

# End-to-End Framework for Continuous Space-Time Super-Resolution on Remote Sensing

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## Introduction & Objectives

### Methodology

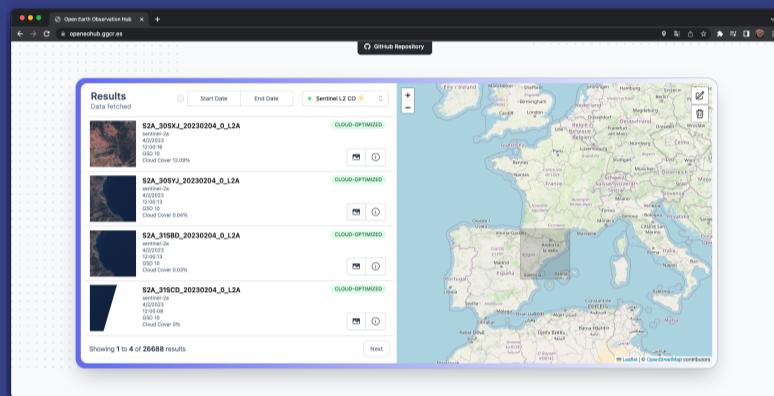
In this present work, we take advantage of already existing Spatial and Spectral techniques and Learning Continuous Image Representation with Local Implicit Image Function (LIIF) [1] by adding the Temporal dimension into the problem, leaning towards a continuous interpolation model of space and time.

We used an incremental methodology consisting on three separate projects. Each project accomplishes an objective towards our final milestone of an End-to-End Framework for Continuous Space-Time Super-Resolution.

## I. Web Service

### Obtain data

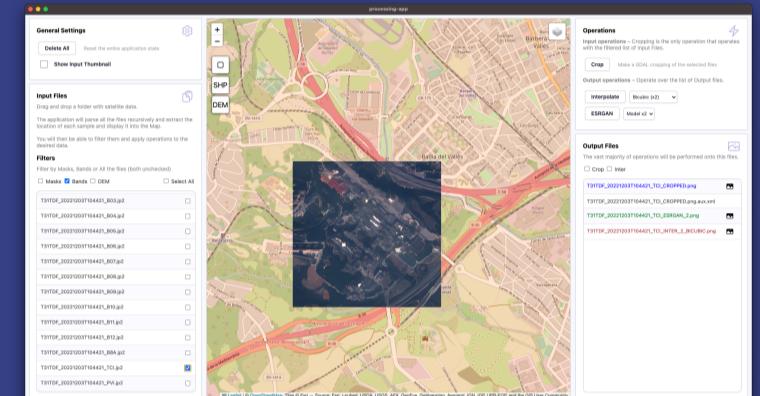
Our Web Provider, with an interactive map that triggers calls to different vendors APIs to download the data directly. We will use Sentinel S2 L2A all through the project.



## II. Cross-Platform App

### Process data

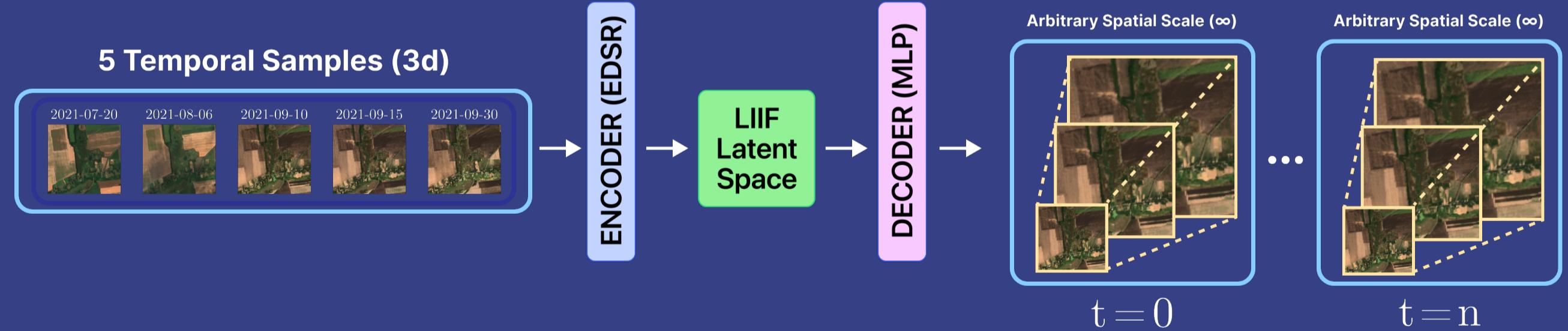
Our own Cross-Platform Application built to process the data, capable of parsing Sentinel data and apply our desired transformations (e.g. crop, interpolation, shapefile support...)



## III. Deep Learning Continuous Space-Time Super-Resolution

In order to apply Deep Learning into our Space-Time super-resolution problem we used the WorldStrat Dataset [2] a paired multi-temporal dataset that allowed us to build our own dataset consisting in a single HR and 5 LR whose interpolation will be very close to the HR date of acquisition, thus making the dataset temporally accurate.

Our framework consists in three interpolation models, the Baseline, the Default LIIF, intended for the spatial dimension and the Temporal LIIF that adds the Temporal dimension making it capable of accepting 3D inputs and generating infinite images for Arbitrary Temporal and Spatial scales.



## Results & Experiments

We made experiments regarding repeated Random Crop Region (128x128, 72x72 and 48x48) made to the input and different Temporal Strategies (Complete, Groups, Pairs, Single) by modifying our input set. This ended up incentivating our model to learn better the mappings between the temporal samples.



## Conclusions

### Infinite Space-Time

The Temporal LIIF with a Groups Temporal Strategy and an initial Random Crop Region of 128x128 was the best model and indeed Temporal dimension lead to better and more accurate results capable of overcoming Bicubic and the original LIIF.

Models	In-distribution		Out-of-distribution
	x2	x4	
Bicubic	23.13	22.48	22.27
Default LIIF	23.70	22.92	22.67
Temporal LIIF	<b>24.96</b>	<b>23.99</b>	<b>23.68</b>

Table. Average of the test set results (PSNR↑) (dB).

## References & Acknowledgement

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[1] Y. Chen, S. Liu, and X. Wang, "Learning continuous image representation with local implicit image function," (CVPR) (2021)

[2] J. Cornebise, I. Oršolic, F. Kalaitzis, "High-Resolution Satellite Imagery: The WorldStrat Dataset – With Application to Super-Resolution," in (NeurIPS) Datasets and Benchmarks (2022)