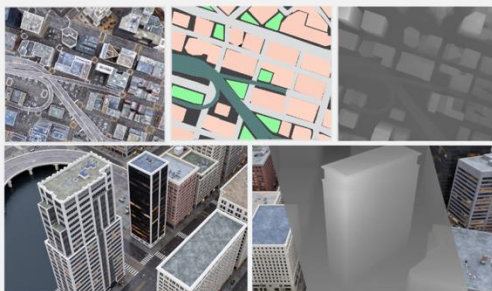


1. Introduction of our work



Task: Generate 3D urban scene on a given satellite image.

Why important: Games, urban simulation, and mapping services; transform real-world into digital twins.

2. How does previous work do?

(1) Geometry Prior-based Methods:

- InfiniCity
- CityDreamer
- GaussianCity

✗ Lack style diversity and texture quality

(2) Image Prior-based Methods:

- CAT3D
- DimensionX
- DreamScene

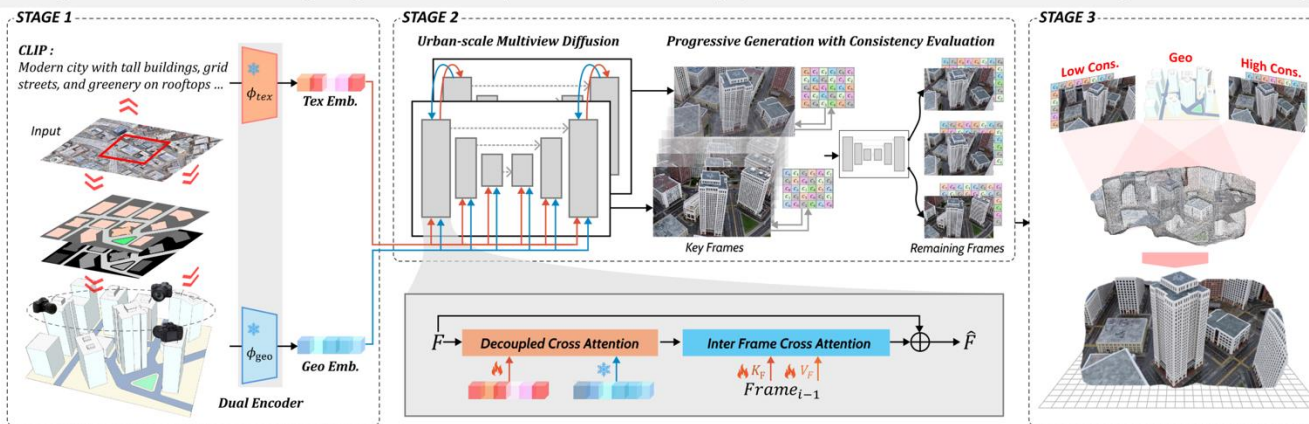
✗ Lack geo. consistency in large scenes

Motivation: How to achieve high texture quality while maintain geometric consistency?

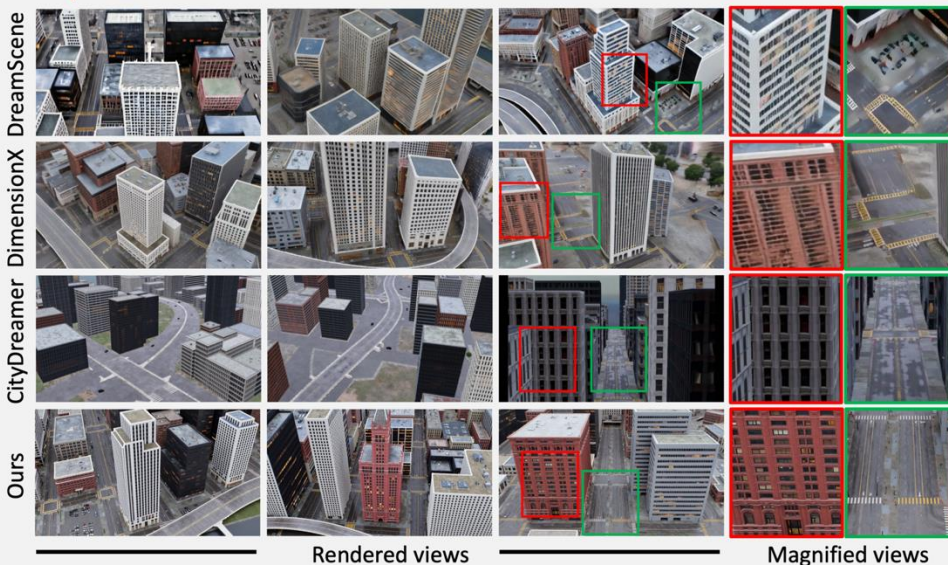
3. Our methods

Pipeline overview: Scene Initialization -> Multiview images Generation -> Robust Reconstruction

Insights: Multiview images gen. with *city-level consistency*; Robust 3D reconstruction on *generated images*



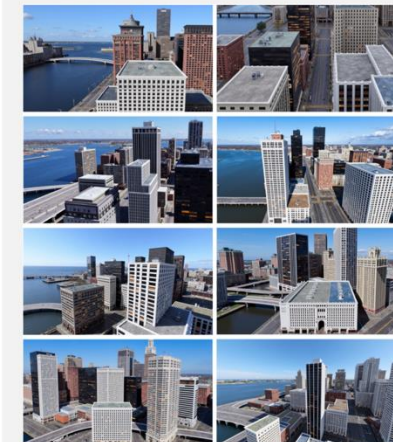
4. Experimental Results



This work was supported in part by the National Key R&D Program of China (Grant No.2023YFF0725001), in part by the National Natural Science Foundation of China (Grant No.92370204), in part by the Guangdong Basic and Applied Basic Research Foundation (Grant No.2023B1515120057), in part by the Education Bureau of Guangzhou.

5. Applications

Example: Make a city in Blender.



Dataset: CityVista, consisting of 500 high-quality city scenes.

Metrics: Texture quality & Geometric consistency.

Qualitative: Our method produces *higher-quality* 3D cities with *better consistency* compared with the baselines.

Quantitative: MagicCity outperforms the baselines *across all metrics*.

	CityDreamer	DimensionX	DreamScene	Ours
FID	155.390	126.890	104.627	86.096
KID	0.251	0.175	0.125	0.087
NIQE	8.632	6.595	6.018	4.553
BRISQUE	86.773	70.207	30.311	28.018
DE	0.157	-	0.223	0.137
CE	0.083	-	0.371	0.072

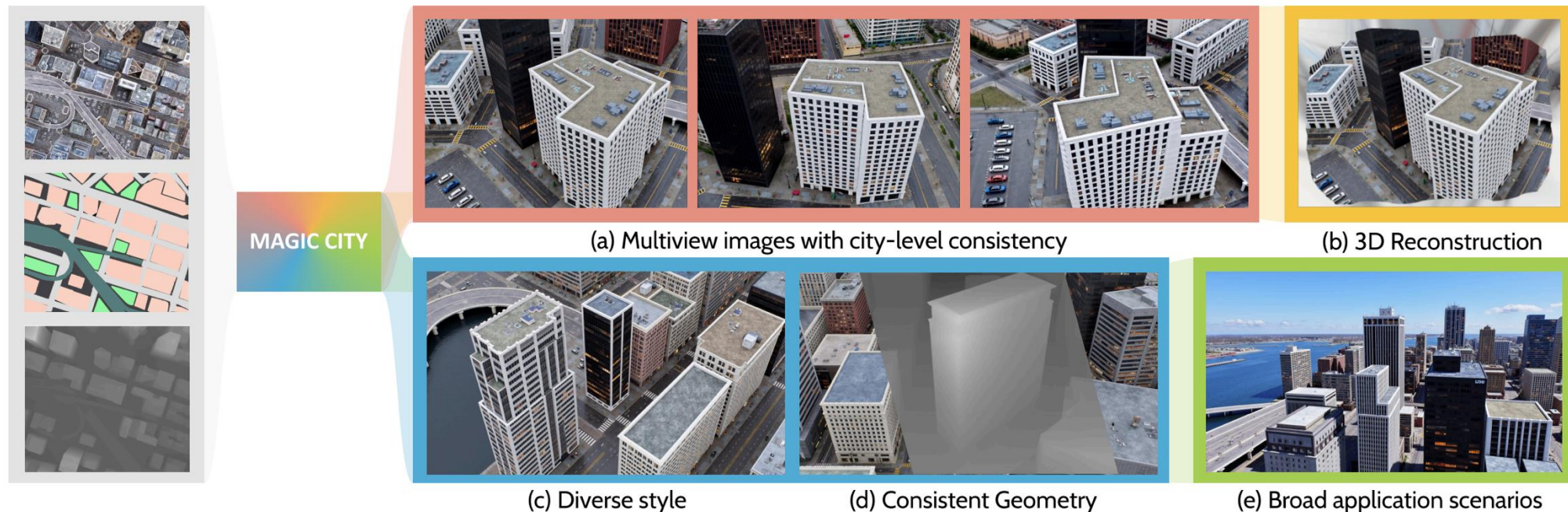
MagicCity: Geometry-Aware 3D City Generation from Satellite Imagery with Multi-View Consistency

➤ Motivation:

- Generating 3D cities supports autonomous driving simulations and model training.
- However, traditional models struggle to generate large scenes with high consistency.

➤ Achievements:

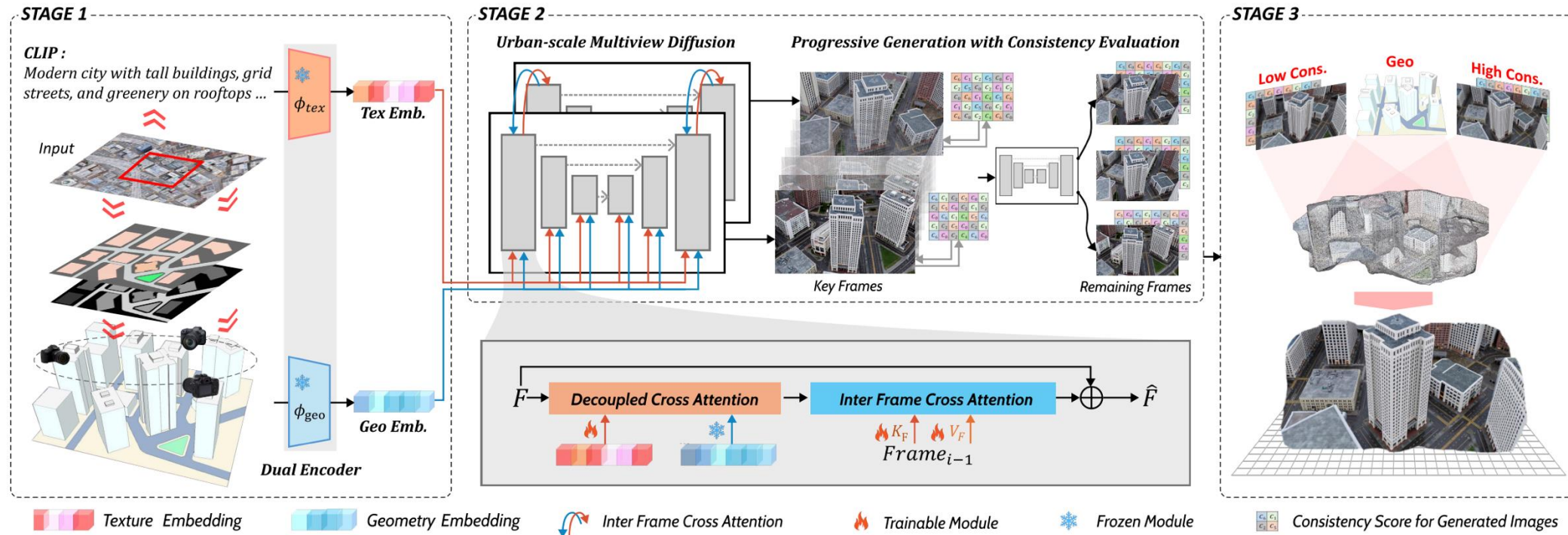
- Given satellite input, our method generates multi-view images with city-level consistency.
- These images are then fed into a robust reconstruction pipeline to generate a 3D city.
- Our approach achieves diverse style generation while maintaining geometric consistency across views.



MagicCity: Geometry-Aware 3D City Generation from Satellite Imagery with Multi-View Consistency

➤ Key Contributions :

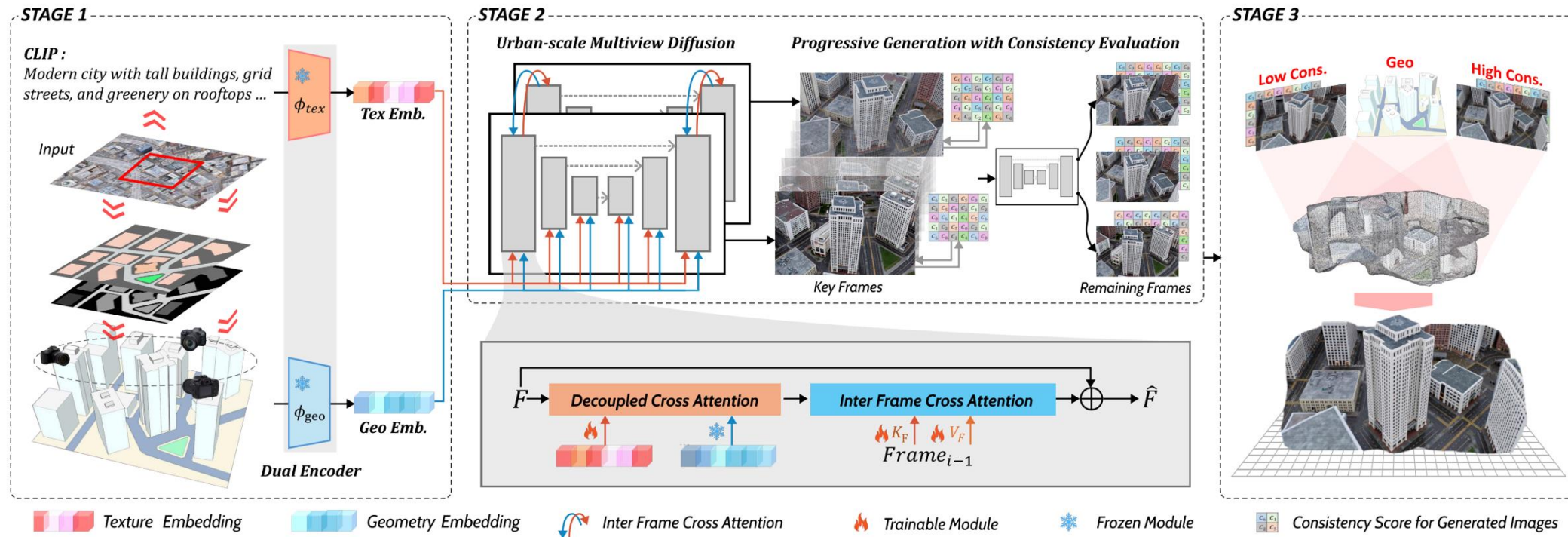
- We introduce **MagicCity**, a novel framework to generate photorealistic 3D cities from satellite imagery while **maintaining scene-level geometric consistency**.
- We propose a city-scale **multi-view** diffusion model that generates **3D-consistent images** by incorporating explicit geometric constraints.
- We develop a **robust 3D Gaussian Splatting strategy** for synthesizing detailed 3D reconstructions from generated multi-view images.



MagicCity: Geometry-Aware 3D City Generation from Satellite Imagery with Multi-View Consistency

➤ Stage 1. Scene Initialization and Dual Encoding

- **Input:** Satellite images (x, y, r, g, b)
- **Scene Initialization:** Segmentation+ Depth maps \rightarrow 3D volume (x, y, z, r, g, b, s)
- **Dual Encoder:**
 - **Texture:** CLIP \rightarrow semantic tokens \rightarrow texture features (f_{tex})
 - **Geometry:** 3D volume \rightarrow multi-view renders \rightarrow geometric features (f_{geo}^i)



MagicCity: Geometry-Aware 3D City Generation from Satellite Imagery with Multi-View Consistency

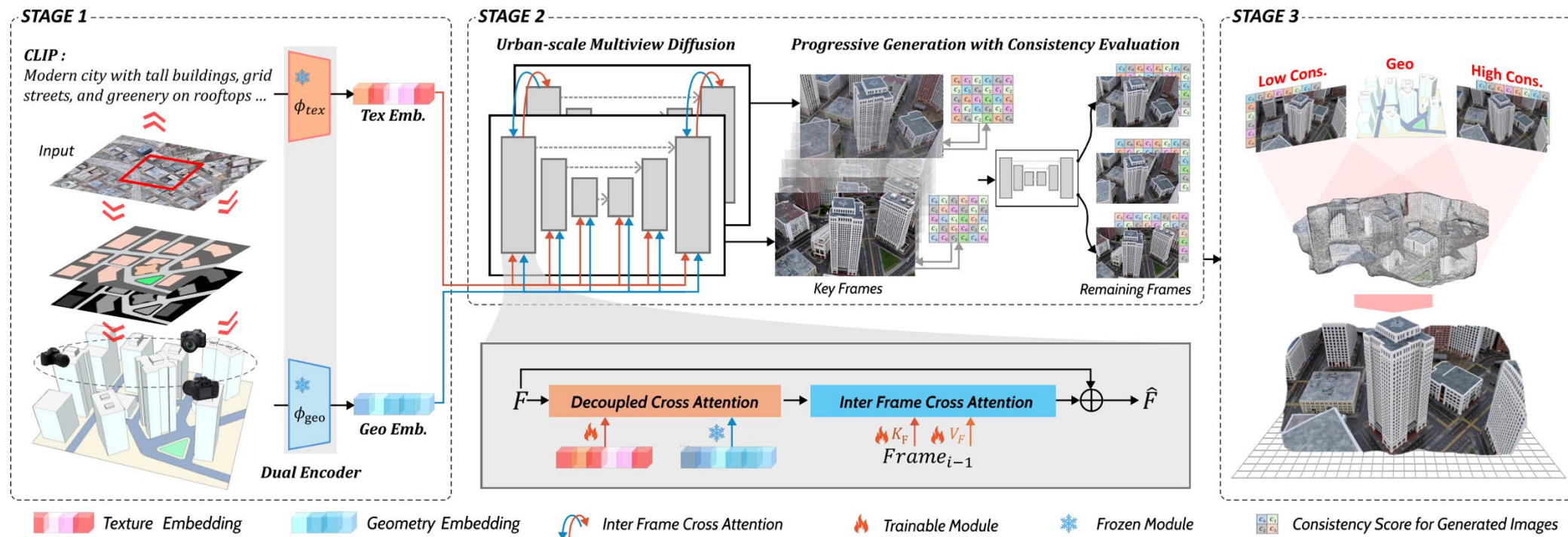
➤ Stage 2. City-scale Multi-view Generation with Consistency Evaluation

➤ **Goal** : Generate **multi-view images** with **city-level consistency**

➤ (1) Dual Embedding Injection: $\tilde{F}_i = F_i + \mathcal{A}(F_i, f_{tex}) + \mathcal{A}(F_i, f_{geo}^i)$

➤ (2) Inter-Frame Cross-Attention: $M_i = \sum_{l \neq i} \text{softmax}(W_q \tilde{F}_i \cdot W_k \tilde{F}_r^T) \cdot W_v \tilde{F}_r$

➤ (3) Consistency Evaluation: $C_i^k = \frac{1}{|V_i|} \sum_{j \in V_i} \cos(f_i^k, f_i^j)$

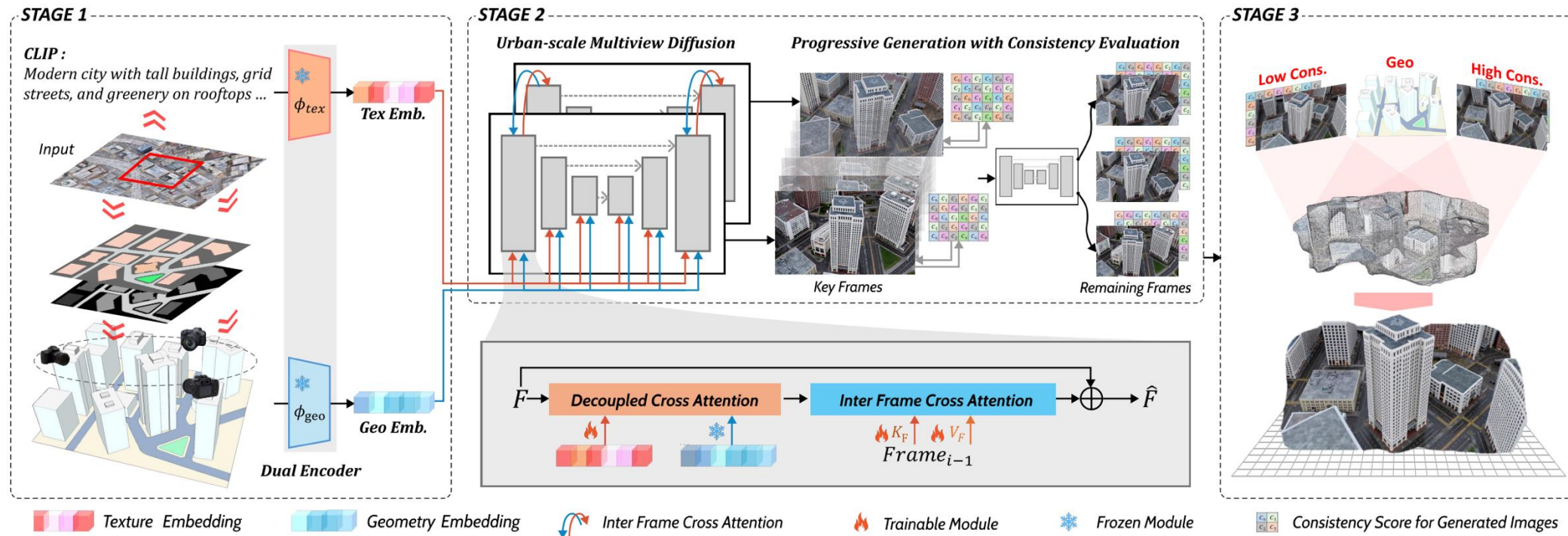


MagicCity: Geometry-Aware 3D City Generation from Satellite Imagery with Multi-View Consistency

➤ Stage 3. Consistency Score-guided 3D Reconstruction

- Challenge: Even SOTA video generation models **lack pixel-level consistency** → poor 3DGS
- Reconstruct 3D cities guided by consistency scores
- Prioritize colors from **high-confidence pixels** or images

- Point Cloud Initialization:
$$c_p = \frac{\sum_k (C_i^k \cdot c_k)}{\sum_k C_i^k}$$
 Optimization:
$$L_p = L_{\text{render}}^p \cdot C_p$$



MagicCity: Geometry-Aware 3D City Generation from Satellite Imagery with Multi-View Consistency

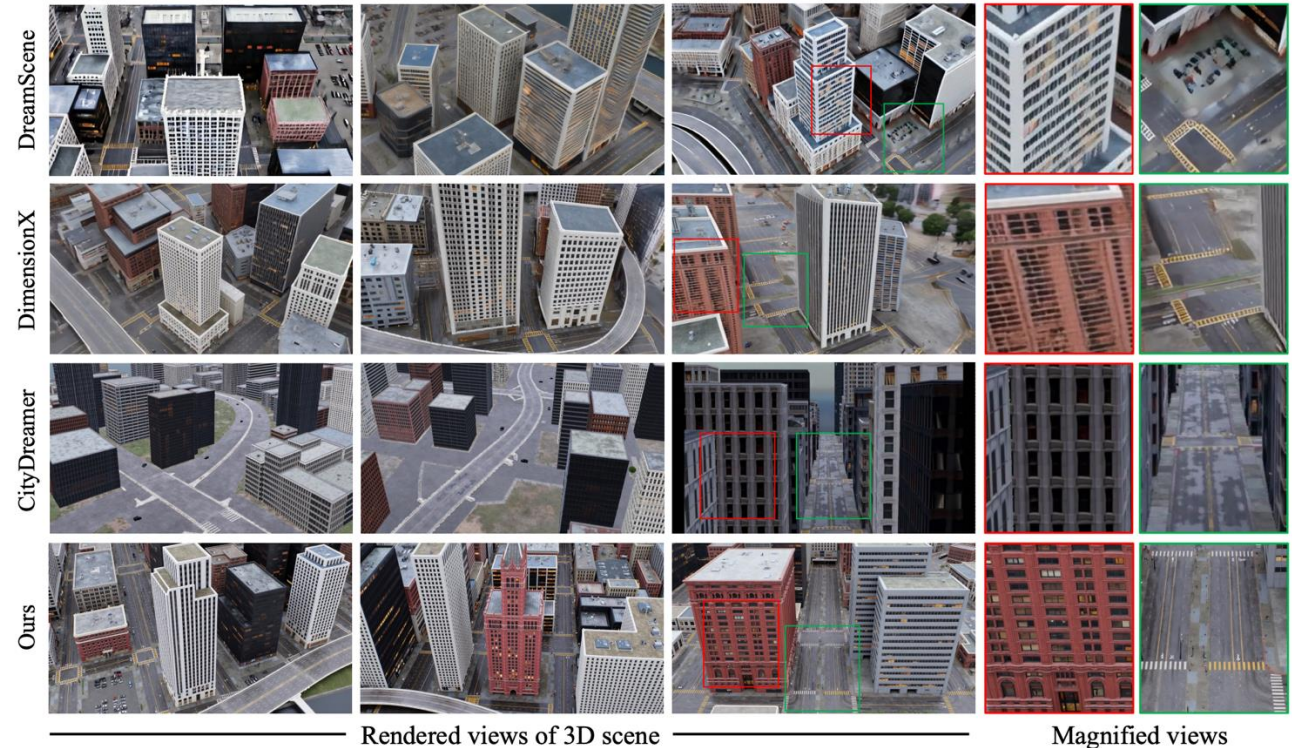
Results :

1. Qualitative Comparison

- Superior structure preservation compared to competitors;
- More realistic textures for buildings and ground details;
- Rich variety without synthetic artifacts;

2. Quantitative Evaluation

- Distribution Metrics: Lowest FID (86.096) and KID (0.087)
- Perceptual Quality: Best NIQE (4.553) and BRISQUE (28.018)
- Geometric Accuracy: Lowest Depth Error (0.137) and Camera Error (0.072)



Method	FID ↓	KID ↓	NIQE ↓	BRISQUE ↓	DE ↓	CE ↓
CityDreamer [38]	155.390	0.251 ± 0.012	8.632 ± 0.709	86.773 ± 11.492	0.157	0.083
DimensionX [35]	126.890	0.175 ± 0.006	6.595 ± 0.425	70.207 ± 7.157	-	-
DreamScene [17]	104.627	0.125 ± 0.002	6.018 ± 0.671	30.311 ± 11.732	0.223	0.371
Ours	86.096	0.087 ± 0.001	4.553 ± 0.412	28.018 ± 5.634	0.137	0.072