Investigating Generalized Strategy for Single-Image Satellite Super-Resolution Using Deep Learning



Sandeep Kumar Jangir, Reza Bahmanyar

Remote Sensing Technology Institute, German Aerospace Centre (DLR), Germany sandeep.jangir@dlr.de, reza.bahmanyar@dlr.de

ESA - LIVING PLANET SYMPOSIUM

Why Super-Resolution?

- Enhances spatial resolution of satellite images
- Improves remote sensing applications (e.g., object detection, segmentation)
- Overcomes limitations of low-resolution sensors and environmental constraints

Challenges in Singe Image Satellite SR

- Domain gaps between sensors and GSDs
- Traditional methods (interpolation, wavelet, sparse representation) lack robustness
- Deep learning needs LR/HR pairs for training and risks hallucinations
- Difficulty generalizing to unseen low-resolution satellite data

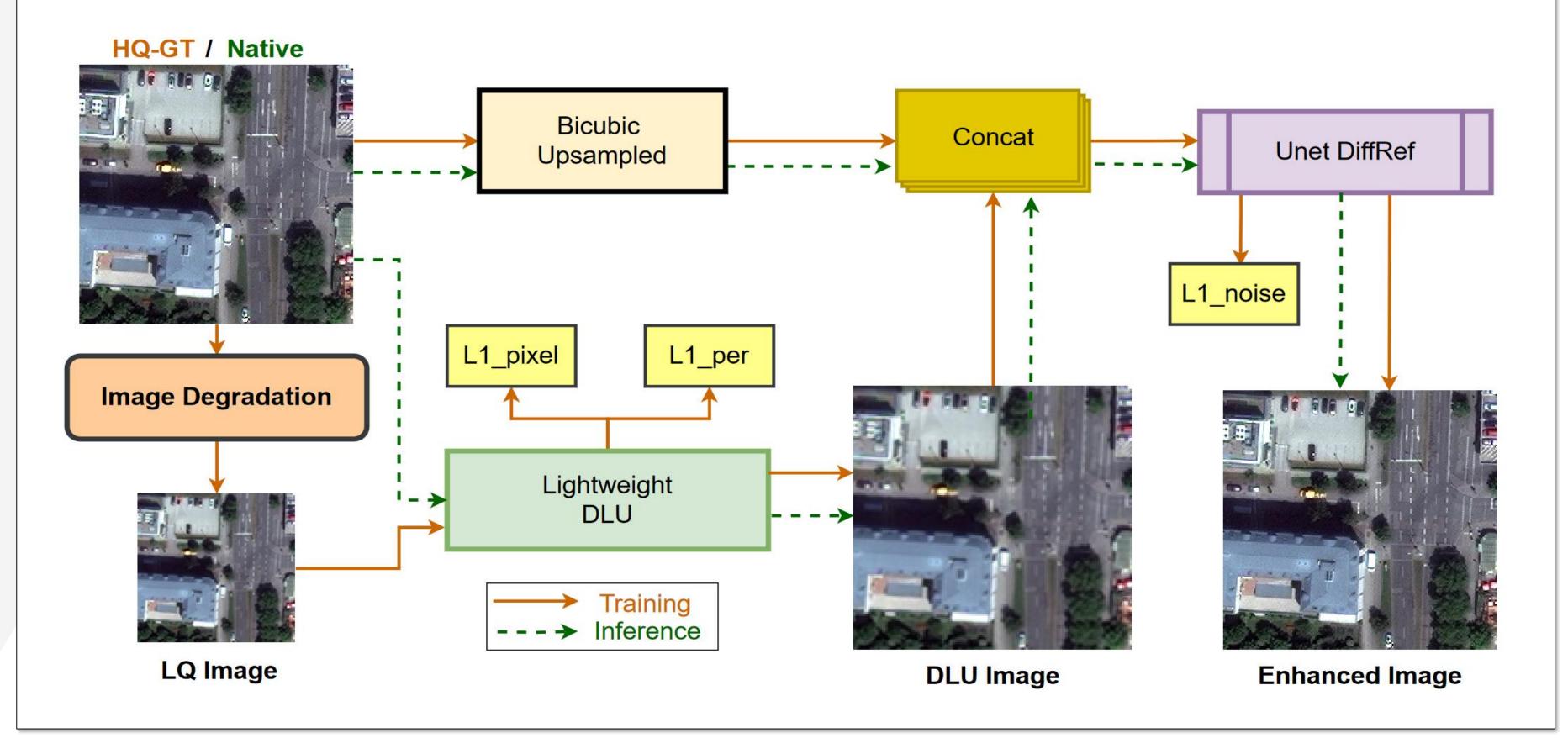
Impact

- Addresses domain gaps in SR
- X2 upscaling minimizes hallucination while improving clarity
- Enhances monitoring, planning, agriculture with minimal detail risks
- Provides robust, generalized SR for diverse low-resolution imagery

Bicubic

Our Approach: U2D2 Framework

- Modular pipeline: Deep Learning Upsampler (DLU) + Diffusion-based Refinement
- Trained on high-resolution aerial/satellite images (GSD < 1 m) for X2 upscaling
- Generalizes to low-resolution Sentinel-2 and similar images



Vehicle Detection

Metrics

• Confusion plot of DINO-OBB comparing results from four SR methods, with a 0.3 confidence threshold and 50% IoU for TP detection.

ESRGAN

RealESRGAN

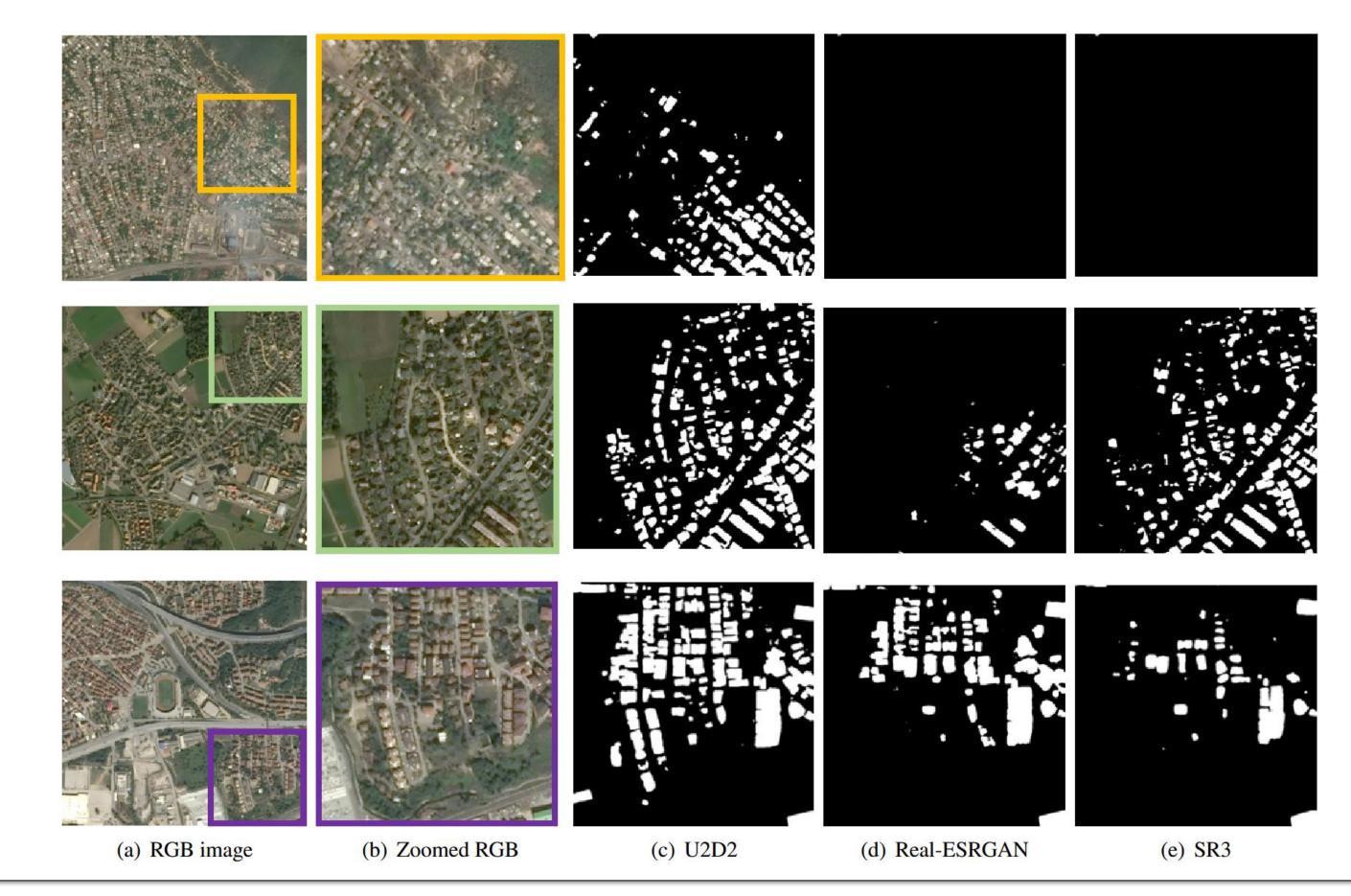
SR3

U2D2

	AP ₅₀ ↑	25.4508	22.5152	26.8578	62.2921	50.4800	68.6954
	TP / TP _{OBB} (+-10°) ↑	73.5007	74.5914	73.6375	78.2391	71.5581	80.2761
_	Bicubic U2D2)2	Real-ESRGAN		SR3	
(a)				0.53 0.42		qai	0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
(b)	0.35						

Building Segmentation

• Building segmentation results from HRNet applied to three SR SPOT scenes, upsampled from 1.2 m to 60 cm GSD using Real-ESRGAN, SR3, and our U2D2 method.



Road Segmentation on Sentinel-2

Objective: Evaluate SR to enhance Sentinel-2 RGB imagery from 10 m to 1.25 m GSD for improved road segmentation at 62.5 cm GSD.

Approach:

- Applied U2D2 framework for SR
- Testing SR and bicubic upsampling strategies.

Exp.	10→ 5 m	5→ 2.5 m	2.5→ 1.25 m	1.25→ 0.625 m
#1	Bicubic	Bicubic	Bicubic	Bicubic
#2	Bicubic	Bicubic	SR	Bicubic
#3	Bicubic	SR	Bicubic	Bicubic
#4	Bicubic	SR	SR	Bicubic
#5	SR	SR	Bicubic	Bicubic
#6	SR	SR	SR	Bicubic

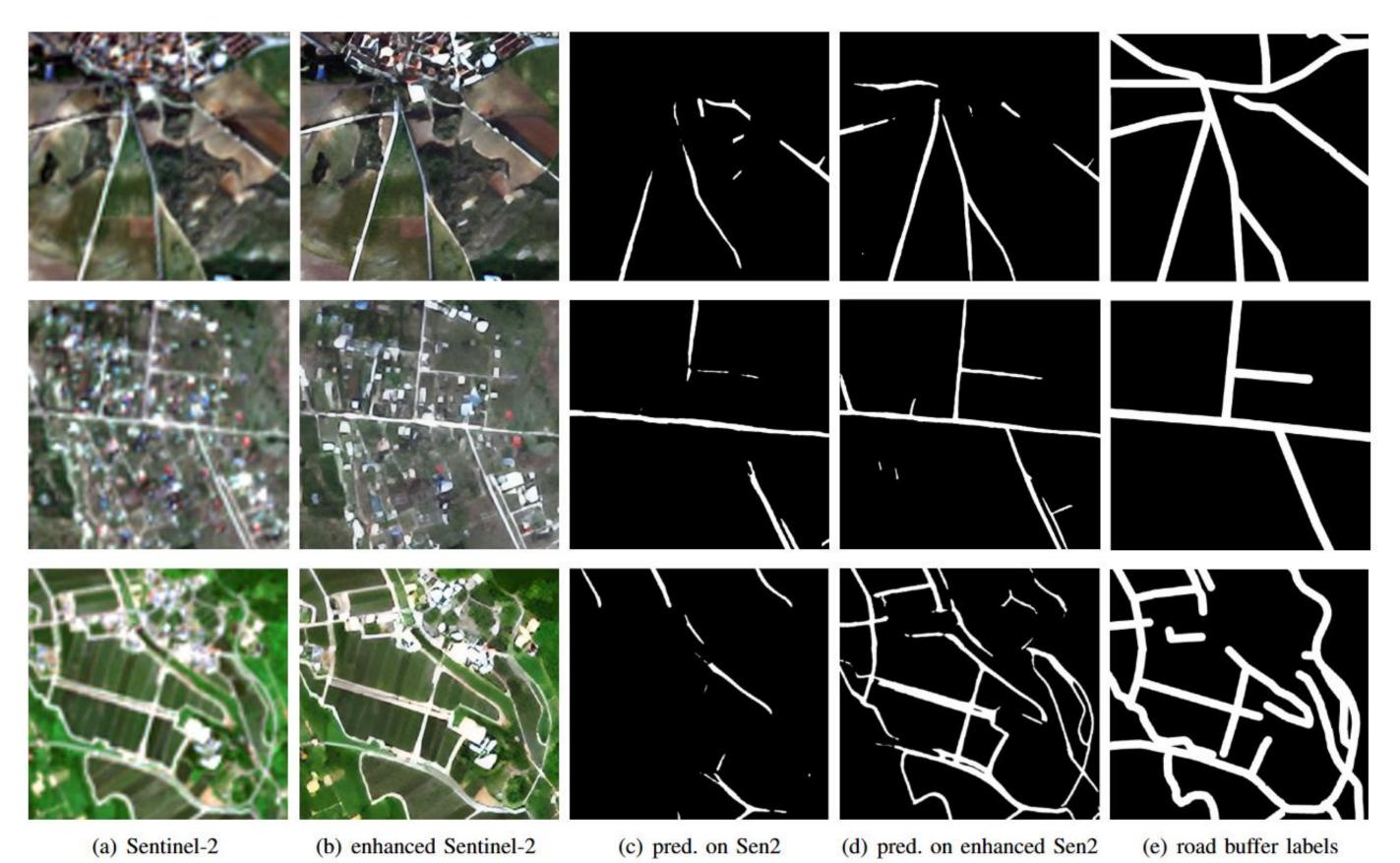
- Used OneFormer (Swin-Transformer) for road segmentation, trained on high-resolution data (30–67 cm GSD).
- Tested on Sentinel-2 patches (Spain, Germany, Kenya, Japan) with manual road annotations.

Results:

- Best SR strategy (SR-SR-Bicubic-Bicubic): 61% quality, 76% completeness, 75% correctness.
- Bicubic-only: 46% quality, 51% completeness, 87% correctness.
- Excessive SR caused artifacts, lowering quality to 55%.
- SR outperformed bicubic, improving road clarity and detection
- Impact: SR enables road segmentation in low-resolution Sentinel-2 data, supporting humanitarian and infrastructure applications despite minor color loss.

Effect of upsampling strategies on road extraction results

Exp	p. Ups. Strategy	Quality ↑ Completeness ↑		Correctness ↑	
#1	B-B-B-B	46.53 %	51.45 %	86.94 %	
#2	B-B-SR-B	53.30 %	67.89 %	71.84 %	
#3	B-SR-B-B	59.91 %	77.45 %	72.77 %	
#4	B-SR-SR-B	56.30 %	69.15 %	76.20 %	
#5	SR-SR-B-B	60.97 %	76.46 %	75.48 %	
#6	SR-SR-SR-B	55.12 %	69.38 %	73.26 %	



• Visual comparison of bicubic upsampling (a) vs. super-resolution (b) on Sentinel-2 RGB images, showing road segmentation results (c-d) and ground truth labels (e) at 62.5 cm GSD for patches from Spain (row 1), Kenya (row 2), and Japan (row 3).