

## 1 Introduction

**Task** Generate 3D urban scene on a given or predicted geometry and render arbitrary 2D views with robust consistency



### Why 3D generation?

- Consistency naturally holds
- Do not need preset trajectory

### Why diffusion models instead of GANs?

- Better performance
- Stability during training

## 2 Related Work

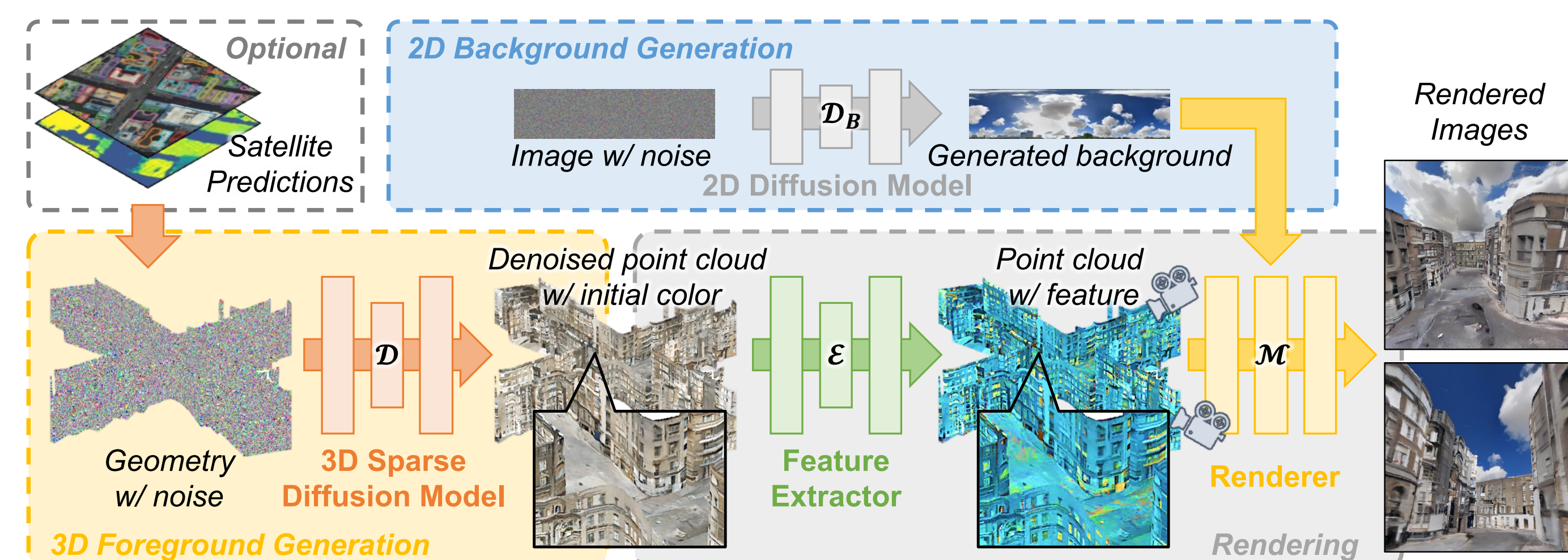
### Foundation work

- Diffusion models
- Point-NeRF
- Minkowski Engine

### Baselines w/ different generative models

- **Sat2Vid**: 3D GAN-based method
- **InfiniCity**: 2D GAN-based method
- **MVDiffusion**: 2D diffusion-model-based method

## 3 Method

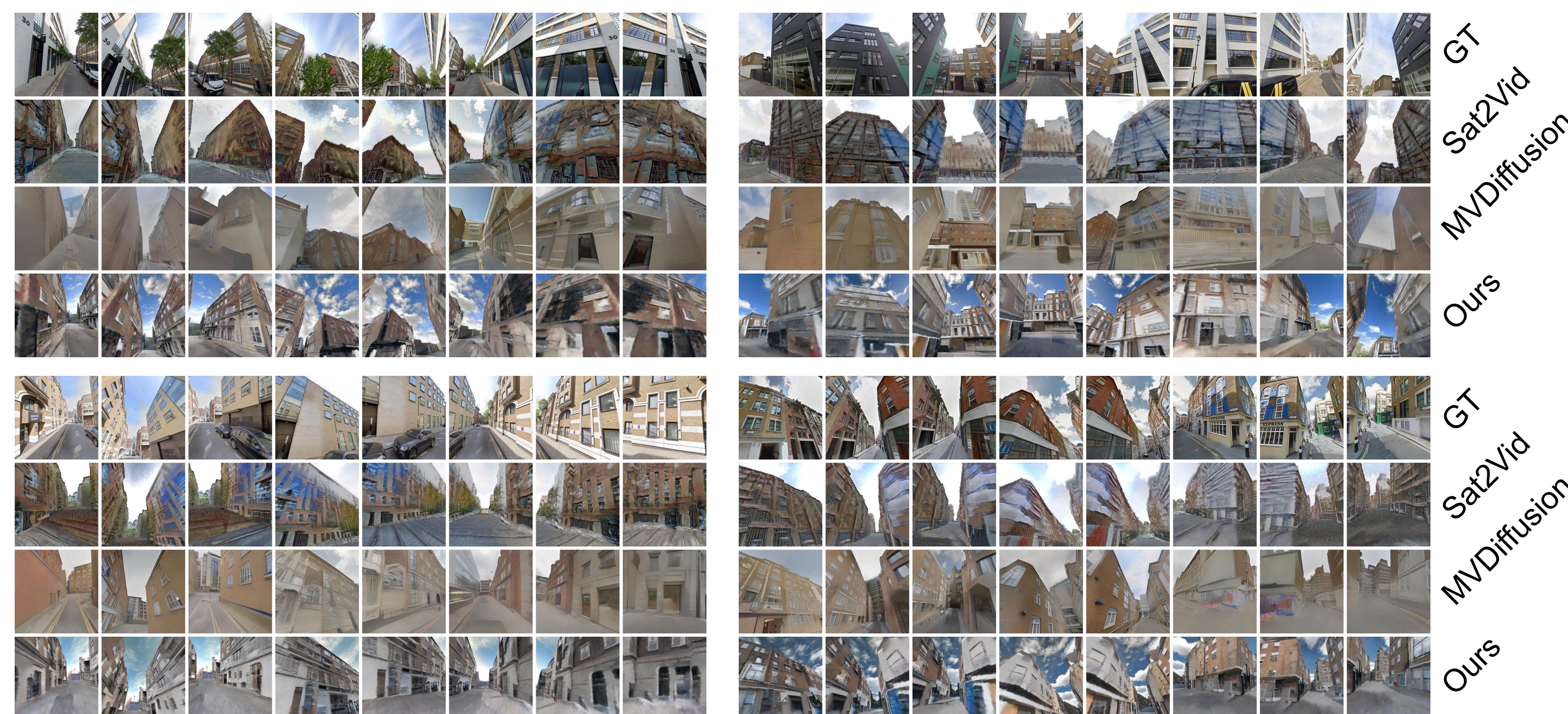


## 4 Experiment

### Baseline comparison

- HoliCity dataset
- GT geometry
- Various metrics

Method / Metric	FVD↓	KVD <sub>×100</sub> ↓	FID↓	KID <sub>×100</sub> ↓	PSNR↑	SSIM↑	LPIPS↓	User study
Sat2Vid	37.06	4.03±0.05	137.84	13.76±0.10	25.25	0.741	0.252	2.92%
InfiniCity	-	-	108.47	8.40±0.10	-	-	-	-
MVDiffusion	22.79	2.36±0.03	<b>50.78</b>	<b>4.14±0.07</b>	17.56	0.593	0.259	15.62%
<b>Ours</b>	<b>20.30</b>	<b>1.90±0.03</b>	71.98	5.91±0.06	<b>31.54</b>	<b>0.956</b>	<b>0.237</b>	<b>81.46%</b>



### Ablation study

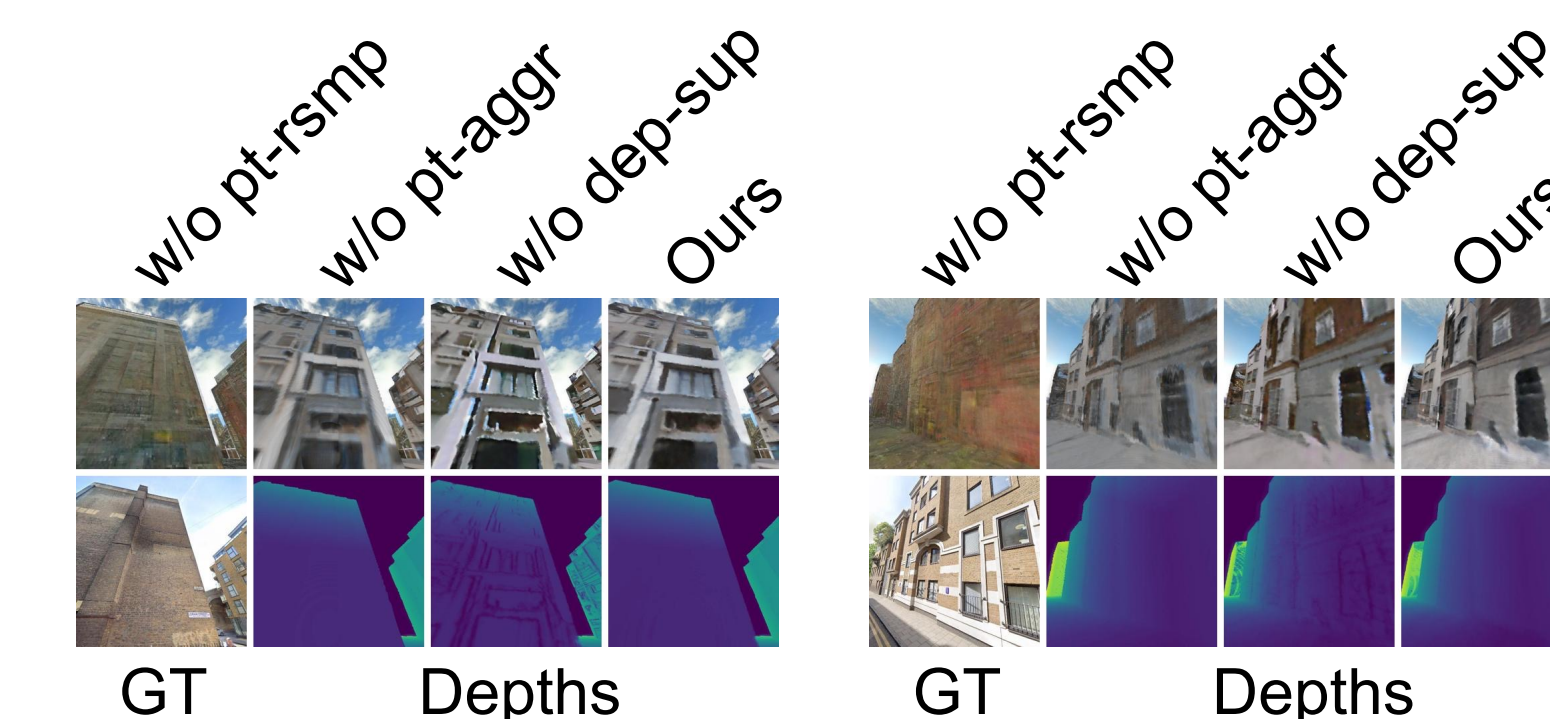
- w/o point resampling
- w/o point aggregation
- w/o depth supervision

w/o & w/ point resampling point weights

Exemplary scene used for training

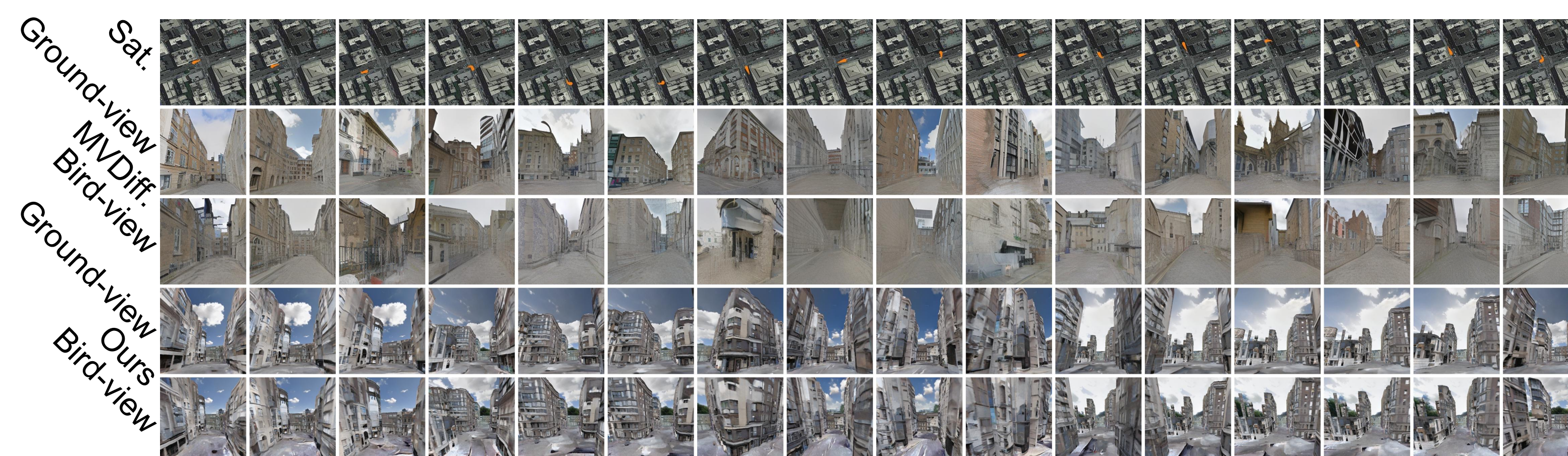


Variant / Metric	FID ↓	KID <sub>×100</sub> ↓	Dep. RMSE
w/o pt-rsmp	131.38	12.66±0.12	-
w/o pt-aggr	85.58	7.79±0.08	3.22
w/o dep-sup	80.40	7.22±0.08	3.44
<b>Ours</b>	<b>71.98</b>	<b>5.91±0.06</b>	<b>3.07</b>



### Model generalization

OmniCity dataset, long-seq generation on predicted geometry



## 5 Conclusion

### Contributions

- 3D sparse diffusion models
- Integrated with neural rendering
- Photorealism & robust consistency
- Large-scale 3D scene generation

### Future directions

- 3D sparse latent diffusion models
- Advanced scene representation
- Conditional generation

arXiv



Code



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