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Master's Thesis

Out-of-distribution detection in 3D semantic segmentation

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I, the undersigned below, declare that this work has not previously been submitted to this or any other university and that it is, unless otherwise stated, entirely my own work.

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Experiments and Results

This chapter discusses the experiments conducted for Out-Of-Distribution (OOD) detection on RandLA-Net using quantified uncertainty from Deep Ensembles and Flipout. In a detailed discussion about RandLA-Net, Deep Ensembles and Flipout can be found in Chapter [$]. In this chapter, we first discuss the training results of RandLA-Net using deep ensembles and flipout on Semantic3D as an In-Distribution (ID) dataset. Furthermore, we compare the Maximum Softmax Probability (MSP) as in [1] and entropy values for the proposed OOD benchmark datasets Semantic3D vs S3DIS and Semantic3D vs Semantic3D w/o colour. Finally, we visualize and evaluate the performance of OOD detection using the AUROC score.

1.1 Deep Ensembles-Semantic3D

In this experiment, we trained 20 models of RandLA-Net over the Semantic3D dataset using random initializations with the experimental setup described in Section [$]. The predictions from these 20 individual models are then averaged to compute the final predictions. The evaluation results of the Deep Ensembles are described in Table 1.1 using meanIoU, per-class IoU and accuracy. The predictions from the Deep Ensembles are depicted in Figure 1.1 and Figure 1.2.

		IoU per class								
Ensemble size	**meanIoU**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**Accuracy**
1	68.19	94.55	81.19	84.67	29.43	81.37	18.85	64.74	90.74	88.78
5	69.51	94.73	81.92	84.42	28.05	**86.41**	28.50	61.03	91.03	90.04
10	69.97	95.25	83.73	86.63	30.36	84.13	18.60	**66.01**	92.61	89.94
15	70.32	95.27	83.54	**88.22**	**32.19**	84.82	26.17	61.67	90.75	**90.57**
20	**70.80**	**95.55**	**84.11**	86.65	29.60	85.41	**29.58**	62.47	**93.06**	90.56

Table 1.1: Illustration of performance of RandLA-Net on Semantic3D over number of ensembles. meanIOU and IOU per-class and overall accuracy are represented here. C1 to C8 are the classes of Semantic3D which are Manmadeterrain, Naturalterrain, Highvegetation, Lowvegetation, Buildings, Hardscapes, Scanningartifacts, and Cars.

[Talk about lower class scores for some classes] From the Table 1.1, we infer that the Deep Ensembles improve the model's overall performance in terms of meanIoU and Accuracy. With an ensemble size of 10, we observe a 2% increment in meanIoU. An increase in ensemble size also results in an improvement in

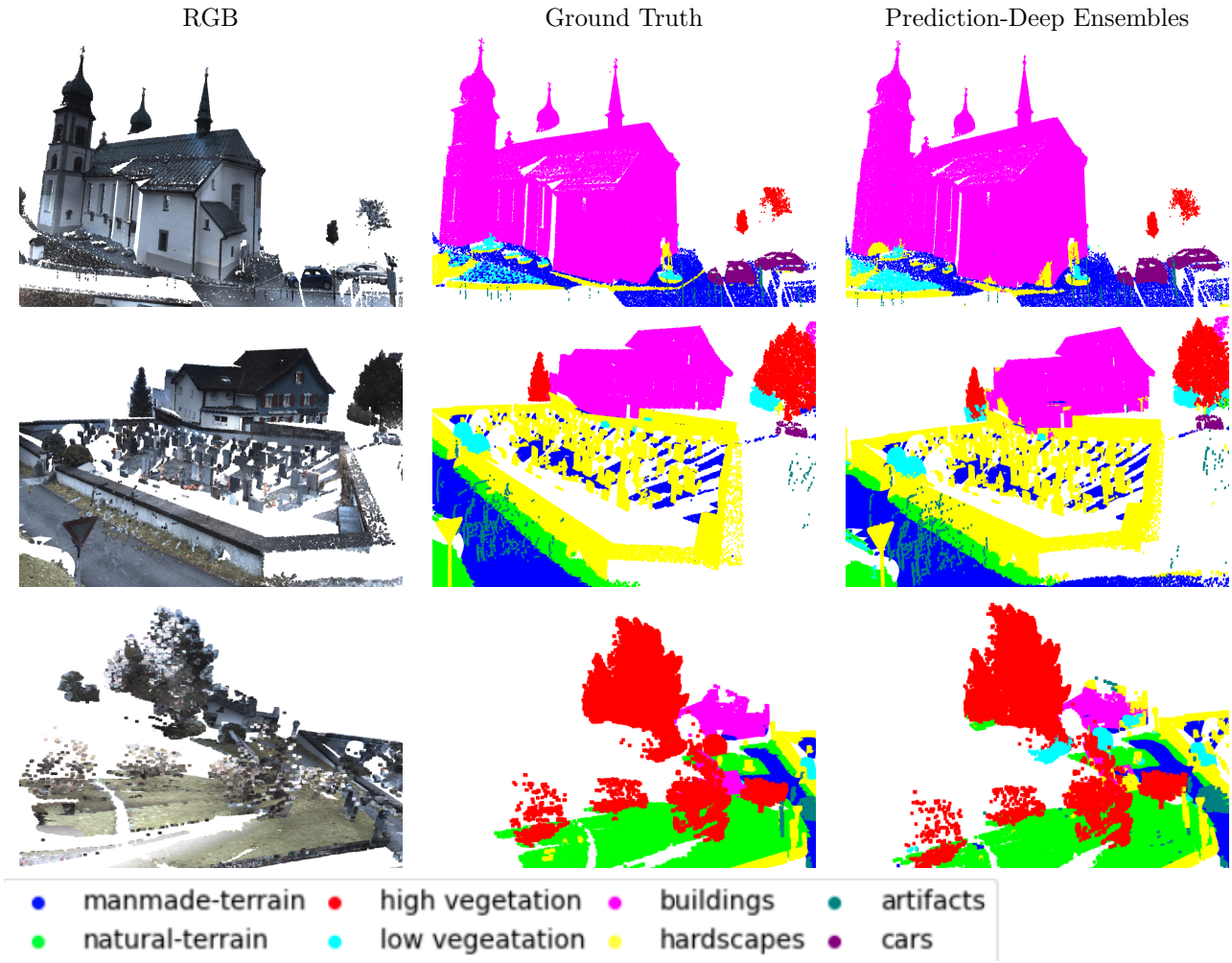


Figure 1.1: Output predictions of the RandLA-Net over the Semantic3D dataset (13 ensemble size) Legend spelling mistake.

per-class IoU performance. Figure 1.2 depicts the improvement in model classifications visually with the increase in ensemble size. From Figure 1.1, we also observe the misclassifications along the edges of the church, trees and ground. The possible explanation for these misclassifications is ambiguity in the feature vector of RandLA-Net. For example, a feature vector for the point along the lower edge of the church contains the part of ground points as the feature vector.

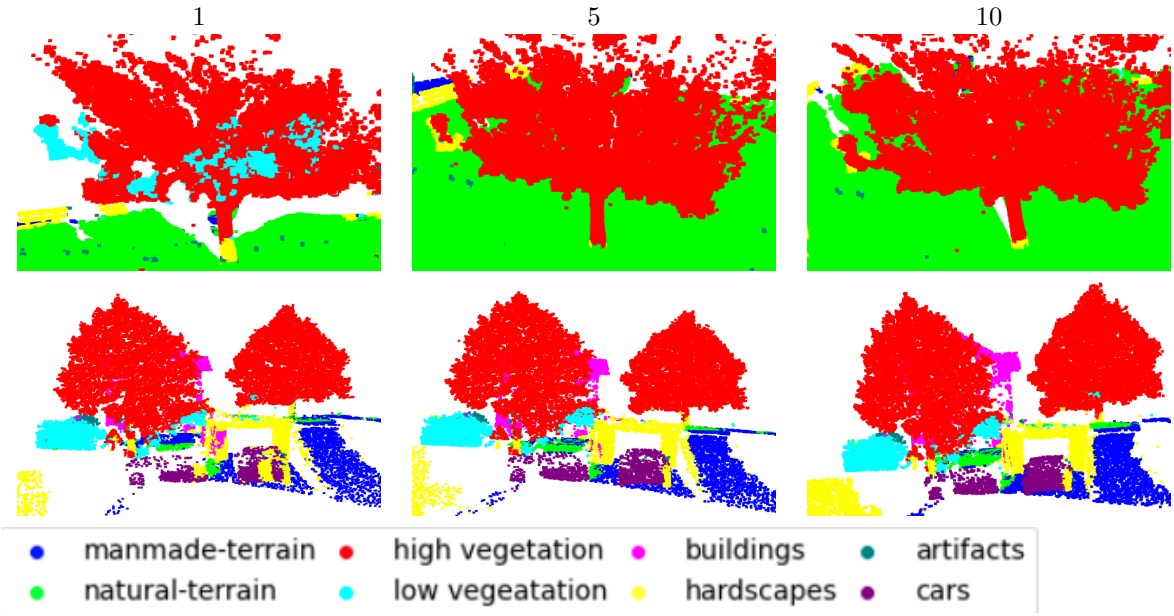


Figure 1.2: Deep ensembles performance on RandLA-Net over the Semantic3D dataset.

1.2 Flipout-Semantic3D

In this experiment, we trained a Flipout version of RandLA-Net as described in Section [$] over the Semantic3D dataset. Like Deep Ensembles, we performed 20 forward passes over the Flipout versioned RandLA-Net and averaged the predictions to obtain final predictions. Table 1.2 describes the performance of Flipout versioned RandLA-Net using meanIoU, per-class IoU and Accuracy. Figure 1.3 depicts the predictions of the Flipout versioned RandLA-Net visually.

		IoU per class								
#Passes	**MeanIoU**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**Accuracy**
1	69.95	94.24	80.09	86.16	22.48	88.70	39.41	57.42	91.12	90.71
5	69.83	94.38	80.21	84.10	23.32	87.80	39.68	57.75	91.43	90.43
10	69.84	94.38	80.16	83.90	23.46	87.73	39.75	57.83	91.47	90.40
15	69.86	94.38	80.17	83.80	23.48	87.73	39.82	57.96	91.57	90.40
20	69.87	94.38	80.18	83.80	23.57	87.72	39.84	57.92	91.57	90.40

Table 1.2: Illustration of performance of Flipout versioned RandLA-Net on Semantic3D. meanIOU and IOU per-class and overall accuracy are represented here. C1 to C8 are the classes of Semantic3D which are Manmadeterrain, Naturalterrain, Highvegetation, Lowvegetation, Buildings, Hardscapes, Scanningartifacts, and Cars.

From Table 1.2, we infer that the Flipout versioned RandLA-Net has a similar performance to the original RandLA-Net model proposed in [2] and also Deep Ensembles with ensemble size one . We also observe a significant improvement in the Hardscapes class represented as C6 in Table 1.2. There is a decrement in performance of classes Lowvegetation represented as C4 and Scanningartifacts represented

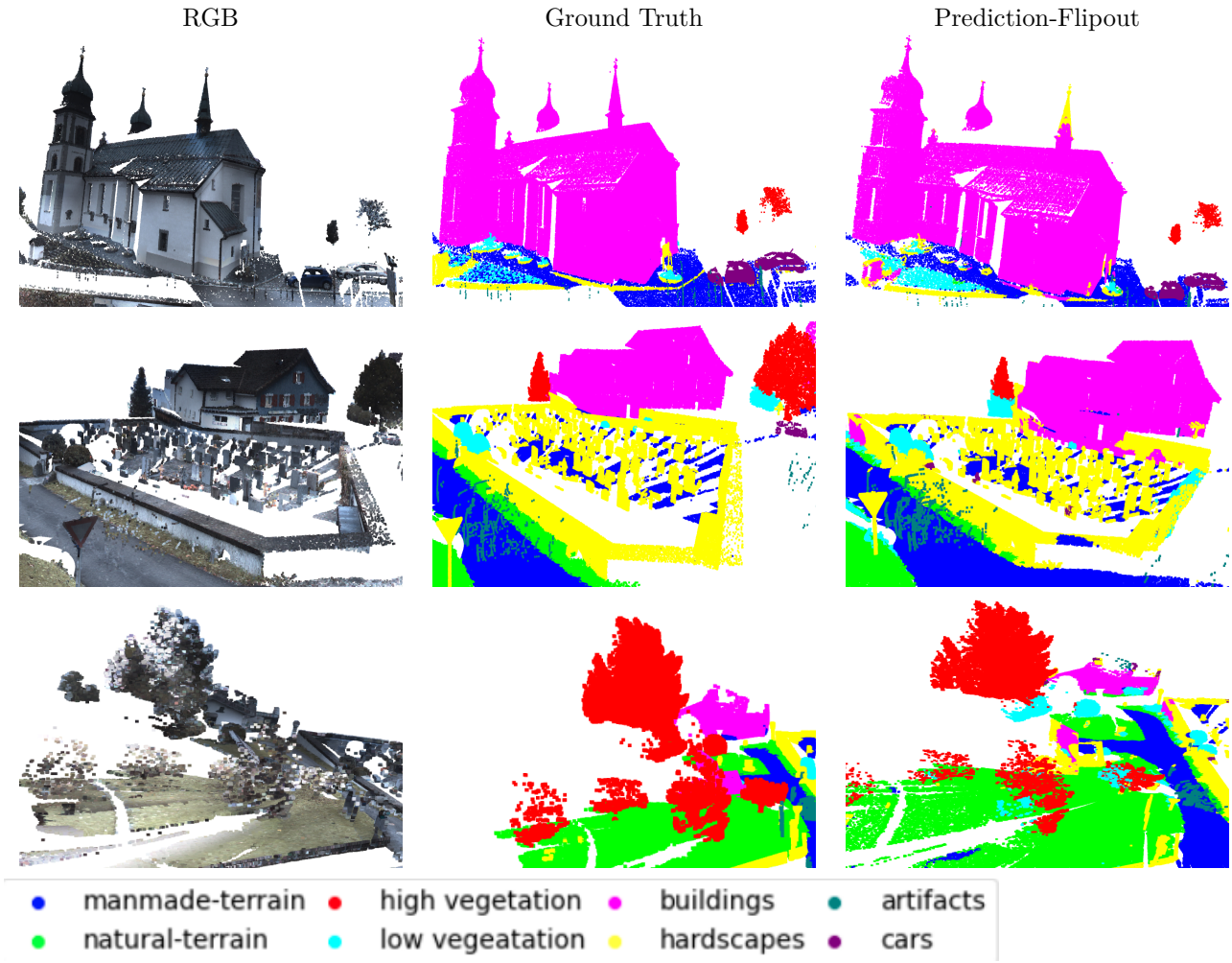


Figure 1.3: Output predictions of the RandLA-Net over the Semantic3D dataset (10 forward passes) Legend spelling mistake.

as C7 in Table 1.2, keeping the overall meanIoU same.

1.3 OOD benchmark - Semantic3D vs S3DIS

In the previous section, we studied the performance of the Deep Ensembles and Flipout over the Semantic3D (In-Distribution) dataset. In this section, we study the predictions of the RandLA-Net model on the S3DIS (Out-Of-Distribution) dataset using Deep Ensembles and Flipout. We also compare the distribution of Maximum Softmax Probability (MSP) and entropy scores for Semantic3D and S3DIS datasets.

Figure 1.4 depicts the predictions of the RandLA-Net model and Flipout versioned RandLA-Net. We observe that most objects, such as ceilings and bookshelves, are labelled as buildings when using Deep Ensembles. We also observe that most point clouds are labelled as hardscapes class when using Flipout versioned RandLA-Net. The classifications on S3DIS datasets are in triangles because of the property of the scanner. As discussed in Section [$], data collected from the Matterport scanner is represented as triangular mesh, and then a point cloud is extracted from this mesh.

1.3.1 Maximum Softmax Probability (MSP)

In this experiment, we study the probability values of the ID dataset (Semantic3D), and OOD dataset (S3DIS) computed using Deep Ensembles and Flipout methods of RandLA-Net. We compute the average of the maximum softmax probability of all the points in the dataset, and this averaged value is called here the mean probability value. Figure 1.5a and Figure 1.5b depicts the mean probability values across the ID (green) and OOD (red) datasets and their variance represented as error bars. Figure 1.5a represents the change in mean probability value to ensemble size. Figure 1.5b represents the change in mean probability value to the number of passes in Flipout. Here, we represent the mean probability values across the odd number of ensembles size and the odd number of passes in case of flipout.

From Figure 1.5a, we can infer that as the increase in ensemble size, the mean probability of the ID (Semantic3D) dataset remains stable. The variance is reduced until the ensemble size of 9 and then stabilizes. In the case of the OOD (S3DIS) dataset, we observe a decrement in mean probability value and then remain the same after an ensemble size of 3 with a larger variance. With the increase in ensemble size, we also observe that the overlap in the variance of ID and OOD is getting lower. This smaller overlap in higher ensemble size should result in higher OOD detection performance. In the case of Flipout, as in Figure 1.5b the mean probability and variance remain mostly the same for the ID dataset. With the OOD dataset, we observed a reduction in the mean probability value in the case of multiple passes. The variance from the Flipout is higher than the Deep Ensembles for the ID dataset. This phenomenon is to be expected because the Deep Ensembles combine predictions from various radomly initializated models and in the case of Flipout same model is used for multiple forward passes.

Figure 1.6 and Figure 1.7 represent the ground truth, prediction and probability map of the ID (Semantic3D) dataset using Deep Ensembles and Flipout respectively. Similarly Figure 1.8 and Figure 1.9 depict the prediction and probability map for OOD (S3DIS) dataset using Deep Ensembles and Flipout respectively. On visual inspection of Figure 1.6 and Figure 1.7, we observed that the probability scores are low for points which are misclassified. The points which lie on the edge of the structures are low

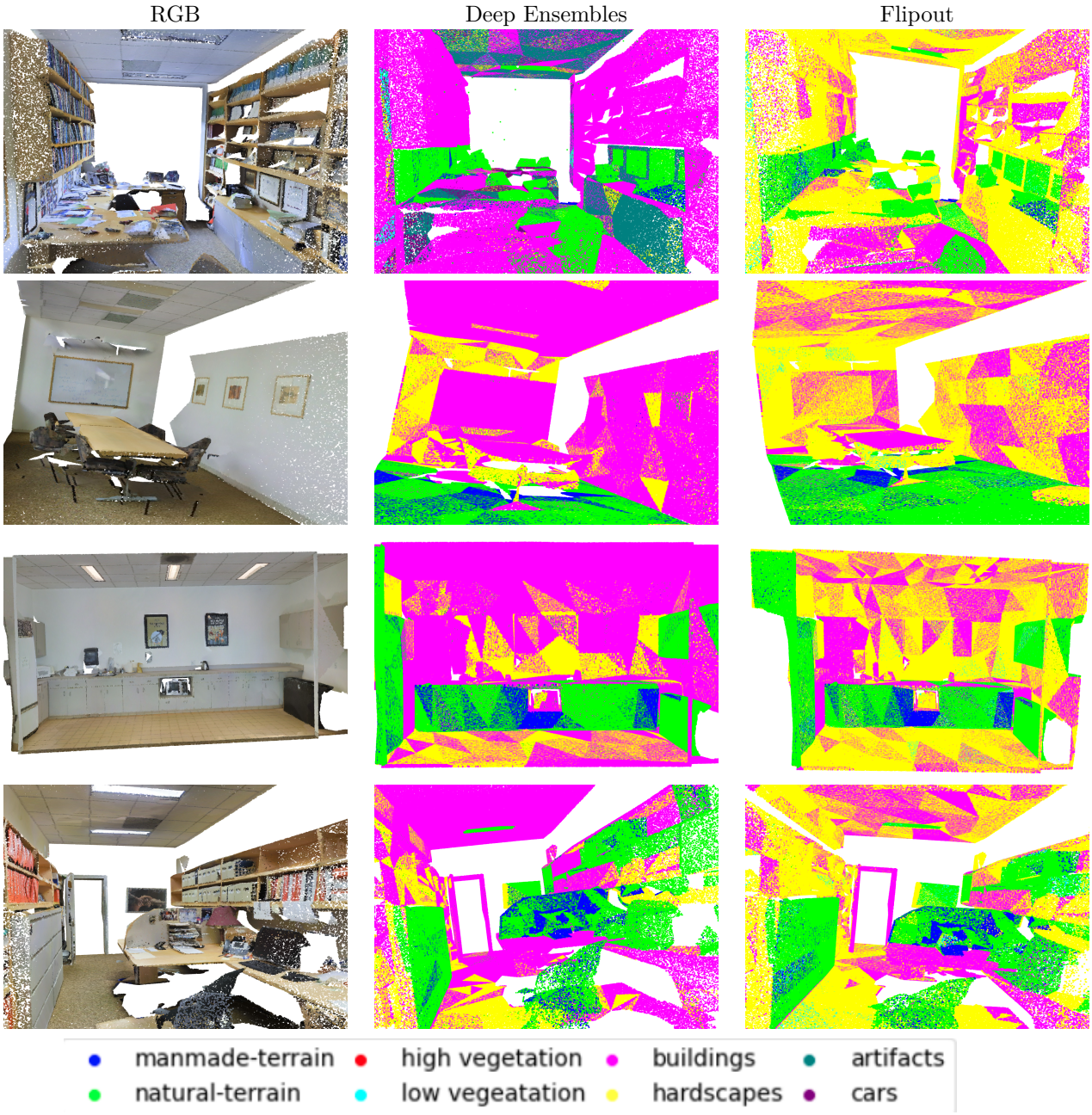
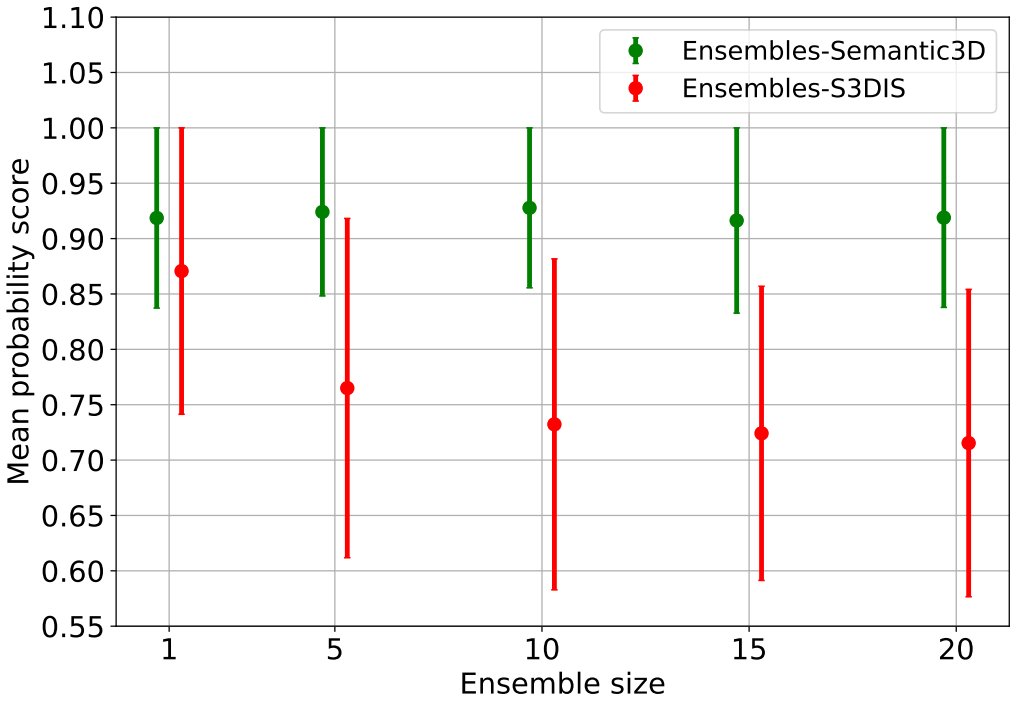
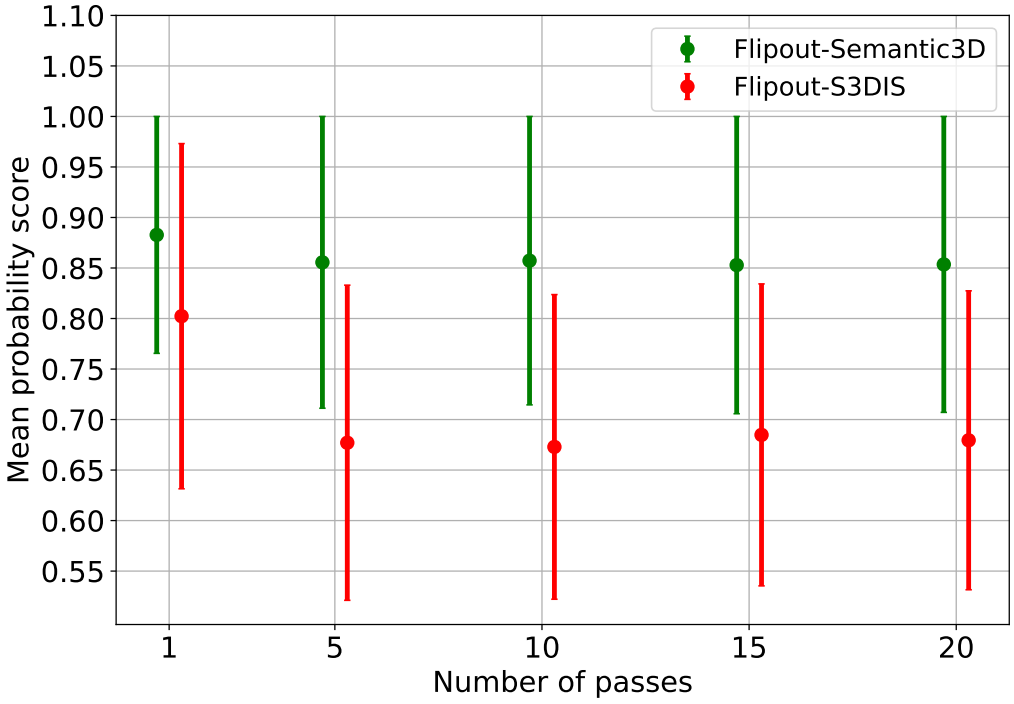


Figure 1.4: Output predictions of the RandLA-Net over the S3DIS dataset.

scored. This effect is profound near the edges of church, and also edges of walls. In case of OOD dataset presented in Figure 1.8 and Figure 1.9, the overall probability scores are low, as the whole point cloud has greener shade than the ID dataset probability map represented in yellow shade.



(a) MSP deep ensembles



(b) MSP flipout

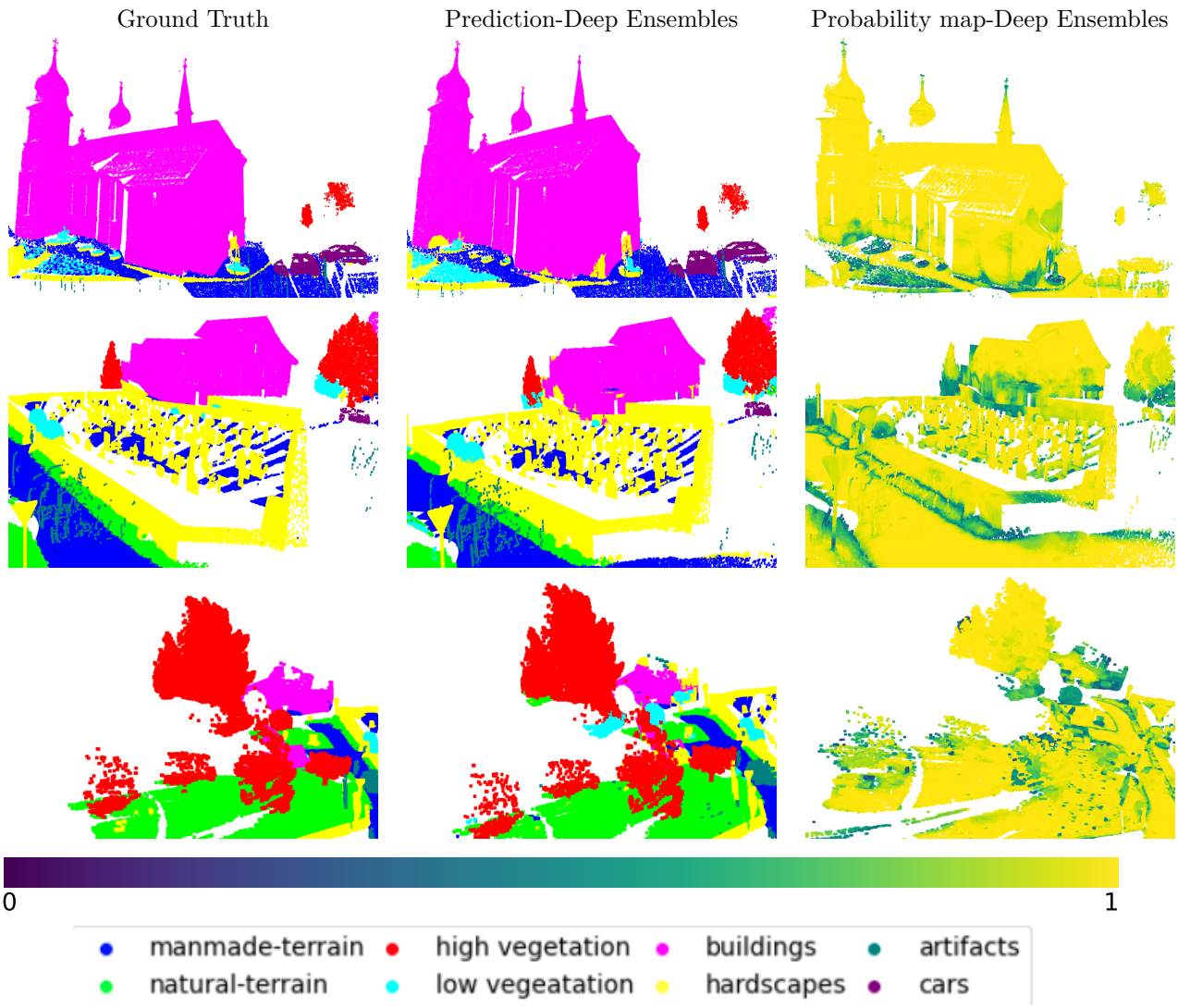


Figure 1.6: Perpoint probability visualization of the semantic3D dataset.

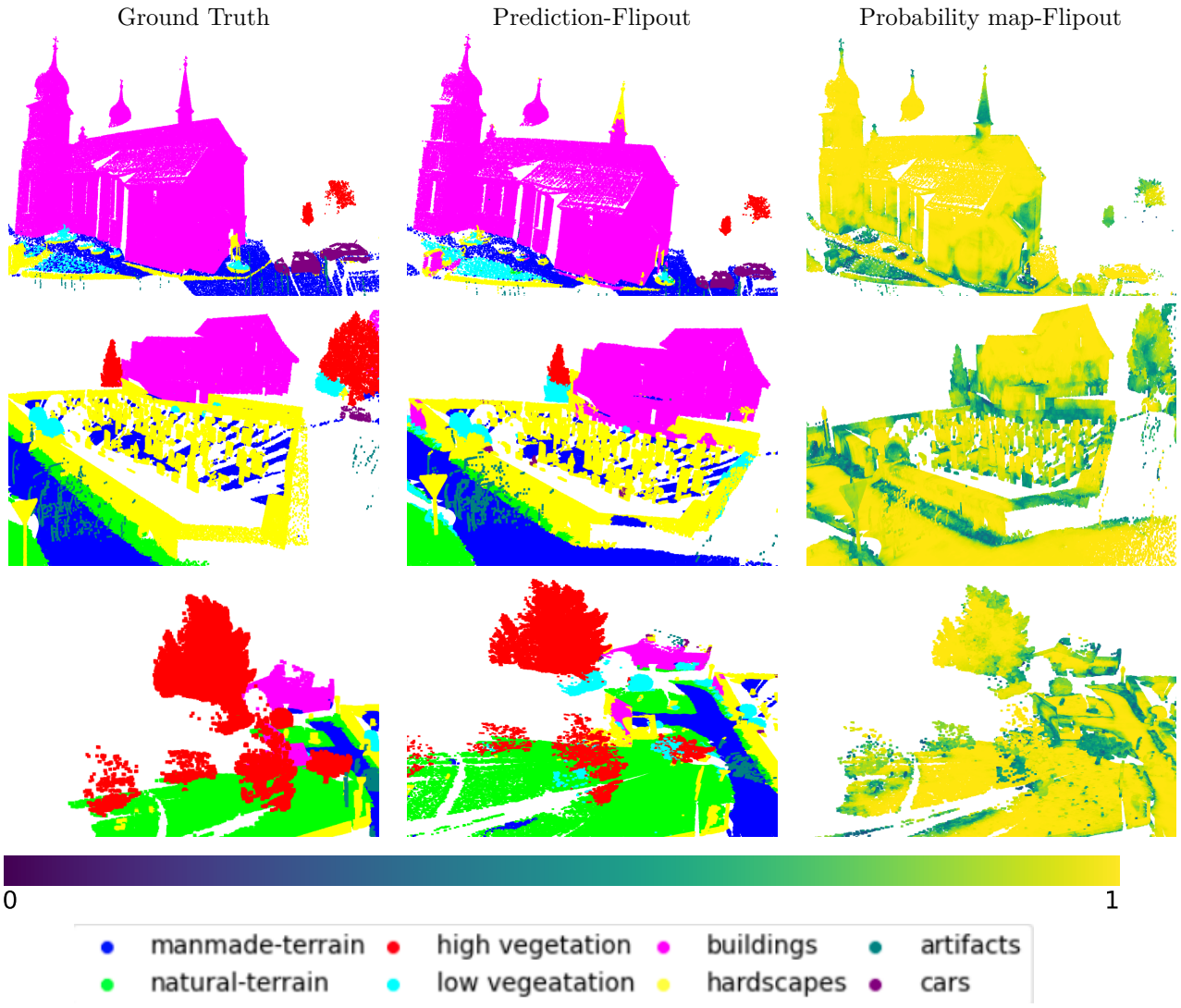


Figure 1.7: Perpoint probability visualization of the semantic3D dataset.

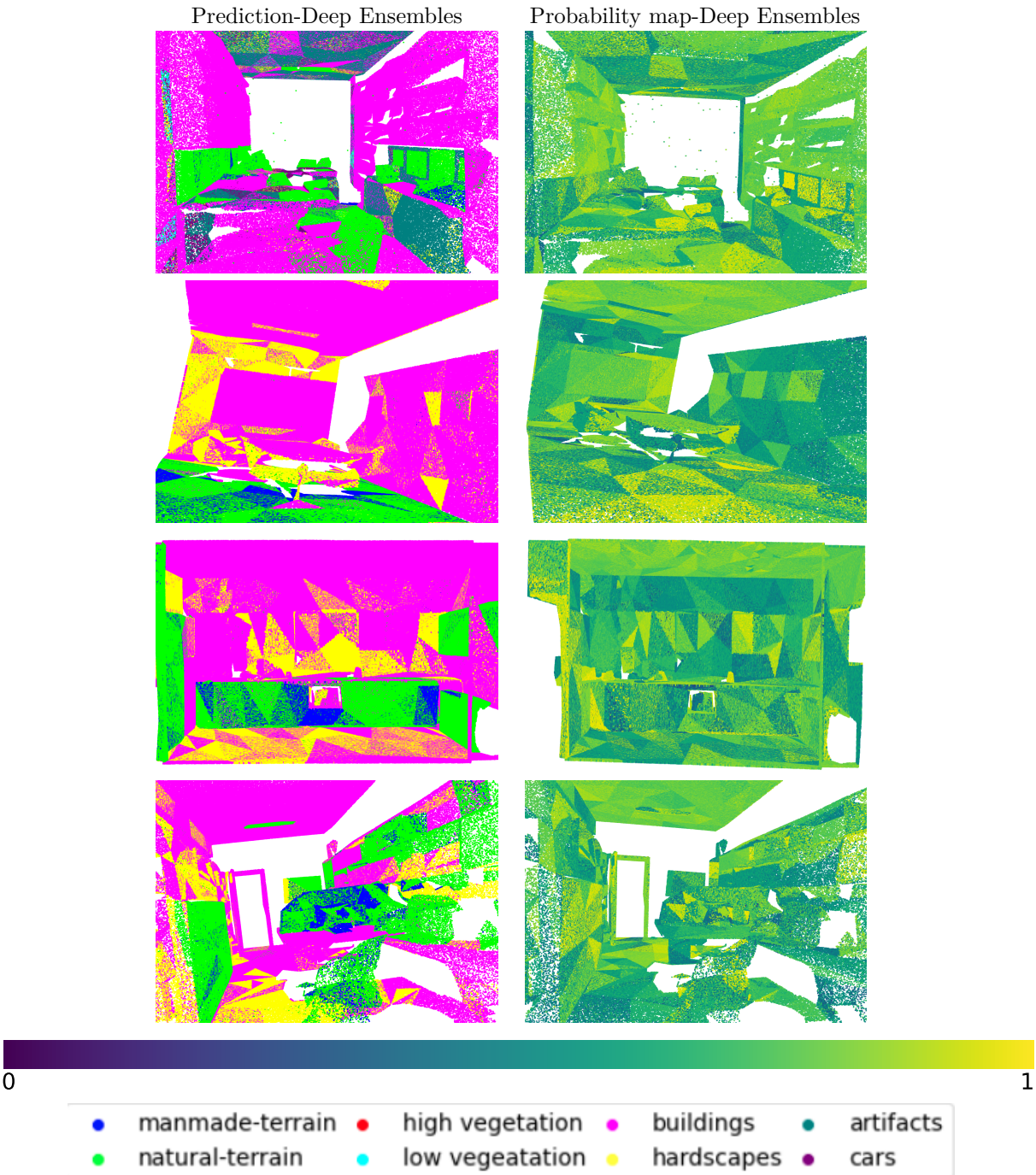


Figure 1.8: Perpoint probability visualization of the S3DIS dataset.

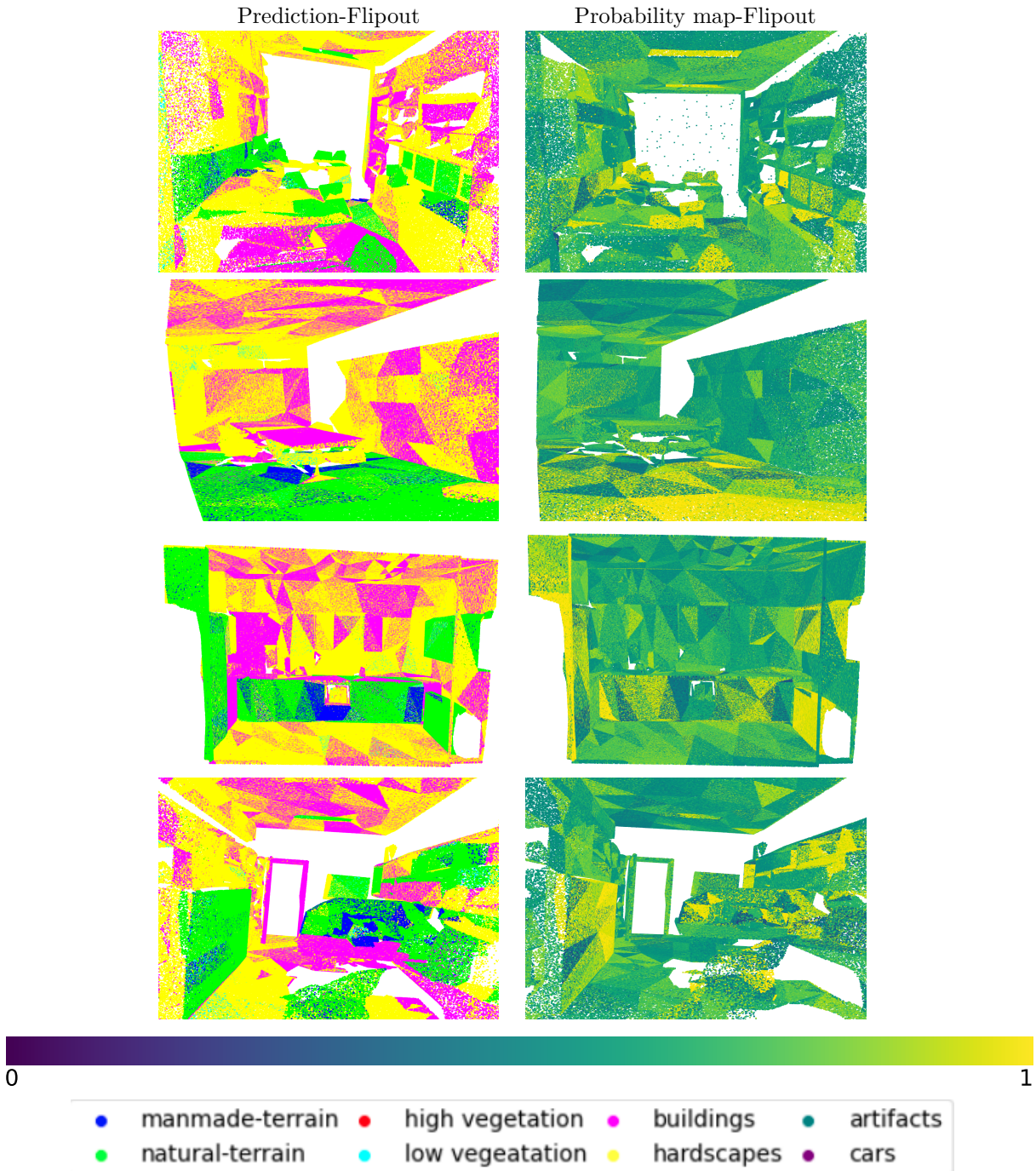


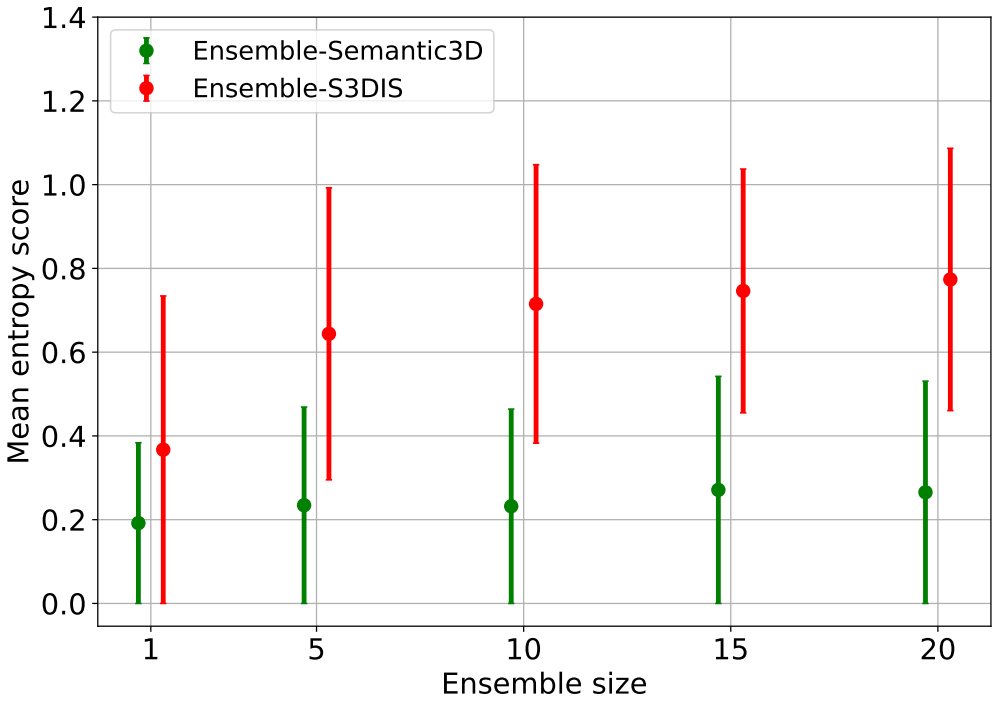
Figure 1.9: Perpoint probability visualization of the S3DIS dataset flipout.

1.3.2 Entropy

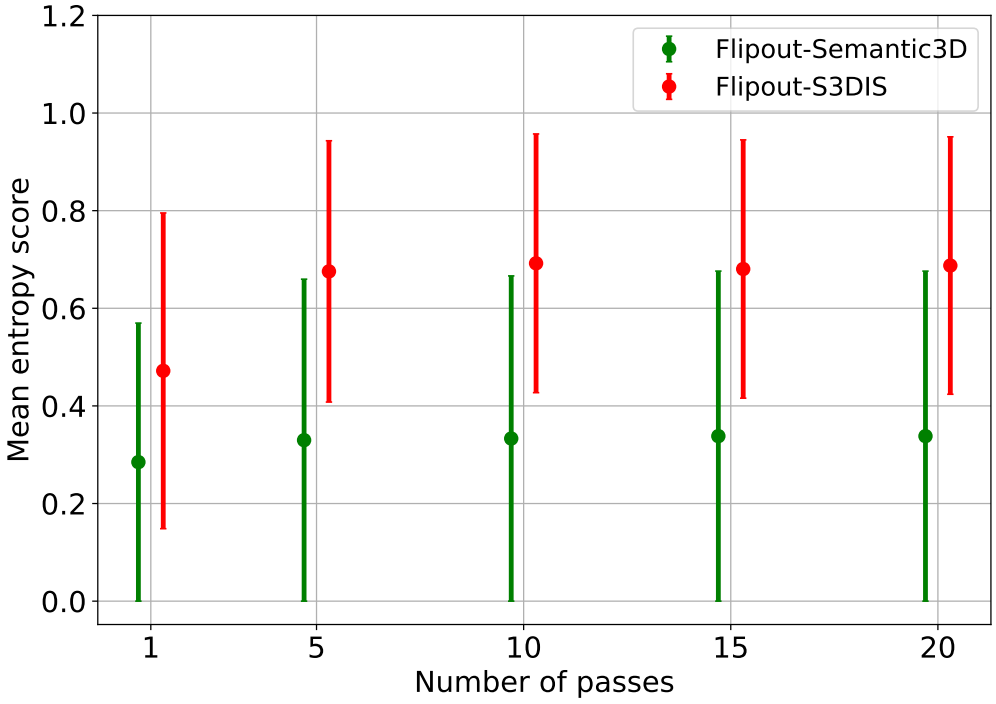
Similar to the experiment in Section [$], in this experiment, we study the distribution entropy values for ID (Semantic3D) and OOD (S3DIS) datasets. Entropy scores are a sum log function of softmax probabilities and detailed discussion in Section [$]. Figure 1.10a and Figure 1.10b depict the mean entropy score and variance plotted as error bars for Deep Ensembles and Flipout methods. Figure 1.11 and Figure 1.12 represents the entropy map for the ID dataset generated using Deep Ensembles and Flipout. Similarly, Figure 1.13 and Figure 1.14 represents the entropy map for the OOD dataset.

From Figure 1.10a and Figure 1.10b, we observe the entropy for the ID dataset is lower because the softmax values are not highly distributed across all the classes. Whereas in the case OOD dataset, the softmax probabilities are highly distributed across all the classes, so we observe a higher entropy score. Similar to the probability score, we also observe a decrement in the variance of entropy score until the ensemble size of 13 and then stabilizes out. Also, we infer that there is a lesser overlap between the error bars of OOD and ID datasets in the case of Deep Ensembles than the Flipout. So in both cases of MSP and entropy, we expect the Deep Ensembles to detect OOD objects better than the Flipout.

On careful observation of Figure 1.11 and Figure 1.12, we infer that overall entropy map is more bluish in shade representing the lower entropy scores. A higher entropy (yellow) is observed at the points of misclassifications and along the edges (similar to the case of probability map in Figures 1.6, 1.7). An example of misclassified points having higher entropy is observed in Figure 1.12, where the misclassified top of the church is greener on the entropy map compared to the rest of the church building. Visually observation of entropy maps for the OOD dataset in Figure 1.13 and Figure 1.14 reveals the colours to be at the higher end of the entropy scale resulting in a more yellowish shade in the case of both Flipout and Deep Ensembles.



(a) Entropy deep ensembles, (mistake in x axis)



(b) Entropy flipout

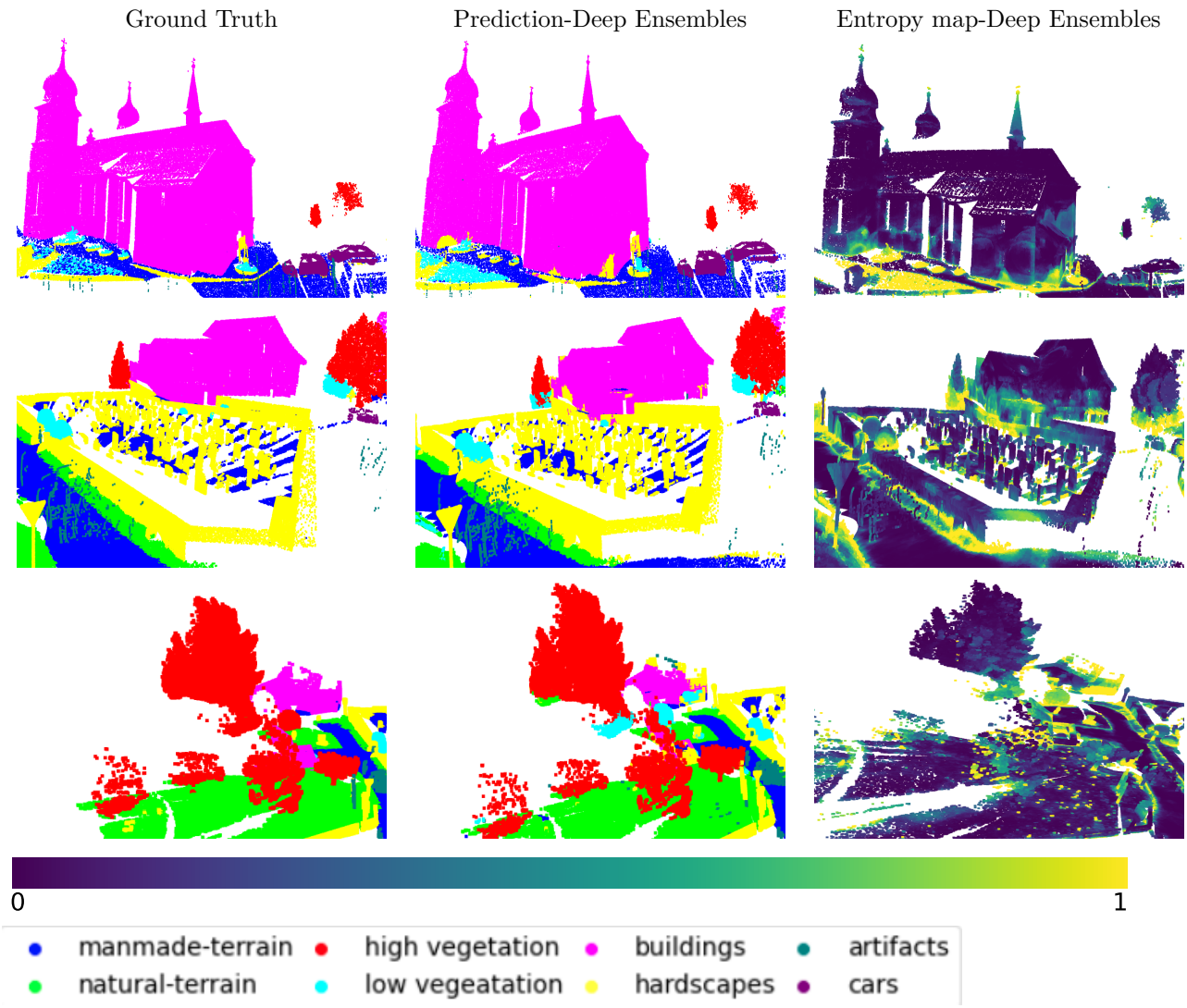


Figure 1.11: Perpoint entropy visualization of the semantic3D dataset-Ensembles. (Chnage the scale)

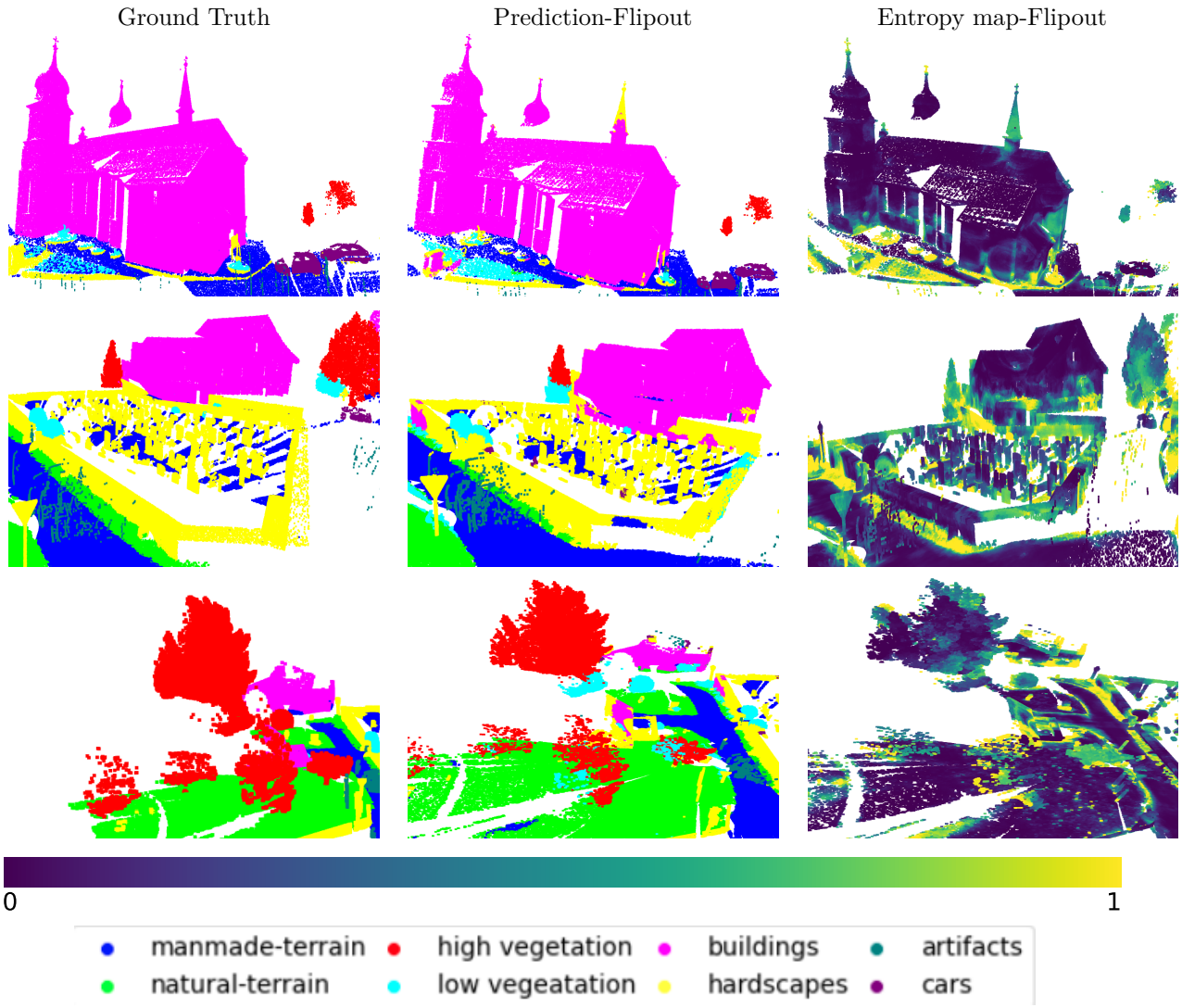


Figure 1.12: Perpoint entropy visualization of the semantic3D dataset.

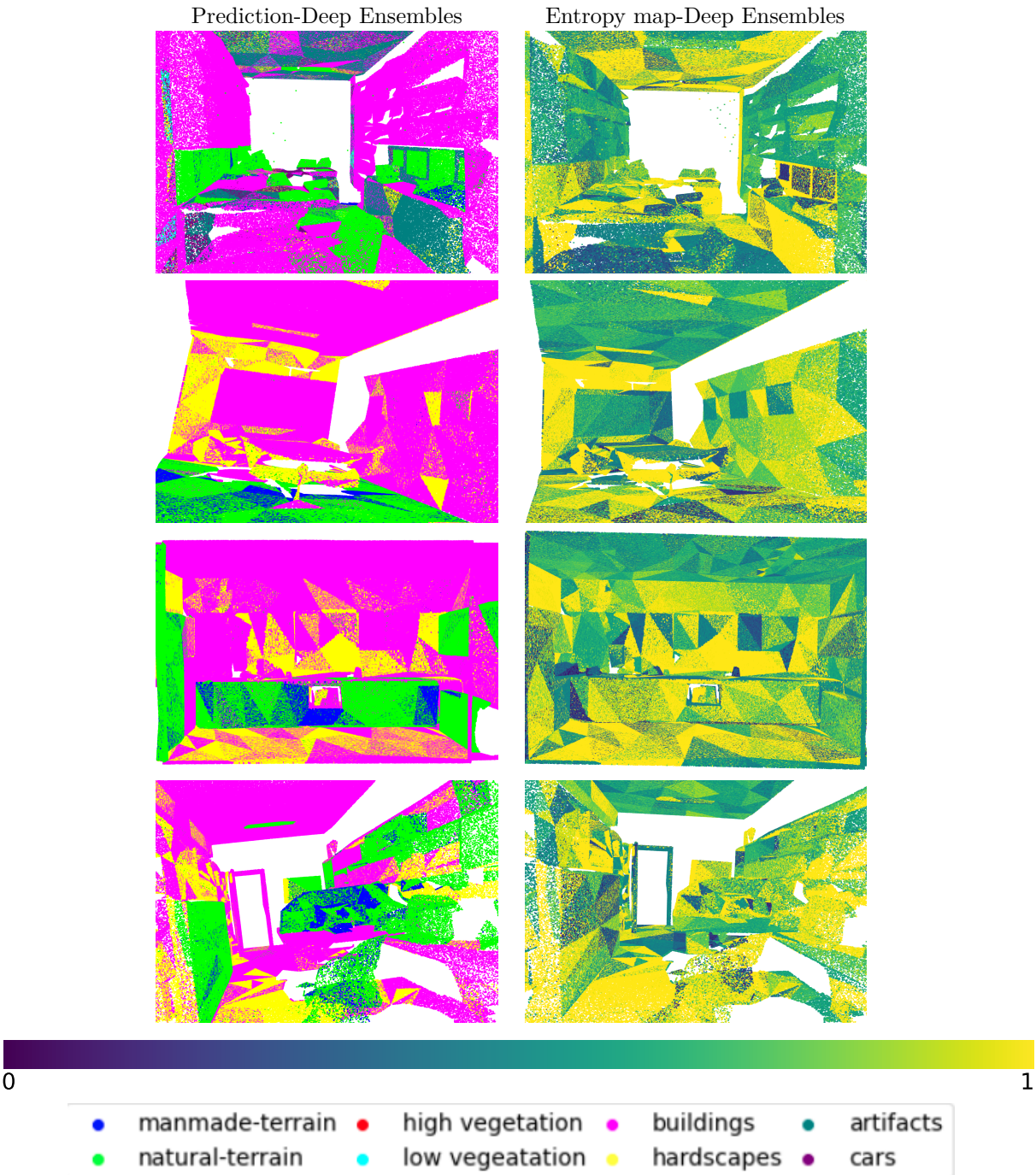


Figure 1.13: Perpoint entropy visualization of the S3DIS dataset.

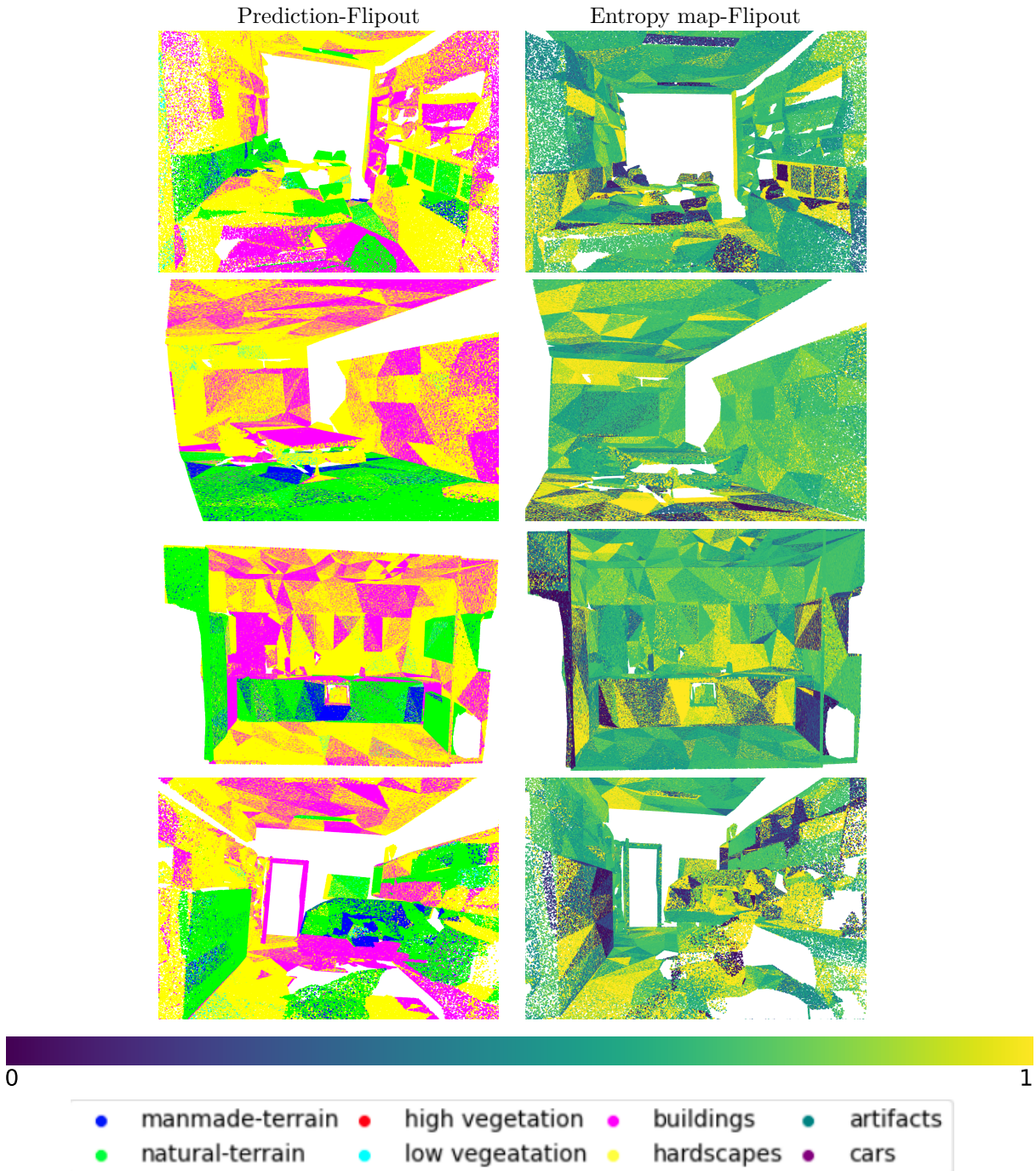


Figure 1.14: Perpoint entropy visualization of the S3DIS dataset flipout.

1.4 OOD detection evaluation - Semantic3D vs S3DIS

In this experiment, we evaluate the performance of the OOD detection using the AUROC scores generated using Maximum Softmax Probability (MSP) and Entropy. Table 1.3 summarizes the AUROC scores compared among Dropout, Flipout and Deep Ensembles techniques for multiple passes (in case of Dropout and Flipout) and ensemble size (in case of Deep Ensembles). Figure 1.15 and Figure 1.16 depicts the probability map and corresponding OOD map from Deep Ensembles and Flipout for In Distribution (ID) dataset. We depict the OOD map in green and red points, where the green colour represents ID points, and the red colour represents OOD points. We classify the OOD map based on the optimal threshold from the corresponding ROC curve depicted in Figure [$]. Similarly Figure 1.17 and Figure 1.18 represents the Entropy map and corresponding OOD map from Deep Ensembles and Flipout for ID dataset. Respectively Figures 1.19, 1.20, 1.21 and 1.22 represents the corresponding probability map, entropy map and their corresponding OOD map for OOD dataset (S3DIS).

Ensemble size/ #passes	Method	AUROC	
		MSP	Entropy
1	Dropout	0.53311	0.53041
	Flipout	**0.69988**	**0.69368**
	Deep Ensembles	0.62020	0.62529
5	Dropout	0.58439	0.57821
	Flipout	0.77885	0.76934
	Deep Ensembles	**0.84013**	**0.83665**
10	Dropout	0.60168	0.59925
	Flipout	0.78728	0.78327
	Deep Ensembles	**0.87929**	**0.87541**
15	Dropout	0.59773	0.59557
	Flipout	0.7667	0.76741
	Deep Ensembles	**0.88486**	**0.88246**
20	Dropout	0.59766	0.59661
	Flipout	0.77331	0.77237
	Deep Ensembles	**0.89338**	**0.89052**

Table 1.3: AUROC scores

From Table 1.3, we can observe that the among all the uncertainty methods used, Deep Ensembles outperform the other methods in classifying ID (Semantic3D) and OOD (S3DIS) datasets. Dropout performs worse among all the three uncertainty methods with Flipout in between Dropout and Deep Ensembles. From the Table 1.3 we also observe that MSP and Entropy score have similar AUROC scores as Entropy is the function of Probability. We also observe that the AUROC maxes out at 10 number of passes for Dropout and Flipout. In the case of Deep Ensembles, after the ensemble size of 10 the gains in AUROC scores are minimal.

From Figures 1.15, and 1.16 we infer that points with lower probability scores are classified as OOD points for ID (Semantic3D) dataset. In the event of OOD detection using entropy score for ID dataset as depicted in Figures 1.17, and 1.18, we observe higher entropy score points are classified as OOD points.

Where as in the case of OOD (S3DIS) dataset, most of the points are classified as OOD points as the OOD dataset has lower probability score and higher entropy overall.

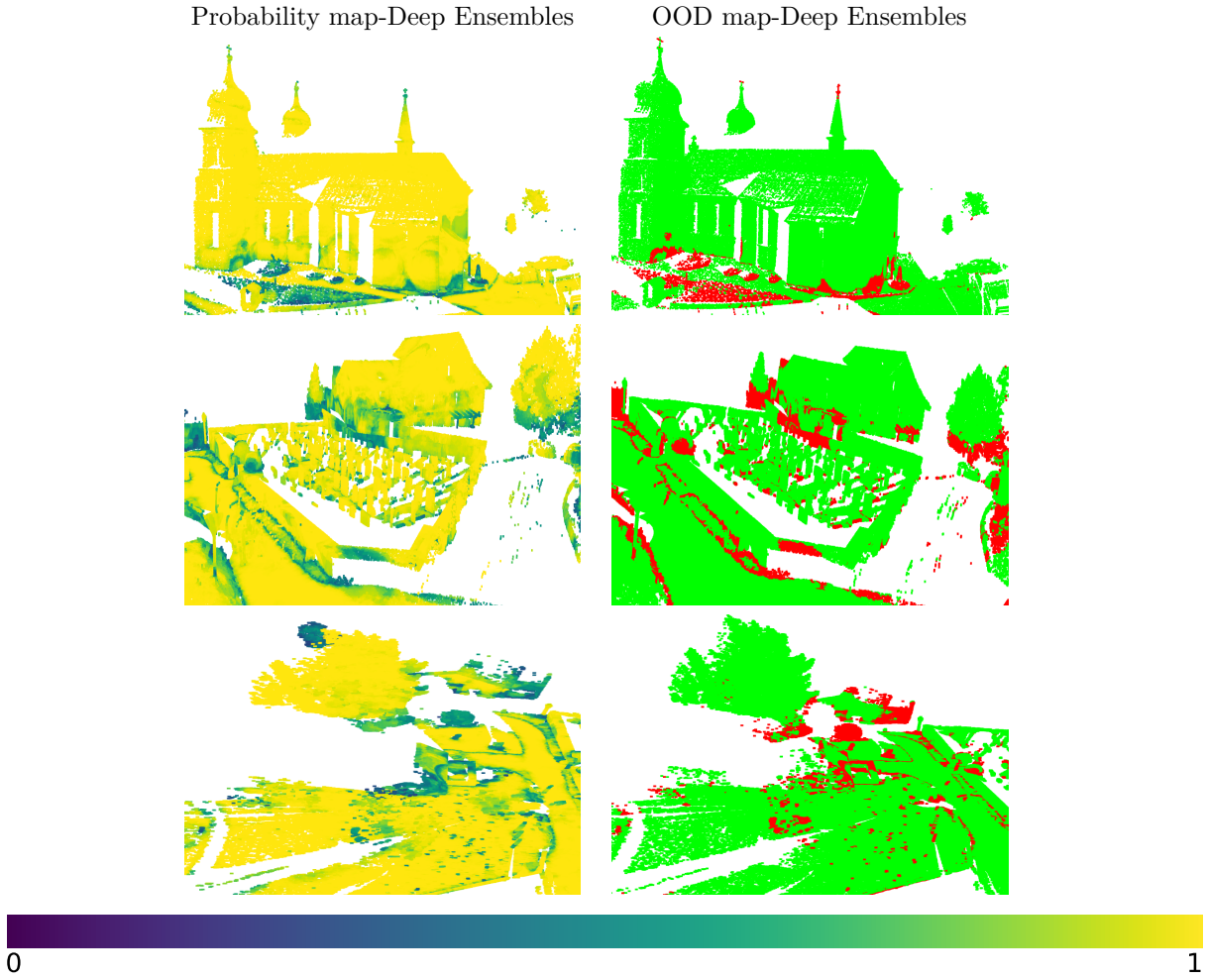


Figure 1.15: OOD point visualization of the semantic3D dataset Deep Ensembles-size 10.

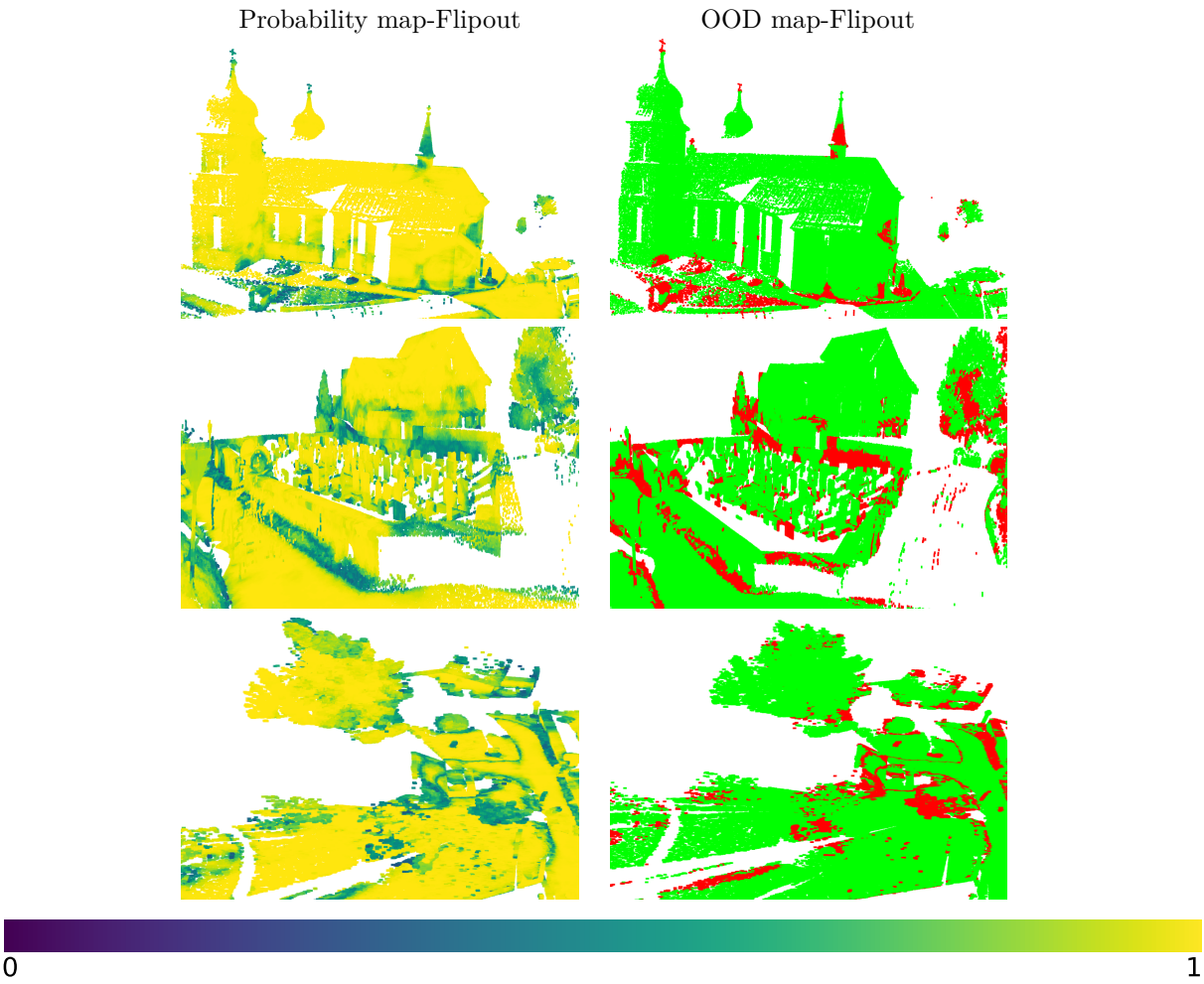


Figure 1.16: OOD point visualization of the semantic3D dataset Deep Ensembles-size 10.

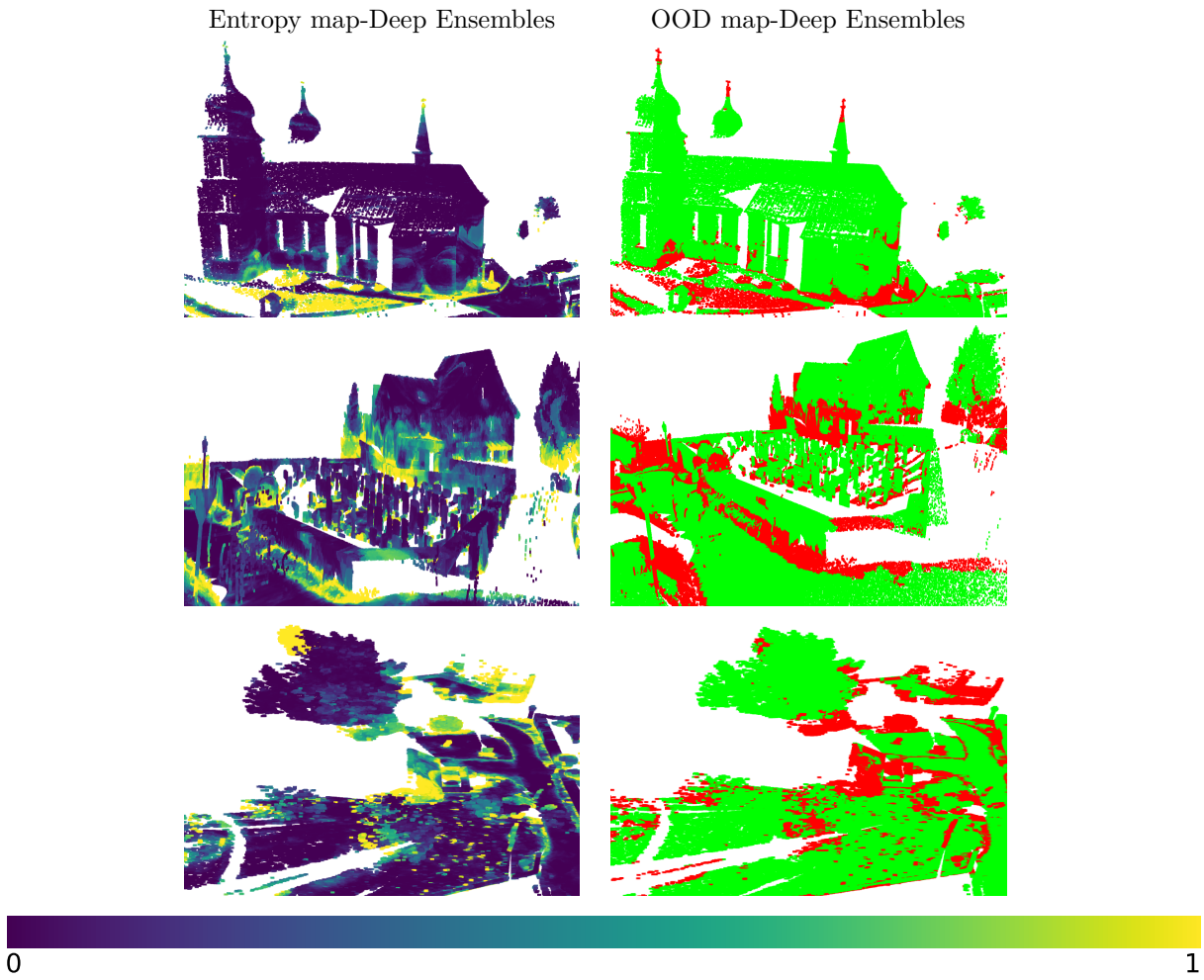


Figure 1.17: OOD point visualization of the semantic3D dataset Deep Ensembles-size 10.

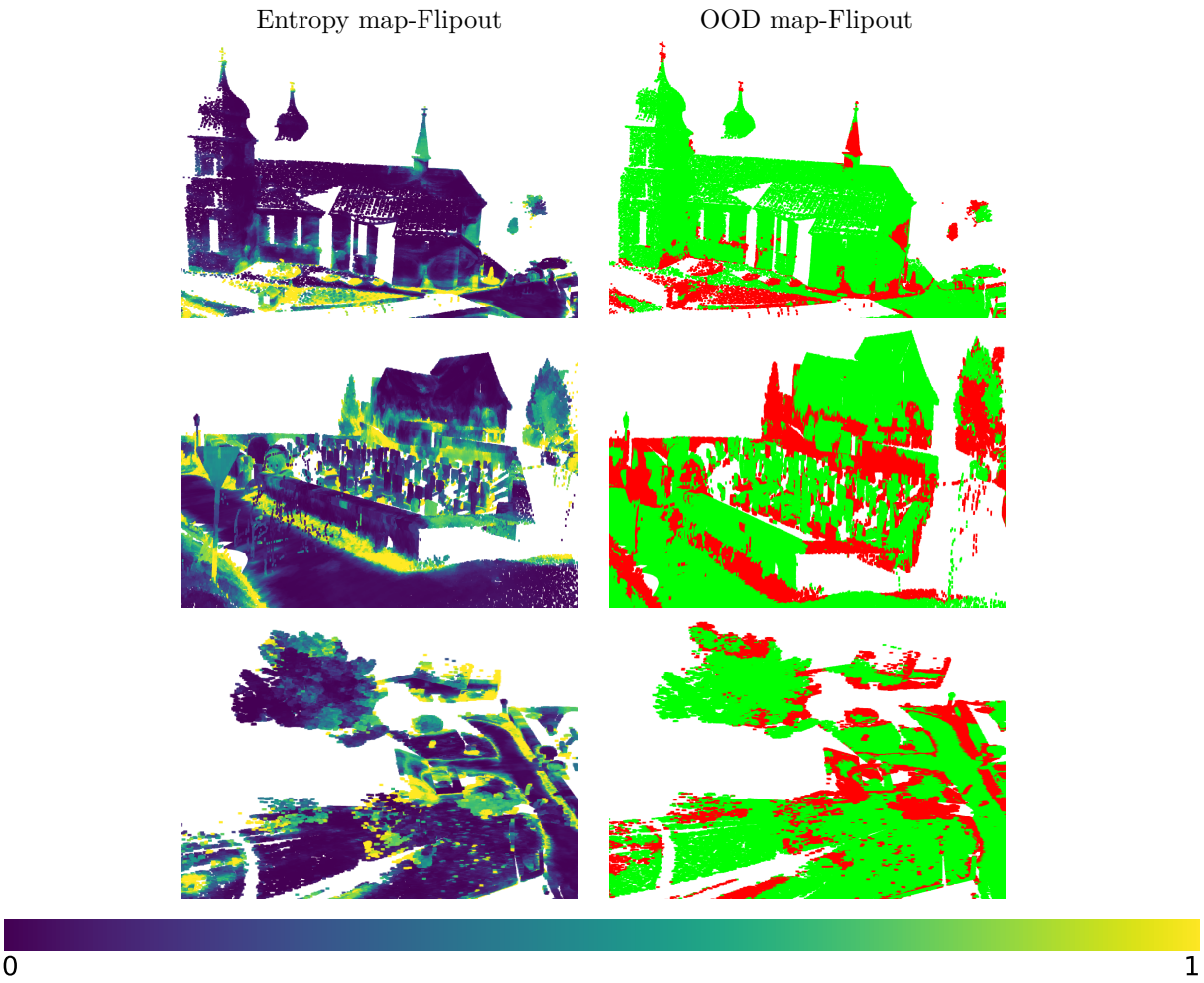


Figure 1.18: OOD point visualization of the semantic3D dataset Deep Ensembles-size 10.

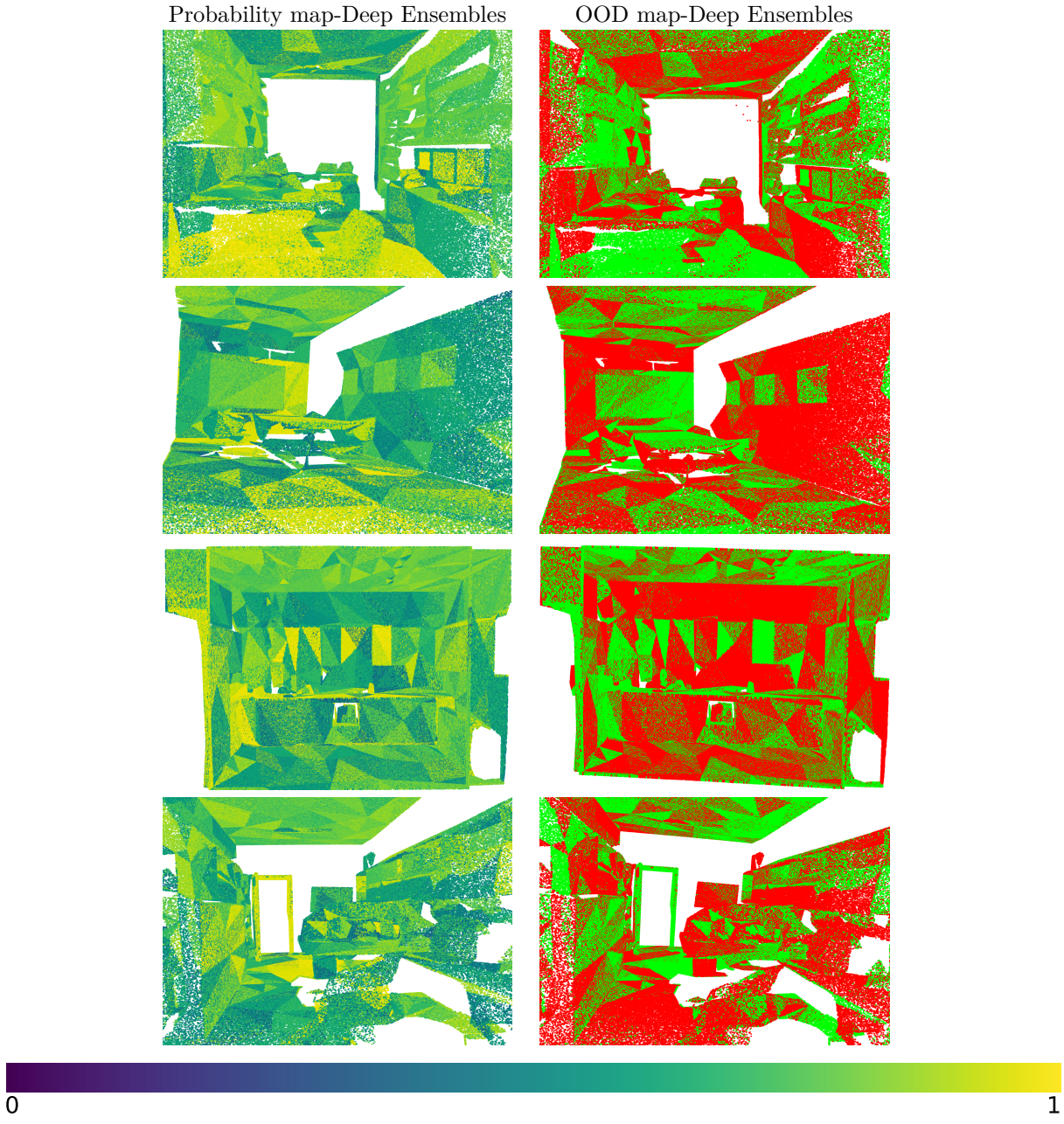


Figure 1.19: OOD visualization of the S3DIS dataset Deep Ensembles.

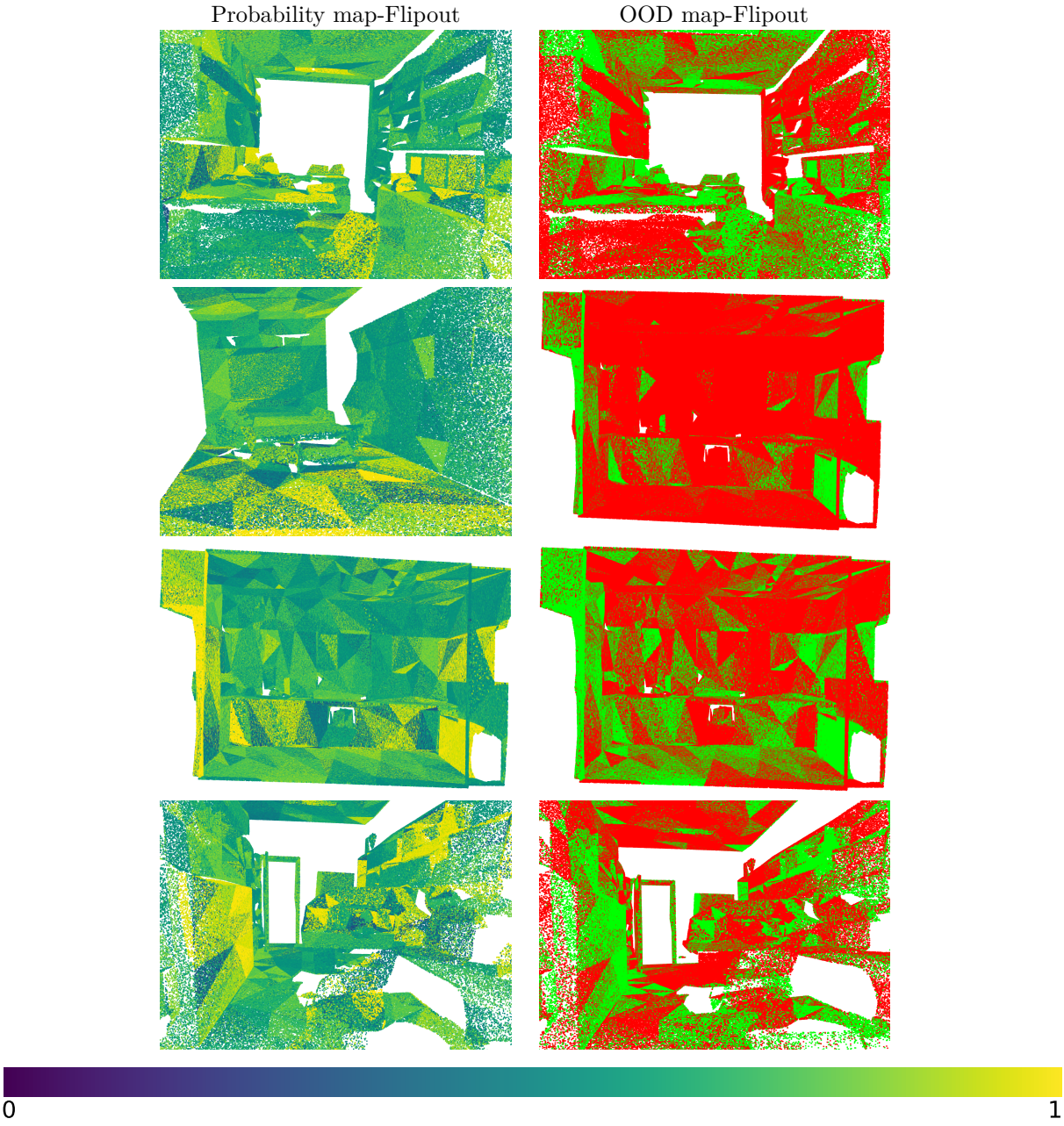


Figure 1.20: OOD visualization of the S3DIS dataset Flipout.

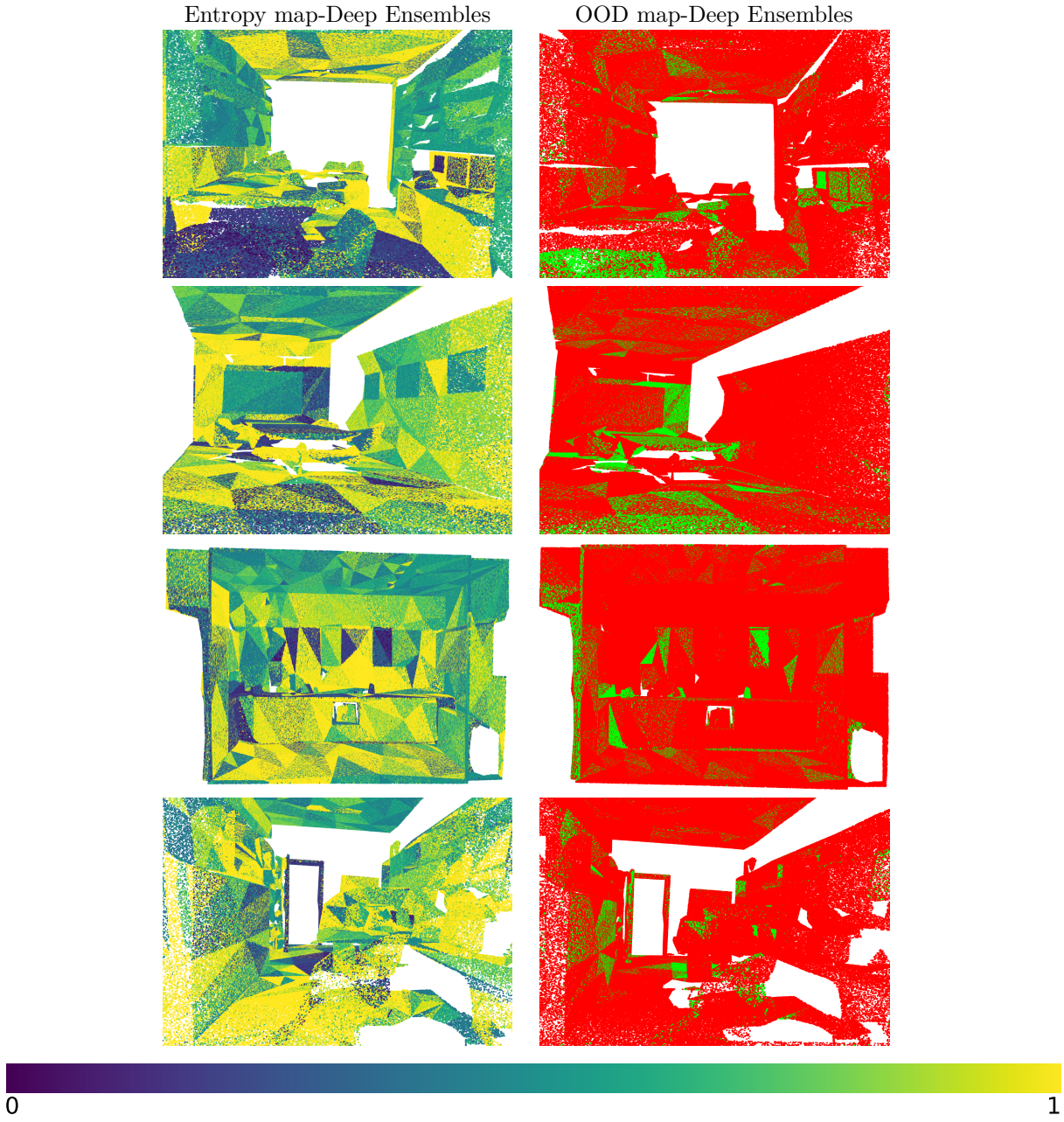


Figure 1.21: OOD visualization of the S3DIS dataset Deep Ensembles.

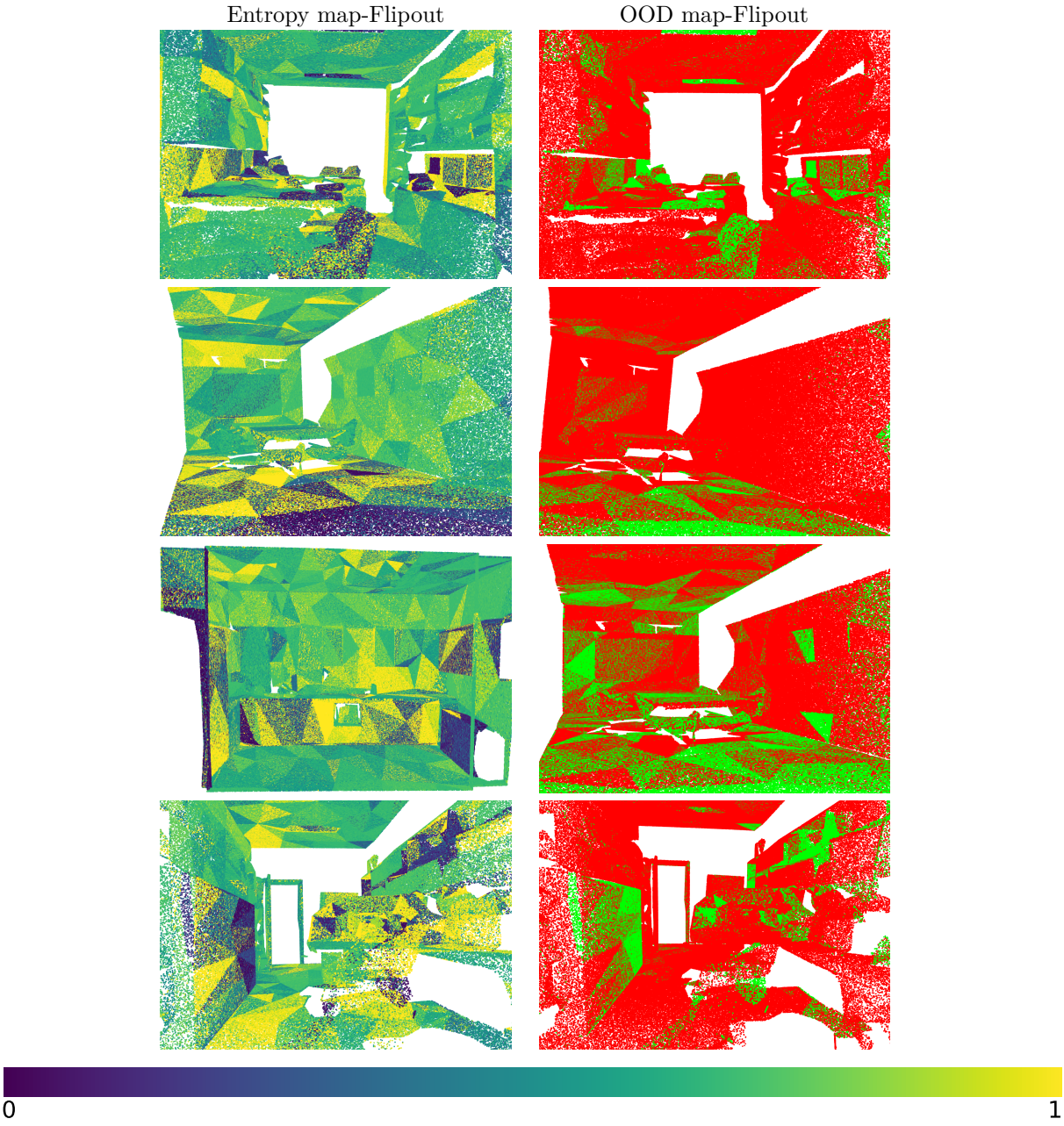


Figure 1.22: OOD visualization of the S3DIS dataset Deep Ensembles.

1.5 OOD Benchmark - Semantic3D vs Semantic3D without color

In this section, we perform similar experiments as in Semantic3D vs S3DIS with a second proposed OOD dataset which is Semantic3D without color. As a quick recap, Semantic3D dataset which is In Distribution (ID) dataset has XYZ and RGB values as features. In this second OOD dataset we remove the RGB values from the ID dataset making Semantic3D without color as OOD dataset. Semantic3D without color (OOD) dataset has identical structural properties to Semantic3D (ID) dataset but colour features are different.

Overall this section summarizes the study the performance of Deep Ensembles and Flipout model on Semantic3D without color dataset. Furthermore, we analyse and compare the probabilities and entropy scores of the new OOD and Semantic3D dataset. Finally, we visualize and evaluate the performance of OOD detection using AUROC score as evaluation metric.

1.5.1 Deep ensembles

This experiment evaluates the performance of the Semantic3D without color (OOD) dataset on Deep Ensembles. Table 1.4 provides the meanIoU, per-class IoU and Accuracy of the OOD dataset. Figure 1.23 provide the visual comparison of predictions between the Semantic3D (ID) and Semantic3D without color (OOD) dataset.

		IoU per class								
Ensemble size	**MeanIOU**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**Accuracy**
1	47.96	78.67	7.21	78.63	23.54	85.37	15.48	45.96	48.83	80.26
5	49.66	80.68	4.49	79.06	26.87	84.87	16.64	48.79	55.85	81.62
10	50.39	80.86	5.17	78.97	27.25	84.52	16.75	48.02	61.54	81.65
15	50.33	81.02	5.04	77.25	27.52	83.18	16.53	47.81	64.25	81.25
20	50.24	81.01	5.15	77.20	27.3	83.60	17.07	47.74	62.83	81.29

Table 1.4: Illustration of performance of RandLA-Net on Semantic3D wihtout color over number of ensembles. meanIOU and IOU per class and overall accuracy are represented here. C1 to C8 are the classes of Semantic3D which are Manmadeterrain, Naturalterrain, Highvegetation, Lowvegetation, Buildings, Hardscapes, Scanningartifacts, and Cars.

On comparison of Table 1.4 and Table 1.1, we derive that by removing the colors of ID dataset we observe a reduction in the meanIoU and Accuracy. We also observe that the class-Naturalterrain represented as green color in Figure 1.23 takes a major blow. This can be correlated with figures in row two of Figure 1.23 where the vegetation between road and fence depicted in first image is misclassified in second image. Row two also shows the misclassification of major part of fence as a building. On further evaluation of such results, we deduce that in case of no color information height of the object is one of the major factor for the classification.

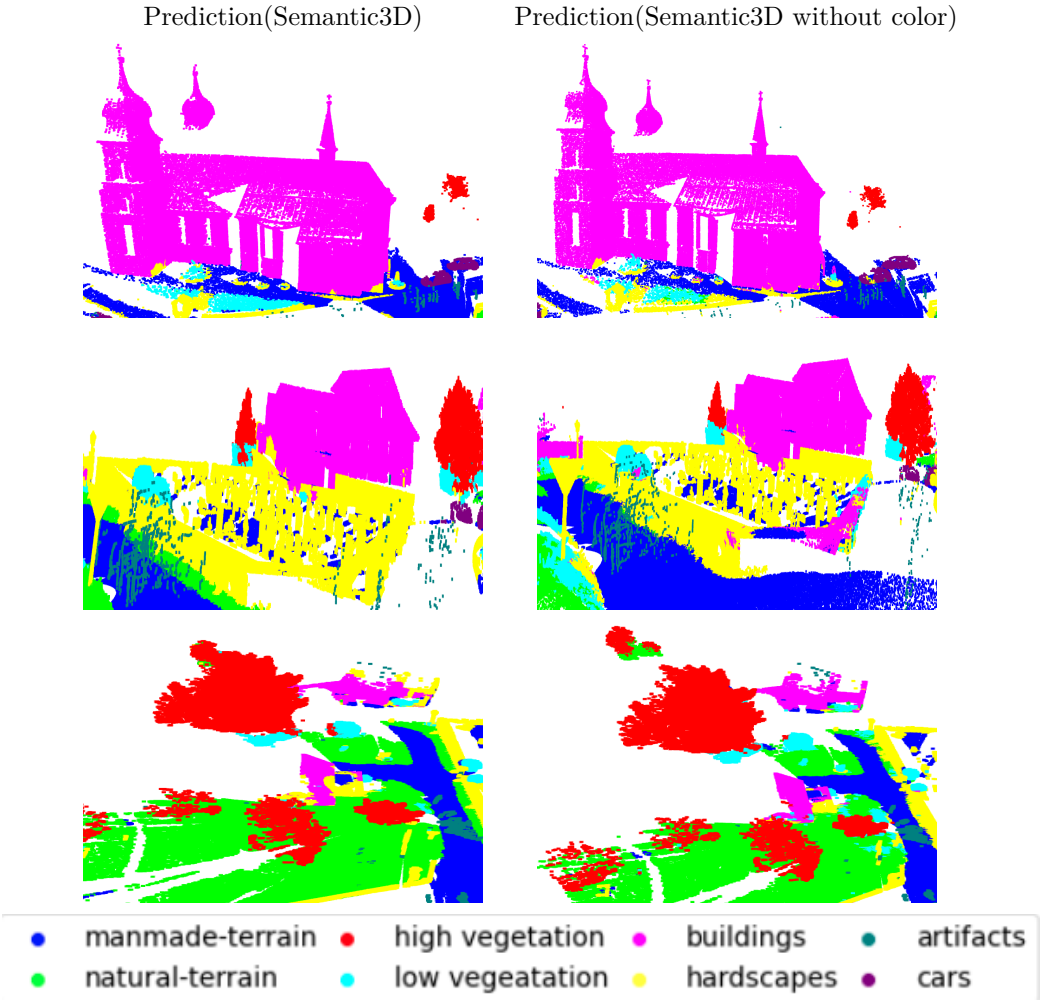


Figure 1.23: Output predictions of the RandLA-Net over the Semantic3D dataset and Semantic3D without color dataset (10 ensembles) Legend spelling mistake.

1.5.2 Flipout

In this experiment we evaluate the performance of Semantic3D (ID) dataset trained Flipout network on Semantic3D without color dataset. Table 1.5 illustrates the metrics of meanIoU, per-class IoU and Accuracy and similarly Figure 1.24 depicts the visual comparison of prediction between Semantic3D and Semantic3D without color.

Similar to the deep ensembles performance on OOD dataset, we observe similar performance on Flipout model also. Even in Flipout model we observe that model is struggling to classify Naturalterrain similar to Deep Ensembles. Visual comparsion of Deep Ensembles performance in Figure 1.23 and Flipout model in Figure 1.24 confirms that Flipout model performs worse in classifying Buildings and Cars.

		IoU per class								
# Passes	**MeanIOU**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**Accuracy**
1	49.53	79.6	6.88	68.51	23.58	86.3	16.4	47.24	67.7	79.85
5	49.1	79.65	6.722	65.46	23.42	85.74	16.1	47.05	68.64	79.11
10	49.08	79.67	6.66	65.11	23.57	85.64	16.11	47.16	68.73	79.05
15	49.03	79.67	6.64	64.88	23.56	85.64	16.06	47.20	68.58	79.00
20	49.02	79.69	6.65	64.87	23.57	85.62	16.06	47.14	68.56	79.00

Table 1.5: Illustration of performance of RandLA-Net on Semantic3D wihtout color over number of ensembles. meanIOU and IOU per class and overall accuracy are represented here. C1 to C8 are the classes of Semantic3D which are Manmadeterrain, Naturalterrain, Highvegetation, Lowvegetation, Buildings, Hardscapes, Scanningartifacts, and Cars.

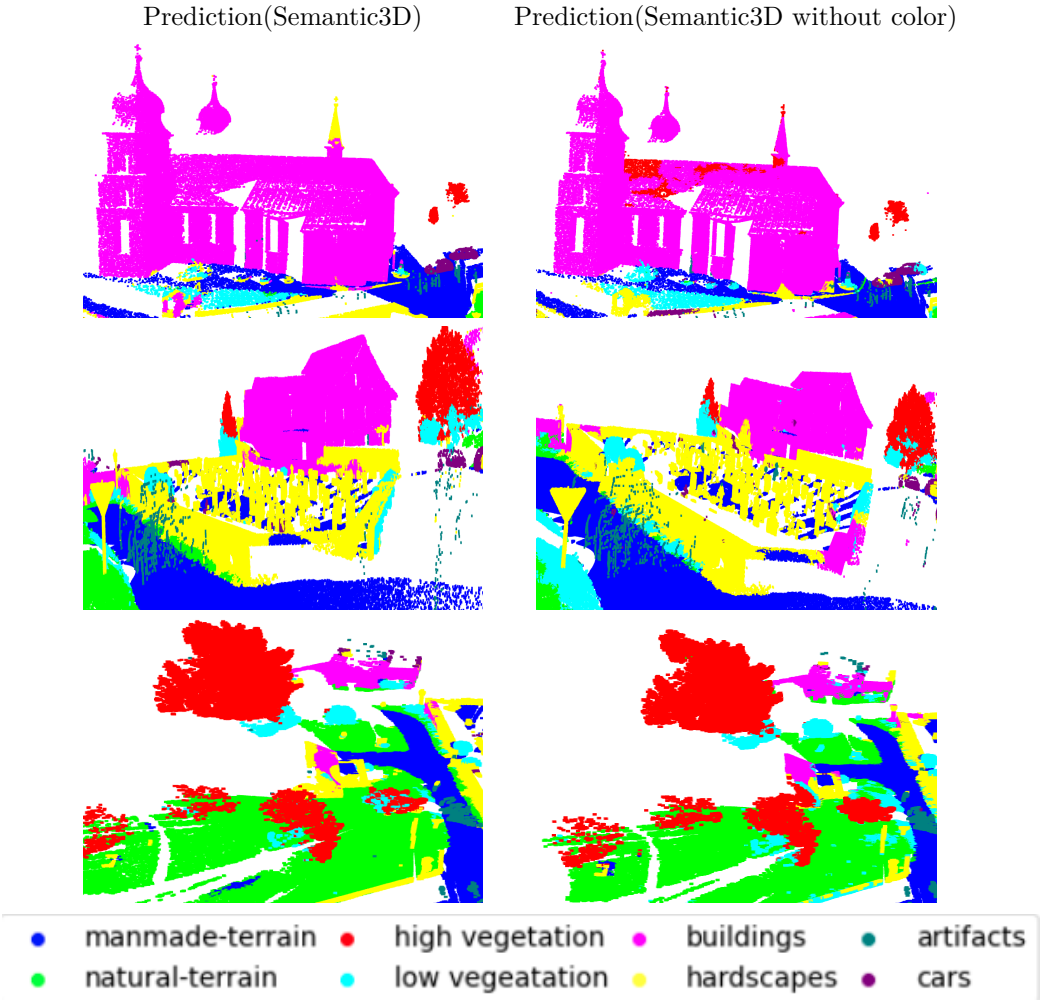
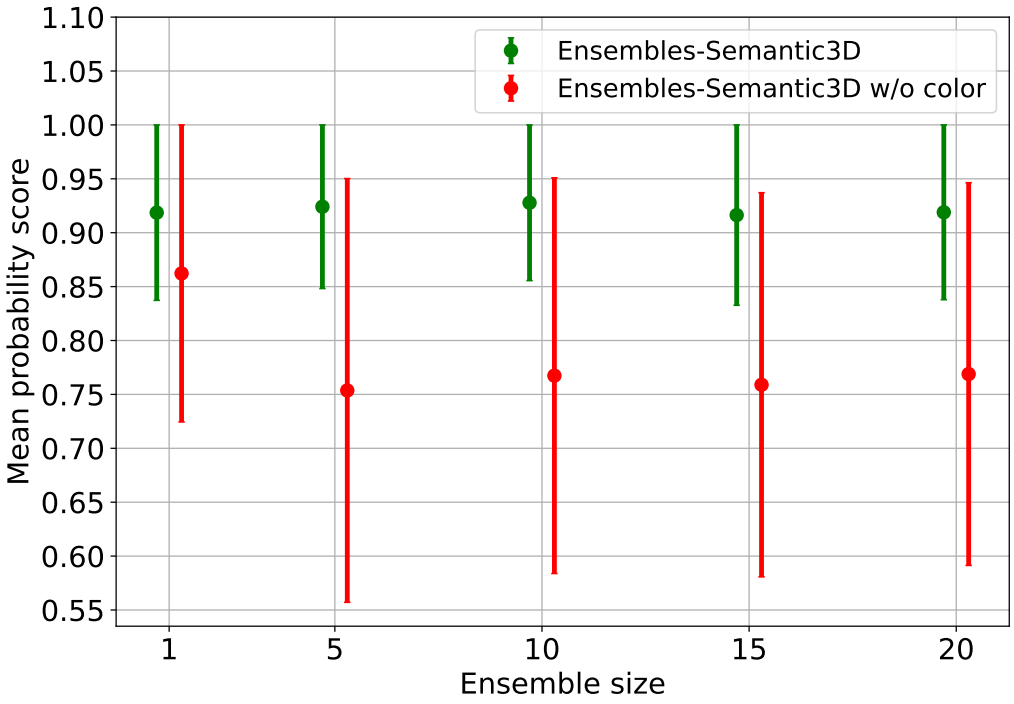


Figure 1.24: Output predictions of the RandLA-Net over the Semantic3D dataset (10 forward passes) Legend spelling mistake.

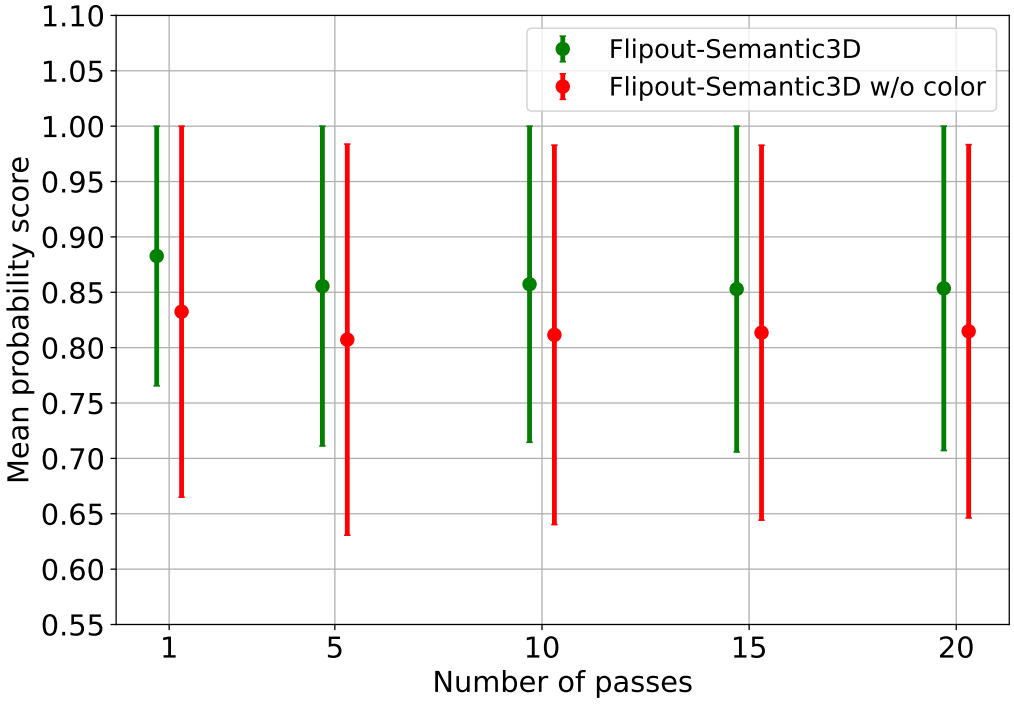
1.5.3 Maximum Softmax probability (MSP)

This experiment focuses on the MSP values for each point in both ID and OOD datasets. We also try to study the distribution of probability values and try to estimate the performance of OOD detection. Figure 1.25a and Figure 1.25b depicts the mean probability value for ID and OOD dataset along with the variance represented as error bars. Figure 1.26 and Figure 1.27 represents the probability map of ID and OOD datasets for Deep Ensembles and Flipout respectively.

From the plots represented in Figure 1.25a, we observe that ID has higher mean probability with lower variance decreasing till ensemble size of 10 and then stabilizing. Where as for the OOD dataset represented in red lines, we observe a bit lower mean probability and higher variance with lot of overlap with the ID probability values. Similar plot for Flipout represented in Figure 1.25b has similar distribution of probability values. The difference in mean probability between ID and OOD for Flipout is small and similar variance. This gives us the intuition that in the scenario, where the OOD object has structural similarity but less richer features, Deep Ensembles performs better at OOD detection than Flipout and this intuition is confirmed by the AUROC score. Study of Figure 1.26 suggests us that the Semantic3D (ID) probabilities are higher than the OOD probabilities which are darker in shade in the case of Deep Ensembles. Similar conclusions can be drawn for the Flipout probability map represented in Figure 1.26. In both the cases, classes that suffer majorly with low probability scores are Naturalterrain, Hardscapes (fences, traffic signs) and these classes have lower IoU score in both cases of Deep Ensembles and Flipout.



(a) MSP deep ensembles



(b) MSP Flipout

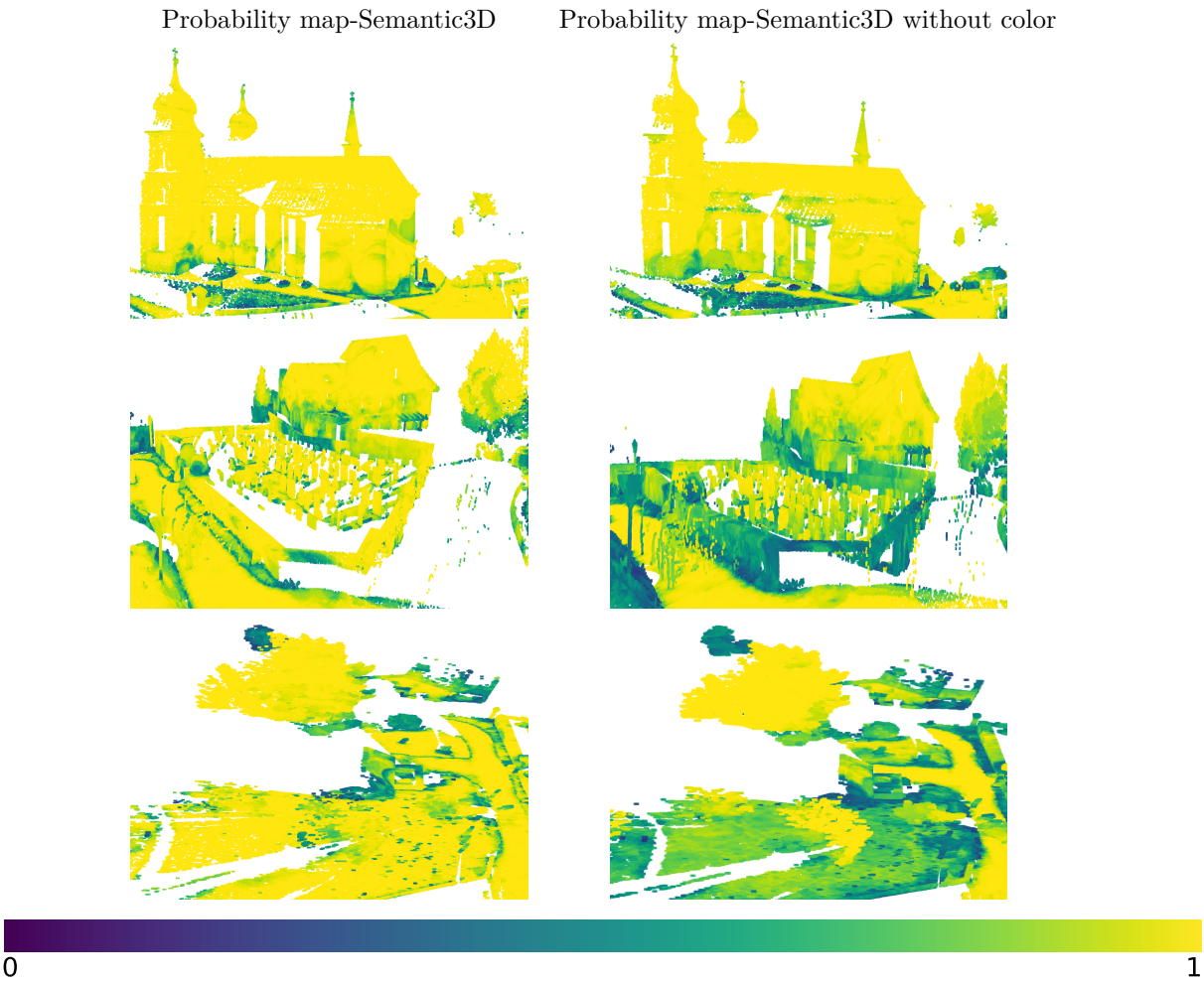


Figure 1.26: Probability map of the RandLA-Net over the Semantic3D dataset (10 ensemble) Legend spelling mistake.

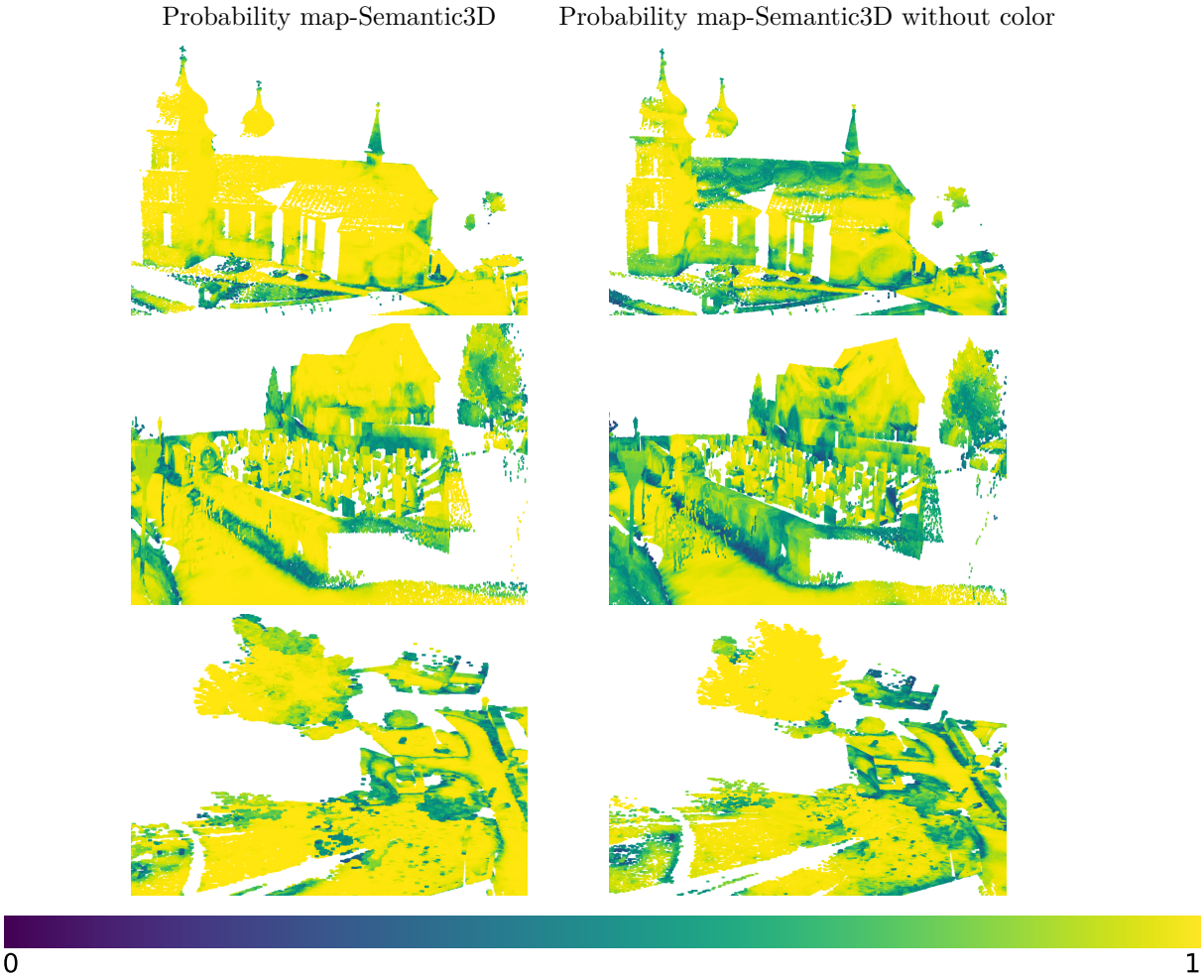
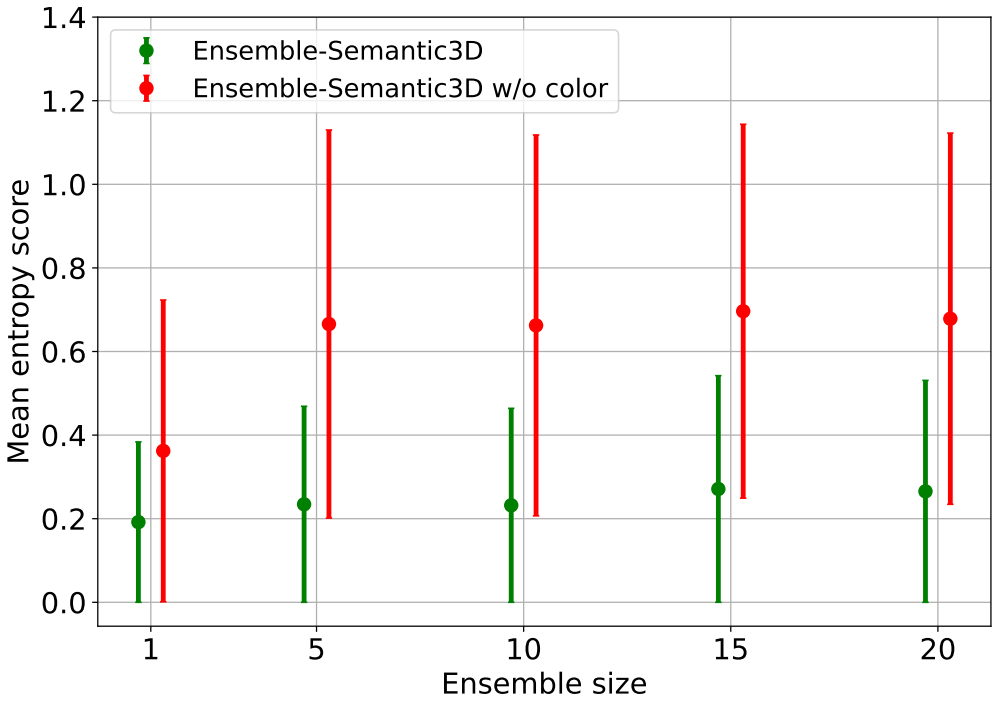


Figure 1.27: Probability map of the RandLA-Net over the Semantic3D dataset (10 number of passes) Legend spelling mistake.

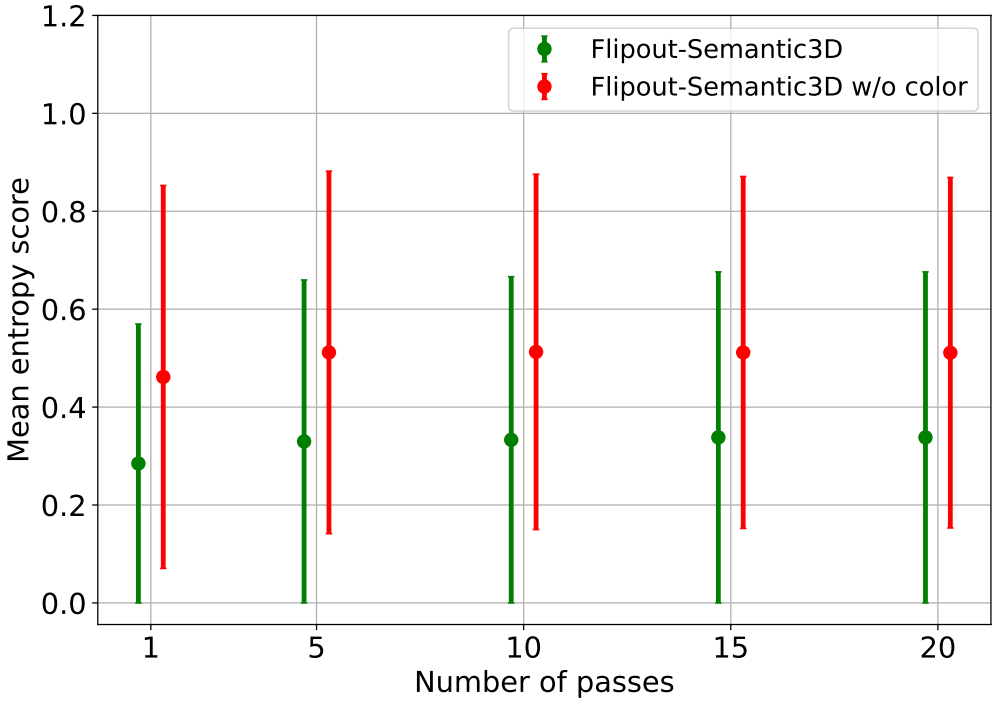
1.5.4 Entropy

Similar to the previous experiment, instead of MSP values, we study the distribution of entropy values in this experiment. Figure 1.28a and Figure 1.28b represent the mean entropy values with variance represented as error bars for both Deep Ensembles and Flipout respectively. Similarly Figure 1.29 and Figure 1.30 represents the entropy map for the ID and OOD datasets for both Deep Ensembles and Flipout respectively.

Simlar conclusions to the MSP experiment can be drawn as entropy values for ID dataset are lower with lower variance and higher mean entropy with larger variance for OOD dataset. Whereas variance of ID dataset entropy values are increasing overall inspite of initial decreasing variance in case of MSP for Deep Ensembles. In the case of Flipout, we observe that difference in mean probability for ID and OOD dataset are small and with large overlap in the variance between the two. In the entropy map, we observe that the OOD dataset has higher entropy score visually when compared to the entropy score of ID dataset. This effect is profound for the classes such as Naturalterrain, Hardscapes (fences, and traffic signs). In this kind of scenario with entropy scores, we expect a similar performance of OOD detection using entropy score compared to MSP



(a) Entropy deep ensembles



(b) Entropy Flipout

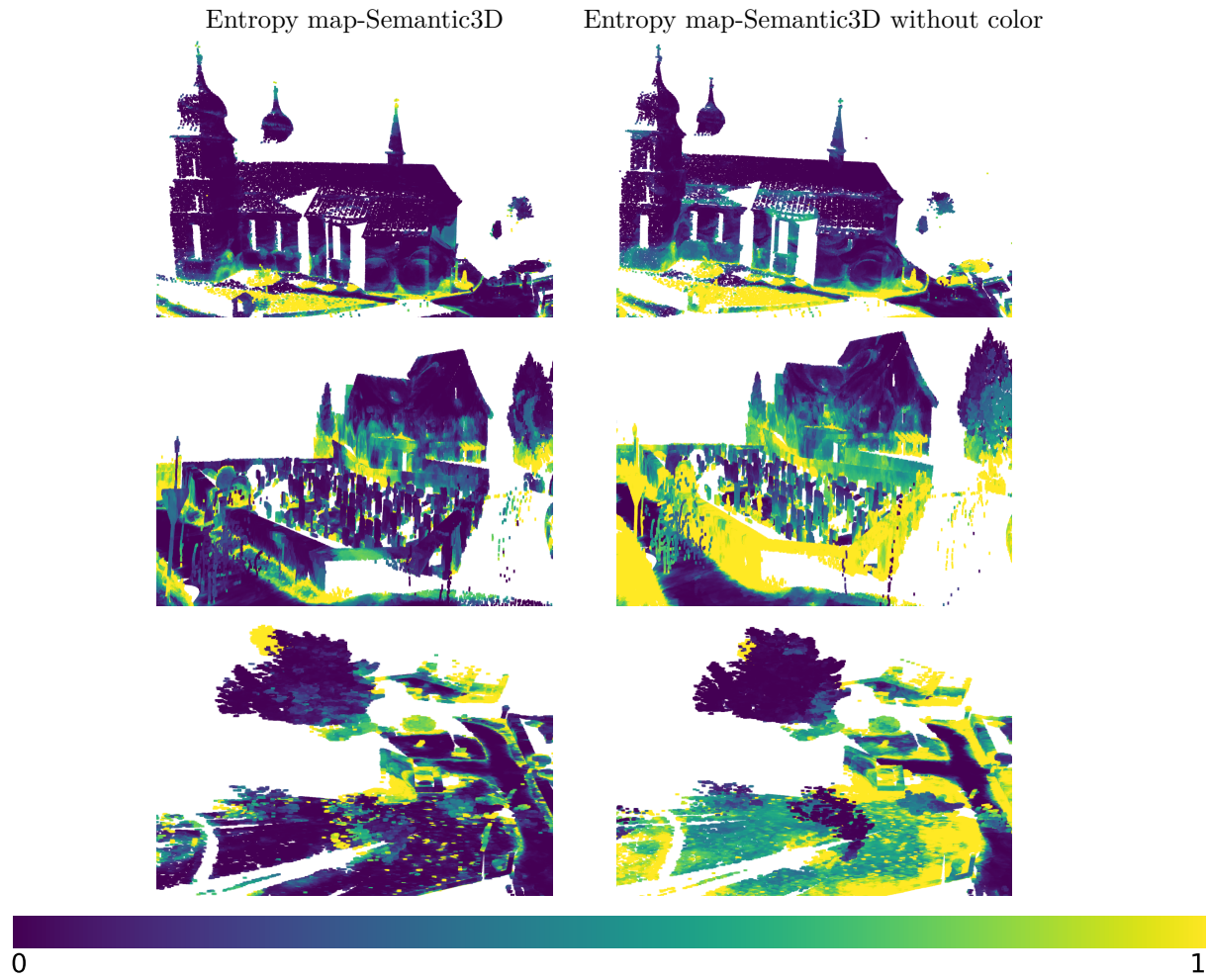


Figure 1.29: Probability map of the RandLA-Net over the Semantic3D dataset (10 ensemble) Legend spelling mistake.

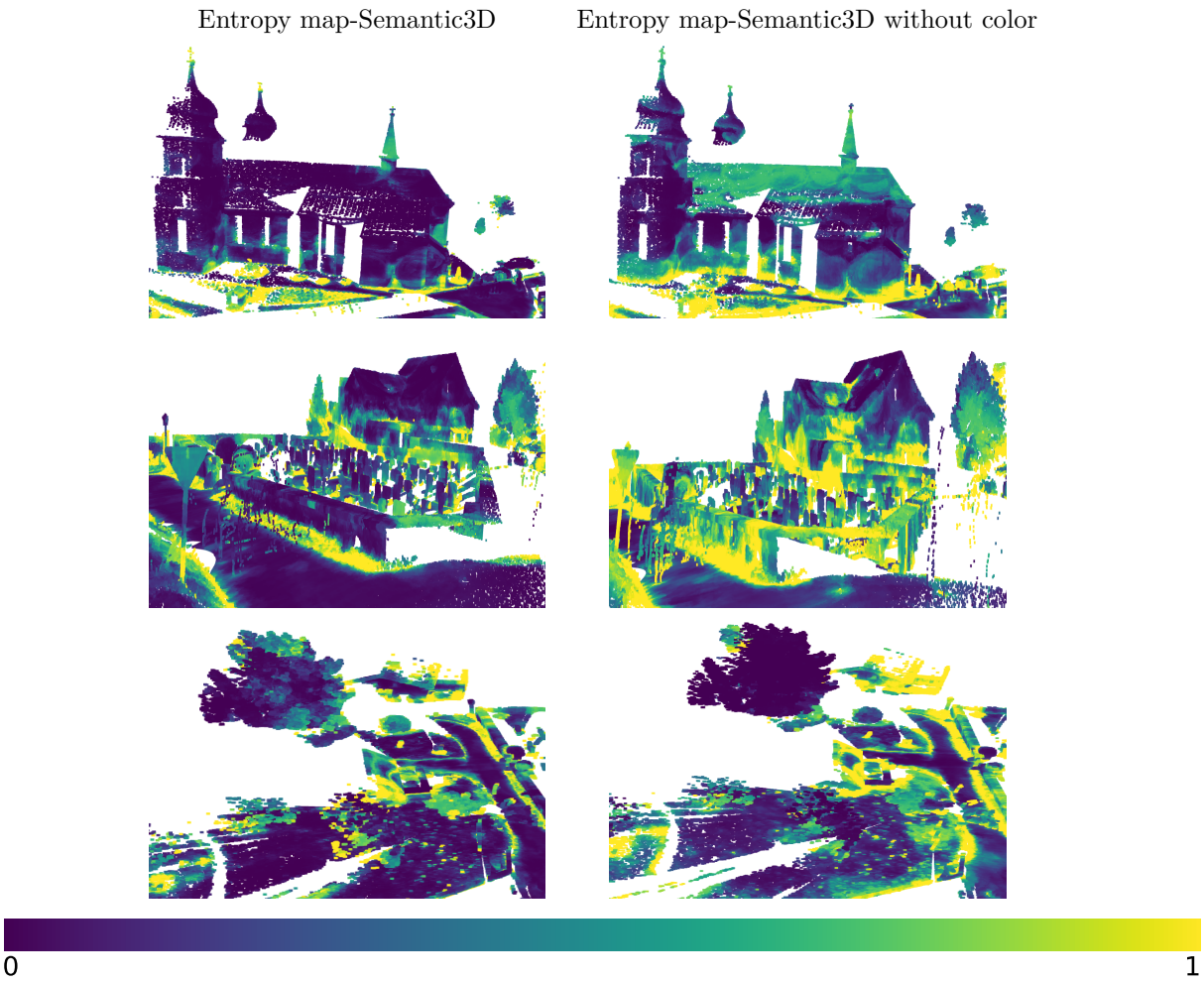


Figure 1.30: Probability map of the RandLA-Net over the Semantic3D dataset (10 number of passes) Legend spelling mistake.

1.6 OOD detection evaluation - Semantic3D vs Semantic3D without color

In this section, we conclude the evaluation of OOD performance using AUROC scores and visual comparisons of the OOD maps. Similar to OOD detection evaluation in Semantic3D vs S3DIS, we provide the performance evaluation of OOD detection for Dropout, Flipout and Deep Ensembles. We also evaluate these methods over multiple ensemble sizes for Deep Ensembles and multiple number of passes for others. Table 1.6 represents the comparison of AUROC scores generated from MSP and Entropy between these three methods. Figures 1.31, 1.32 represents the side by side comparison of OOD map generated from probability scores with thresholds from ROC curve for both ID and OOD datasets. Similarly Figures 1.33, 1.34 represents the OOD maps generated from entropy scores with thresholds from ROC curve for both ID and OOD datasets.

Ensemble size/ #passes	Method	AUROC	
		MSP	Entropy
1	Dropout	0.66349	0.65908
	Flipout	0.64221	0.66157
	Deep Ensembles	**0.67855**	**0.67866**
5	Dropout	0.69448	0.68507
	Flipout	0.63743	0.66536
	Deep Ensembles	**0.76769**	**0.77120**
10	Dropout	0.68568	0.68004
	Flipout	0.63712	0.66535
	Deep Ensembles	**0.77837**	**0.78142**
15	Dropout	0.68975	0.68347
	Flipout	0.63022	0.65976
	Deep Ensembles	**0.77302**	**0.77881**
20	Dropout	0.68447	0.68199
	Flipout	0.63017	0.65934
	Deep Ensembles	**0.77031**	**0.77584**

Table 1.6: AUROC scores

From Table 1.6, we can infer that Deep Ensembles perform better among all other uncertainty techniques. In this case of OOD dataset, Dropout performs slightly better than Flipout. AUROC scores for Deep Ensembles increase until the ensemble size of 10 and then started to decrease. Also the AUROC scores for entropy are slightly better than the AUROC scores from MSP values. A common inference from the OOD maps is that the classes of Naturalterrain, Hardscapes (fences and traffic signs) are labelled as OOD points in OOD dataset. In case of OOD labelled points in ID dataset, the misclassifications and edges of buildings and fence are labelled as OOD points. A study of OOD maps for Semantic3D without color from Deep Ensembles represented in Figures 1.31, 1.33 for both probability and entropy scores reveal that buildings, and large trees are classified as ID objects.

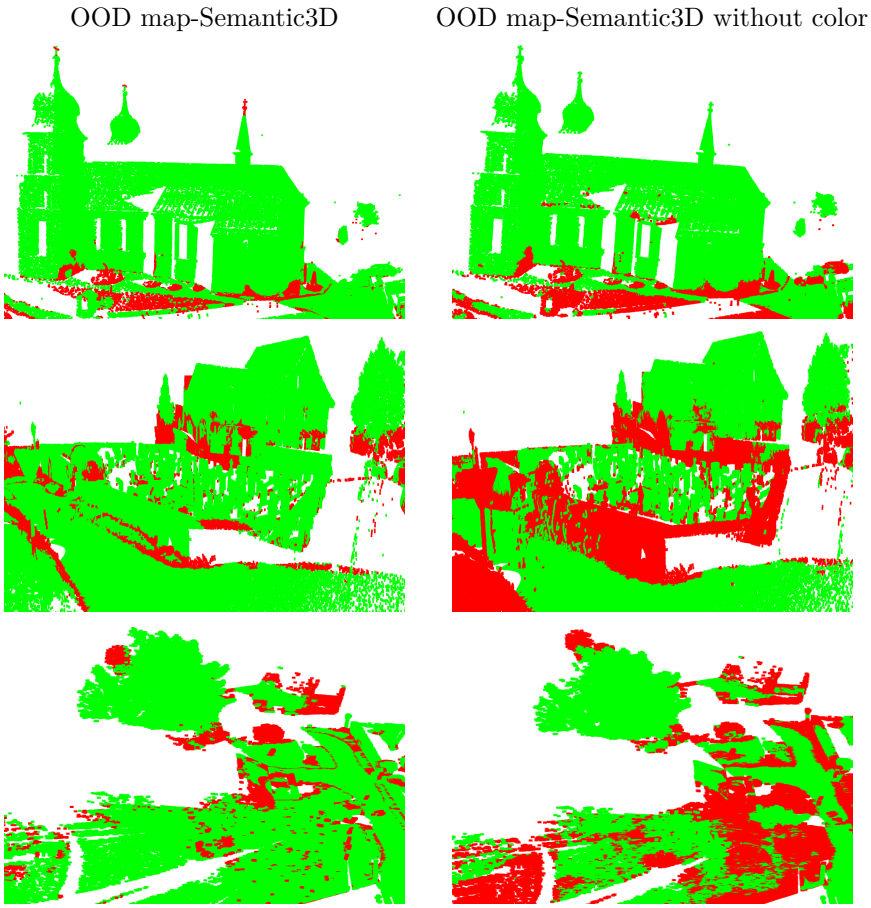


Figure 1.31: OOD map of the RandLA-Net over the Semantic3D dataset (10 ensembles) Legend spelling mistake.

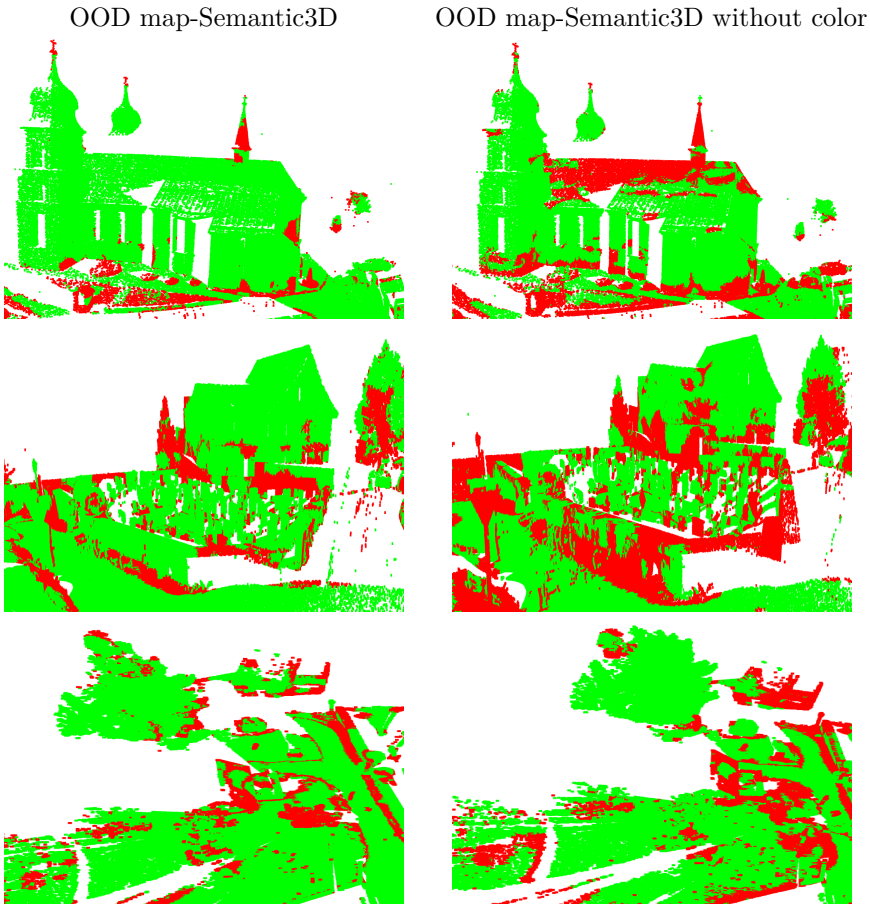


Figure 1.32: OOD map of the RandLA-Net over the Semantic3D dataset (10 ensembles) Legend spelling mistake.

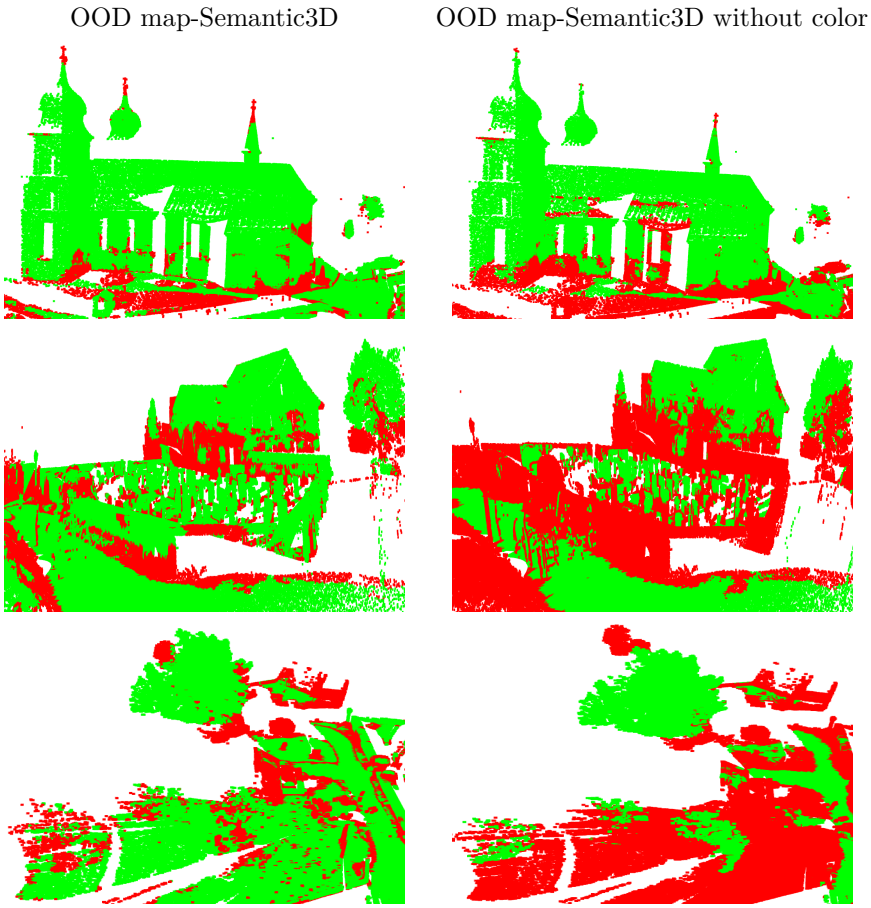


Figure 1.33: OOD map of the RandLA-Net over the Semantic3D dataset (10 ensembles) Legend spelling mistake.

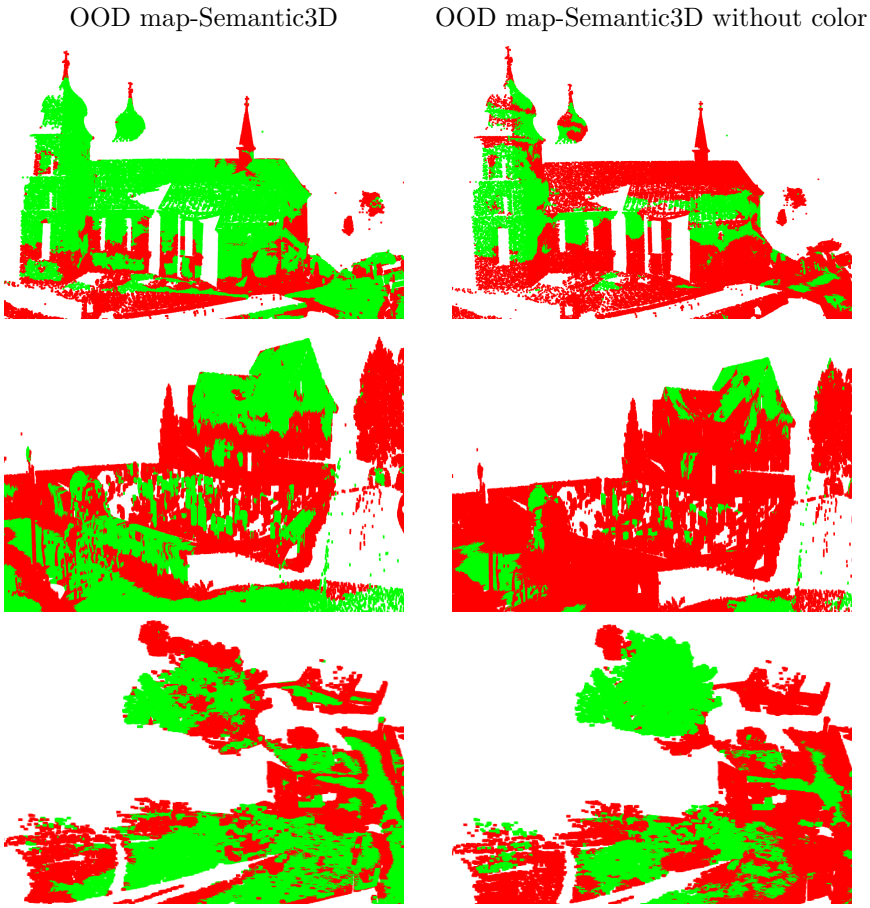


Figure 1.34: OOD map of the RandLA-Net over the Semantic3D dataset (10 ensembles) Legend spelling mistake.

References

[1] Dan Hendrycks and Kevin Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. *arXiv preprint arXiv:1610.02136*, 2016.

[2] Qingyong Hu, Bo Yang, Linhai Xie, Stefano Rosa, Yulan Guo, Zhihua Wang, Niki Trigoni, and Andrew Markham. Randla-net: Efficient semantic segmentation of large-scale point clouds. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.