

Predicting Landsat Reflectance with Deep Generative Fusion

Shahine Bouabid
Maxime Rischard

Maxim Chernetskyi
Jevgenij Gamper

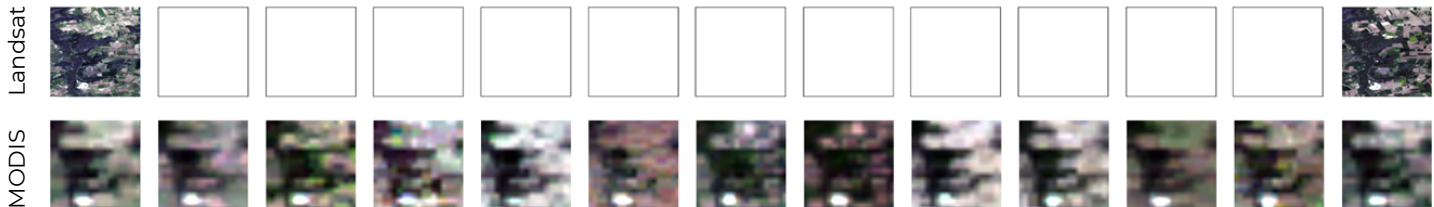
Cervest Ltd.



Motivation

- **Precision agriculture** and **humanitarian response** could benefit from detailed imagery
- Public missions bound to **trade-off** between **Spatial** and **Temporal** resolution

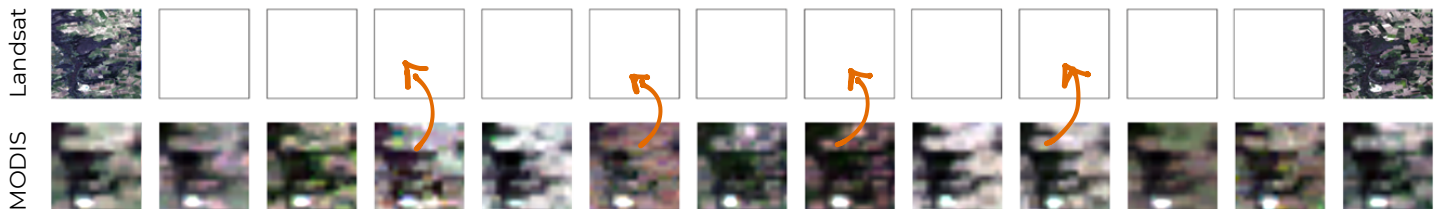
	Landsat	MODIS
Revisit cycle	16 days	1-2 days
Ground resolution cell size	30 m	250-500 m



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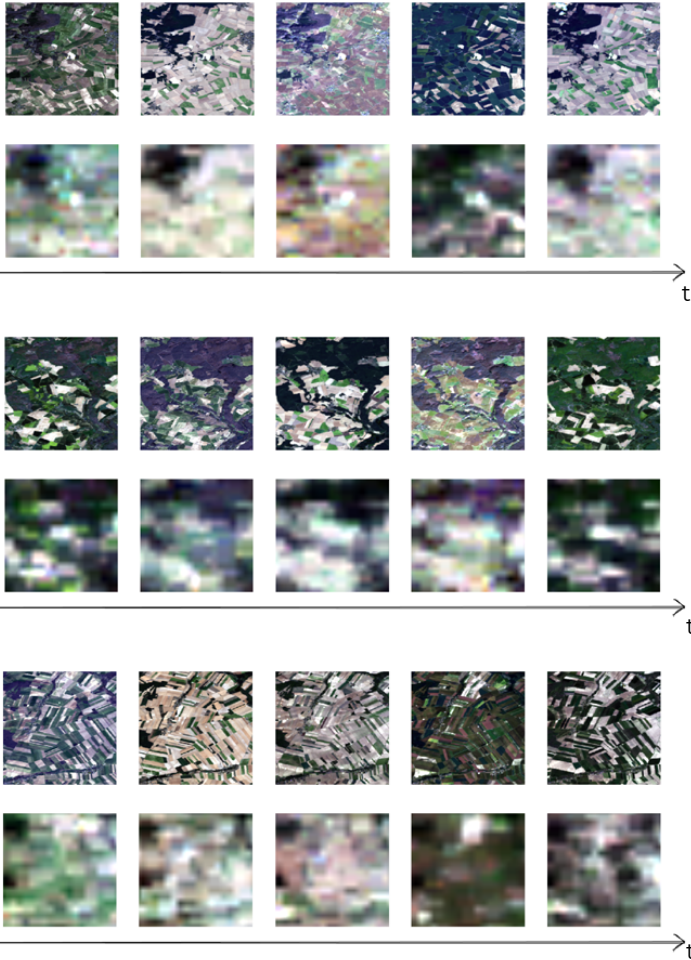
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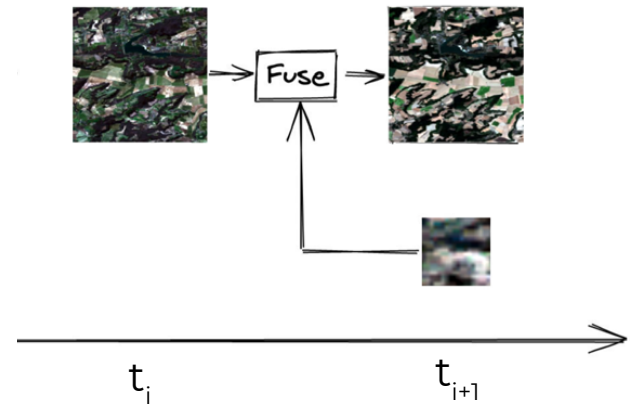


Predict in-between ?

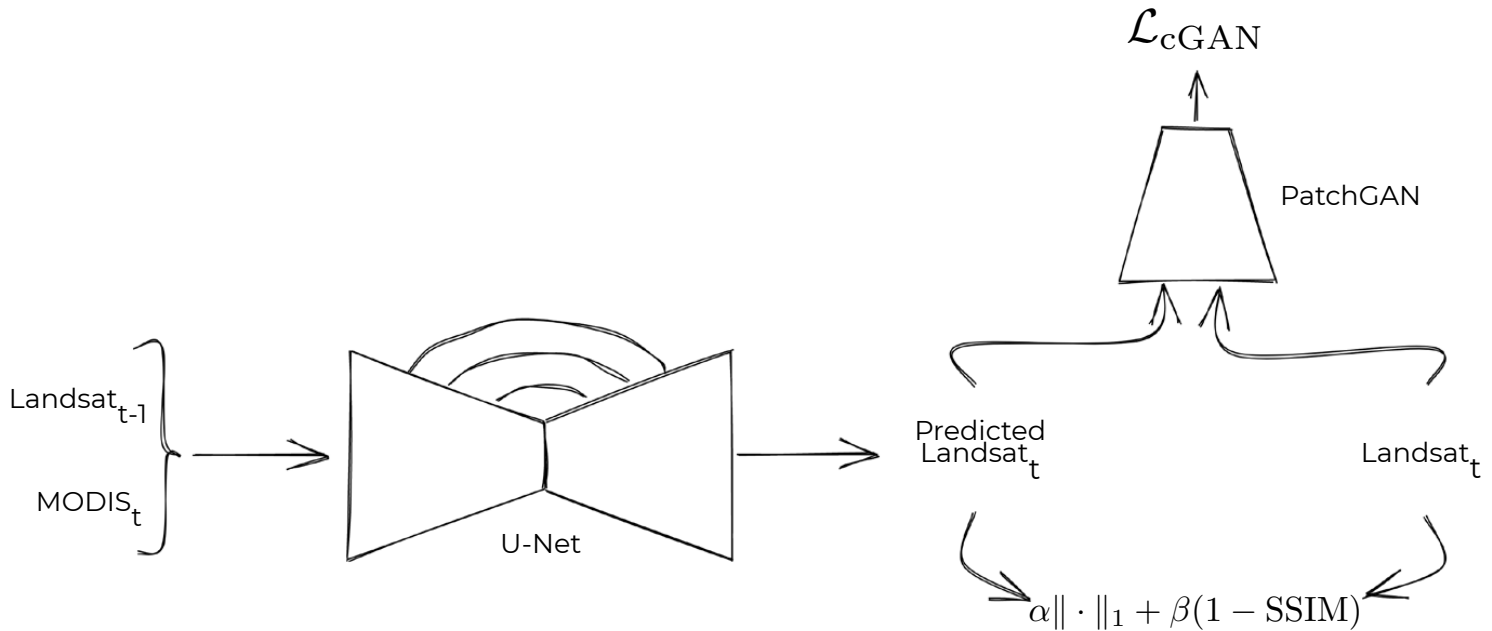
Dataset and Problem



Time series of co-registered
Landsat-MODIS **(256, 256) patches** for
550 locations and **14 dates** on
near-infrared, red, green and blue bands



Experiment



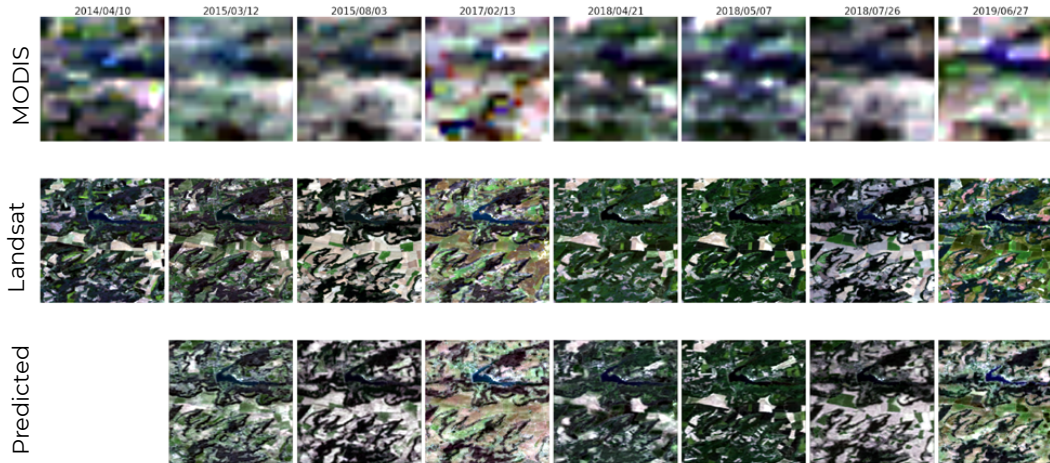
L1 supervision → low-frequency components
SSIM supervision → high-frequency components

Results

Substantial test Image Quality Metrics improvement against SOTA

Method	PSNR				SSIM				SAM (10^{-2})
Band	NIR	R	G	B	NIR	R	G	B	
Bilinear Upsampling	20.0	19.0	21.0	21.1	0.568	0.550	0.633	0.639	3.87
ESTARFM [36]	19.6	20.2	21.8	22.3	0.555	0.640	0.688	0.696	4.88
cGAN Fusion + L_1	22.1	21.8	23.7	23.8	0.675	0.697	0.747	0.747	2.75
cGAN Fusion + L_1 + SSIM	22.3	22.0	23.9	24.0	0.694	0.714	0.761	0.760	2.70

Table 1: Image quality scores on testing set; cGAN models scores are averaged over 3 independently trained models



Captures and blends coarse reflectance in ground instances

Blurred predictions, struggles to fuse into small fields

SSIM improves stability of adversarial training