Zoom and Boom: How Satellites Expose Urban Expansion Secrets

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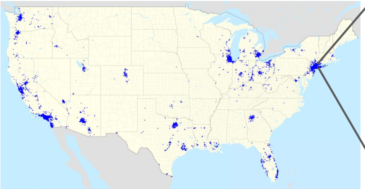
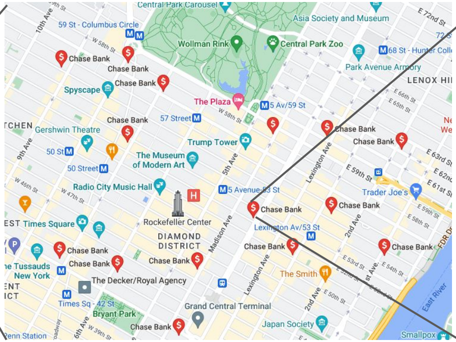
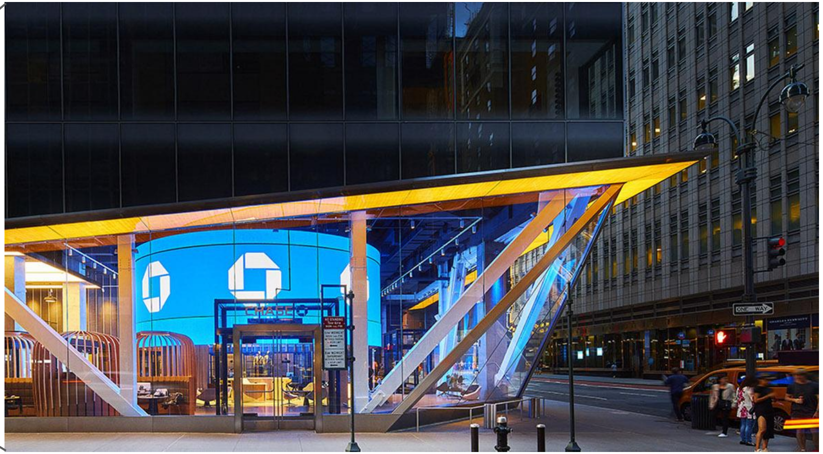
01 PROJECT GOAL

BRANCH PLACEMENT

Over 4700 Chase branches, optimizing network key for **profitability**







PROJECT RELEVANCE

Where would you place a new retail branch?

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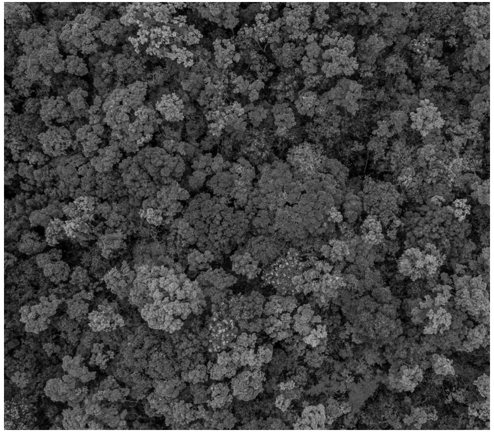
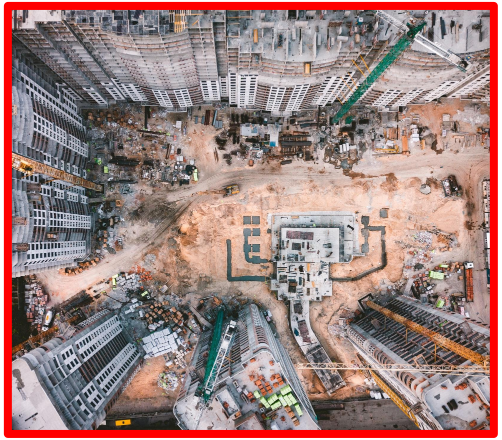
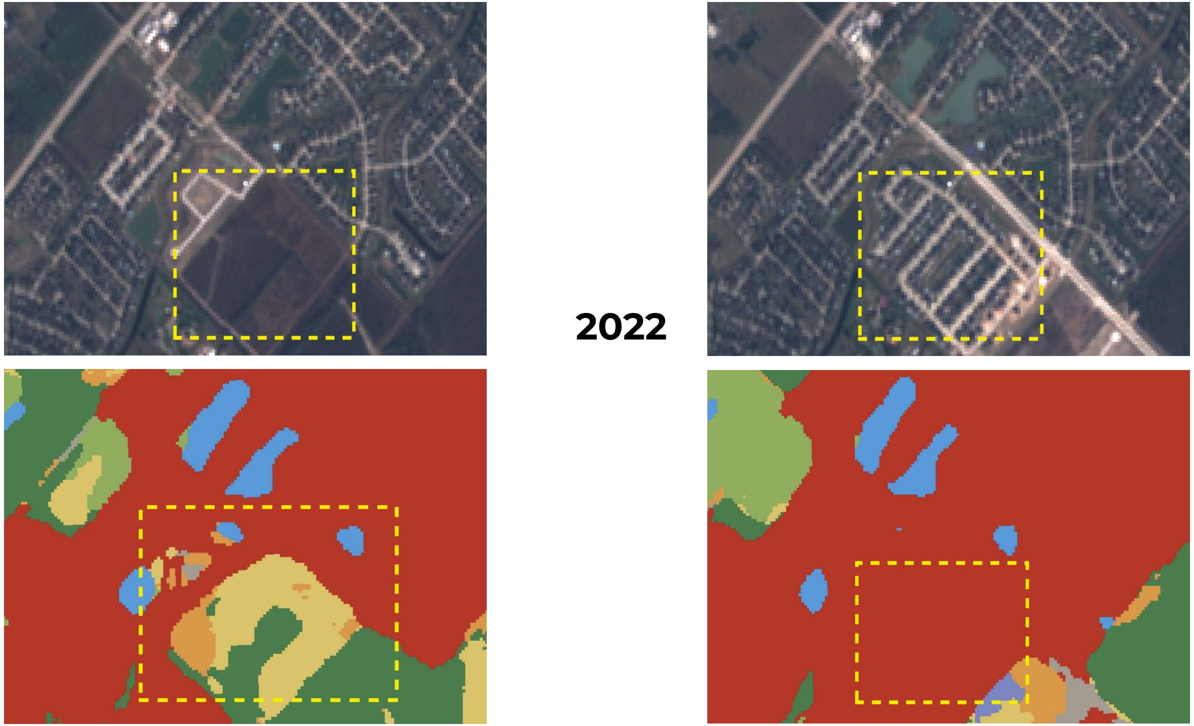




PROJECT GOAL

Predict future **urbanization rate** in any given area



2016

2022

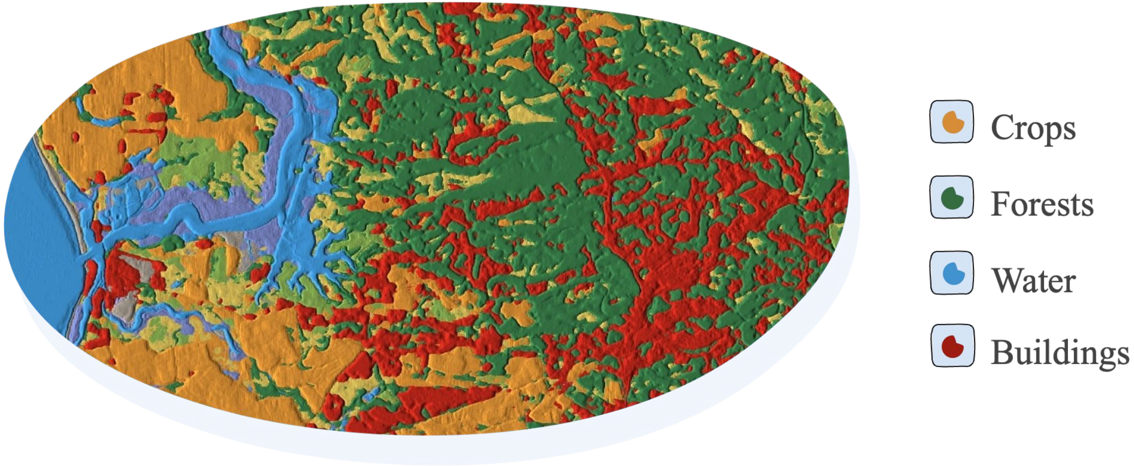
Satellite Images

Dynamic World Segmentation
(red = built)

02 THE DATASET

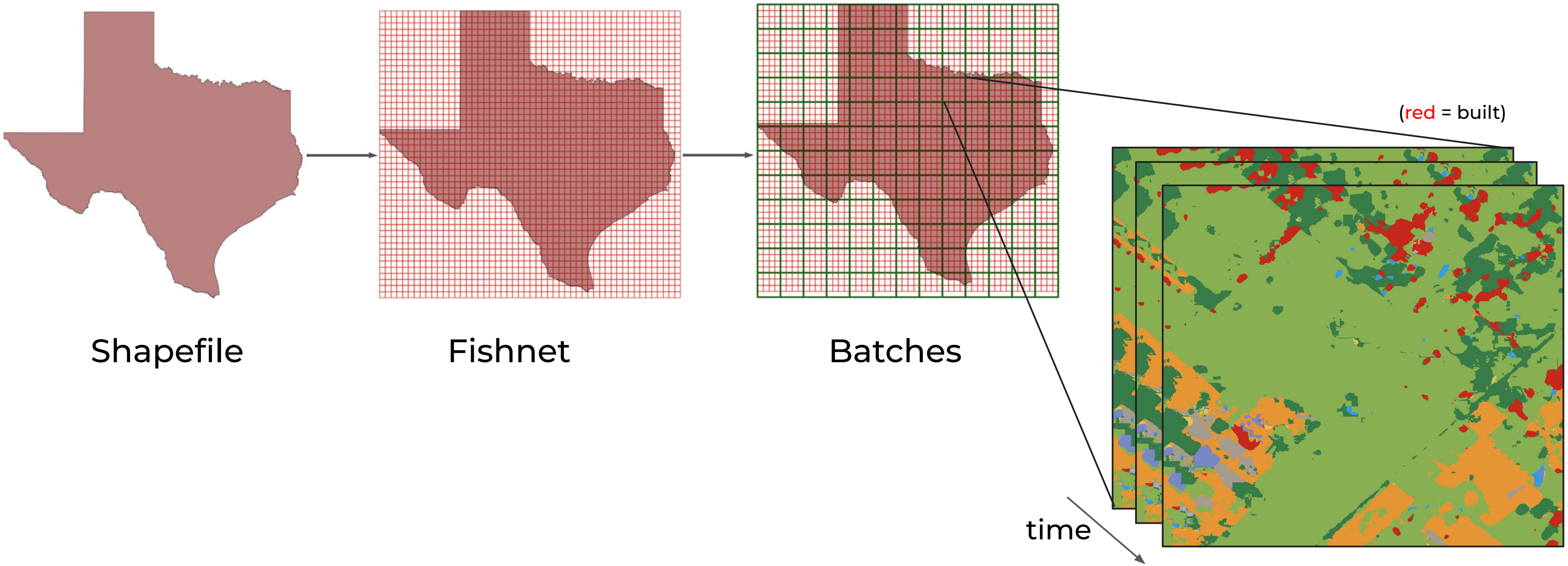
DYNAMIC WORLD

Google's 10m-resolution land cover segmentation, from 2016 to present, with daily images and nine labels.



DATA EXTRACTION

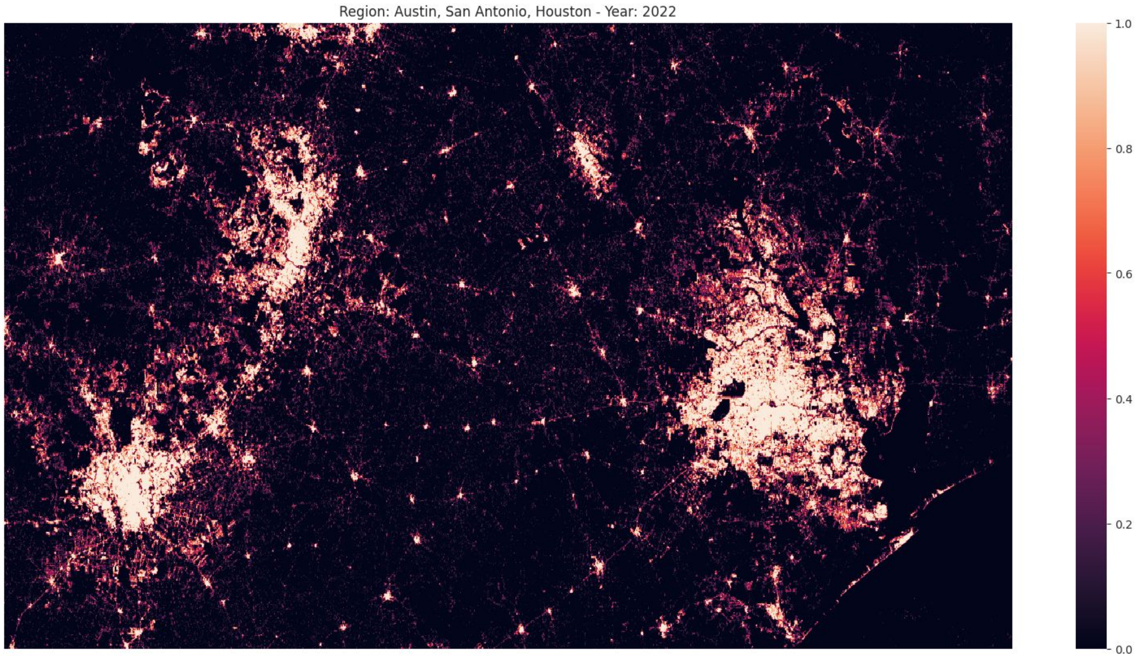
Create a fishnet over the desired area. Extract in batches called *regions*.
We extract one image per batch (region) per year.



QUANTIFY URBANIZATION

Percentage urbanization as average number of red pixels for each fishnet tile.
Map shows percentage urbanization in different regions.

urb = 0.72



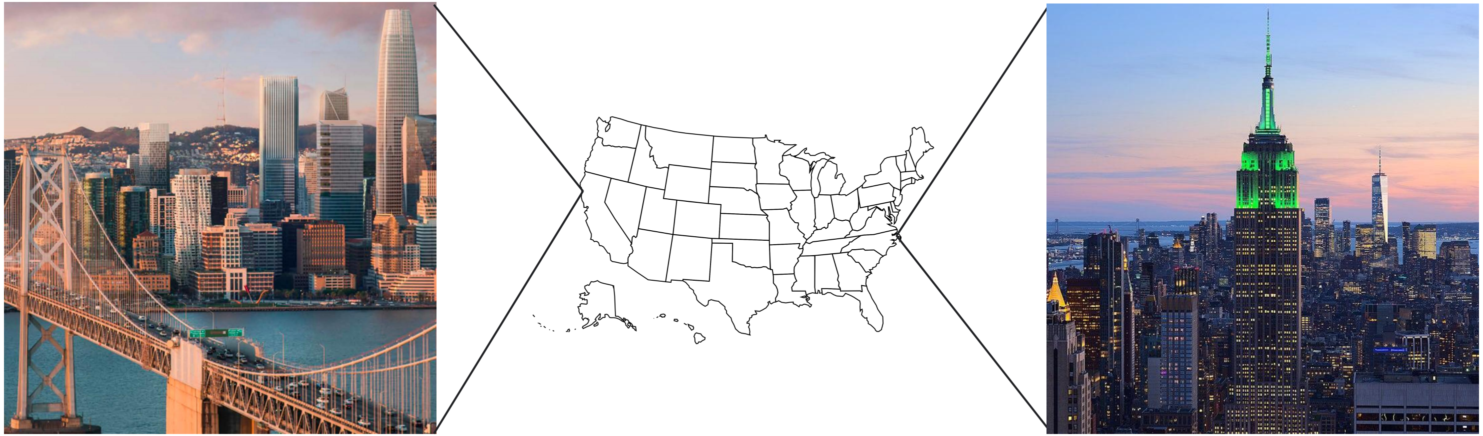
Area fully urbanized

Area not urbanized

03 ANALYTICAL METHODS

SPATIO-TEMPORAL RELATIONSHIP

Spatial component:
Macro-trends, urbanization in different regions is correlated



SPATIO-TEMPORAL RELATIONSHIP

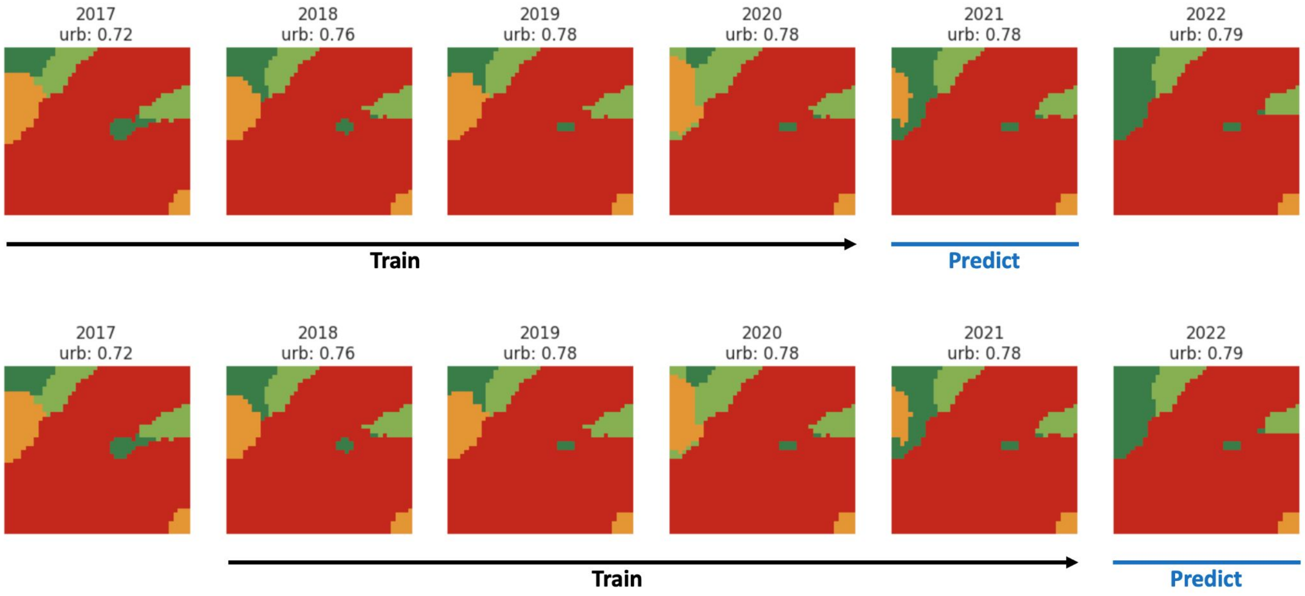
Temporal component:
Different regions follow specific urbanization patterns




1900 | 1960 | 1990 | **2025**

VIDEO PREDICTION

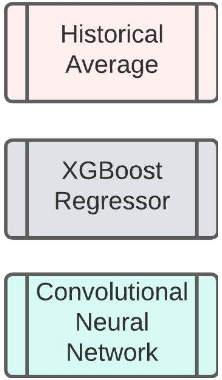
Capture spatio-temporal relationships using previous frames (**past satellite images**) to predict future ones (**next year urbanization**)



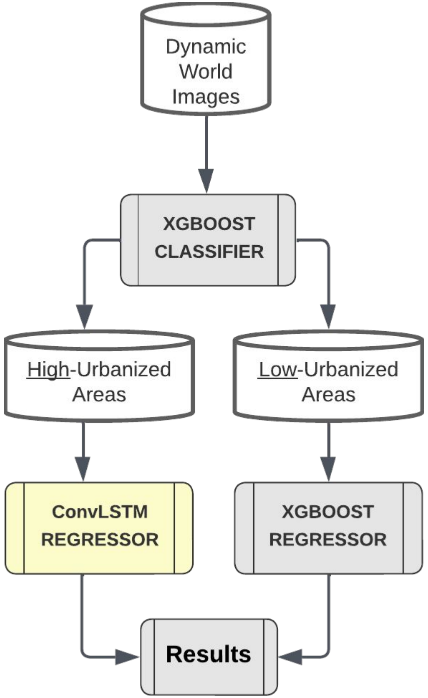
MODELING PIPELINE

Complex sequence of classification and regression tasks to improve upon baselines

Baselines



Modeling pipeline



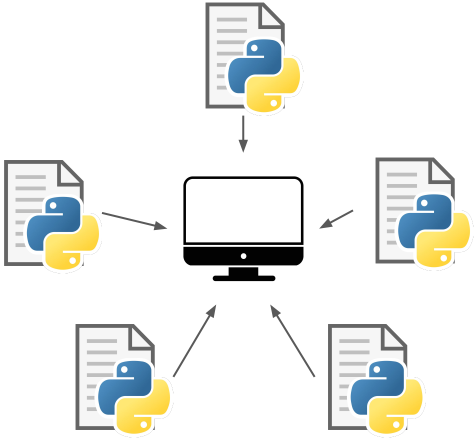
04 RESULTS AND IMPACT

CODE MEANT TO LAST

Adding new feature(s)
that improve
downstream models

	Feature	Urbanization prediction	Feature
Region			
Region			

Scalable and reusable **codebase**



EVALUATION METRICS

Our approach (ConvLSTM) outperforms baselines on principal metric (MAE)

	MAE	RMSE	R^2
Historical Average	0.024	0.047	0.973
XGBoost	0.010	**0.022**	**0.992**
ConvLSTM	**0.009**	0.026	0.981

Ensemble learner for further improvement

05 FUTURE APPLICABILITY

THEORETICAL USE CASES IN FINANCIAL SERVICES

Same **methodological framework** applicable to a variety of other projects

Real Estate Investment

Collateral Risk Assessment

Natural Disasters Evaluation

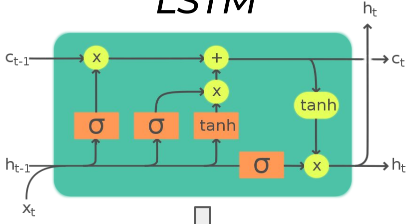
THANK YOU

APPENDIX

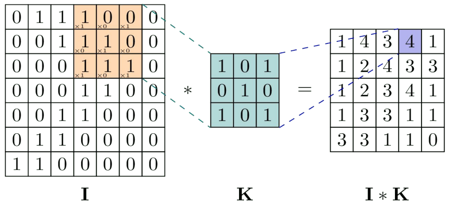
Convolutional LSTM

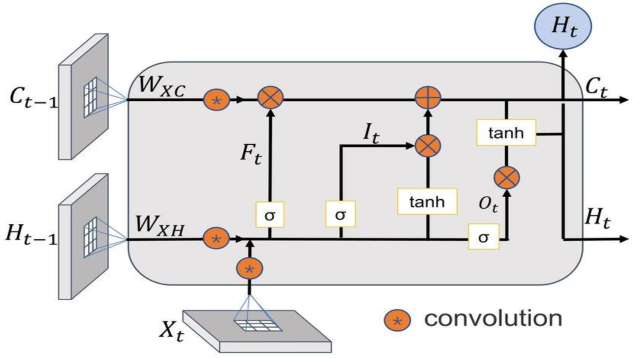
Convolutional Long-Short Term Memory Neural Network.
Convolutions enable to learn spatial features, LSTMs to capture temporal relationships

LSTM



Convolution





Convolutional-LSTM

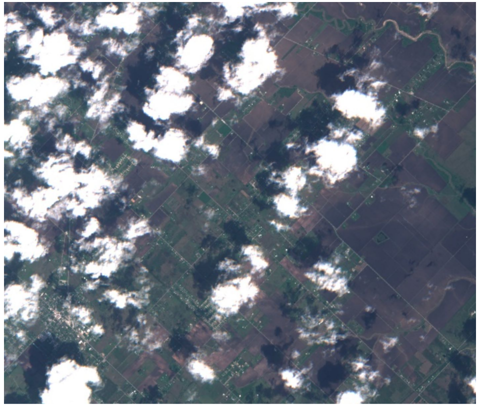
Source: Learning Multiscale Temporal–Spatial–Spectral Features via a Multipath Convolutional LSTM Neural Network for Change Detection With Hyperspectral Images

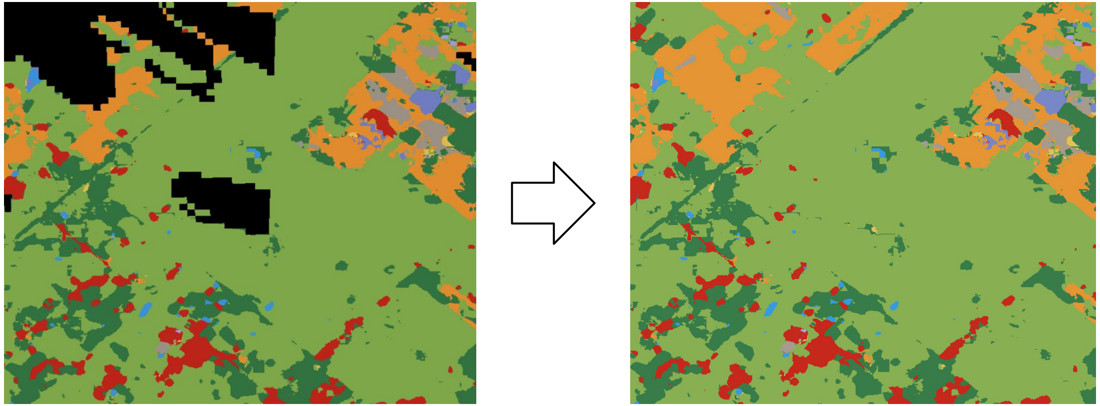
Night Time Light

Additional data source that captures vertical urbanization

Data Preprocessing

Clouds cause missing pixels, data imputation to restore correct image





Code architecture

Clean and organized code, adherence to **best practices**, ensuring reusability and knowledge transfer.