

Leaf/Wood discrimination in ULS LiDAR using Neural Network

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Background

- Leaf-wood separation is crucial for estimating leaf area or wood volume.
- Tropical forests pose challenges: tall, dense, and hyper-diverse.
- ULS offers efficient, high-density data collection over extensive forest areas.
- SOUL** (Semantic segmentation On ULS)[1] uses only point coordinates as input and outperforms state-of-the-art alternatives on ULS point clouds.

Contributions

The contribution of our work is three-fold:

- 1.** SOUL is the first approach developed to tackle the challenge of semantic segmentation on tropical forest ULS point clouds.
- 2.** We propose a novel data preprocessing method called Geodesic Voxelisation Decomposition (**GVD**) used to partition the data.
- 3.** We mitigate the issue of imbalanced classes by employing a new loss function named rebalanced loss.

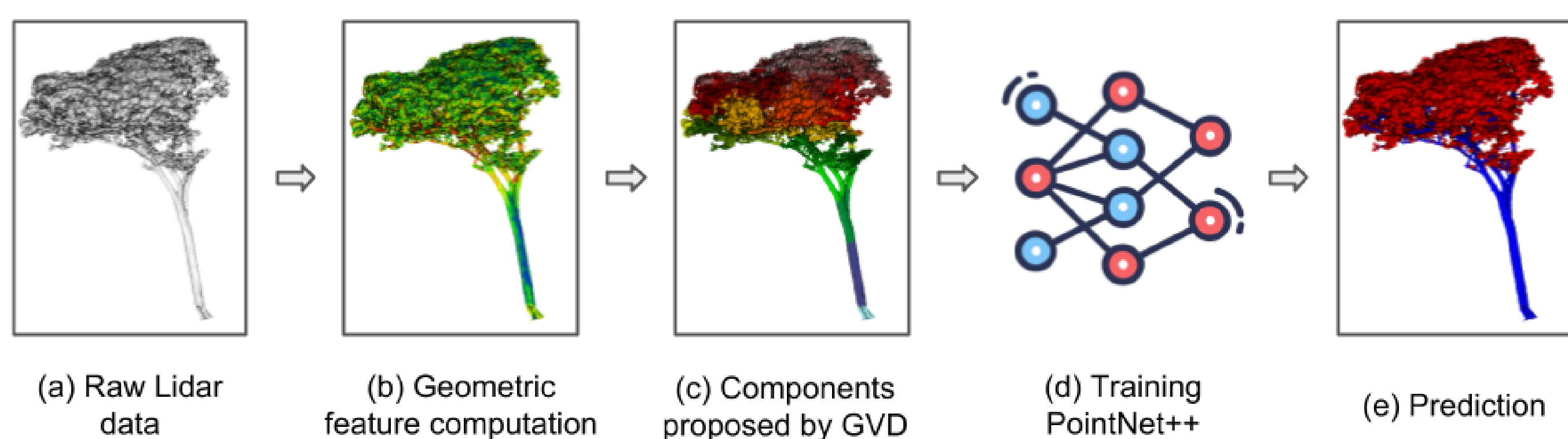


Figure 1. Overflow of SOUL.

Methodology

(a) Data cleaning

Filter out returns below -20 dB, and eliminate noise and ground points.

(b) Geometric feature computation

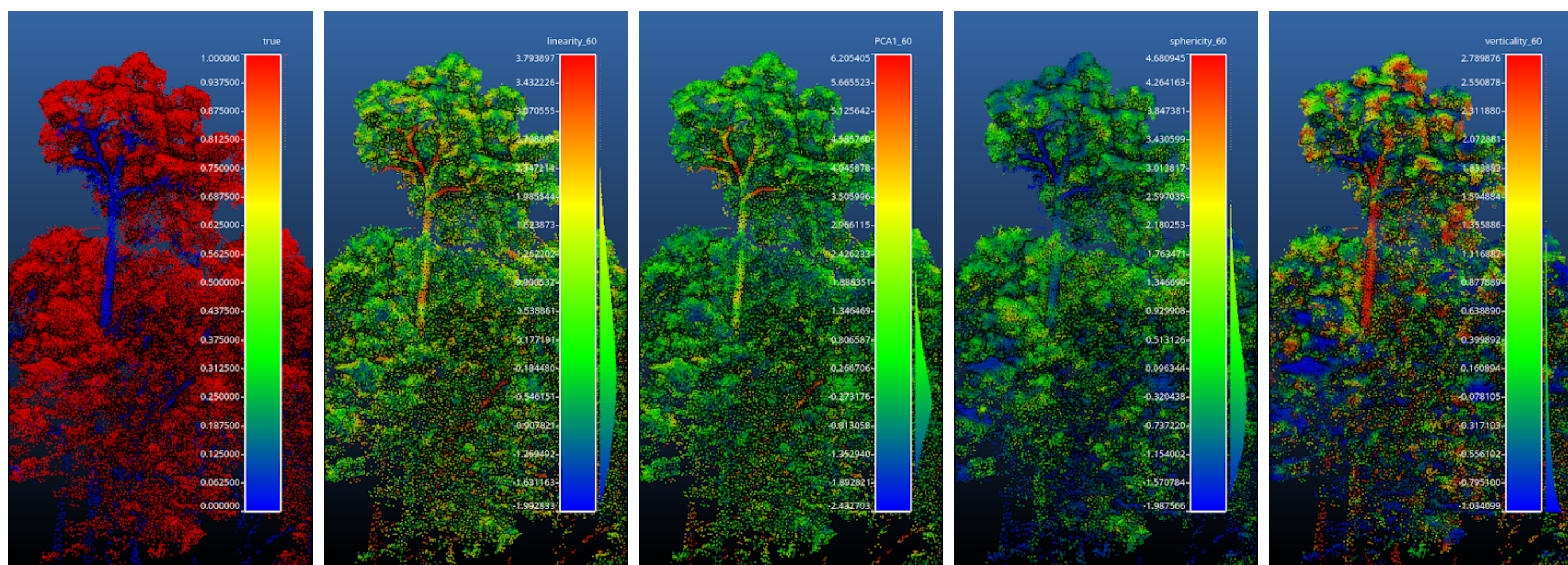


Figure 2. Four point-wise features introduced at this stage.

(c) Data pre-partitioning

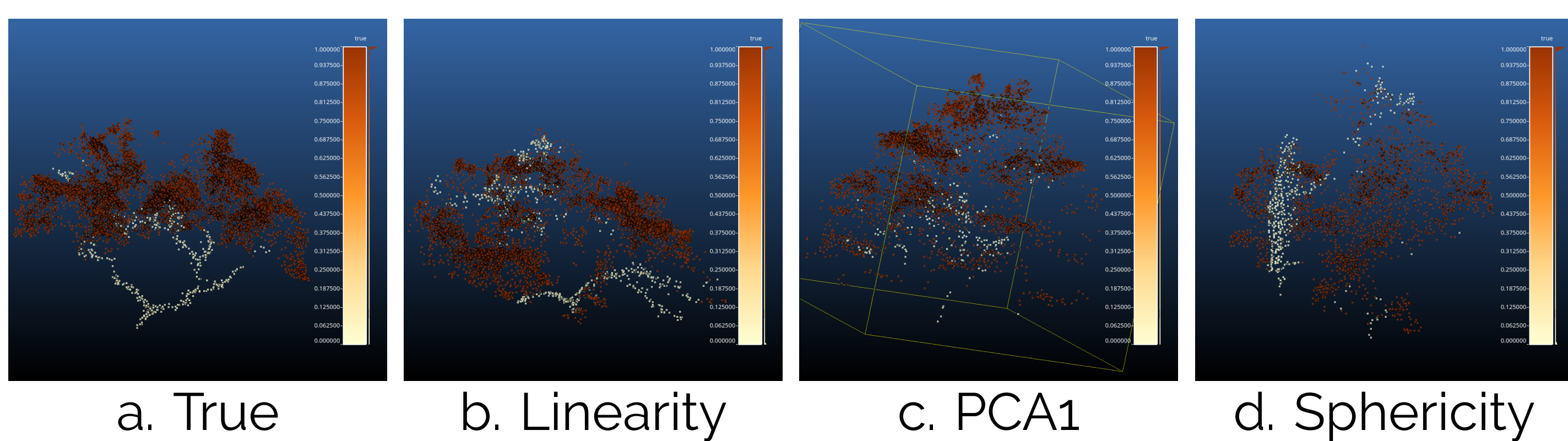


Figure 3. GVD decomposition.

(d) Training deep neural network

Rebalanced loss, denoted as L_R , is used to address class imbalance issue.

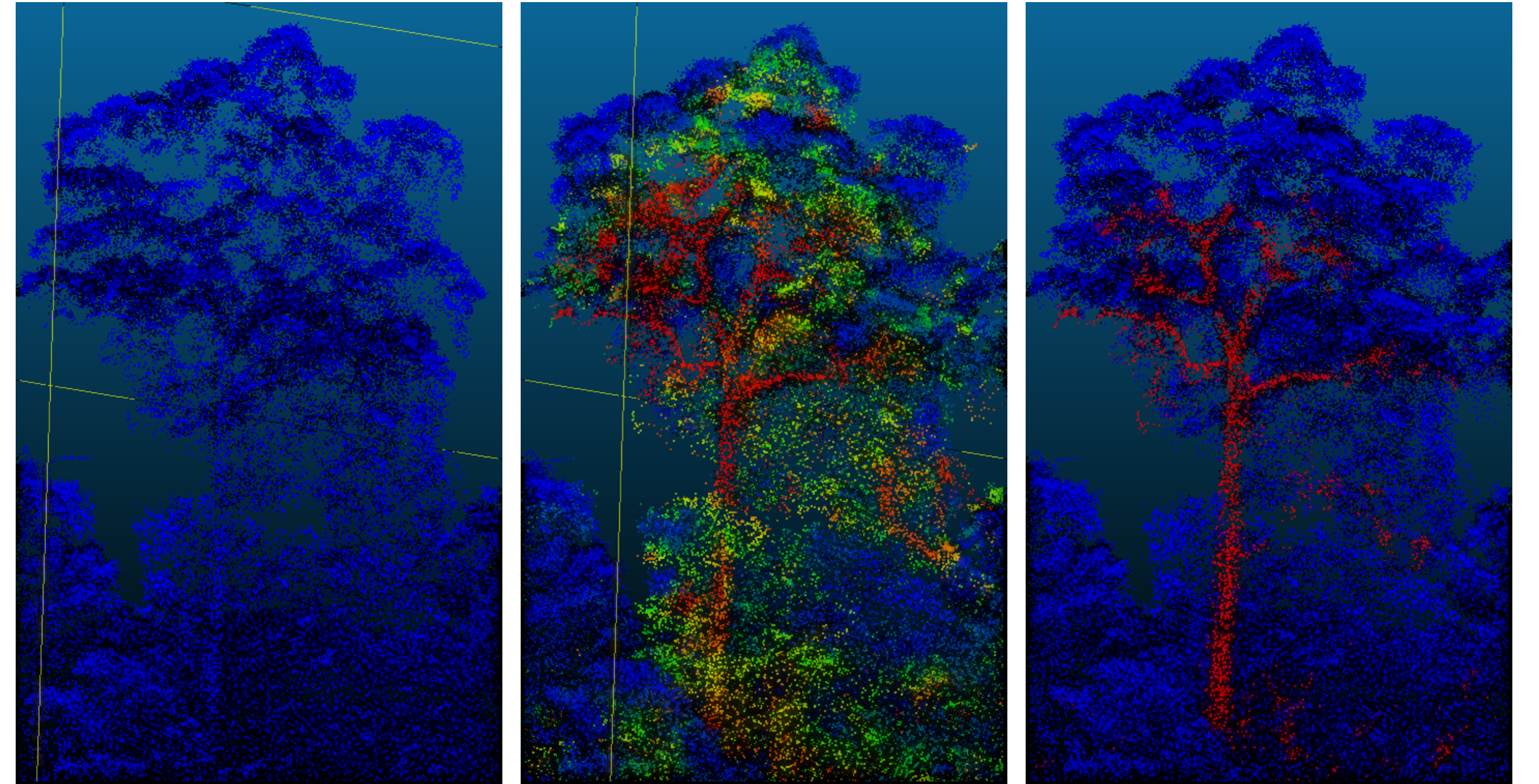
$$L_R(Y_{B_k}) = - \sum y_k \log(\hat{p}_k) + (1 - y_k) \log(1 - \hat{p}_k), \quad y_k \in (B'_{k,0} \cup B_{k,1}). \quad (1)$$

where Y_{B_k} specifies the ground truth label of the batch B_k , $\hat{p} \in [0, 1]$ is the model's estimated probability for the label $y = 1$ and $B'_{k,0}$ is defined as

$$B'_{k,0} = \begin{cases} \text{downsampling}(B_{k,0}, |B_{k,1}|), & \text{if } |B_{k,0}| \geq |B_{k,1}| \\ B_{k,0}, & \text{otherwise.} \end{cases} \quad (2)$$

Results

The issue of class imbalance has been addressed



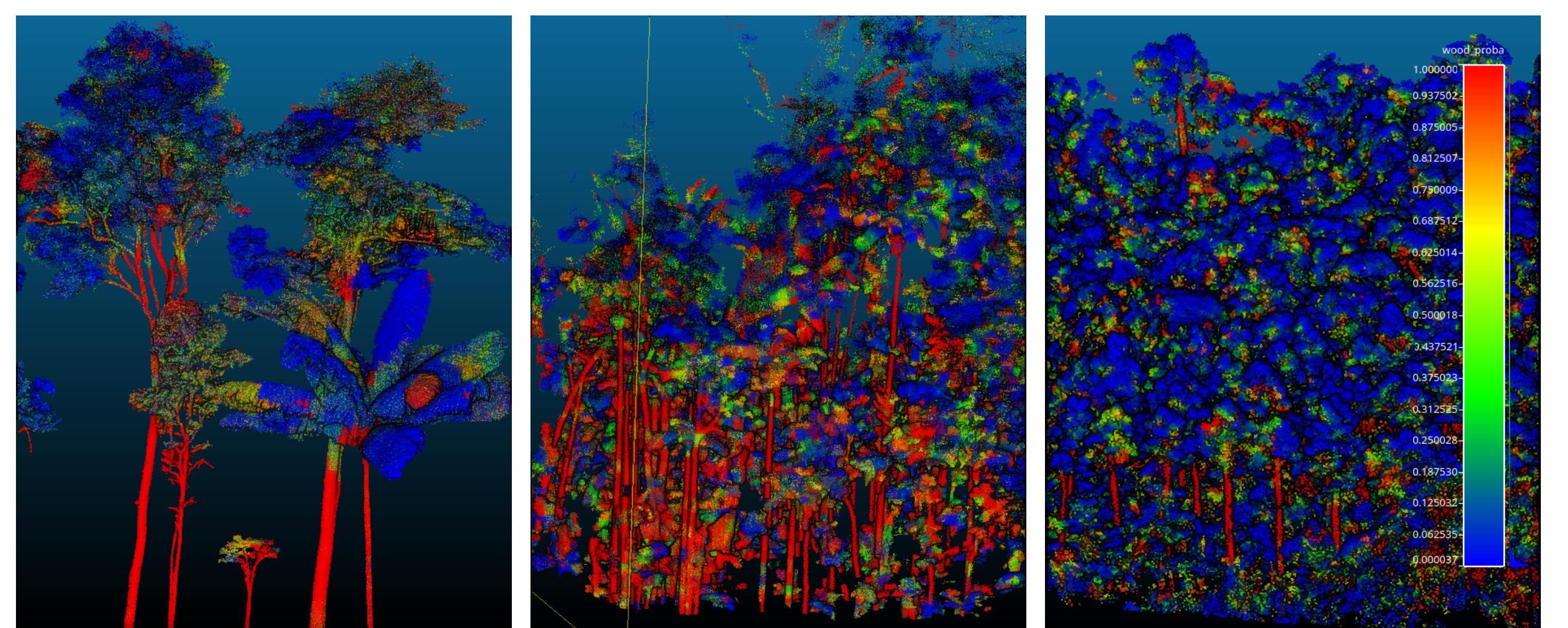
a. FSCT

b. SOUL

c. Ground Truth

Figure 4. Test SOUL on ULS dataset, French Guiana

SOUL excels at discriminating within the canopy



a. Paracou, French Guiana - TLS

b. NSW, Australia - MLS

c. Sandhausen, Germany - ULS

Figure 5. Test SOUL on different LiDAR, different sites.

Methods	Accuracy	Recall	Precision	Specificity	G-mean	BA ¹
FSCT	0.974	0.977	0.997	0.13	0.356	0.554
FSCT + retrain	0.977	1.0	0.977	0.01	0.1	0.505
LeWos	0.947	0.97	0.975	0.069	0.259	0.520
LeWos (SoD ²)	0.953	0.977	0.975	0.069	0.260	0.523
SOUL (focal loss)	0.942	0.958	0.982	0.395	0.615	0.677
SOUL (rebalanced loss)	0.826	0.884	0.99	0.631	0.744	0.757

¹ BA (Balanced Accuracy) $BA = \frac{1}{2}(\text{Recall} + \text{Specificity})$.

² SoD (Significant of Difference).

Table 1. Comparison of different methods

Conclusions

- SOUL** outperforms existing methods in complex forest environments, with generalisation capability across different forest datasets.
- GVD** refines training samples through one partition process.
- Rebalanced loss** resolve the class imbalance issue on forest point cloud.

Perspectives

- Creating a **universal framework** based on SOUL that can effectively handle various types of forest lidar data, including ULS, TLS, MLS, and ALS.
- Extending **SOUL** to other complex lidar scenes beyond forests.

References

[1] Y. Bai, J.-B. Durand, F. Forbes, and G. Vincent. "Semantic segmentation of sparse irregular point clouds for leaf/wood discrimination." 2023.

Acknowledgements & Video

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