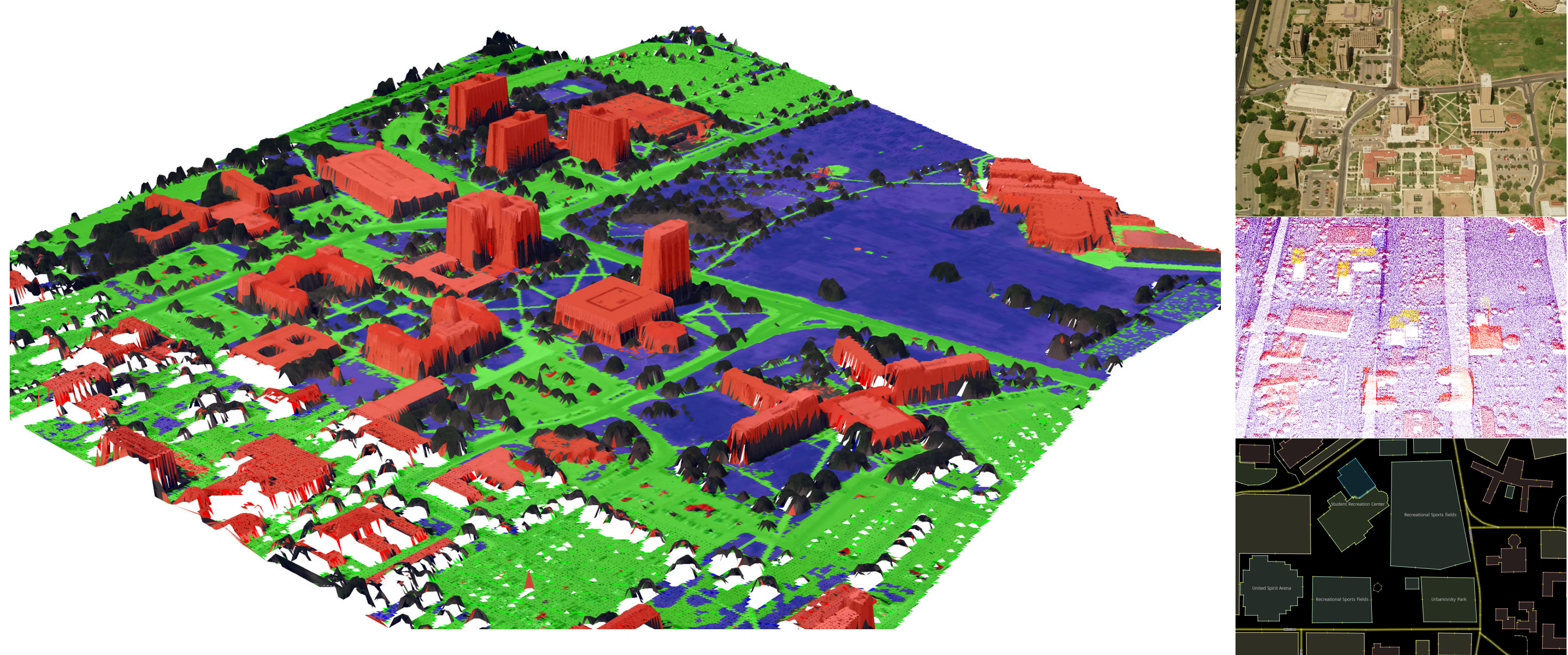


Motivation



Motivation: Semantic information can be easily obtained but is not commonly incorporated into 3D reconstructions.

Goal: Leverage semantic information in 3D scene reconstructions.

Approach: Novel probabilistic model that couples semantic labels and scene reconstructions from multi-modal data.

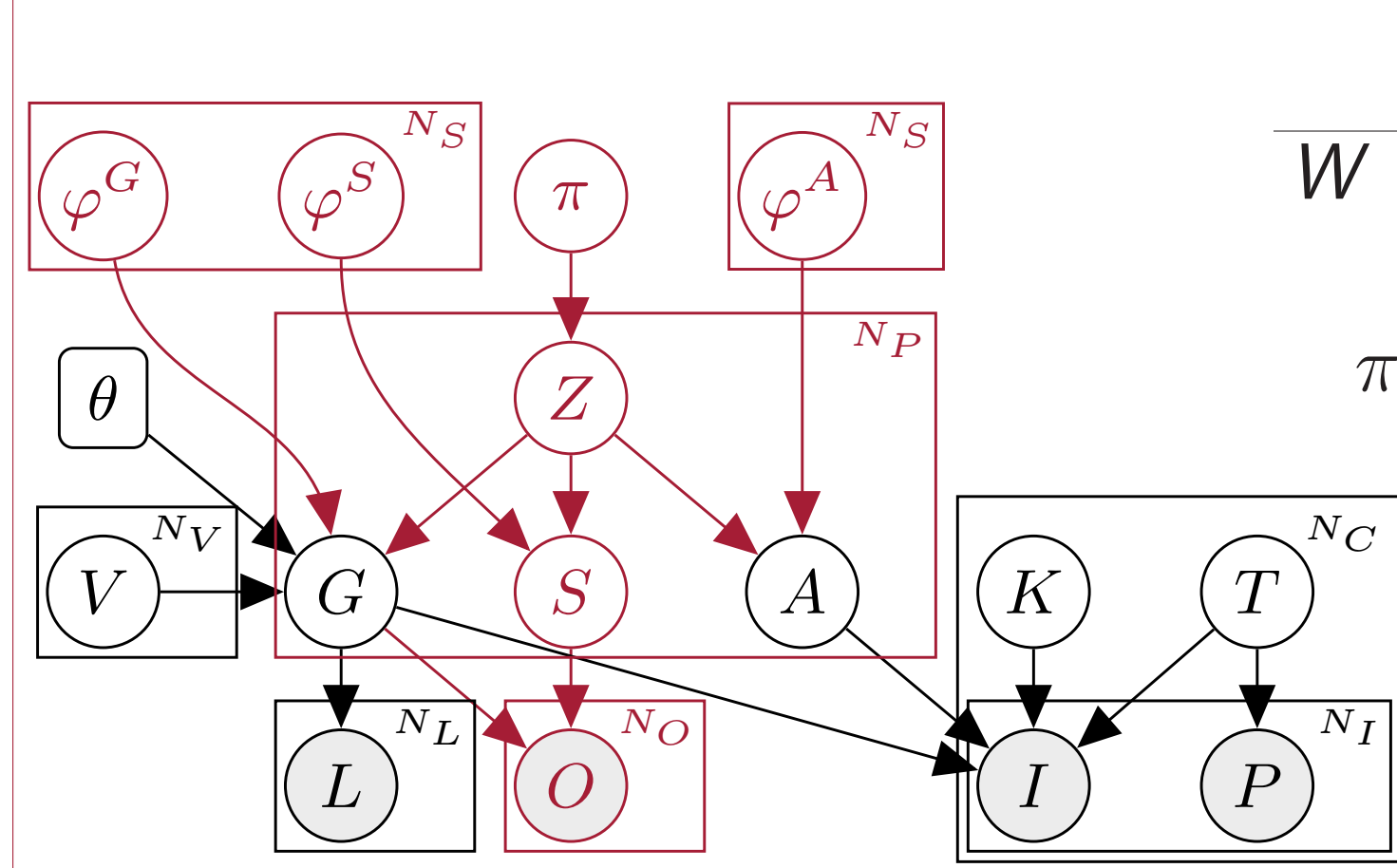
Key Contributions

- ▶ The generative **semantically-aware aerial reconstruction (SAAR)** model.
- ▶ Semantically-consistent aerial reconstructions from **multi-modal data**.
- ▶ The new **Synthetic City (SynthCity)** dataset for quantifying labeling and reconstruction accuracy.

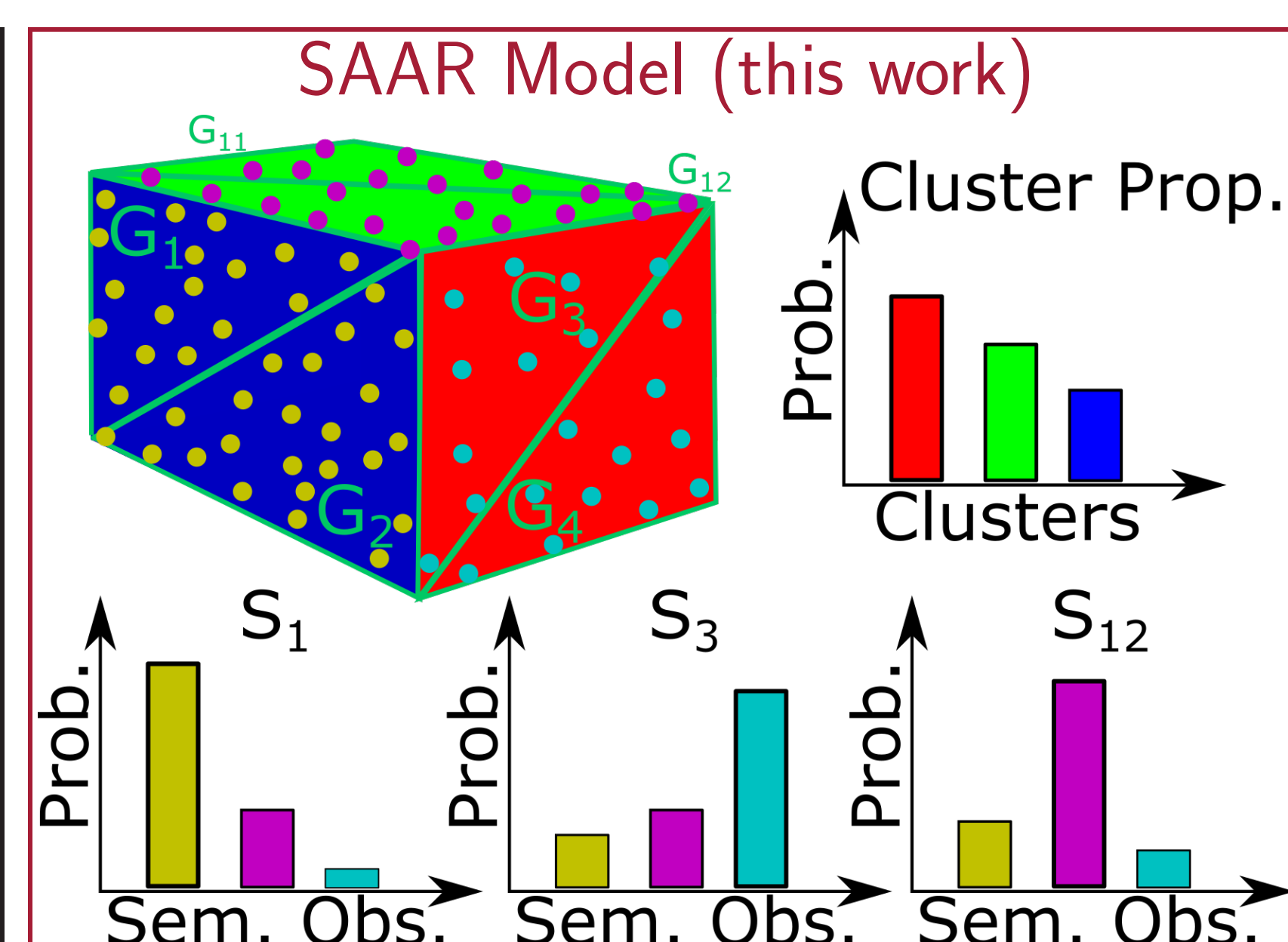
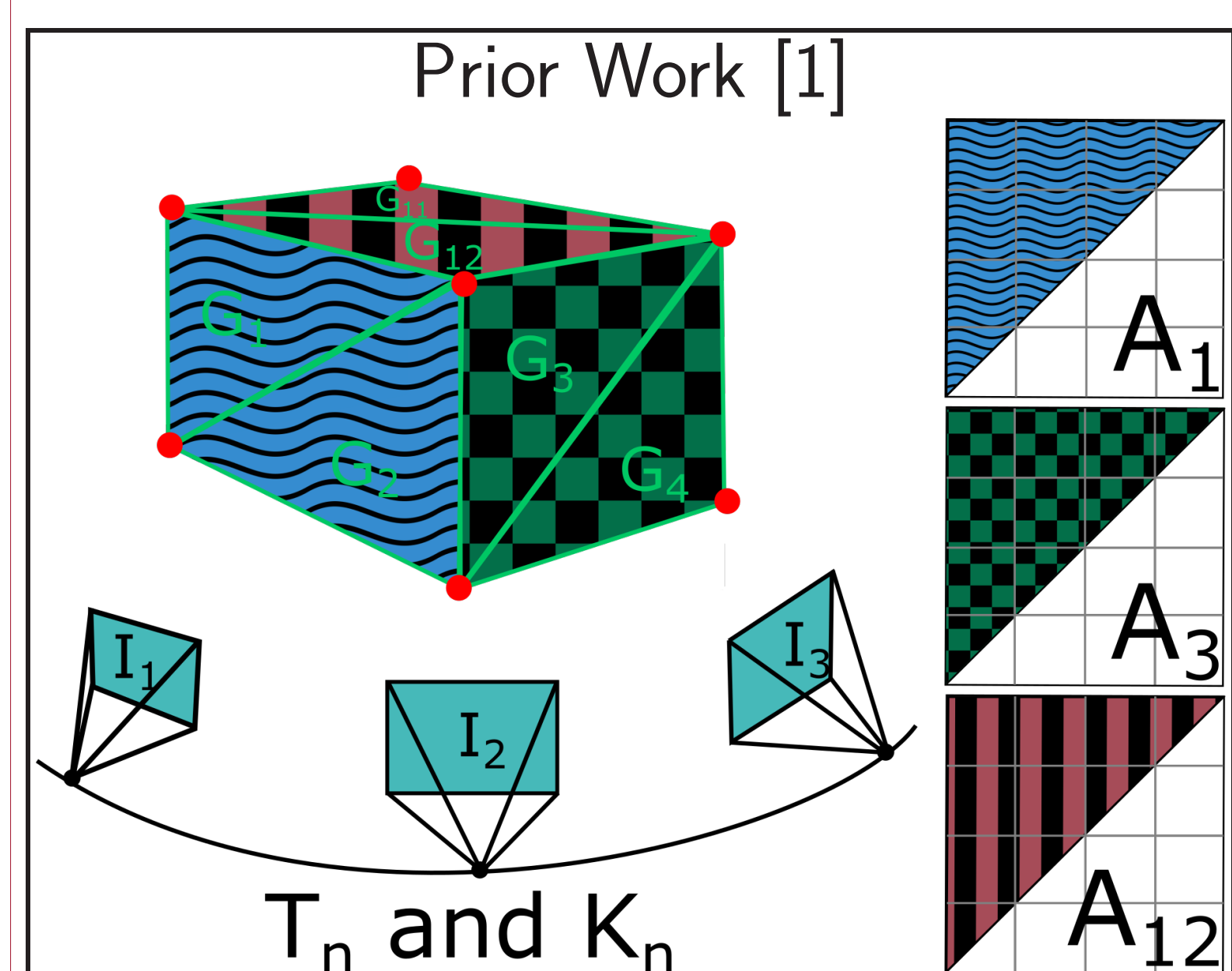
We empirically demonstrate several advantages of the model including:

- ▶ The ability to **handle noisy data** and the ability to **predict missing data**.
- ▶ Evidence of **improved reconstructions** when using semantic information.

Graphical Model Representation



Variable	Description
$\mathcal{W} = \{G, A, S, Z\}$	Primitive's geometry, appearance, semantic category, and cluster assignment
$\pi, \varphi^G, \varphi^A, \varphi^S$	Cluster proportions and parameters
K, T	Camera parameters
L, I, P	LiDAR, images, GPS observations
O	Semantic point cloud observation
V	Primitive vertex location
θ	Connectivity matrix



Joint Probability Distribution:

$$p(\mathbf{L}, \mathbf{I}, \mathbf{P}, \mathbf{O}, \mathbf{T}, \mathbf{K}, \mathbf{V}, \mathbf{W}, \varphi, \pi; \theta) = p(\mathbf{W}, \varphi, \pi | \mathbf{V}; \theta) \prod_{v=1}^{N_V} p(V_v) \prod_{l=1}^{N_L} p(L_l | \mathbf{G}) \times \prod_{o=1}^{N_O} p(O_o | \mathbf{S}, \mathbf{G}) \prod_{c=1}^{N_C} p(T^c) p(K^c) \prod_{n=1}^{N_I} p(I_n^c | \mathbf{G}, \mathbf{A}, K^c, T^c) p(P_n^c | T^c)$$

Structured Prior:

$$p(\mathbf{W}, \varphi, \pi | \mathbf{V}; \theta) = p(\pi) \prod_{k=1}^{N_S} p(\varphi_k) \prod_{m=1}^{N_P} p(Z_m | \pi) p(G_m | \varphi^G, Z_m, \mathbf{V}; \theta) p(S_m | \varphi^S, Z_m) p(A_m | \varphi^A, Z_m)$$

- ▶ Structured prior is a **multi-feature cluster model**.
- ▶ Can be thought of as prior on the parameters of the primitives.

Observation Models

For learning clusters we use:

- ▶ Appearance pixels (3D Gaussian)
- ▶ Pixel location (3D Gaussian)
- ▶ Pixel orientation
 - ▶ Modeled as Tangent space Gaussian (TG) or Manhattan Frame (MF) [2].
- ▶ Semantic observation
 - ▶ Modeled as categorical data. The assignment to primitive is sampled.

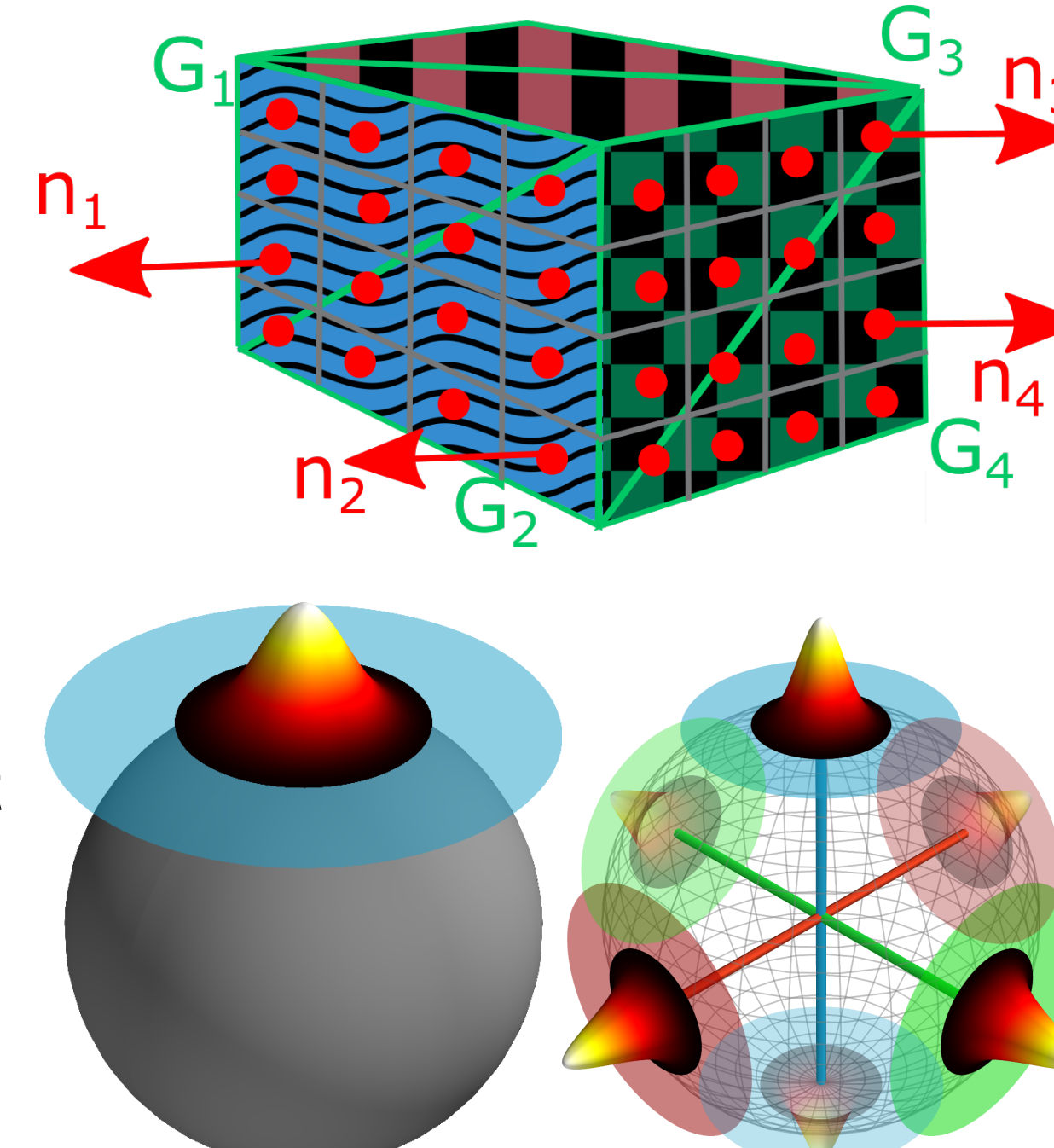
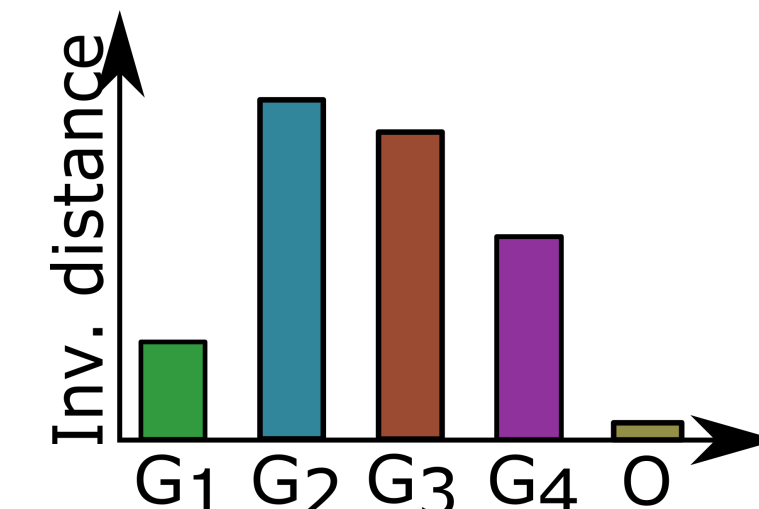
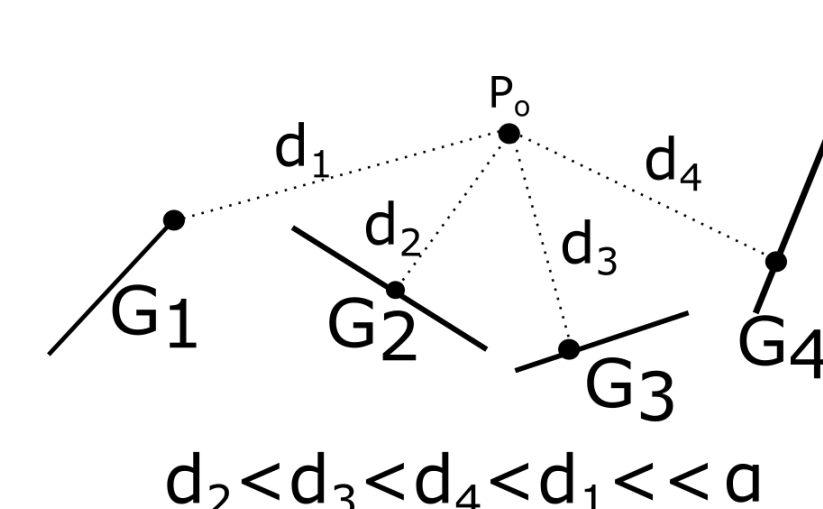
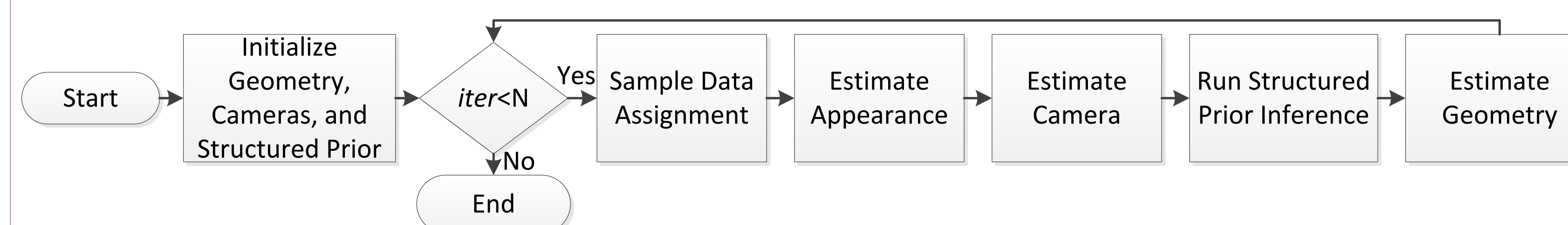


Fig. 1: L-R: Tangent space Gaussian (TG) and Manhattan Frame (MF).

Inference

Full Inference:



Appearance Update:

$$p(\mathbf{A} | \mathbf{I}, \mathbf{G}, \mathbf{K}, \mathbf{T}, \mathbf{Z}, \varphi^A) \propto \prod_{c=1}^{N_C} \prod_{n=1}^{N_I} \prod_{k=1}^{N_S} p(I_n^{n,c} | \mathbf{G}, \mathbf{A}, K^c, T^c) \prod_{m=1}^{N_P} \prod_{i=1}^{N_A} p(A_{m,i} | \varphi^A, Z_m)$$

Geometry Update:

$$p(\mathbf{V}, \mathbf{G} | \mathbf{L}, \mathbf{O}, \mathbf{Z}, \mathbf{S}, \mathbf{T}, \mathbf{K}, \mathbf{A}, \varphi^G; \theta) \propto \prod_{o=1}^{N_O} p(O_o | \mathbf{G}, \mathbf{S}) \prod_{l=1}^{N_L} p(L_l | \mathbf{G}) \prod_{v=1}^{N_V} p(V_v) \times \prod_{c=1}^{N_C} \prod_{n=1}^{N_I} p(I_n^c | \mathbf{G}, \mathbf{A}, K^c, T^c) \prod_{m=1}^{N_P} p(G_m | \varphi^G, \mathbf{V}; \mathbf{Z}, \theta)$$

Structured Prior Inference: Gibbs sampler, alternate label and parameter updates

Label Posterior:

$$p(Z_m = k | \mathbf{Z}_{\setminus m}, \mathbf{G}, \mathbf{A}, \mathbf{S}, \pi, \varphi) \propto p(G_m | \varphi_k^G) p(A_m | \varphi_k^A) p(S_m | \varphi_k^S) \pi_k$$

Parameter Posteriors:

$$p(\pi, \varphi | \mathbf{Z}, \mathbf{G}, \mathbf{A}, \mathbf{S}) \propto p(\pi | \mathbf{Z}) \prod_{k=1}^{N_S} p(\varphi_k^A | A_{I_k}) p(\varphi_k^G | G_{I_k}) p(\varphi_k^S | S_{I_k}), \quad I_k = \{m : Z_m = k\}$$

Synthetic City (SynthCity) Dataset

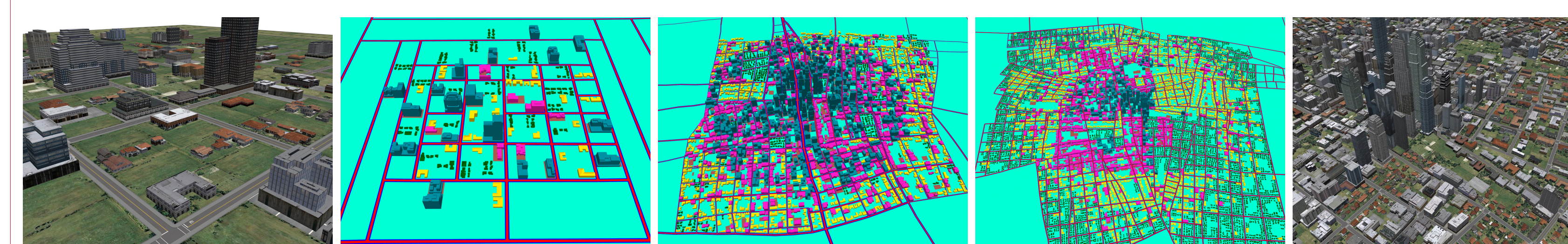


Fig. 2: L-R: View of ToyCity2, ground-truth geometry color-coded according to semantic label (ToyCity2, City3, City1-1), and view of City1-1.

Cluster Results

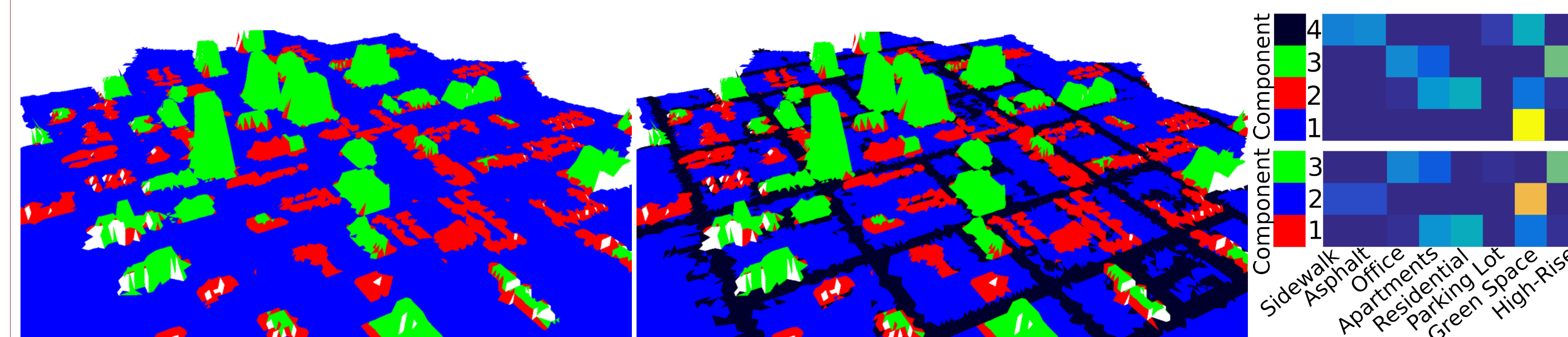


Fig. 3: ToyCity2 clusters. L-R: view of MF-3 and MF-4 (colors indicate cluster assignment); semantic mixture components φ^S . The effect of adding one more cluster is to split ground (MF-3 blue) into ground (MF-4 blue) and roads (MF-4 black).

Predicting Missing Appearance

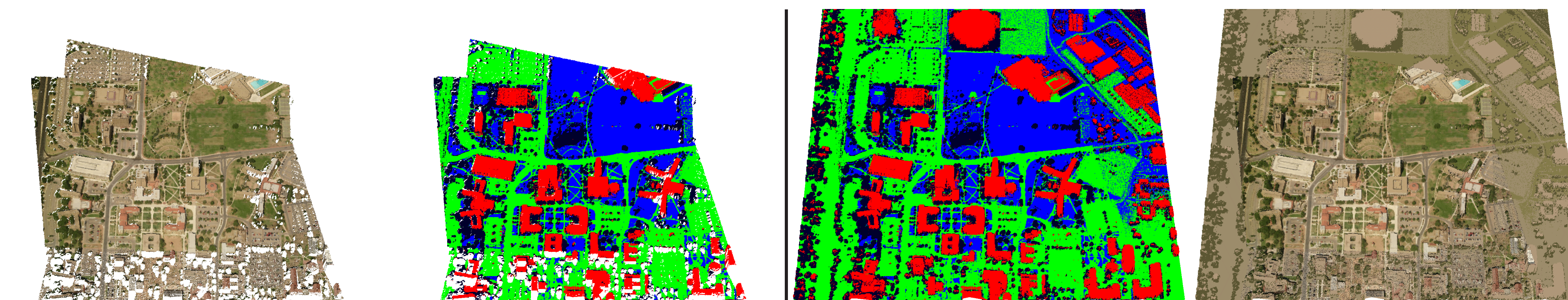


Fig. 4: Left: Visible primitives' appearance and cluster assignment. Right: Cluster assignment and appearance for all primitives. Non-visible cluster assignment based on all available attributes; appearance predicted based on cluster parameters.

Ablation Study SynthCity Toy2

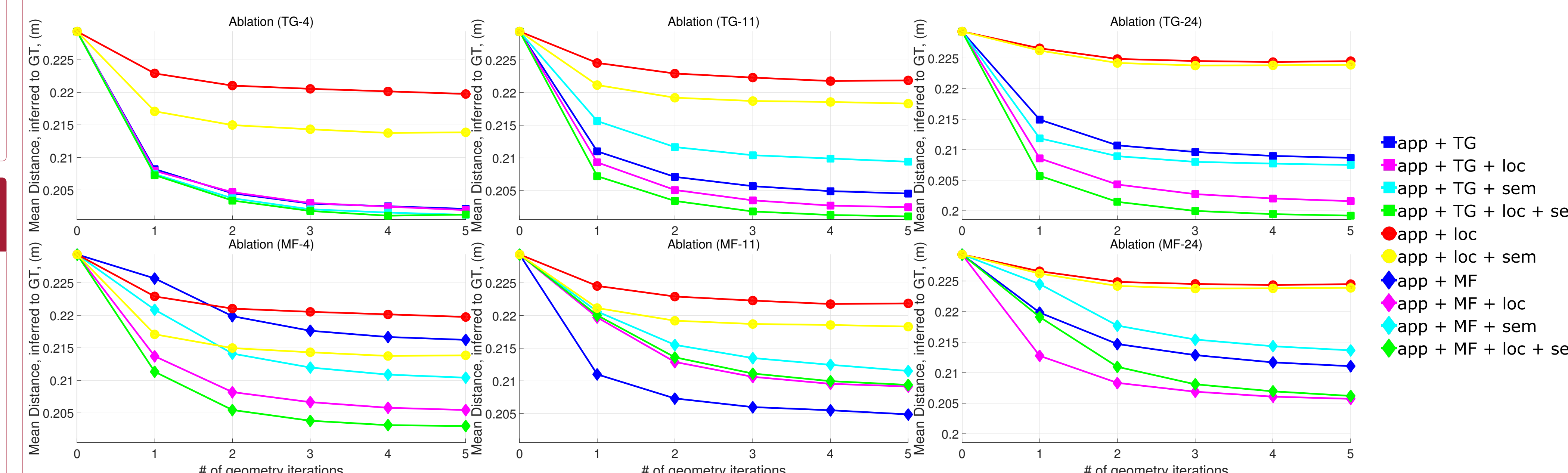


Fig. 5: Columns: Number of clusters (N_S): 4, 11, 24. Rows: TG and MF models (square and diamond markers) respectively; color indicates combination of modalities. Generally, adding more modalities improves reconstructions.

Improved Reconstructions

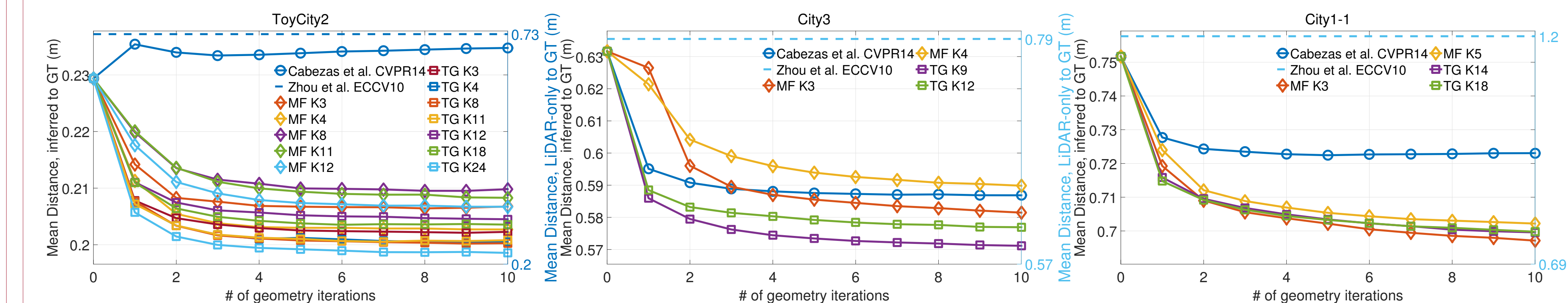


Fig. 6: Mean reconstruction geometry error for three cities of SynthCity under the the baseline model (no semantics) and SAAR (left y-axis); and the LiDAR-only method of [3] (right y-axis).

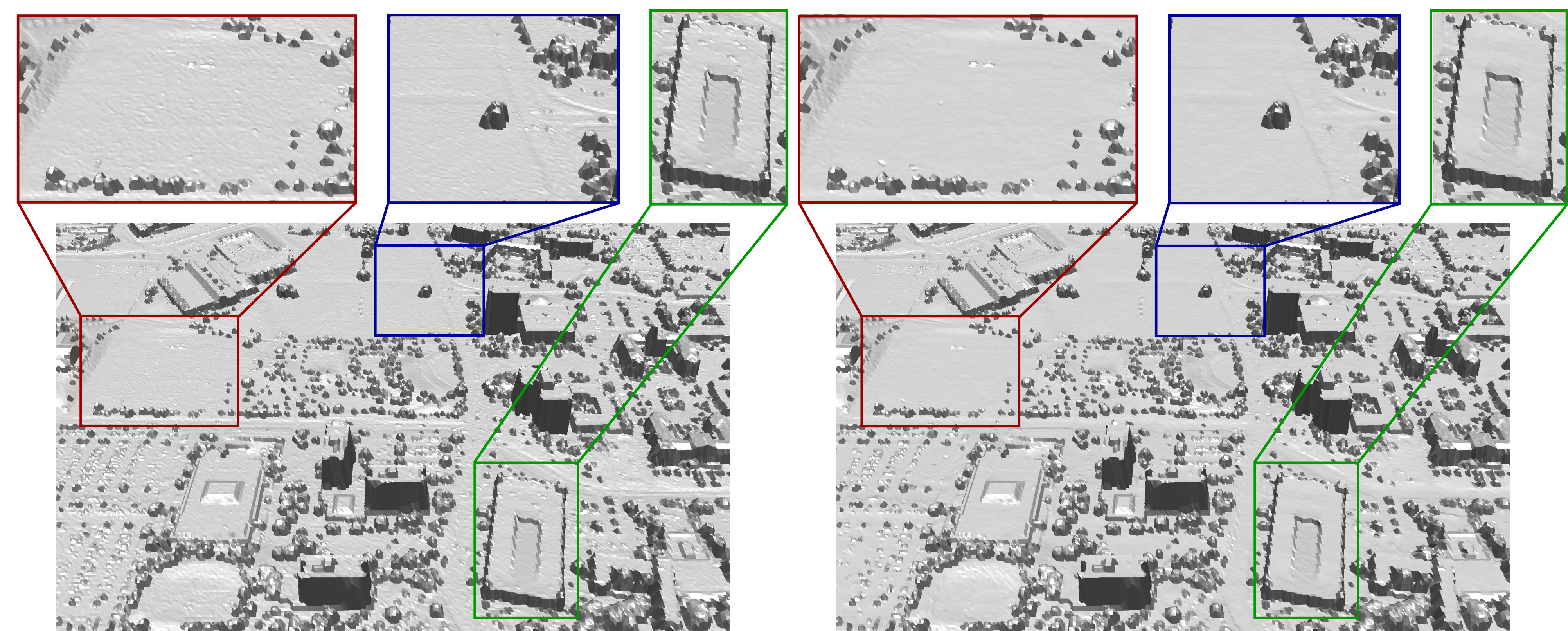


Fig. 7: Lubbock reconstructions. L-R: [1] and SAAR (MF-4). Note the regularized flat horizontal surfaces in SAAR.

Acknowledgments

We thank Sue Zheng, Christopher Dean, and Oren Freifeld for general and helpful discussions. This work has been partially supported by ONR MURI (N00014-11-1-0688) and by VITALITE (ARO MURI W911NF-11-1-0391). We gratefully acknowledge the support of NVIDIA corporation in this research.

- [1] R. Cabezas, O. Freifeld, G. Rosman, and J.W. Fisher III. Aerial Reconstructions via Probabilistic Data Fusion. CVPR, 2014
 [2] J. Straub, G. Rosman, O. Freifeld, J. J. Leonard, and J.W. Fisher. A mixture of Manhattan frames: Beyond the Manhattan world. CVPR, 2014
 [3] Q.Y. Zhou, U. Neumann. 2.5D Dual Contouring: A Robust Approach to Creating Building Models from Aerial LiDAR Point Clouds. ECCV, 2010