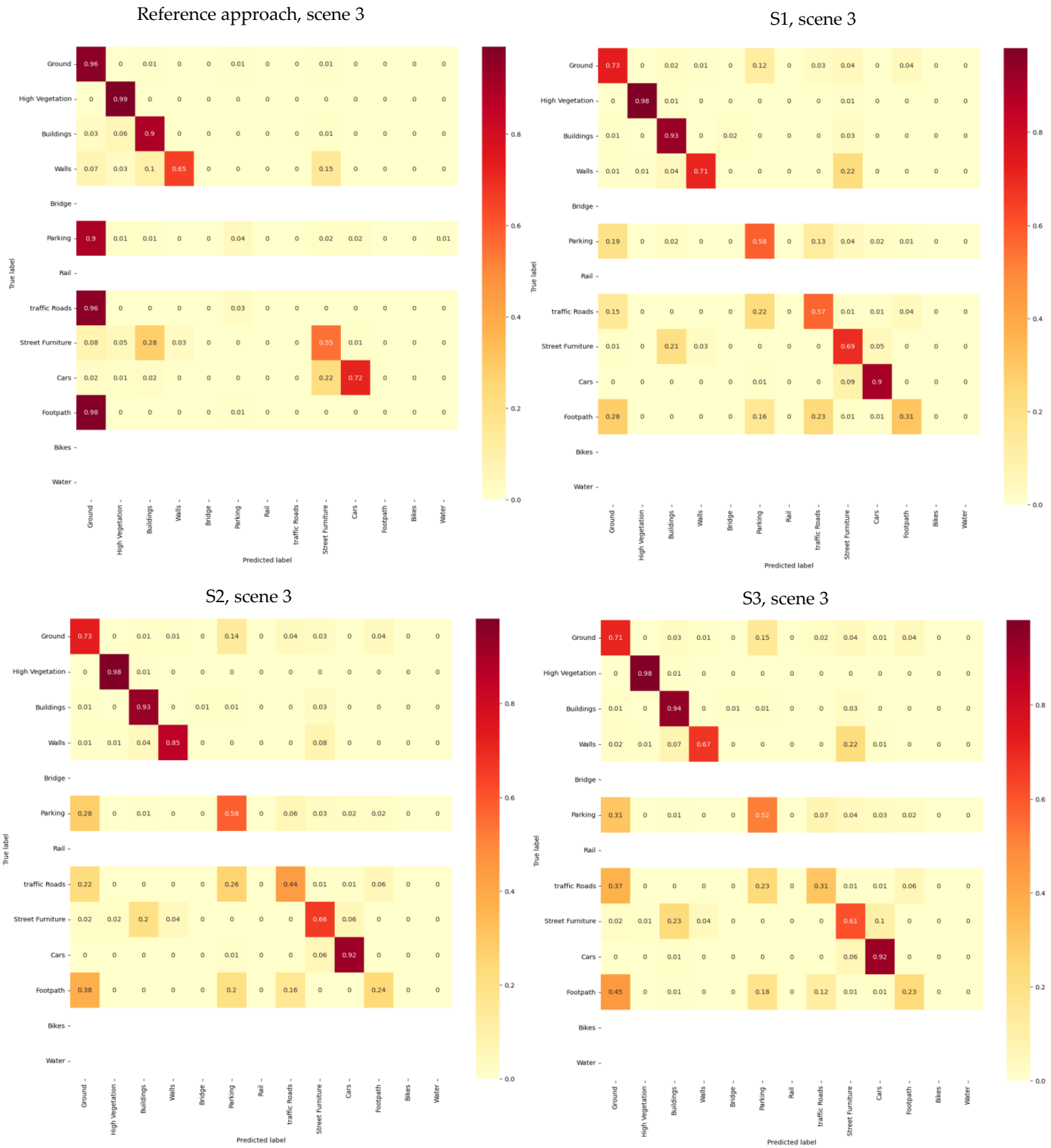


Figure 2. Normalized Confusion matrix of evaluated semantic segmentation approaches over the scene 3

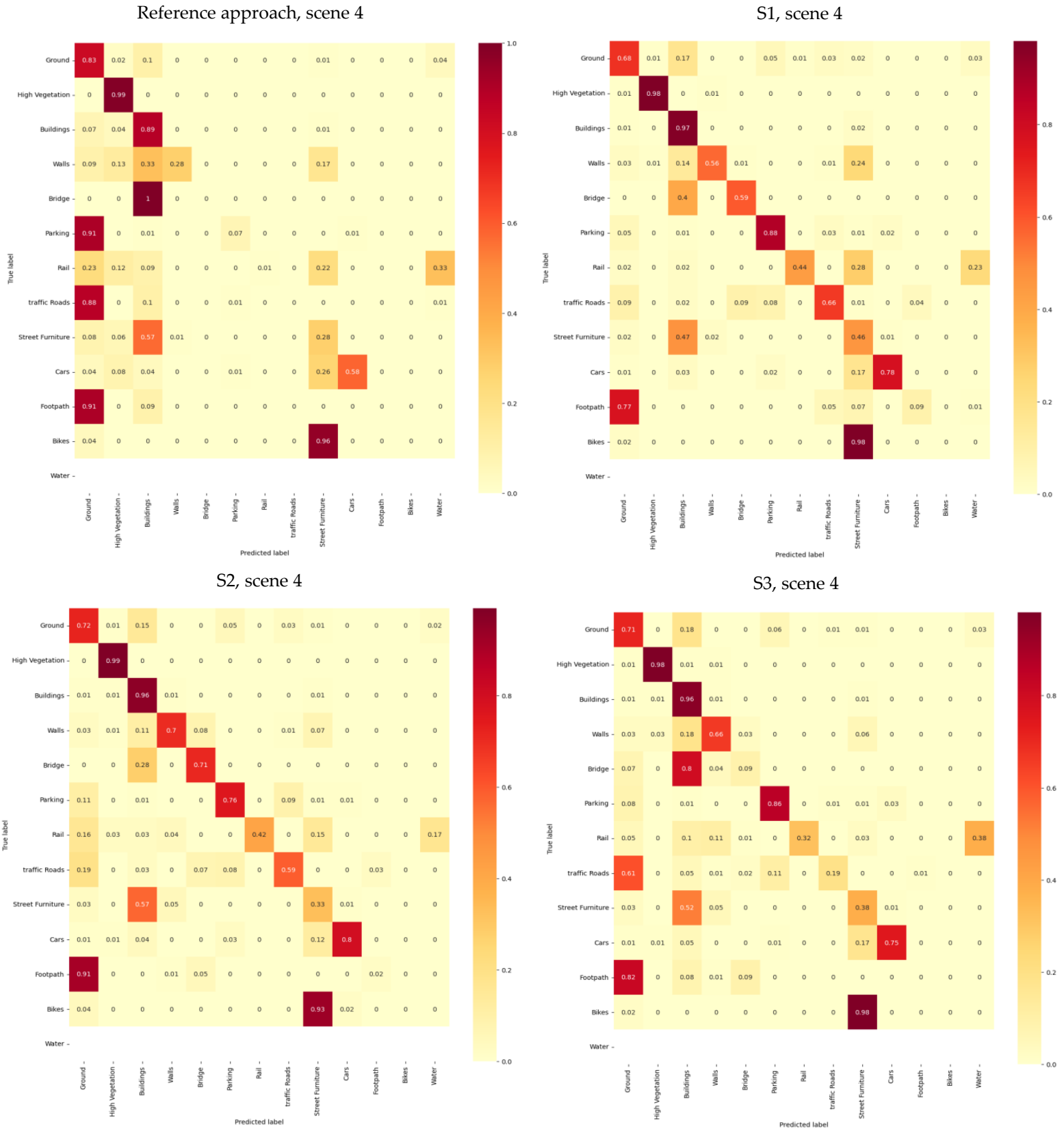


Figure 3. Normalized Confusion matrix of evaluated semantic segmentation approaches over the scene 4