

Using Neural Networks to Predict Microspatial Economic Growth

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From Raw Daytime Imagery to Urban Policy Insights

Imagery





Conv2D: Conv2D: Conv2D: Max-Pool: 20x20x32 40x40x32 40x40x32 40x40x32 Vectorize: 3200x1 Fully Connected Network

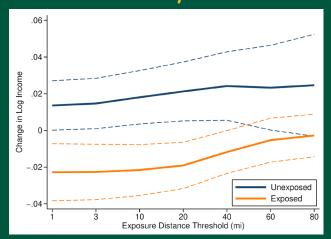
Block x 3

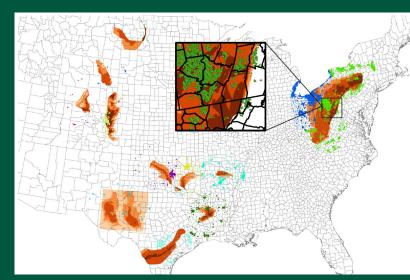
Modelling

Demographic Controls

Predicted Value

Policy





Prediction

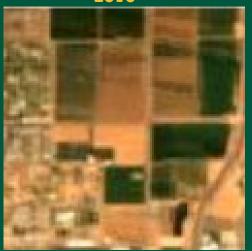
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The Raw Daytime Imagery

2000



2010



Source: Landsat 7 annual summer composites of contiguous US, constructed through Google Earth Engine

Resolution

- Spatial: 30m pixels, 2.4km images
- Spectral: RGB, IR, UV, Panchromatic
- **Temporal:** 16-day revisit window

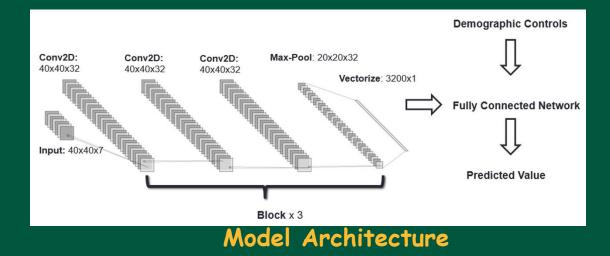
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Modelling Changes in Urban Settlement

Task: Predict population and residential income for each image

Ground Truth: 2000 and 2010 block-level US Census population and income

Model: Convolutional neural network learns the land-cover features that best predict urban settlement patterns (population and income distribution, changes)





Generating New Data For Spatial Applications

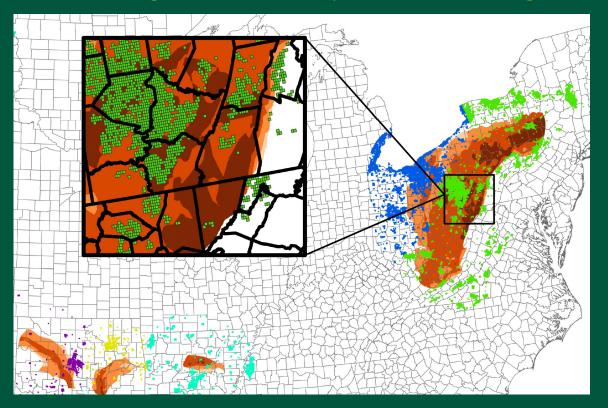
Model R^2 is 0.9 in out-of-sample year

• Imprecisely measured outcome does not bias treatment effects

Deploy the model to predict outcomes in out-of-sample periods

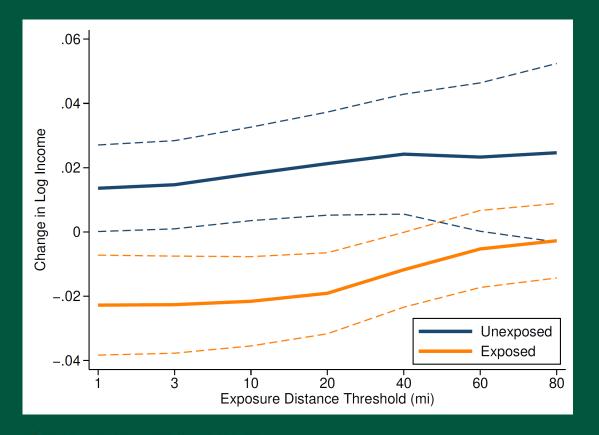
- 2001-2009, 2011-2019: years without super-local decennial Census data
- Effectively filling in the time-series of neighbourhood outcomes with the CNN

Neighbourhoods Exposed to Fracking



Measuring The Spatial Impact of Fracking

Residential Development Effects



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Neighborhoods near wells grew less

- Driven by population declines
- Effect persists up to 20 miles
- Indicates industrialization channel, rather than local hazards (pollution)
- Places with local control saw no adverse effects (contained drilling)

THANK YOU!

