

# *Satellite Vision*

## Satellite and Spatial Data for Public Policy

*Instances from Indian Economic Survey*

*Parth Khare*

*IDFC Training session*

September 5<sup>th</sup>, 2019

# Section I: Satellite Imagery

## *Remote Sensing to Computer Vision*

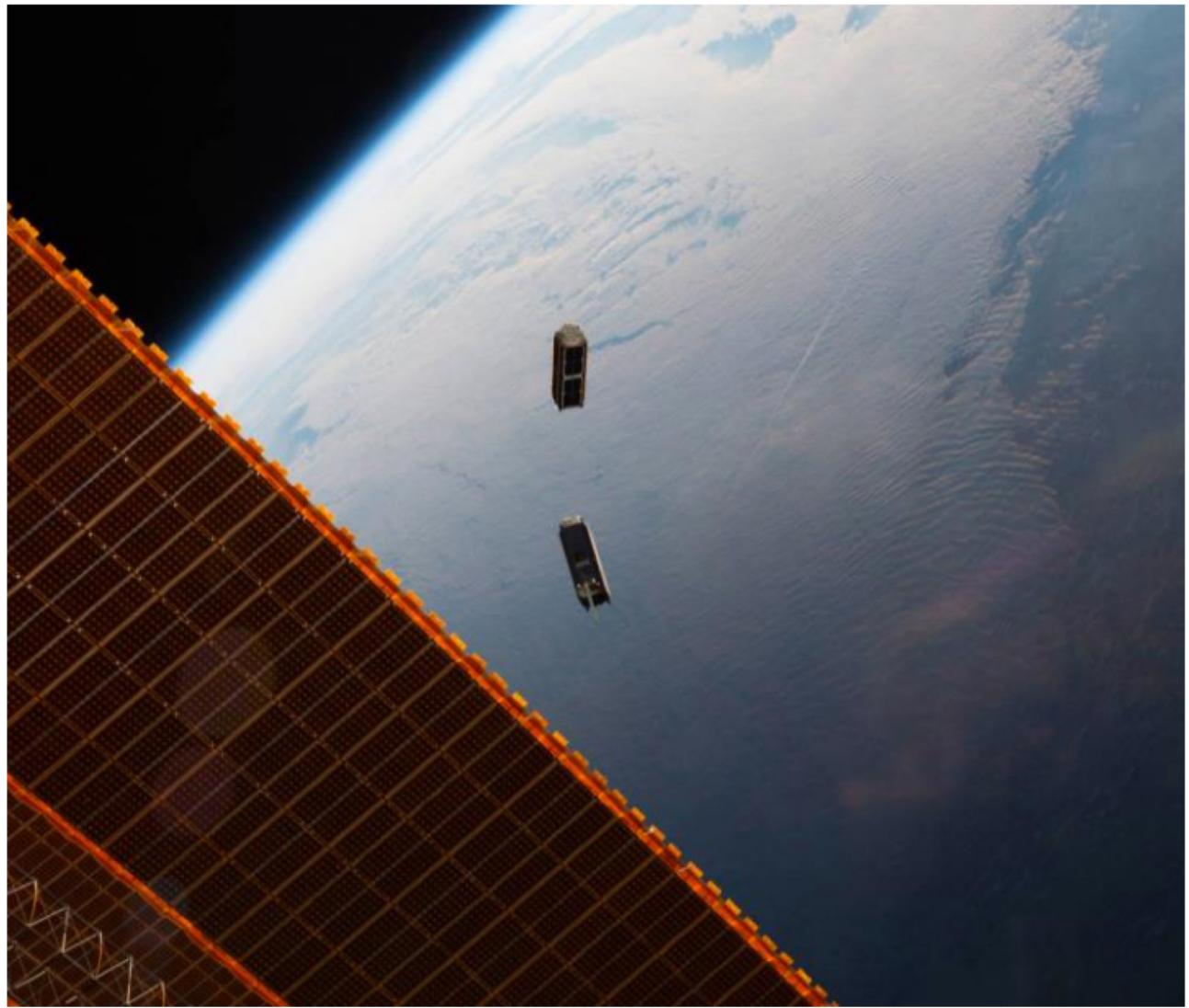
# *Policy & Data: Emerging economies*

## *Leveraging data externality*

- Satellite data free from human error and intentional field survey biases
- Volumes of private data (behavioral consumer) being collected holding high potential for public policy
- Census is conducted in 10 years span, so significant changes in poverty cannot be captured
- Dynamic changes need to be understood for effective policy
- Tools and platforms to learn data sciences R, Python
- Big Data, lesser time, need for dynamic visual tools

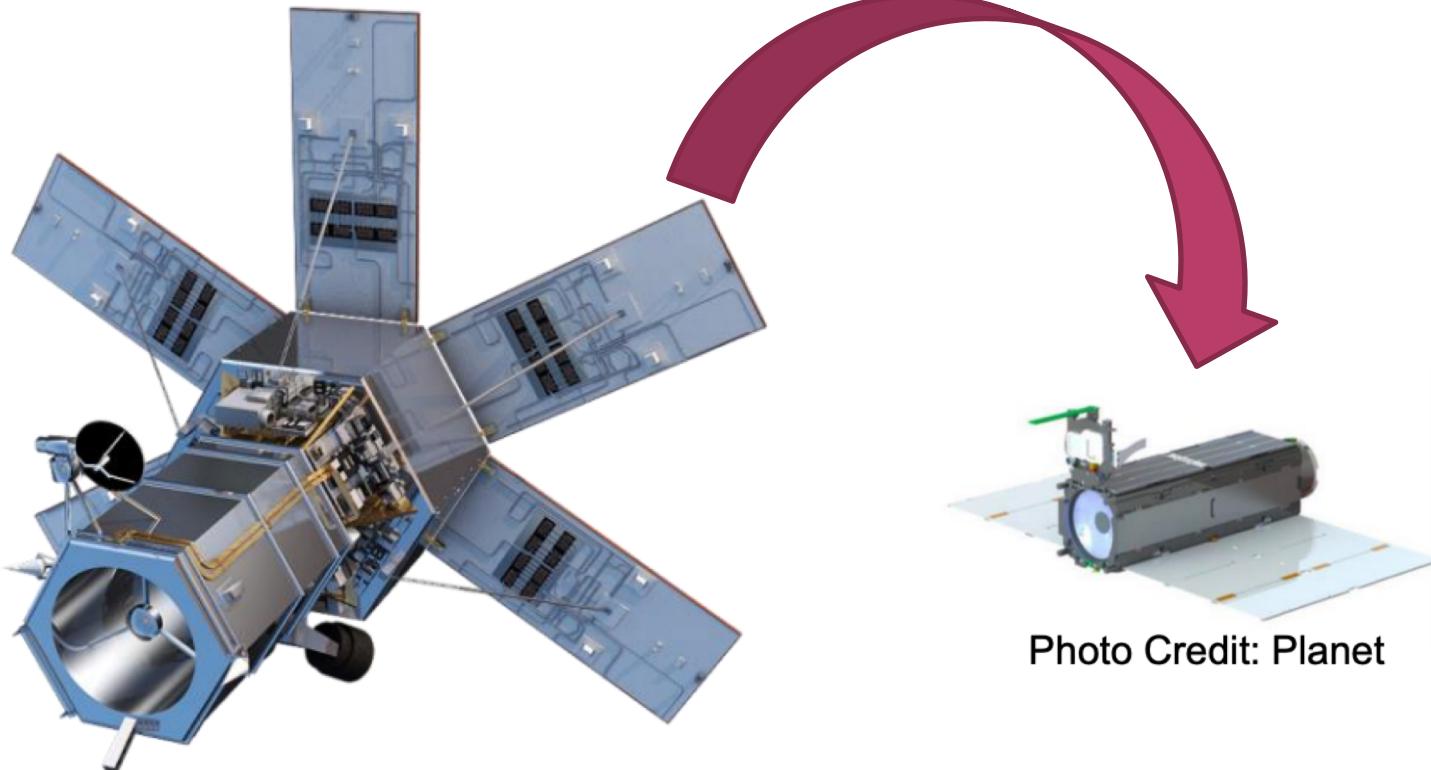
# 4857 Satellites

- Untapped resource
- LUC to Machine Learning to Computer Vision
- Emerging countries



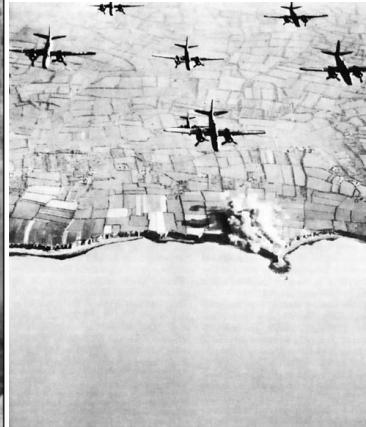
Source: NASA

# Build & Scale



- Release 1972 Landsat (1990)
- Worldview
- Leaner satellites ~5,000 lb to ~10 lb
- Improved frequency
- But resolution compromised (0.5m – 3m)

# World War: Photometry/Connect the pixels?

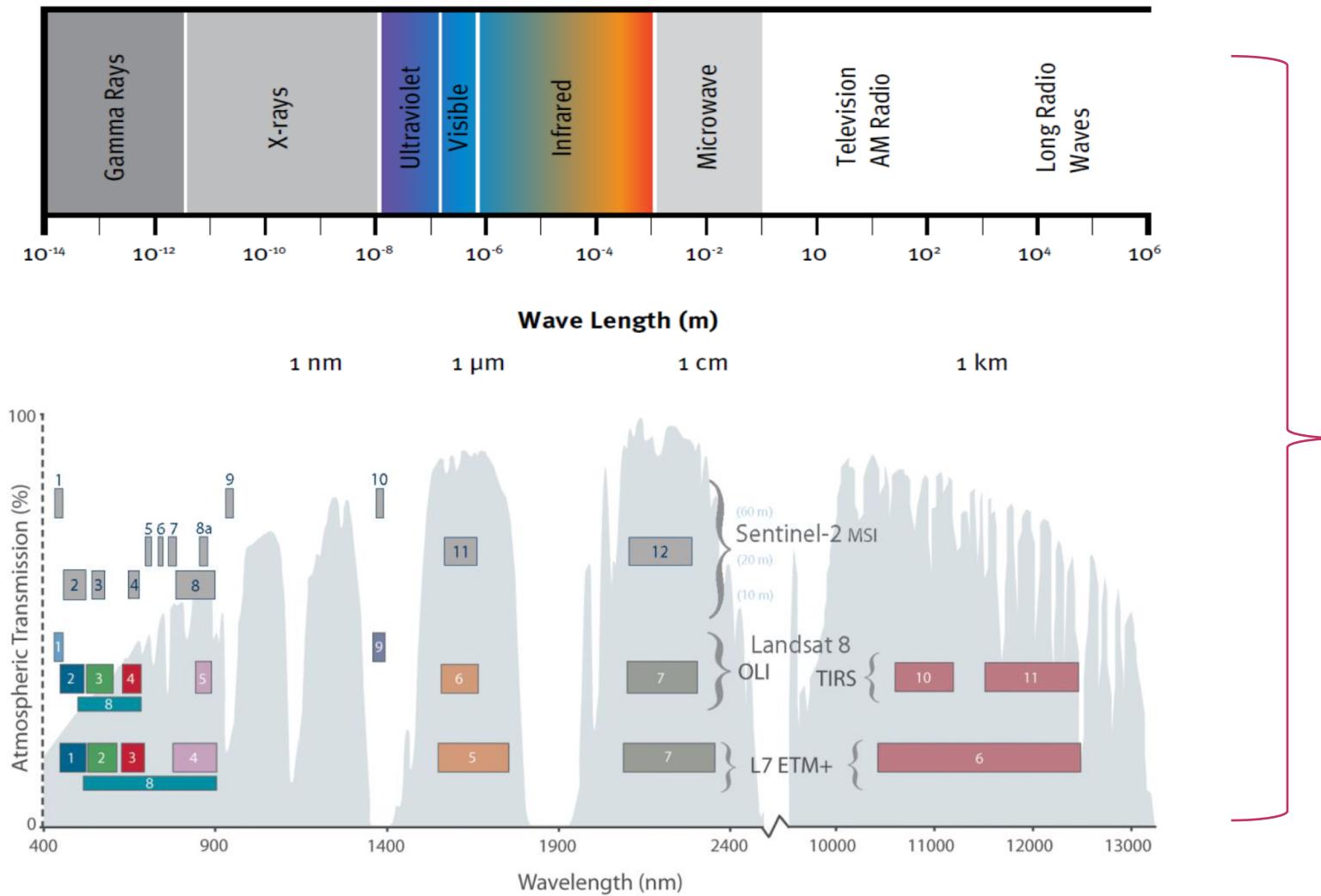


Source: BBC



Source: Eurosense

# Deconstructing imagery to data: pixel

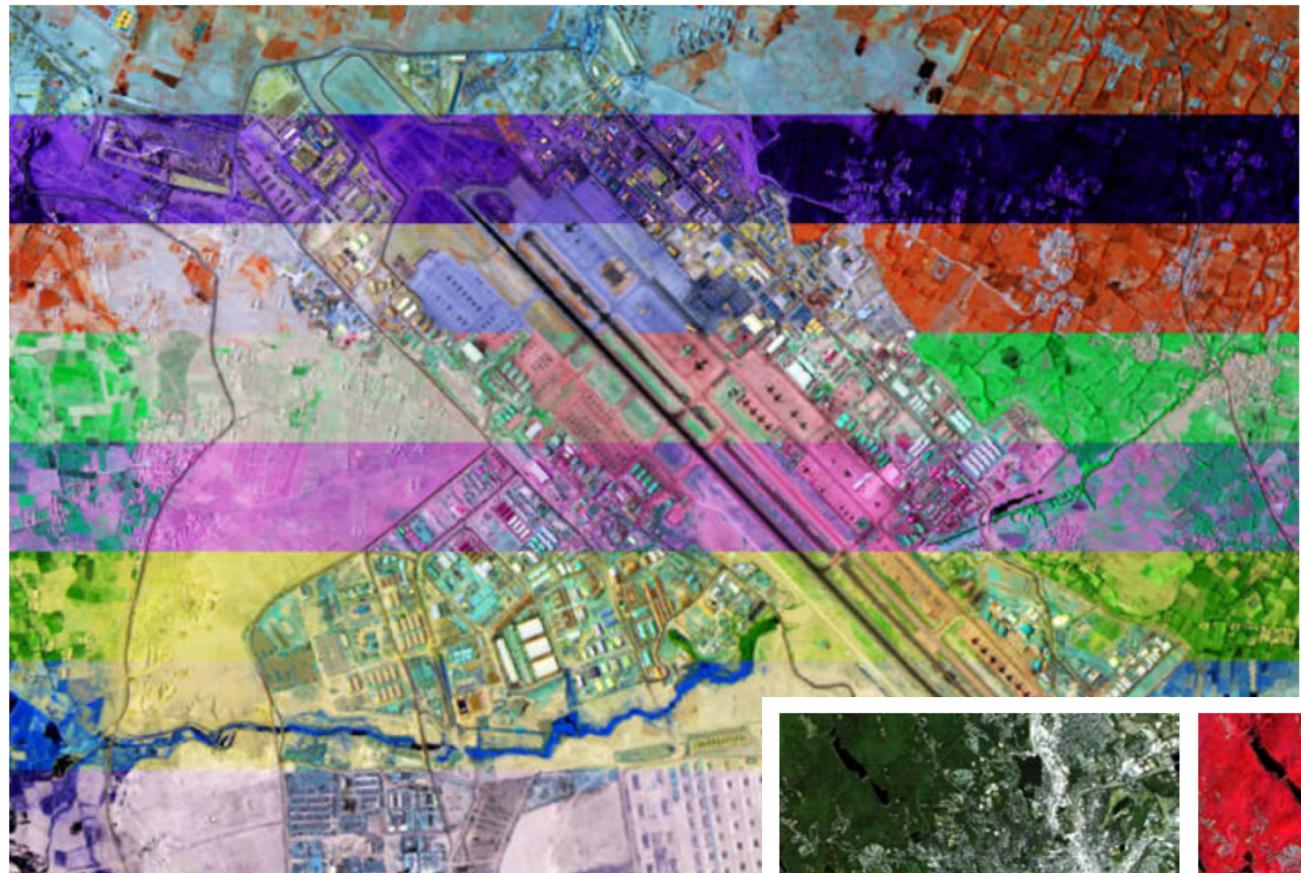


Source: NASA, LANDSAT

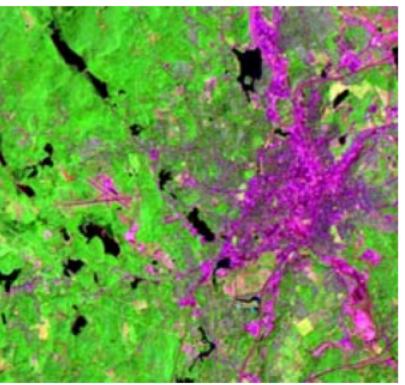
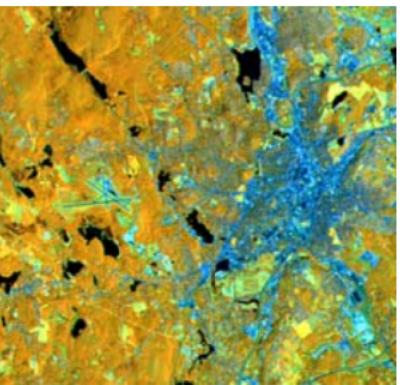
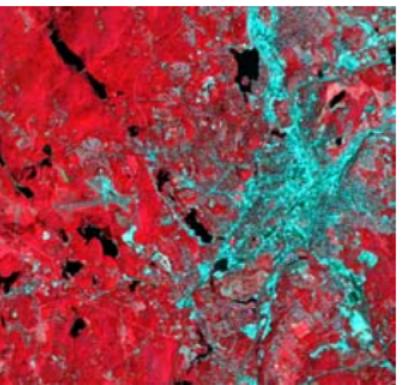
General | Projection | Histogram | Pixel data [selected]

Row	0	1	2	3	4	5	6
0	010.408	011.313	011.313	010.106	010.709	010.860	01
1	010.106	010.408	010.559	009.654	011.162	011.313	01
2	010.106	009.050	009.503	009.654	010.408	010.408	01
3	009.654	009.654	009.503	009.654	010.408	011.313	01
4	010.257	009.955	011.162	011.011	011.011	010.559	01
5	009.804	010.257	010.860	010.408	011.463	010.559	01
6	009.804	009.654	010.559	010.860	010.559	01	01
7	010.106	010.408	010.106	010.559	011.463	010.106	01
8	011.162	009.955	010.408	010.860	010.559	010.860	01
9	010.709	010.709	010.408	011.313	011.313	010.408	01
10	010.408	010.860	010.408	010.257	010.709	010.559	01
11	010.860	010.559	010.257	010.709	010.709	011.011	01
12	011.313	010.106	010.559	010.860	010.860	010.709	01
13	011.313	010.559	010.559	010.709	010.559	010.709	01
14	011.162	010.709	011.011	011.011	011.463	010.408	01
15	011.463	011.313	011.011	011.162	010.408	010.709	01
16	011.463	011.313	010.860	010.408	009.804	010.709	01
17	011.614	011.313	010.559	009.654	010.408	011.011	01
18	011.614	010.106	011.011	010.860	009.955	010.408	01
19	011.162	011.313	011.463	010.257	010.559	010.408	01
20	011.313	011.313	010.408	010.709	010.106	010.106	00
21	010.559	010.106	010.106	011.162	011.162	009.955	00
22	010.709	010.408	010.106	010.860	010.559	010.709	01

# Spectral Bands



Source: DigitalGlobe



# Cleaning & Preprocessing

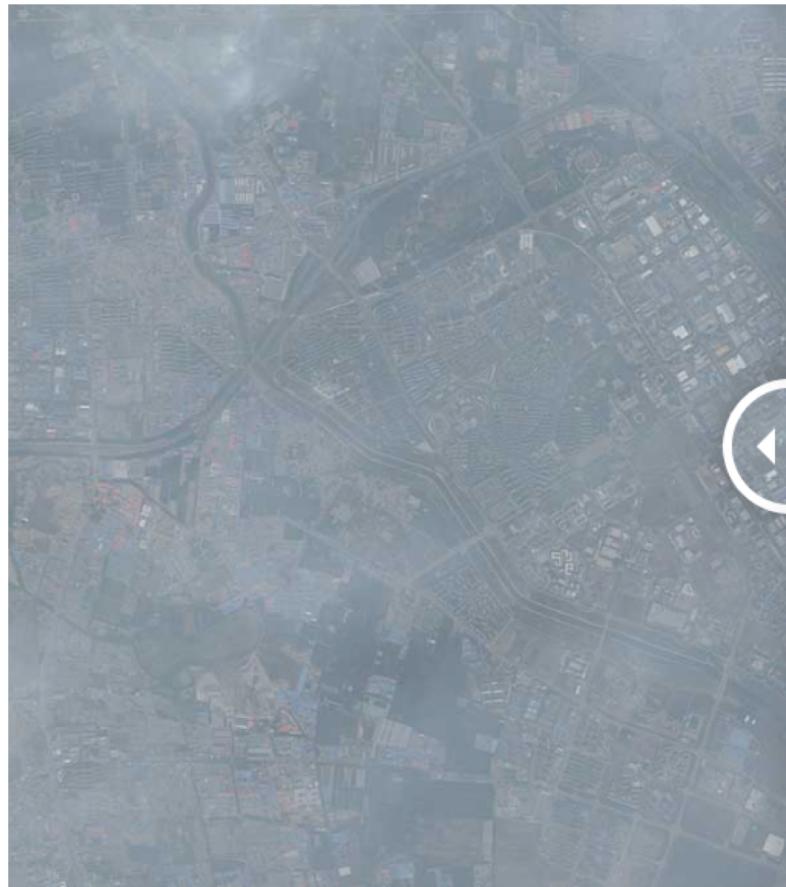


IMAGE BEFORE ACOMP PROCESS

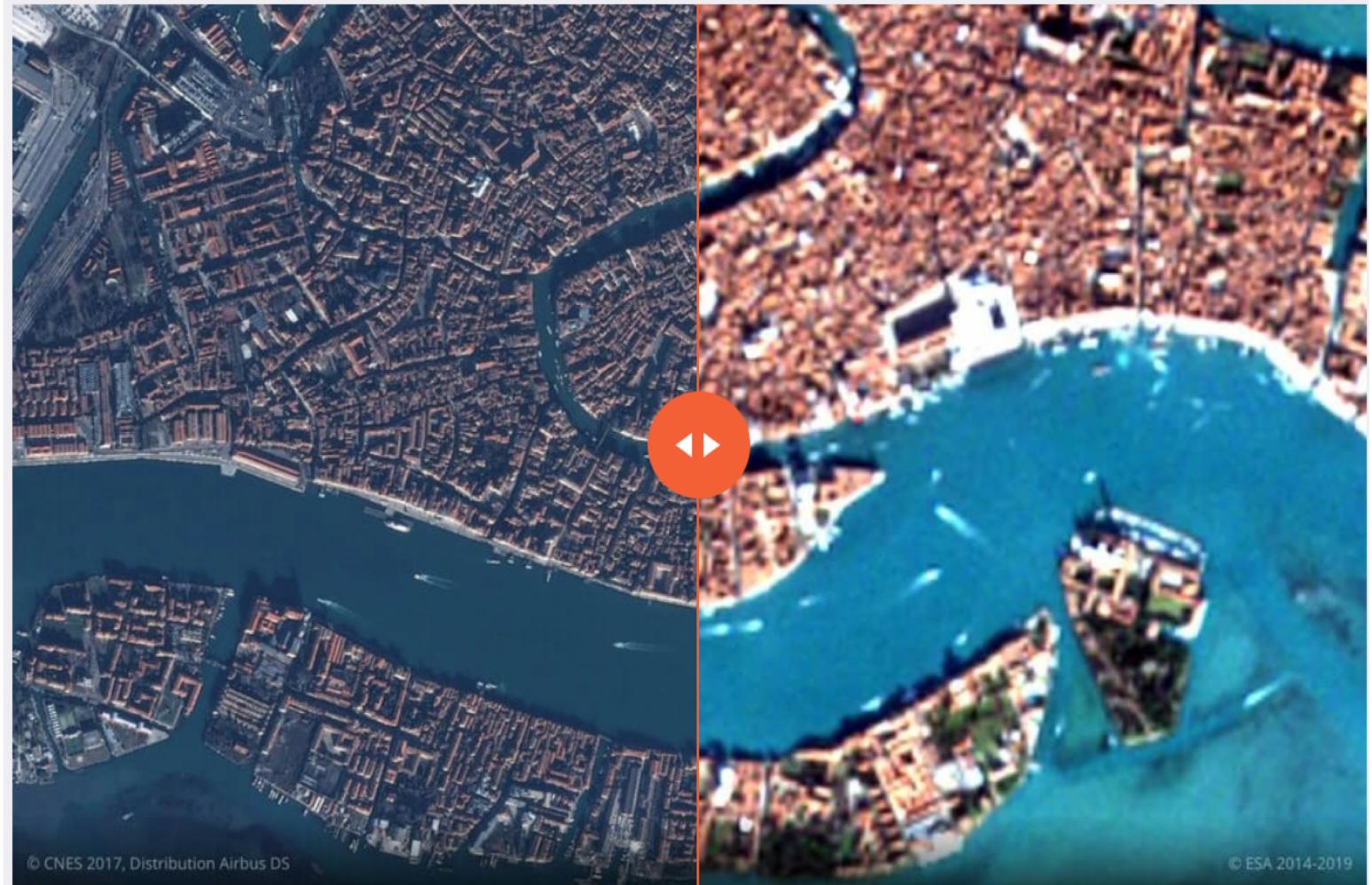


IMAGE AFTER ACOMP PROCESS

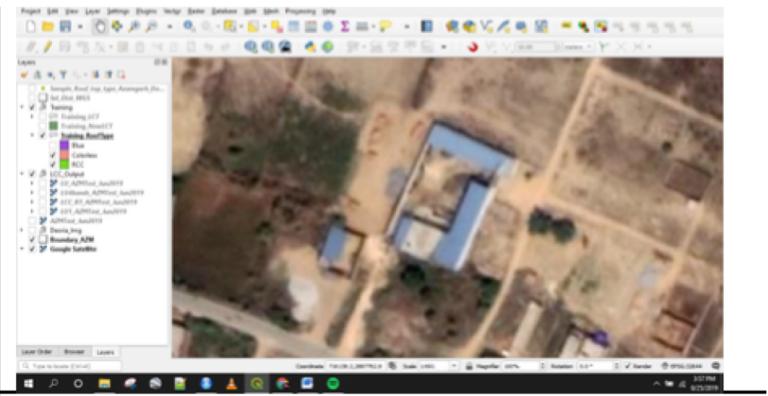
Source: Digital Globe

- Atmospheric Correction
- Radiometric calibration
- Further: SAR Lidar, DTM

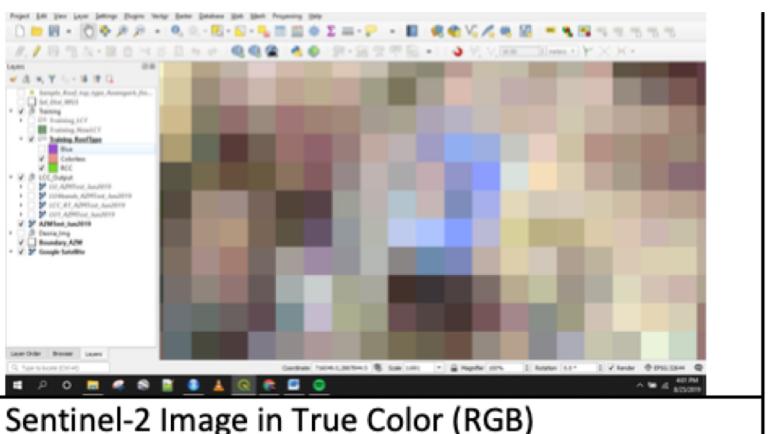
# *Use Cases & Resolution*



*Source:* EOS



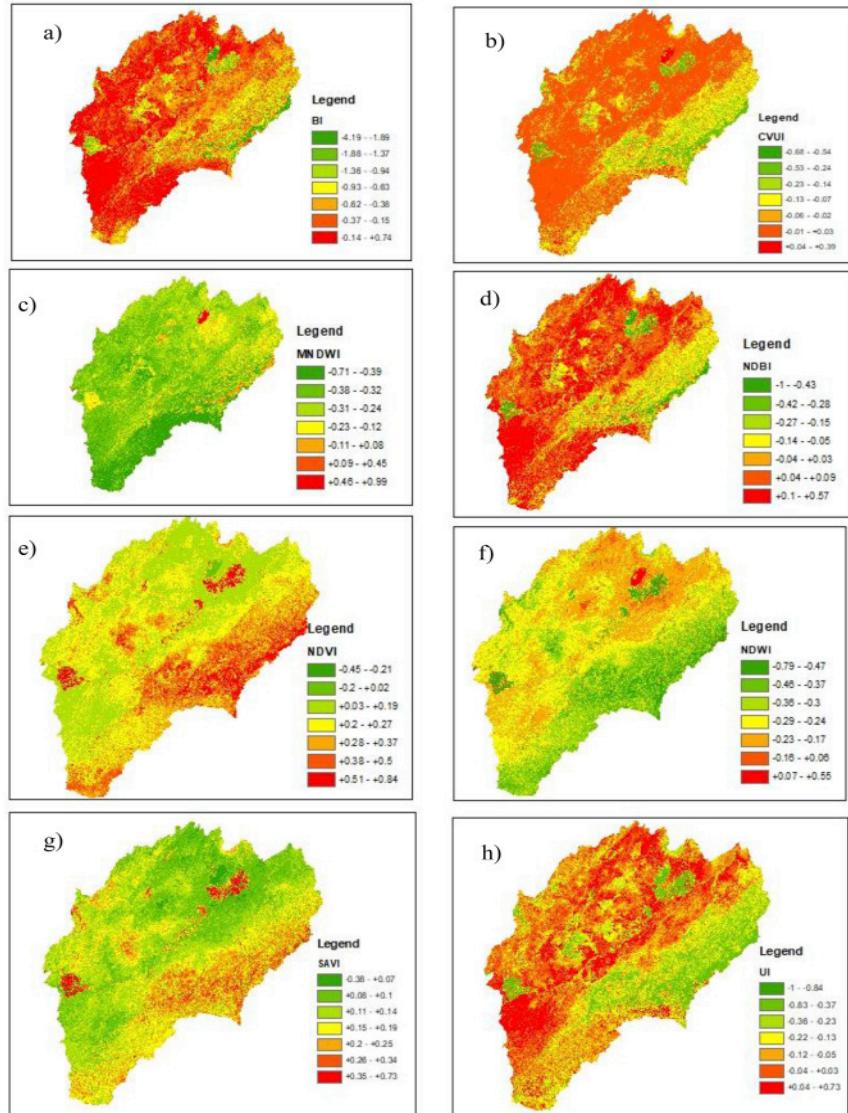
## Google Sat Imagery



Sentinel-2 Image in True Color (RGB)

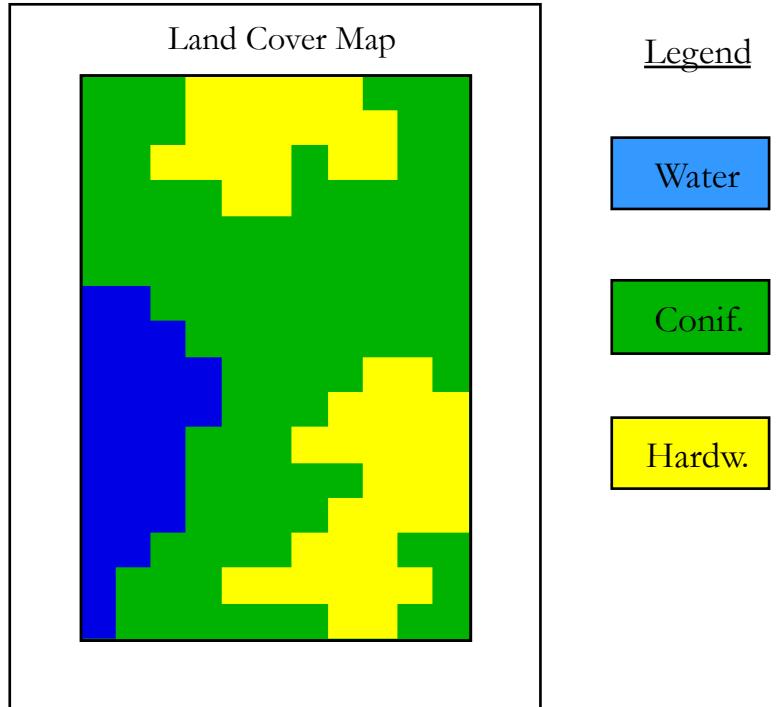
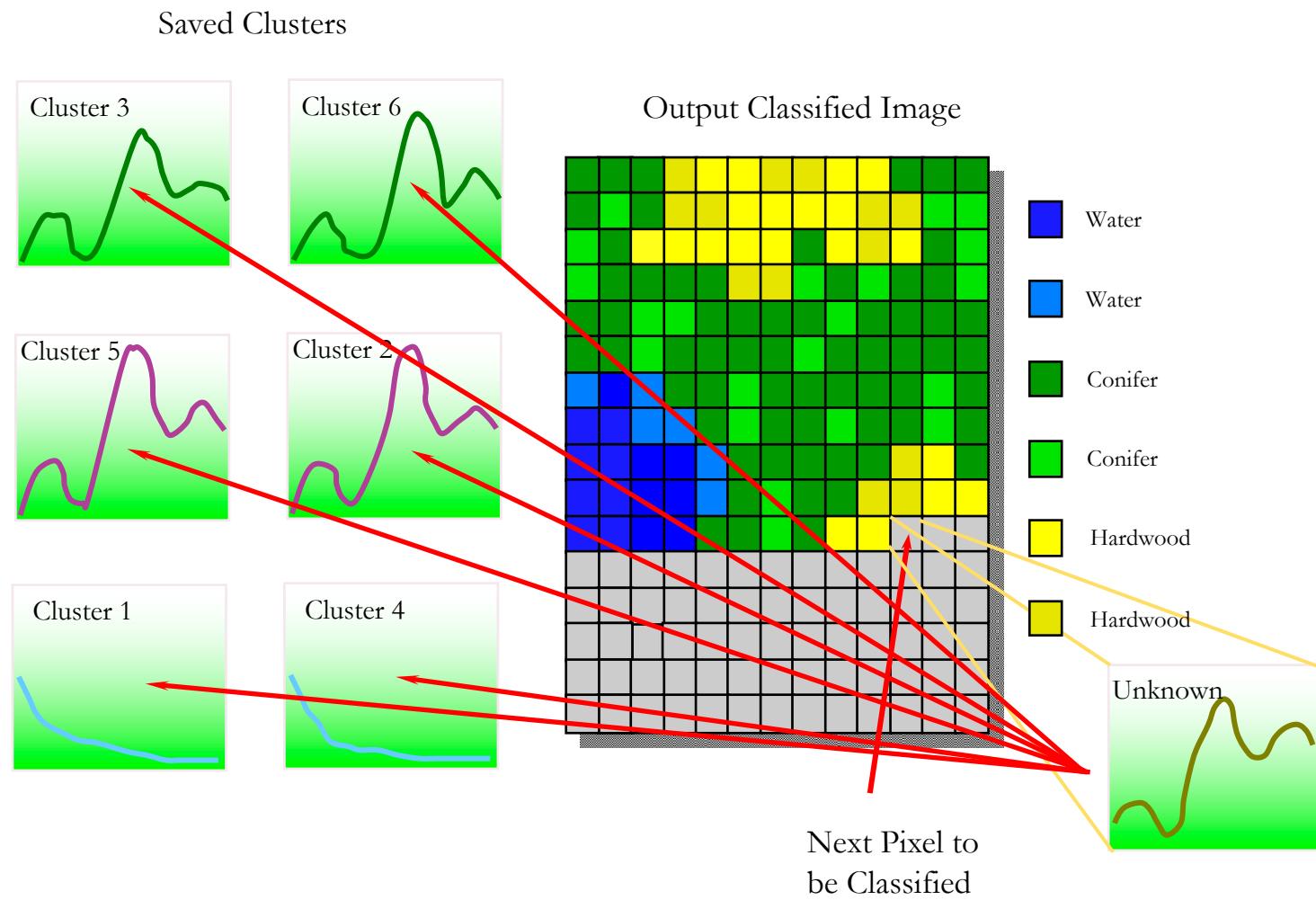
- Nature of task
  - Resolution, Bands & Pricing
  - Pan sharpening/SRM (R&D)
  - Free resources: end

# Appropriation of Remote Sensing Data Science



- Conventional LUC
- Lillesand and Kefer 1987
- Lower Resolution
- Non parametric methods and distribution

# Unsupervised & Supervised

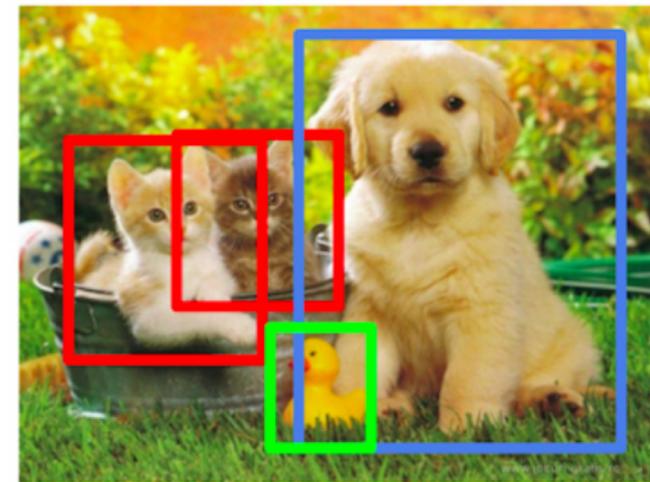


- Evolution Stages
  - Stage I: NDBI to Supervised
    - Training costly
  - Stage II: Parallel (Unsupervised)
  - Stage III: CNN

# Computer Vision: 101

- Classification is passe
- Classification models
  - Identifying/filtering object of interest
- Detection models
  - Bounding box over specified objects
- Segmentation models
  - Exact outline of the object

**Object Detection**



CAT, DOG, DUCK

**Instance Segmentation**

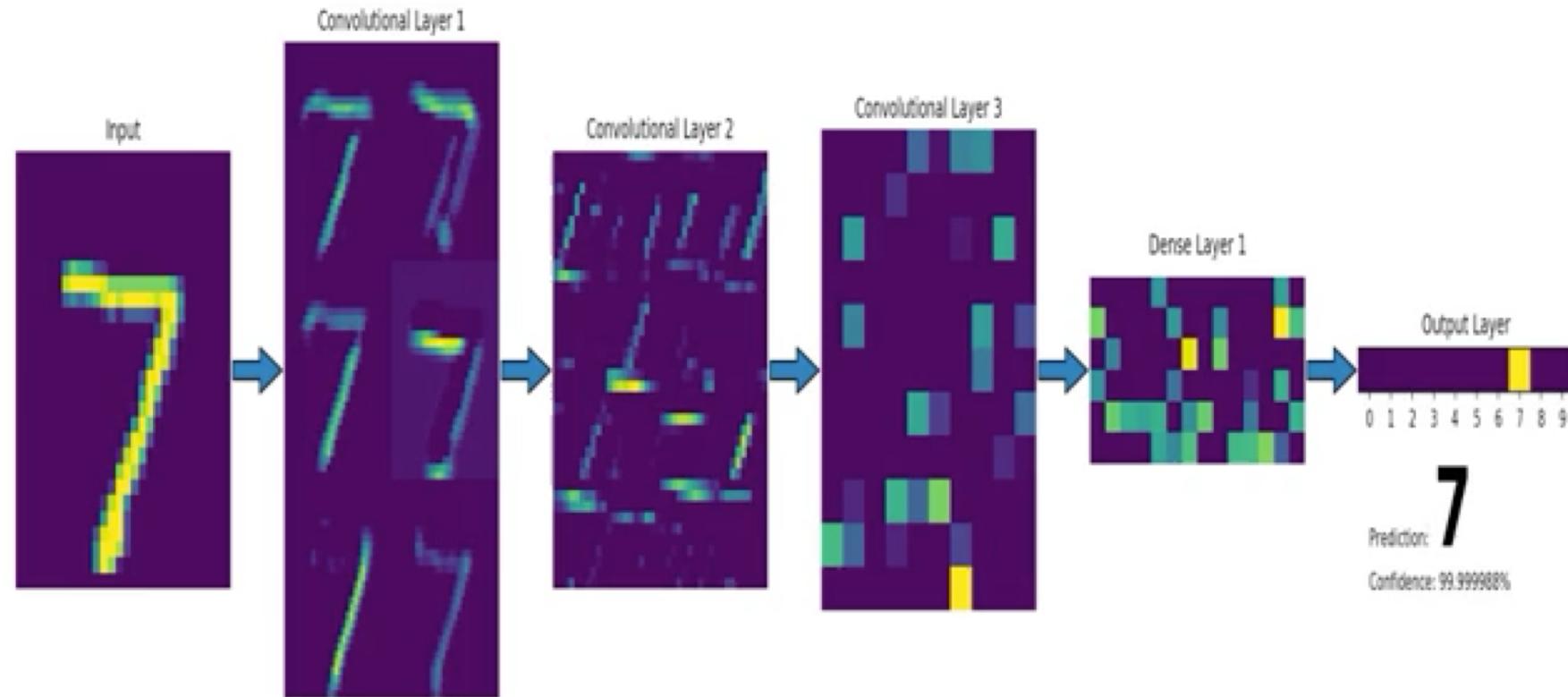


CAT, DOG, DUCK

Multiple objects

Source: Clerify

# Deep Learning: pixel is dead peek into CNN black-box

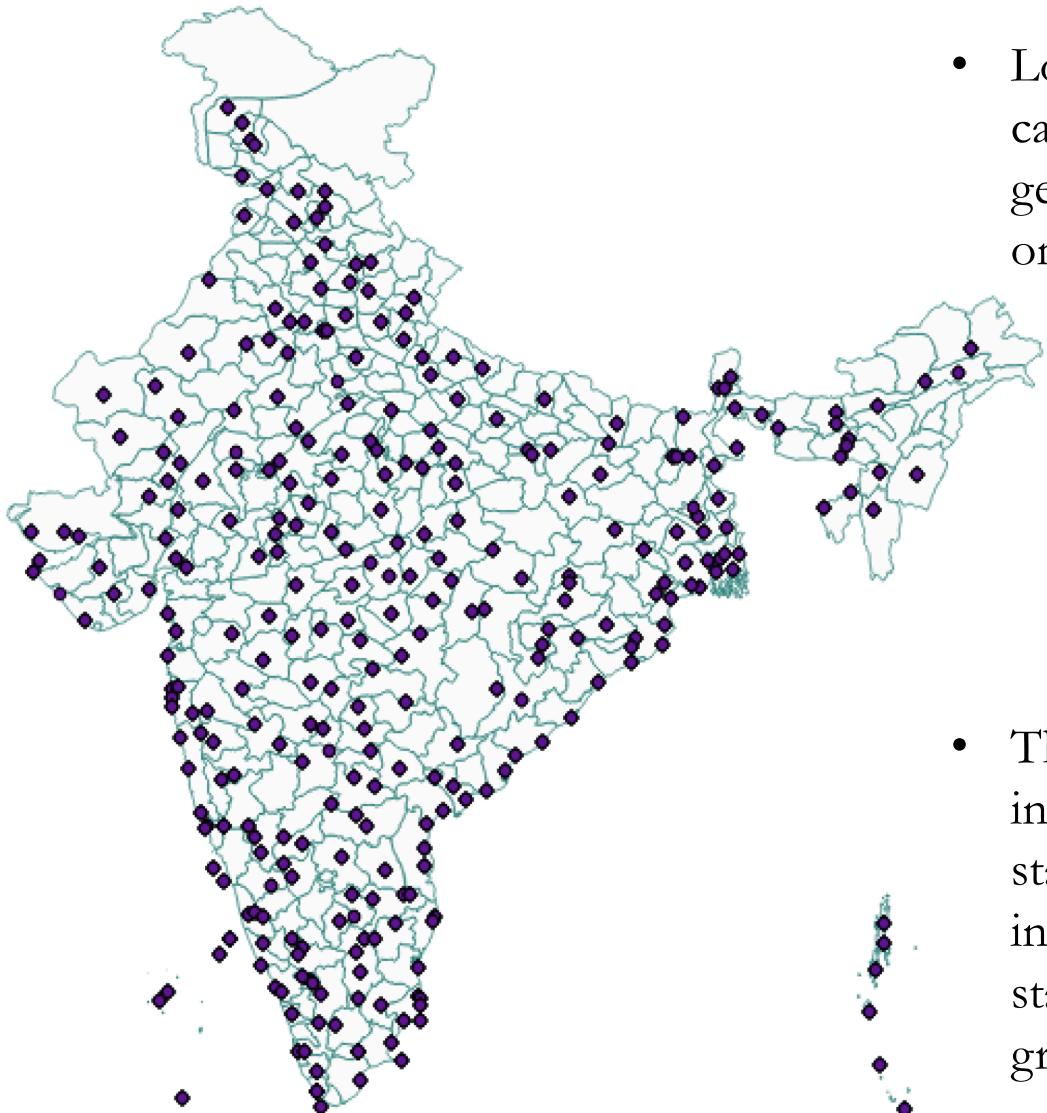


Source: KDNuggets

# *So what is spatial data?*

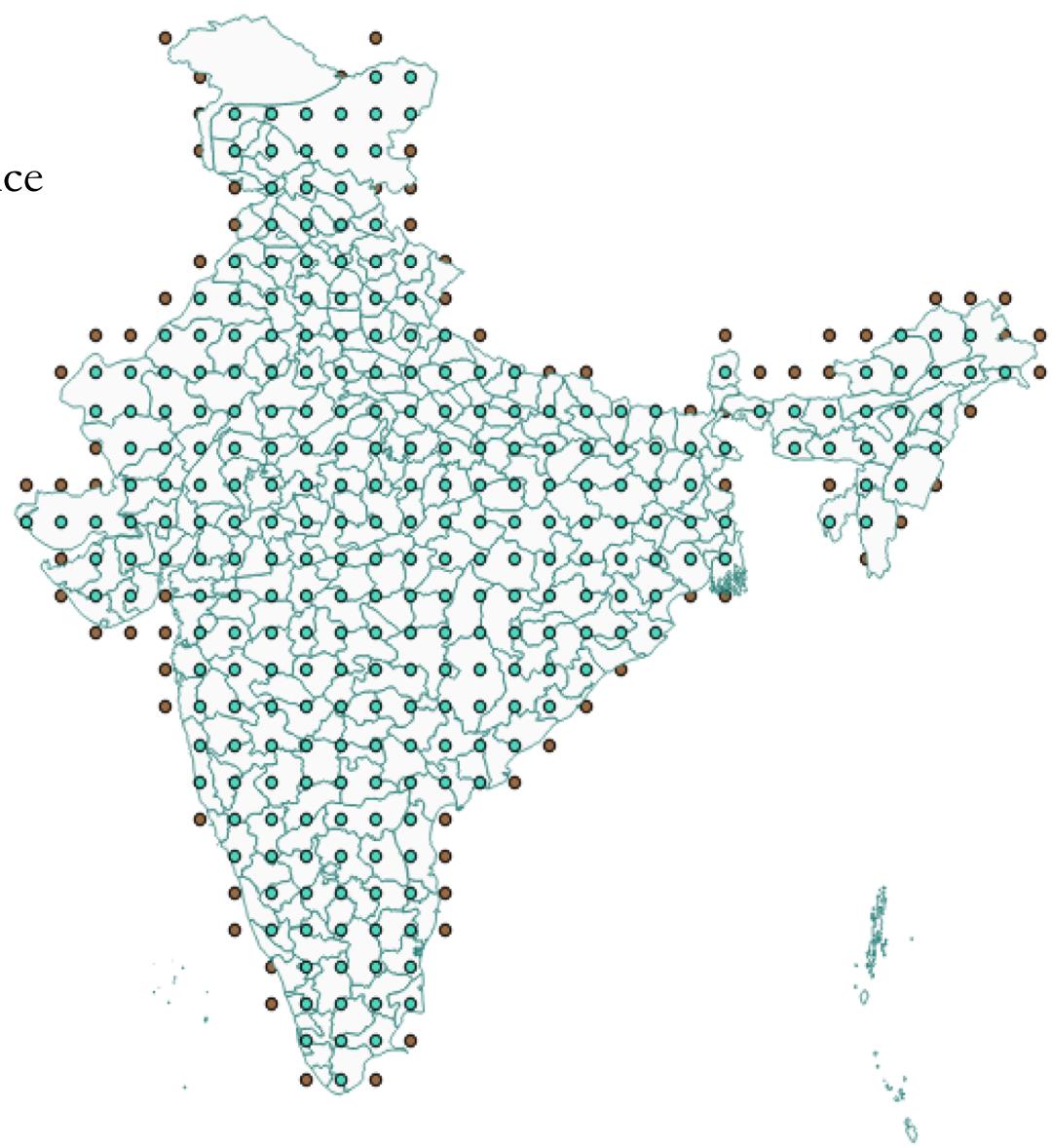
- Raster: (\*.tiff, \*.png)
  - Ready to use: Nightlights, Aerosol Optical Depth (AOD: ppm)
  - Extraction
- Vector: (\*.shp, \*.geojson)
  - Shapefiles: points, line, polygons
- Tools:
  - Operational: ArcGis, Qgis
  - Programming: Python/R
    - R > : raster ease
    - Python >: scaling/automation
- Cloud: GPU's/Tensorflow, Keras,

# *Power of location in public analytics*



Source: [parthkhare.github.io](https://parthkhare.github.io)

- Location of station can bias their geographical influence on crops

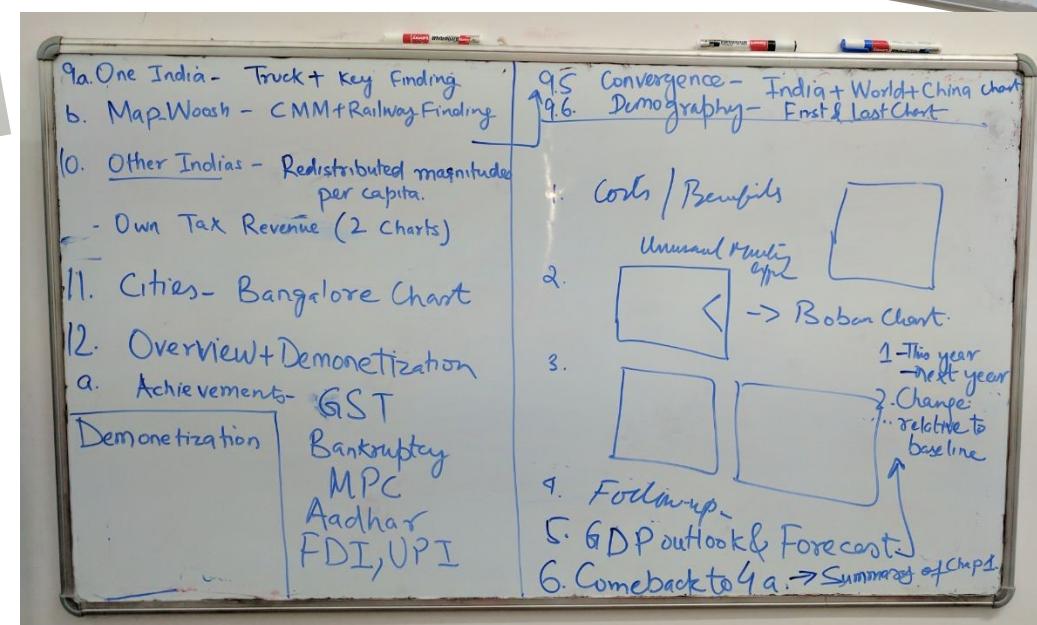
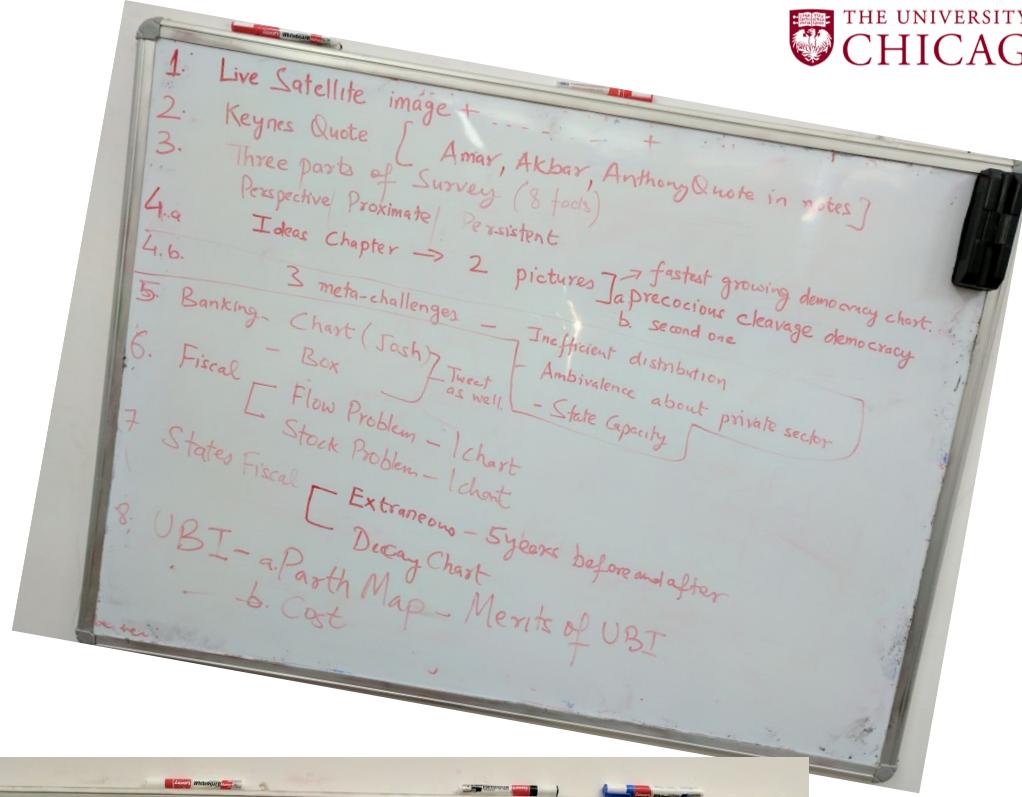
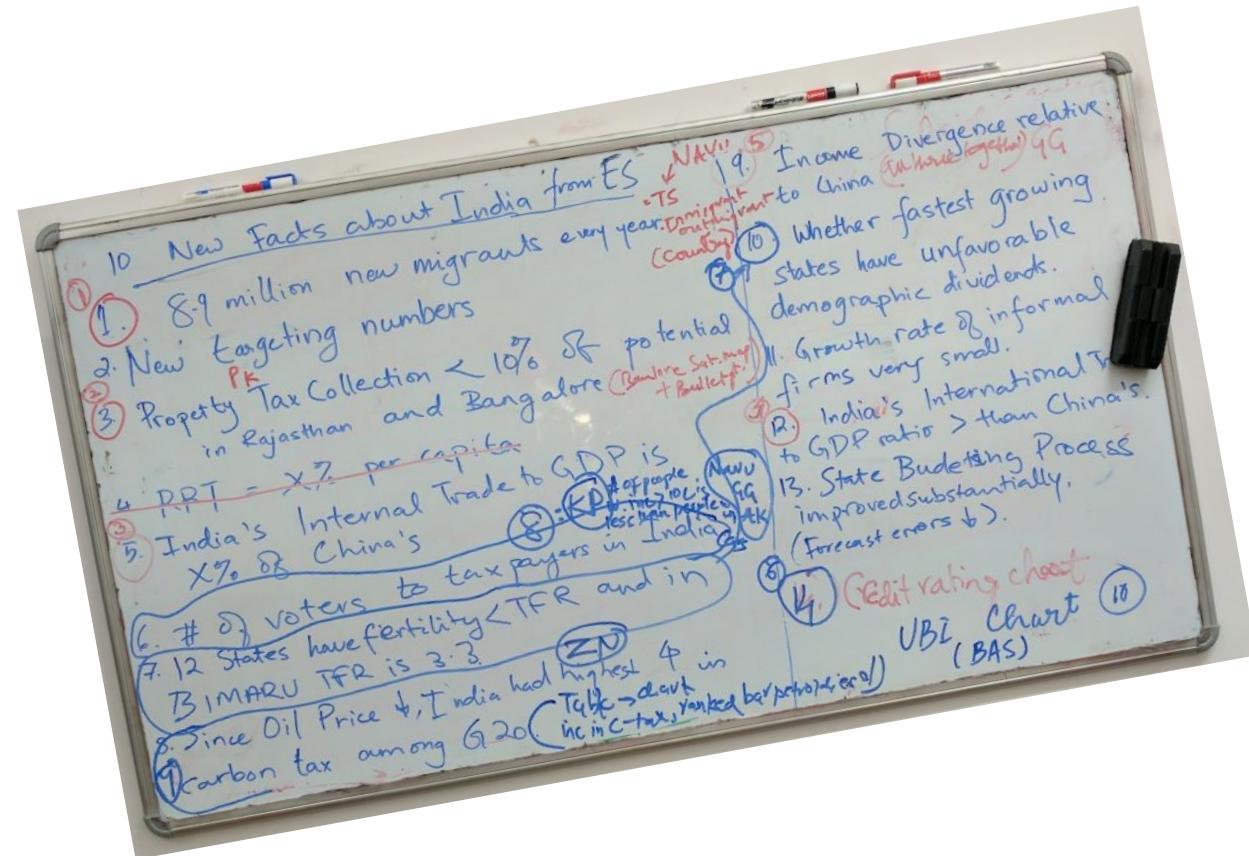


- Therefore, after increasing the stations, we spatially interpolated the stations on an even grid

# Section II. A: Public Policy

## *Deployed Applications at MoF*

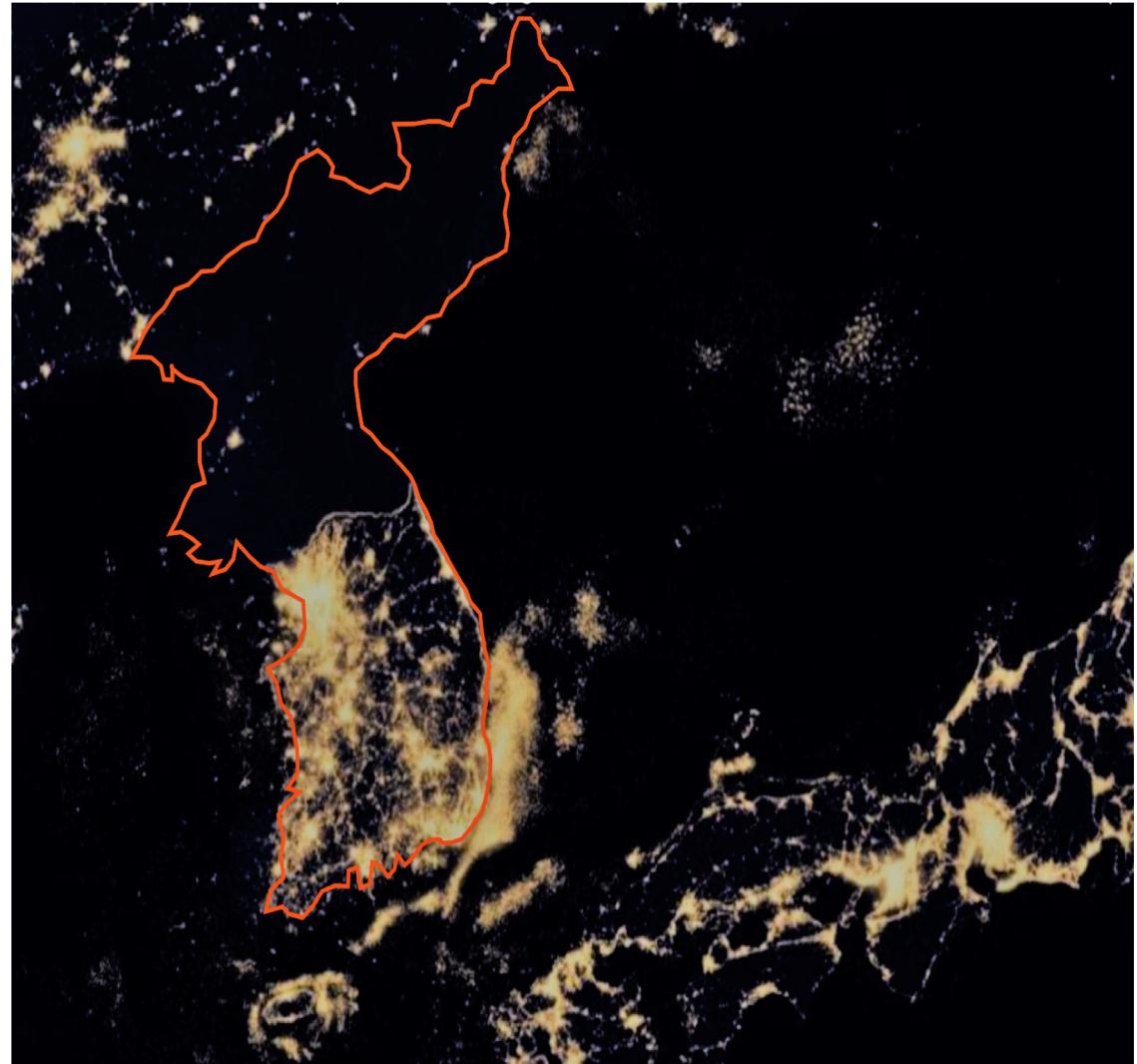
# Deconstructing Economic Survey



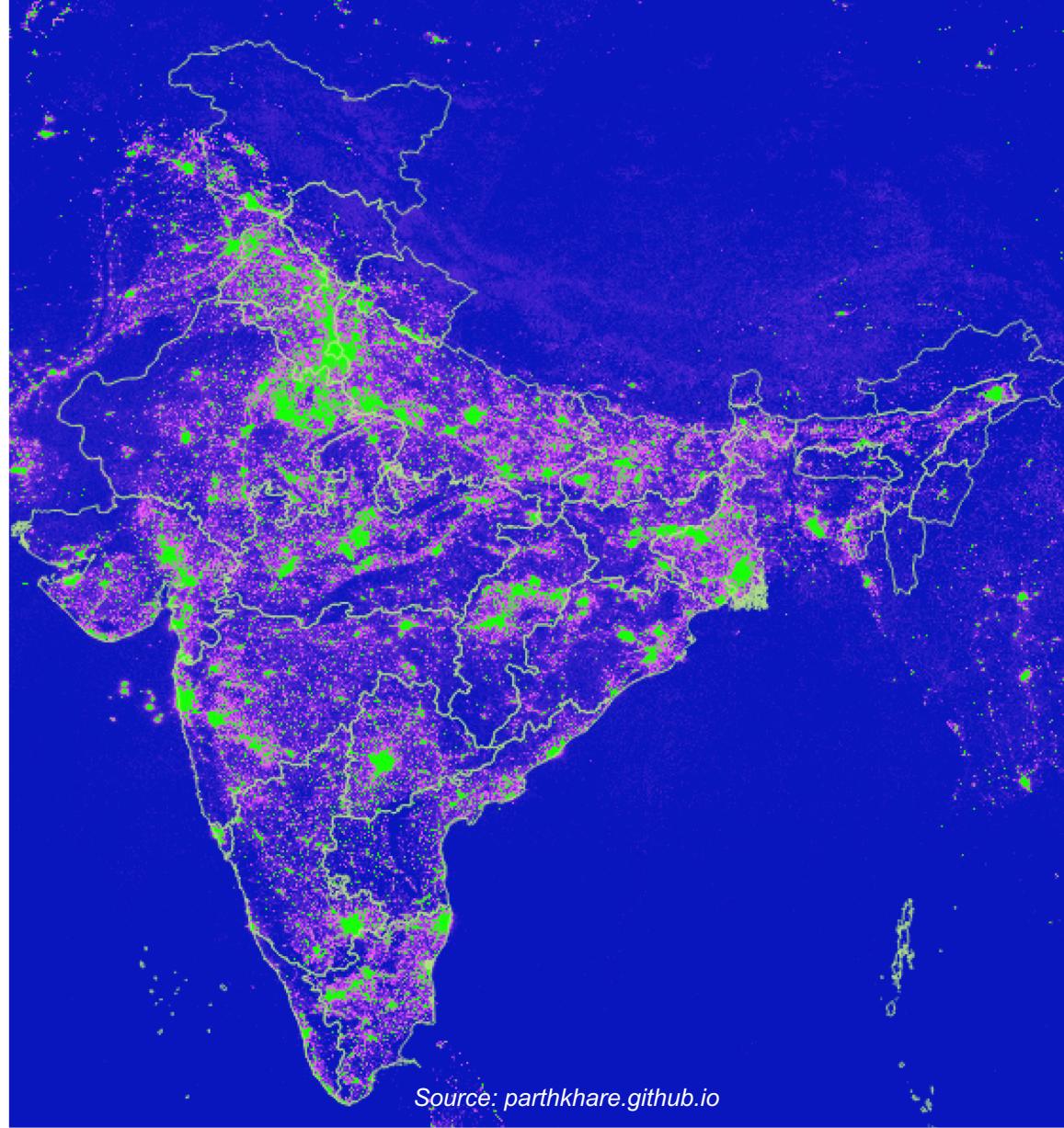
# Policy making & Data: Economic Survey

- *New Data*: Satellite Imagery
  - Realizing Fiscal Space: Property Tax
  - Implications CSS: Urbanisation Rate {migration/flux}
- *Improving Data Capacity*: Ground Stations: Weather
  - Ramifications for IPCC: RCP protocol
- *Out of Box use*: Passenger
  - Dynamic assessment

# Visualizing Data: Impact & Audience

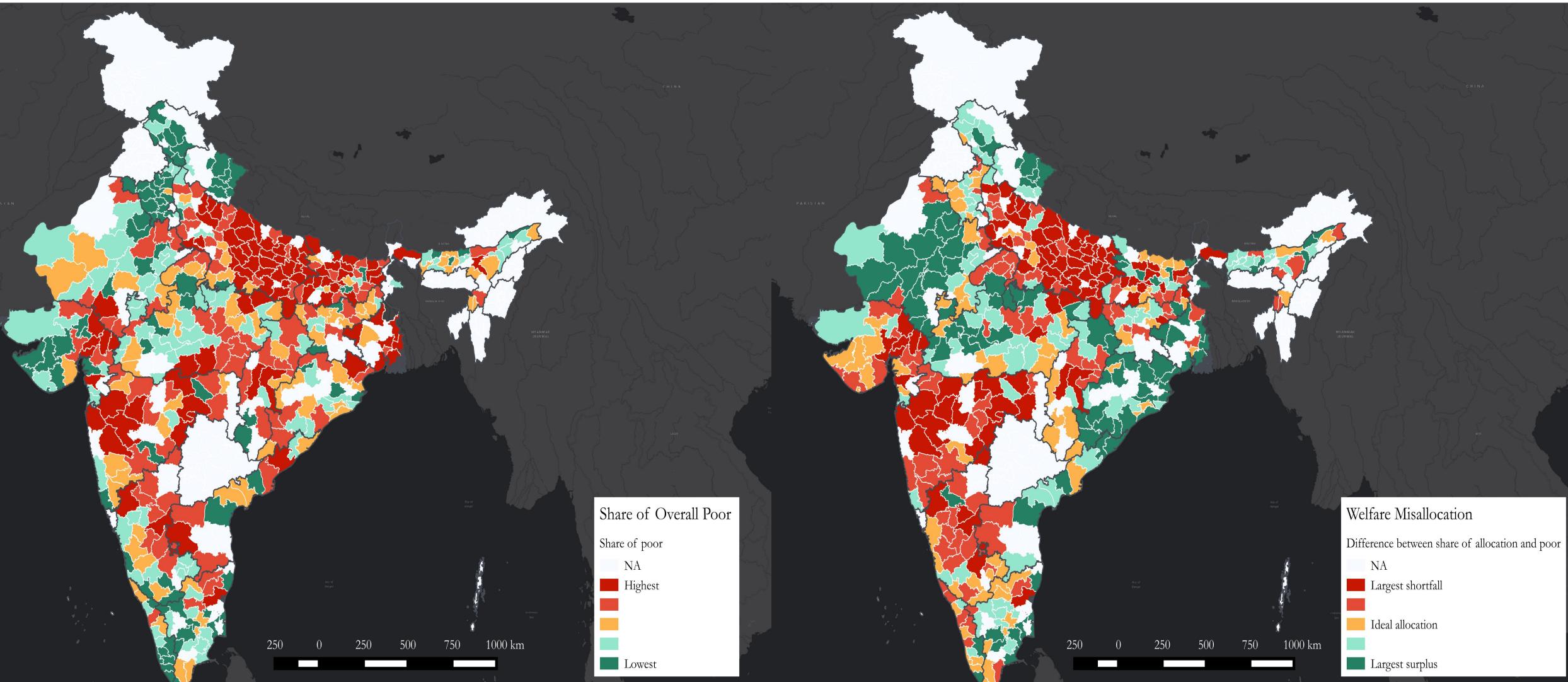


Source: NOAA



Source: [parthkhare.github.io](https://parthkhare.github.io)

# Where are the poor & what are the districts of misallocation



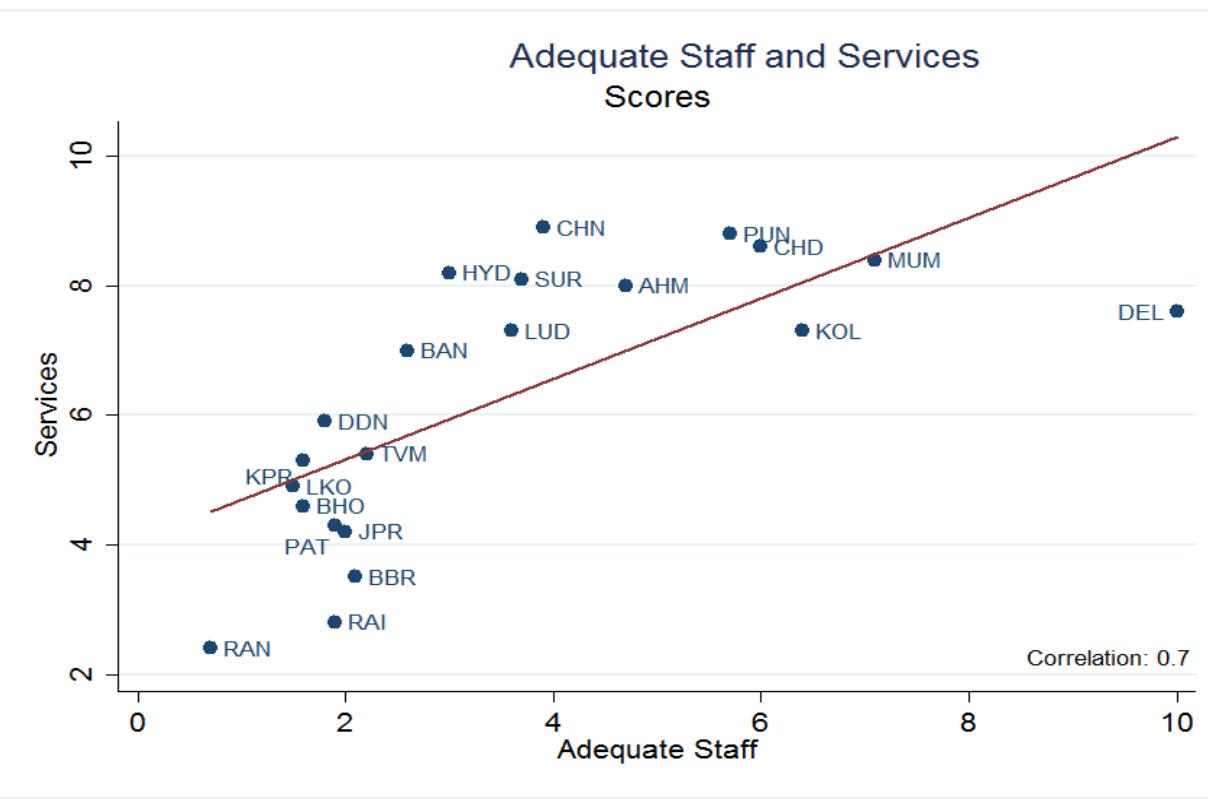
Source: Economic Survey 2017

# *Section I: Satellite Data*

- Free from human error
- Free from intentional field survey biases
- Dynamically updated
  - Census estimates in 10 years, thereby
  - Fails to capture the spurts and flux through demography mobilization
- Better assessment of Social Sector Funding/Grants to States, ULB's, Panchayati Raj
  - Helps planned expenditure and revenue collection

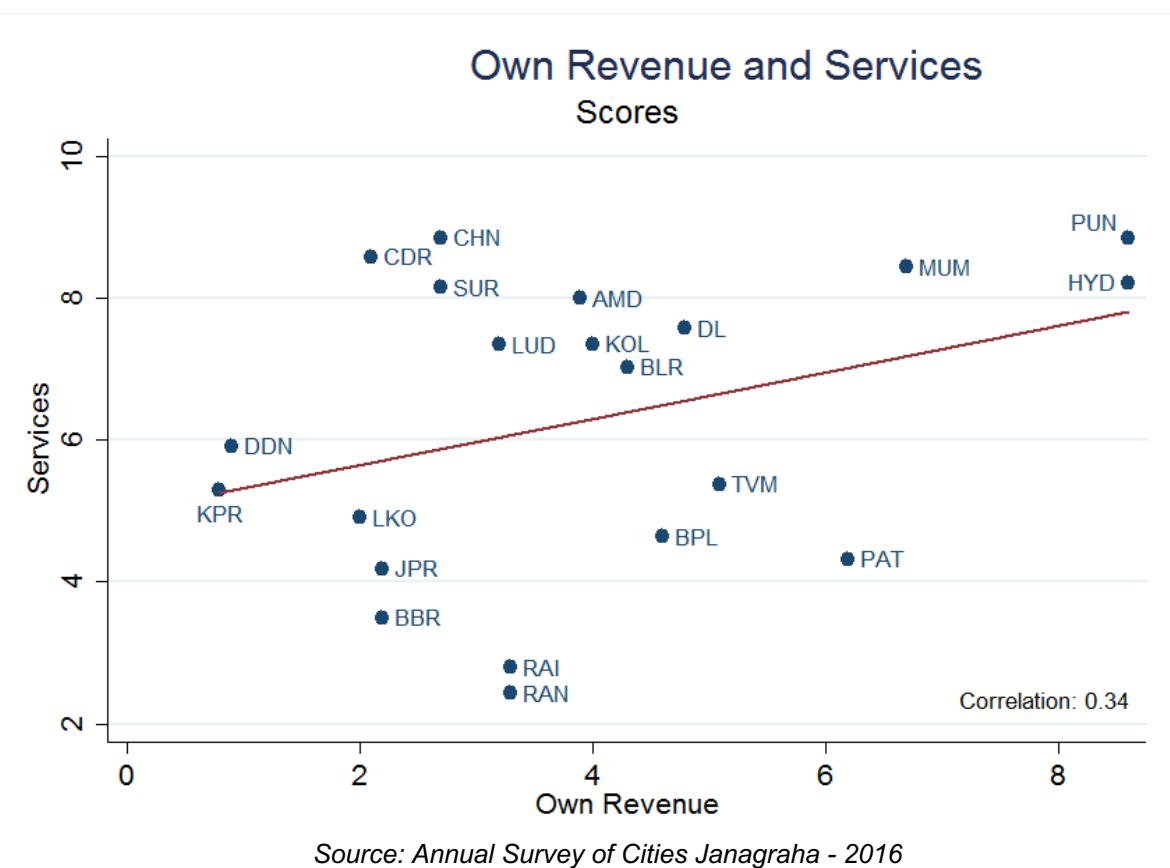
=> BMC's implementation, 15<sup>th</sup> Finance Commission proposal forest detection,

# Property Tax I: Motivation [Revenue Capacity]



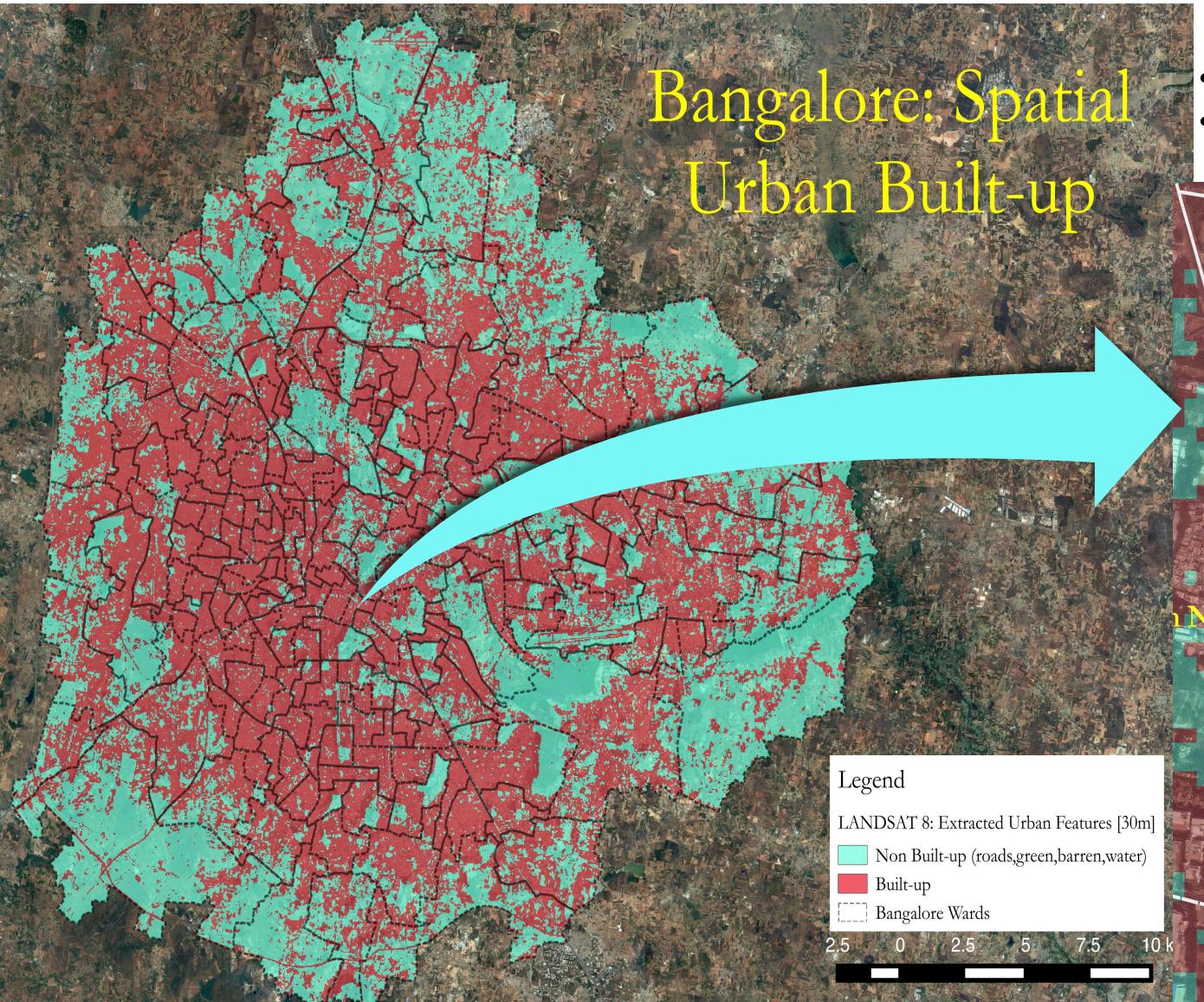
- Efficiency from Self Financing: Cities that generate their revenue tend to provide better services
- Driven by
  - Size of the tax base,
  - Efficiency in tax collection and
  - Level of economic activity in the city area

- Cities do not maximize their tax potential
- Power to impose more taxes does not imply more revenue

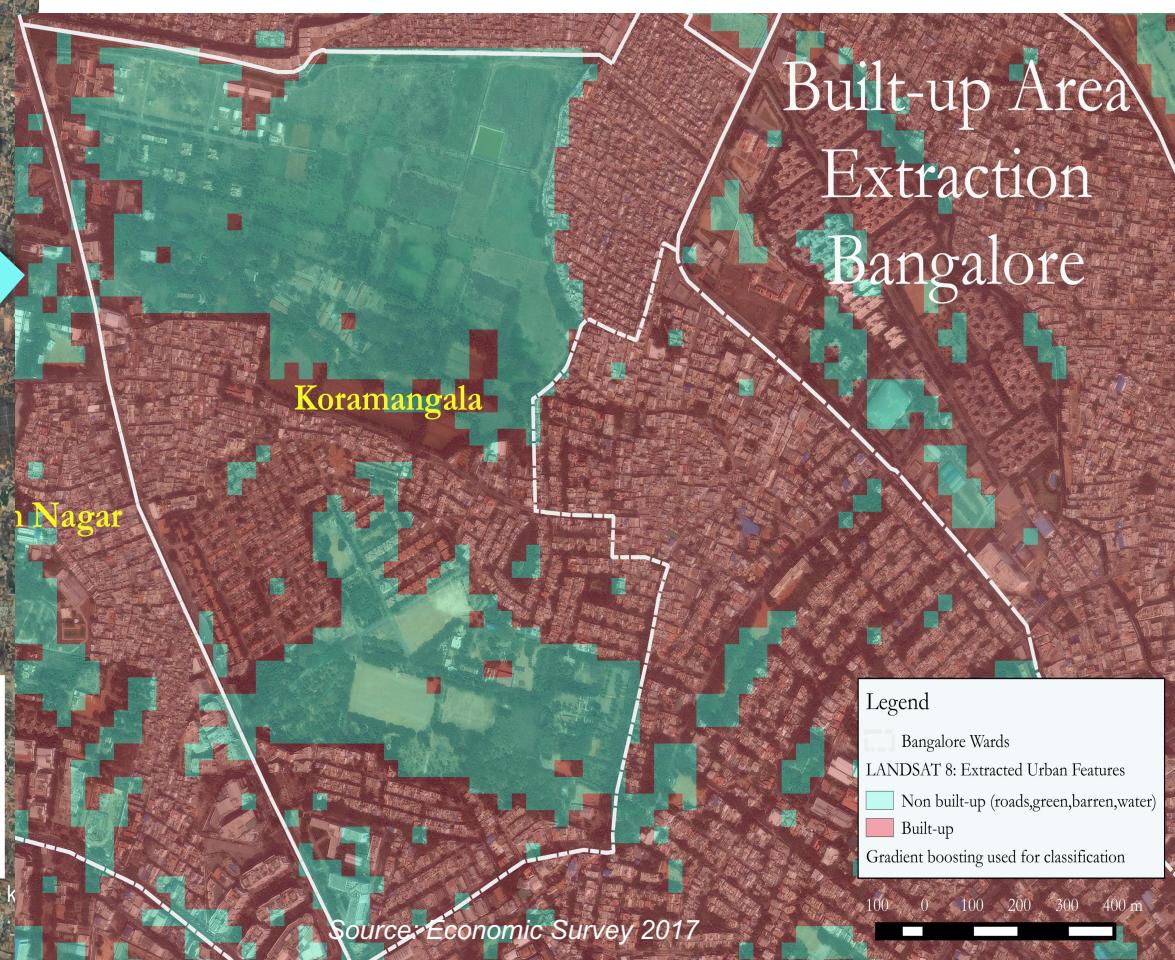


Source: Annual Survey of Cities Janagraha - 2016

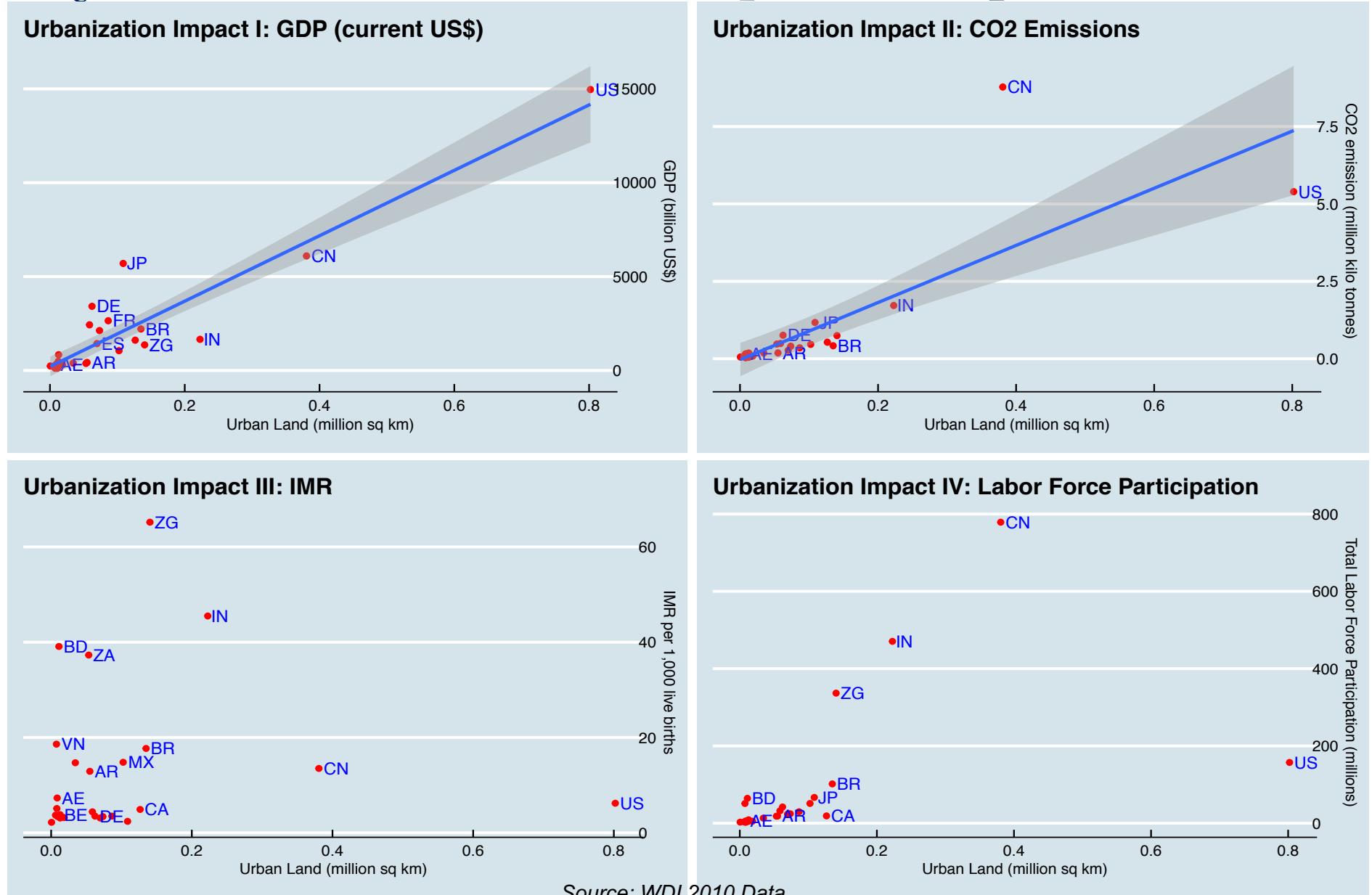
# Property Tax II: Open Source Data + Municipality



- Jaipur can collect **more than 90%** of its current property tax
- Bangalore can collect **more than 80%** of its current property tax



# Urbanization Rate I: Motivation [Bi-causal]



# Urbanization Rate II: Re-define

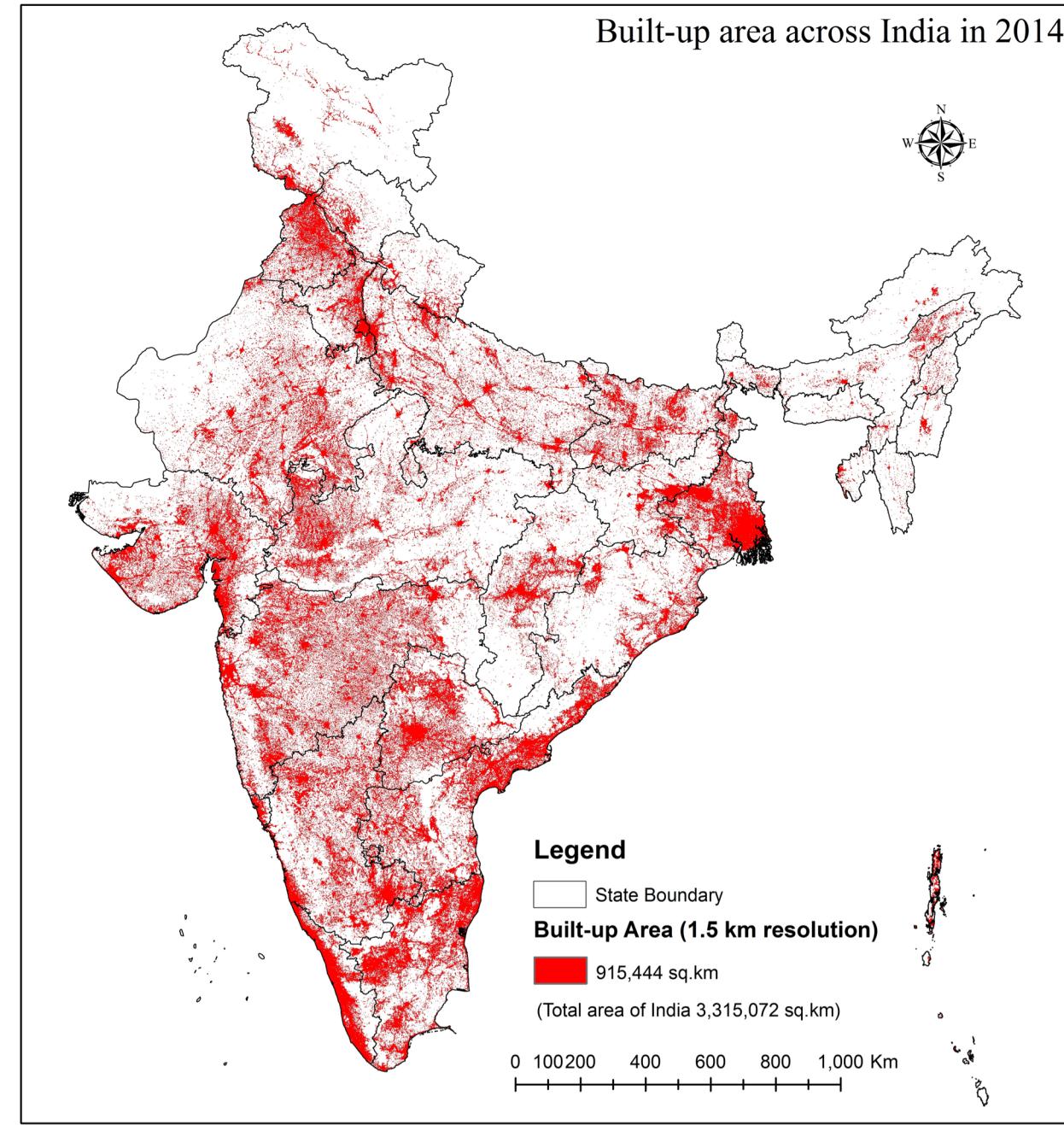
**Census  
2011  
[31.16%]**

Population of at least 5000

Density of at least 400 persons per sq. km

75 percent of male working population is engaged in non-agricultural activities

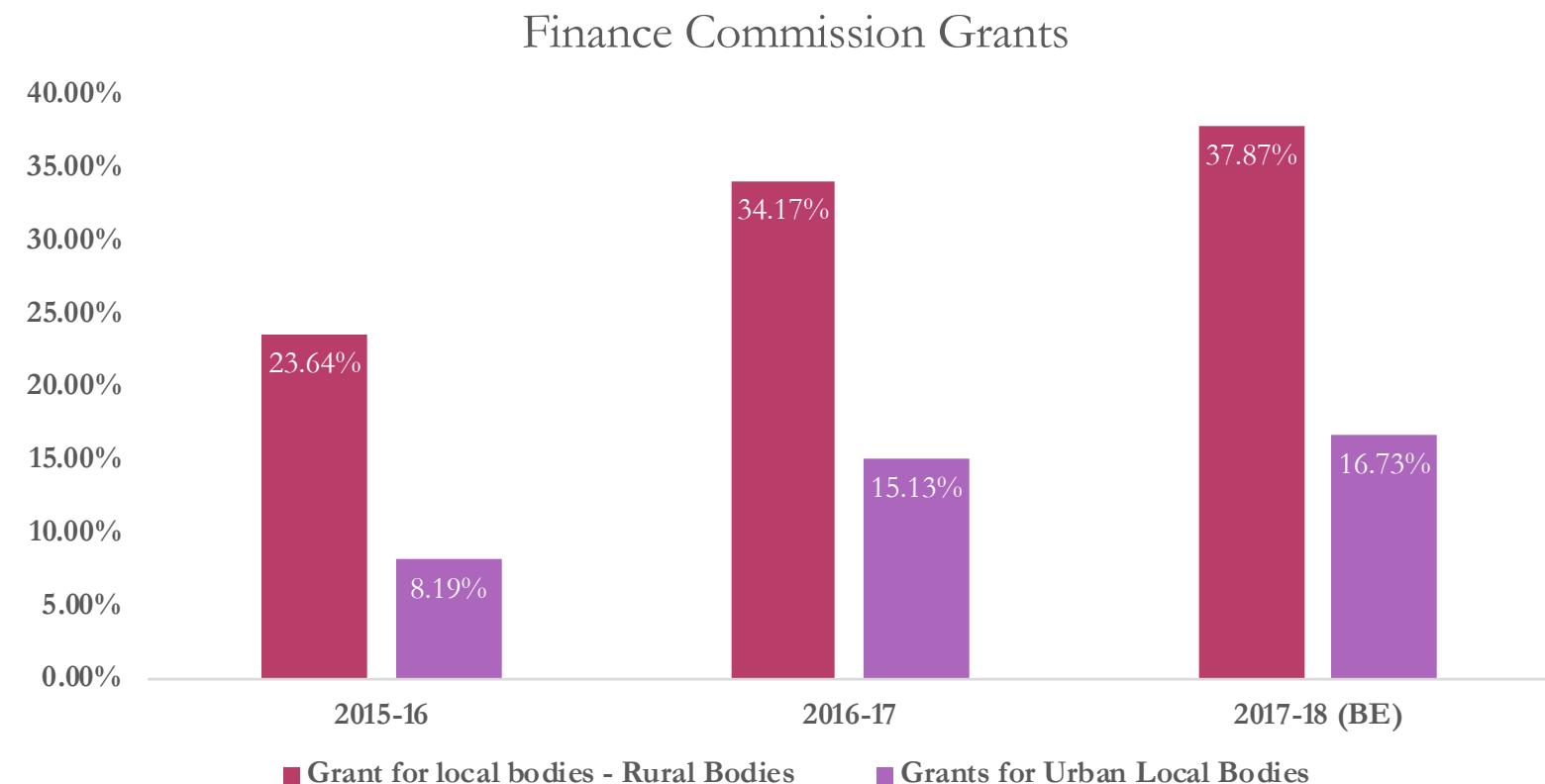
- Need for renewal (Census definition unchanged since 1961)
- Inconsistency among different governmental definitions
- Underestimation of extent of urbanisation (when compared to definitions of other countries)
- Survey based
- Migration Bias
- 27.1% – 31.2% in 10 years with 2 digit growth



Source: Economic Survey 2017 II

# Urbanization Rate III: Policy Implication(s)

- Economic growth closely linked to urbanisation
  - North America/ Europe were 50% in 1940s, 80% now
- Cities the gateways to globalization
  - 80% of all FDI into China in 1990 went to top 20 cities

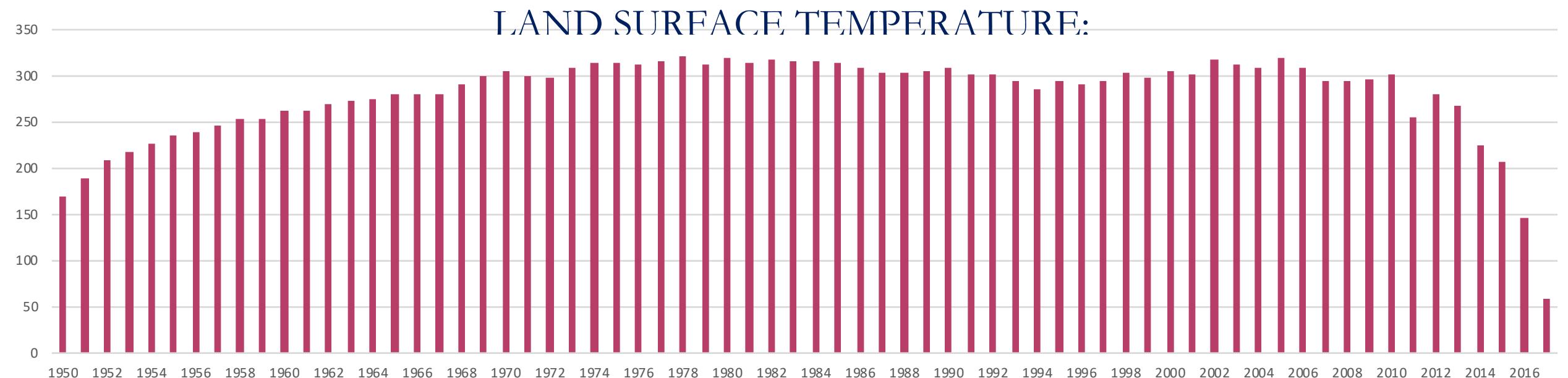
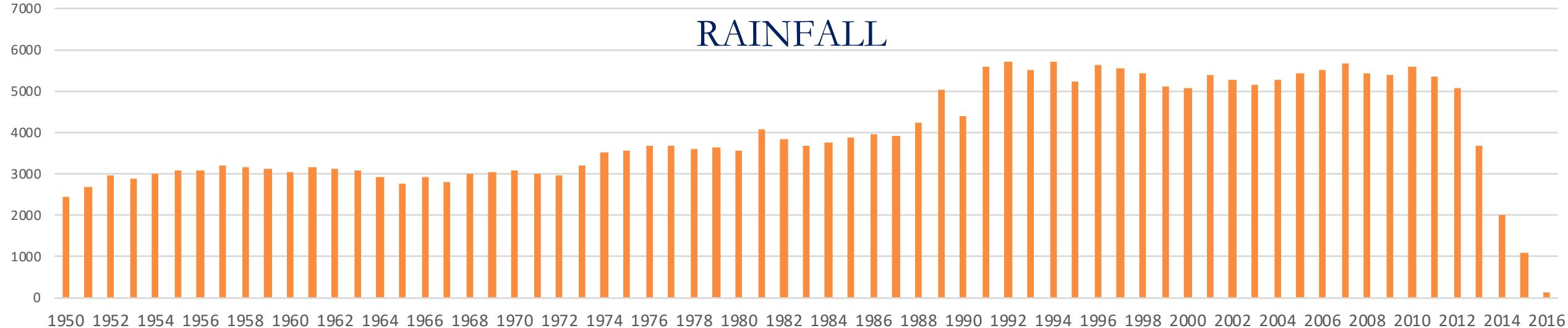


# *Section II: Climatology Data*

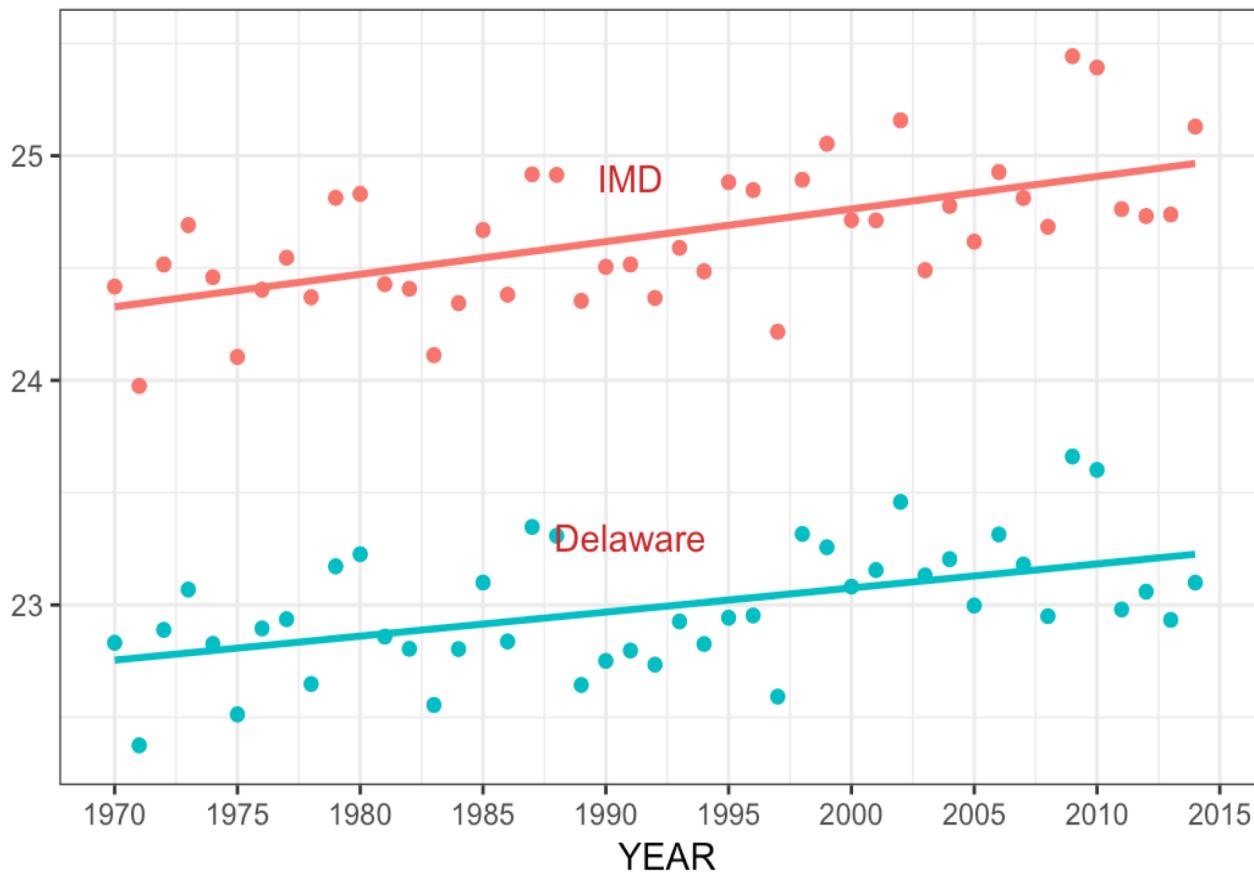
- Ground Stations
- Climate Data on Rainfall & Temperature
  - One of earliest sources of recorded data in India
  - Yet observations from all ground stations not leveraged properly
- Divergence with International Results
  - also seen in groundwater/air quality data

=> 6 months on data, global divergence IPCC

# Climate Change'd' I: Motivation [Ground Stations]

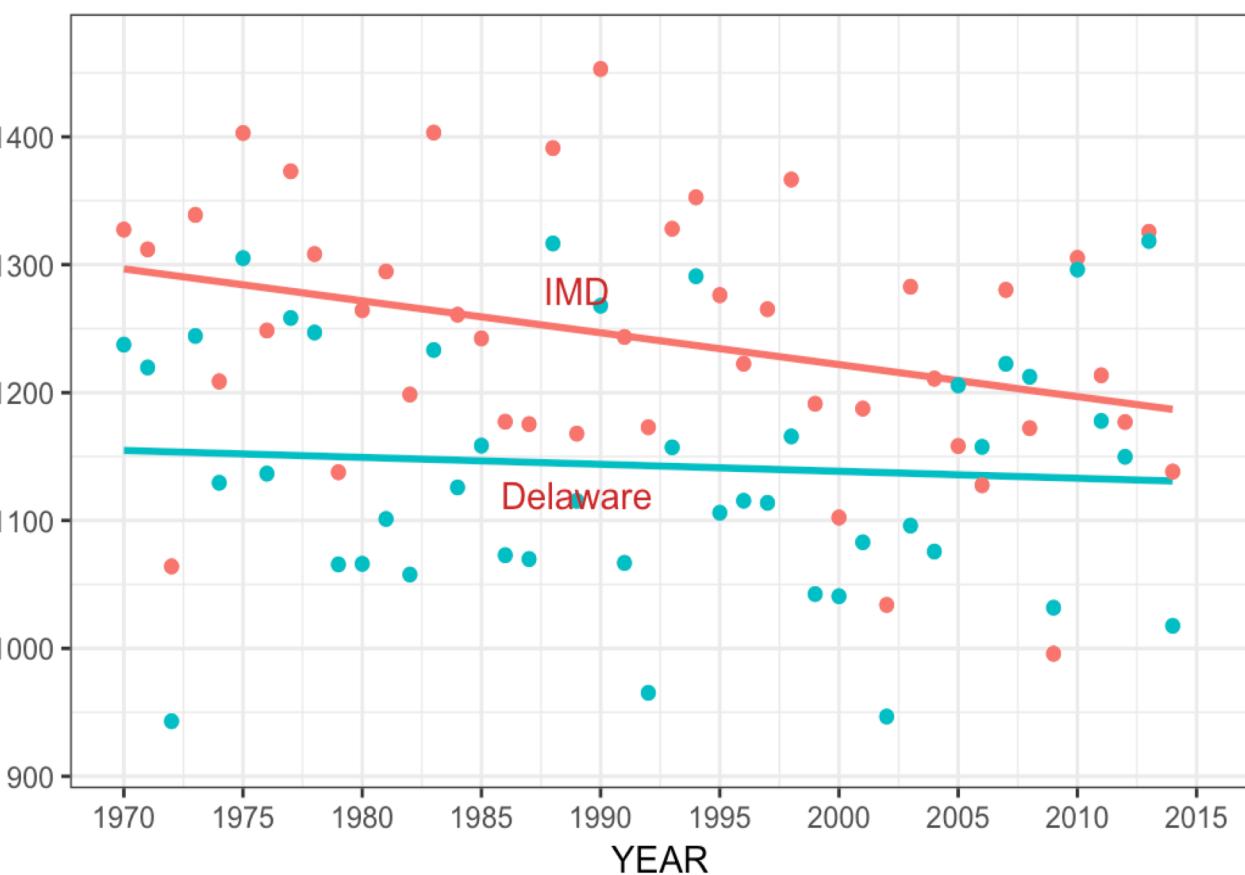


# Climate Change'd' I: Motivation [Leverage Data Density]



IMD: 210 Stations   University of Delaware: 45 Stations

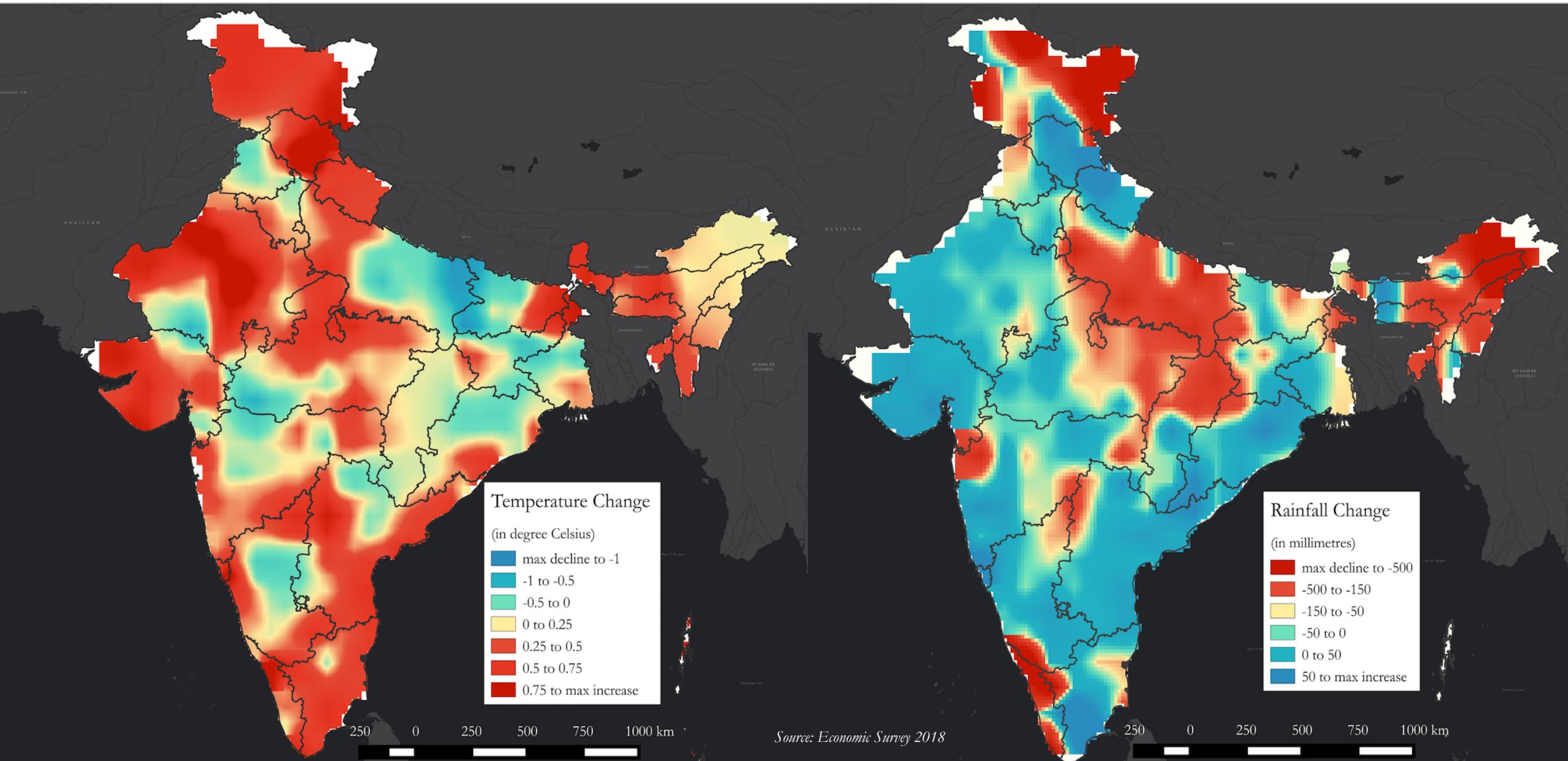
- International source of Indian Data with far fewer stations
- Upkeep: sourcing from magnetic tapes/Fortan



IMD: 2140 Stations   University of Delaware: 300 Stations

Source: Economic Survey 2018

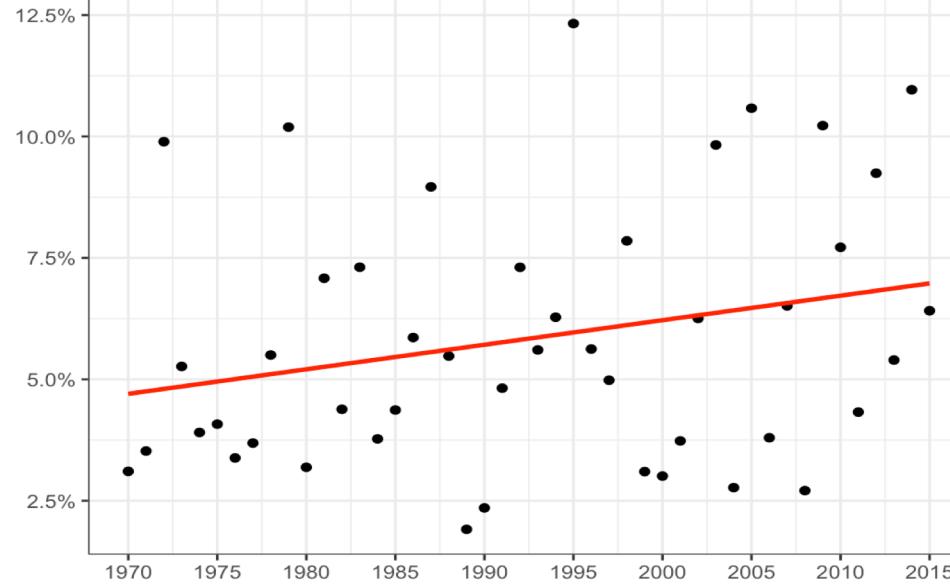
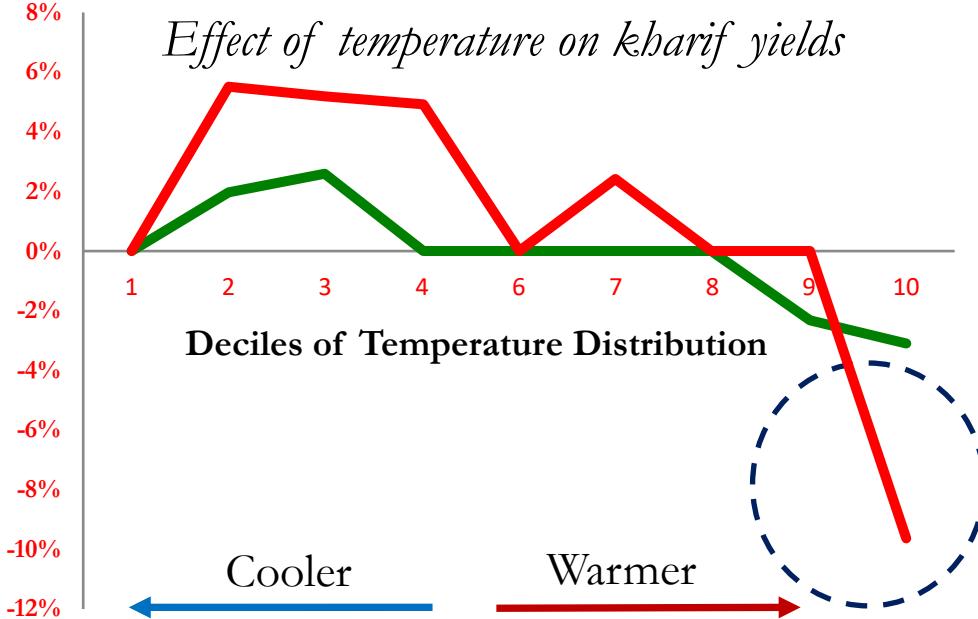
# Climate Change'd' II: Change in weather patterns between the last decade and 1950-1980



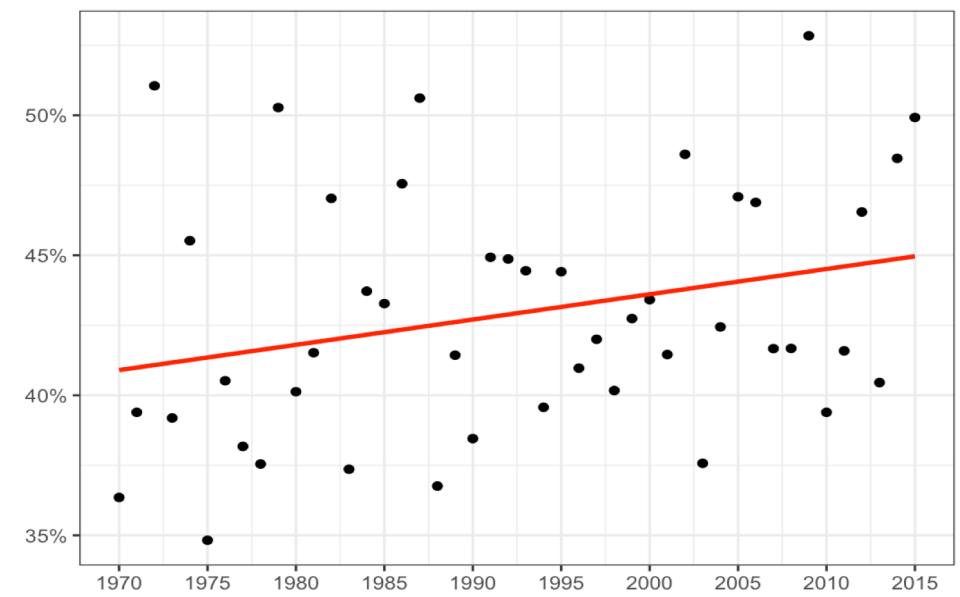
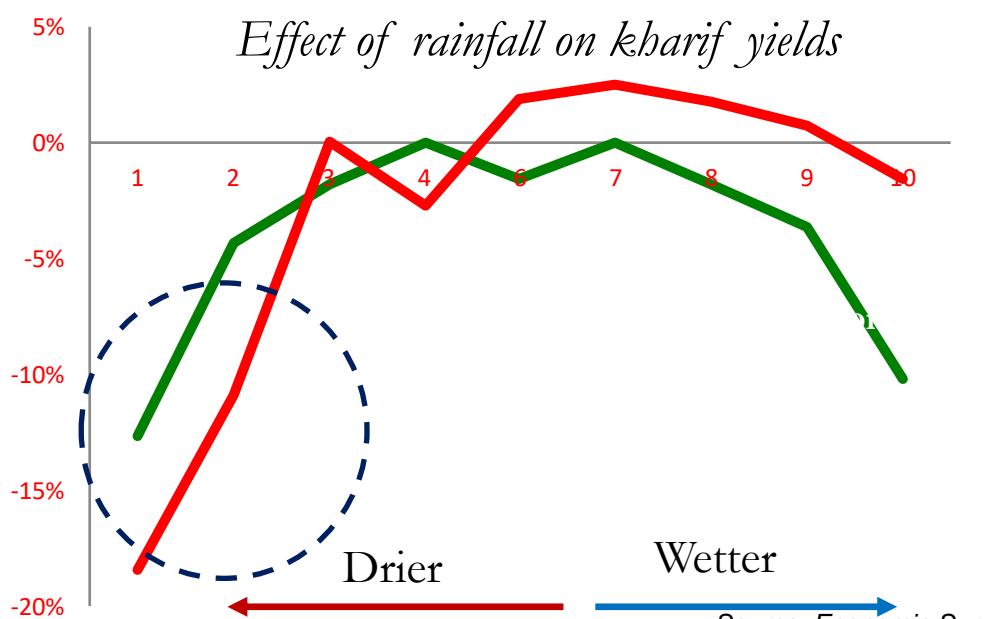
Source: Economic Survey 2018

*Hot Days*

(percent of kharif days with very high temperature)

*Effect of temperature on kharif yields**Dry Days*

(percent of kharif days with less than 0.1mm rainfall)

*Effect of rainfall on kharif yields*

Source: Economic Survey 2018

# *Section II: Passenger Migration*

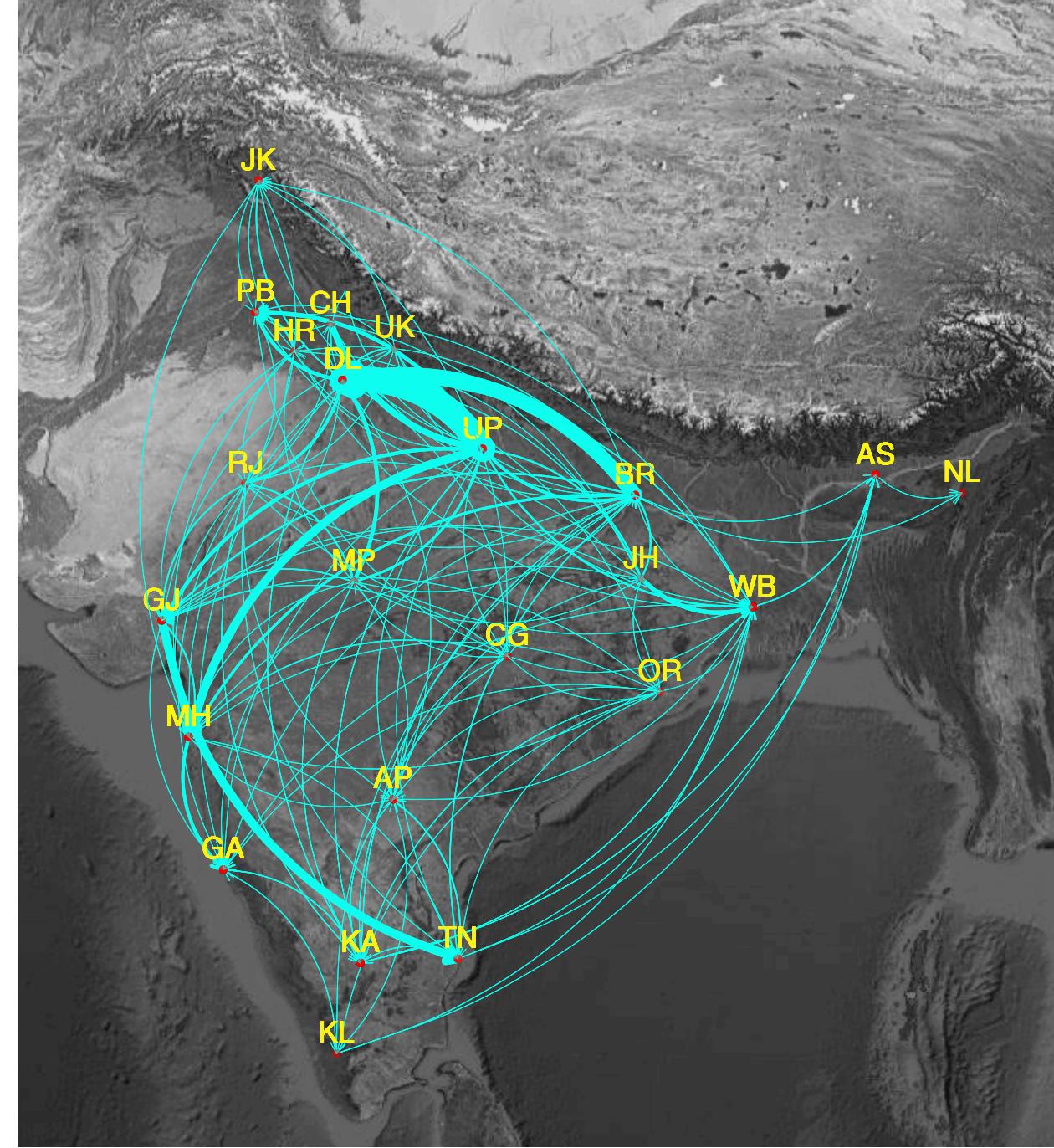
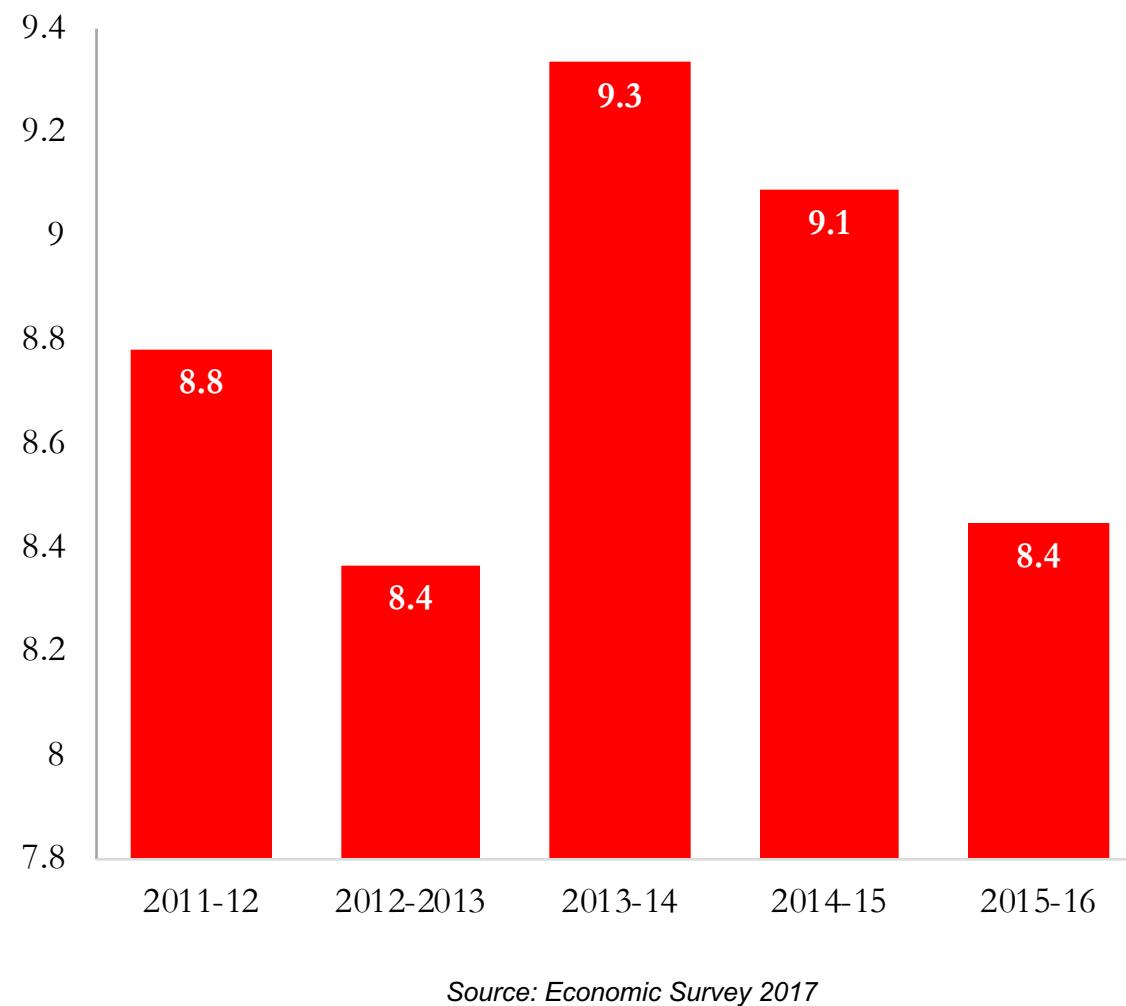
- Unreserved passenger traffic data between every origin destination pair for the years 2011-16 was obtained
- Railway 5 years data density:
  - 4,57,88,175 points for 1 years of unreserved tickets, which showed the annual mobility in India from 4 million to 9 million
  - 250 million rows
- Passenger movement {break-journey}
- Discerning day journeys
- Validation with Holiday festival season

=> BMC's implementation, 15<sup>th</sup> Finance Commission proposal forest detection,

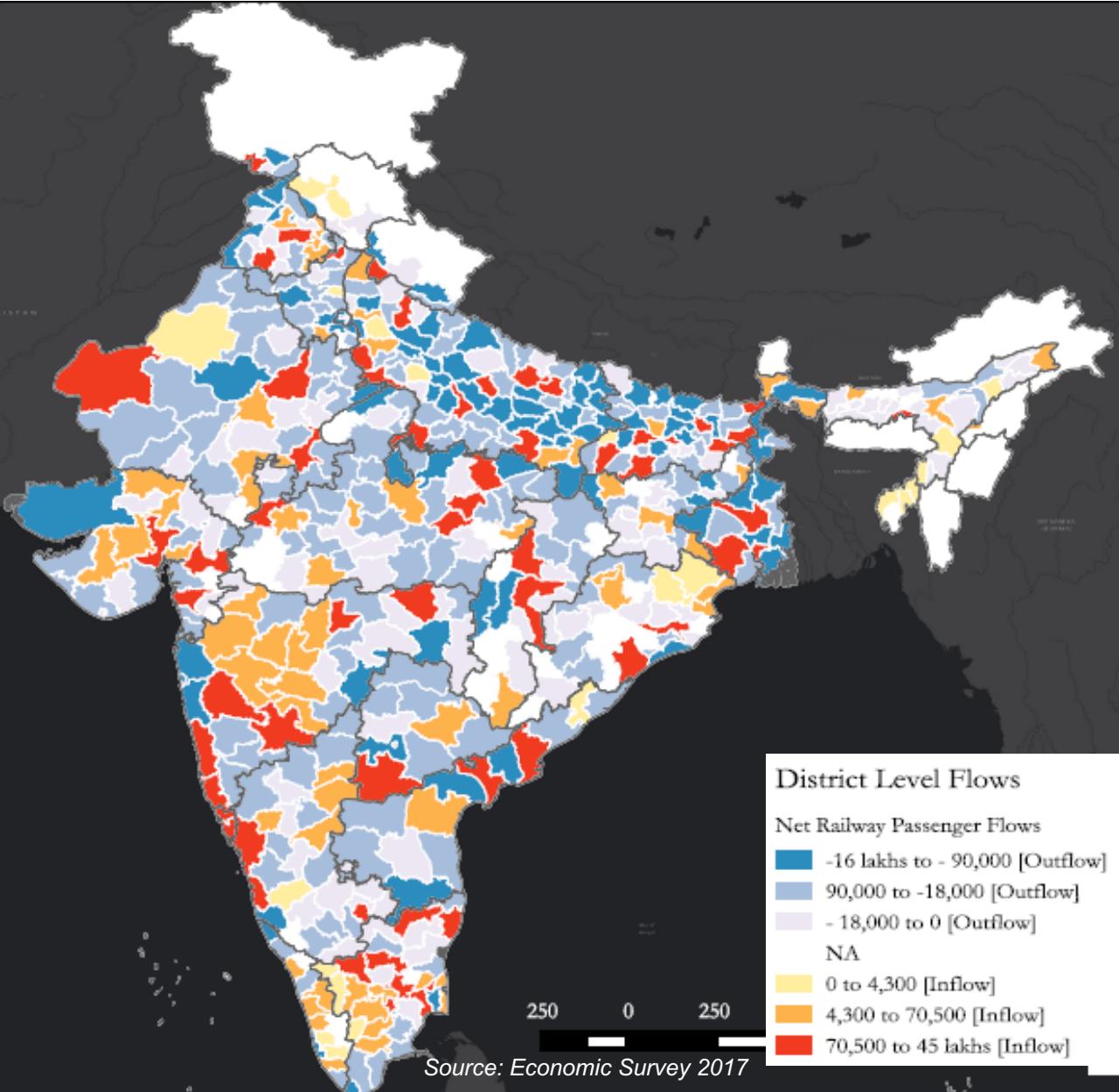
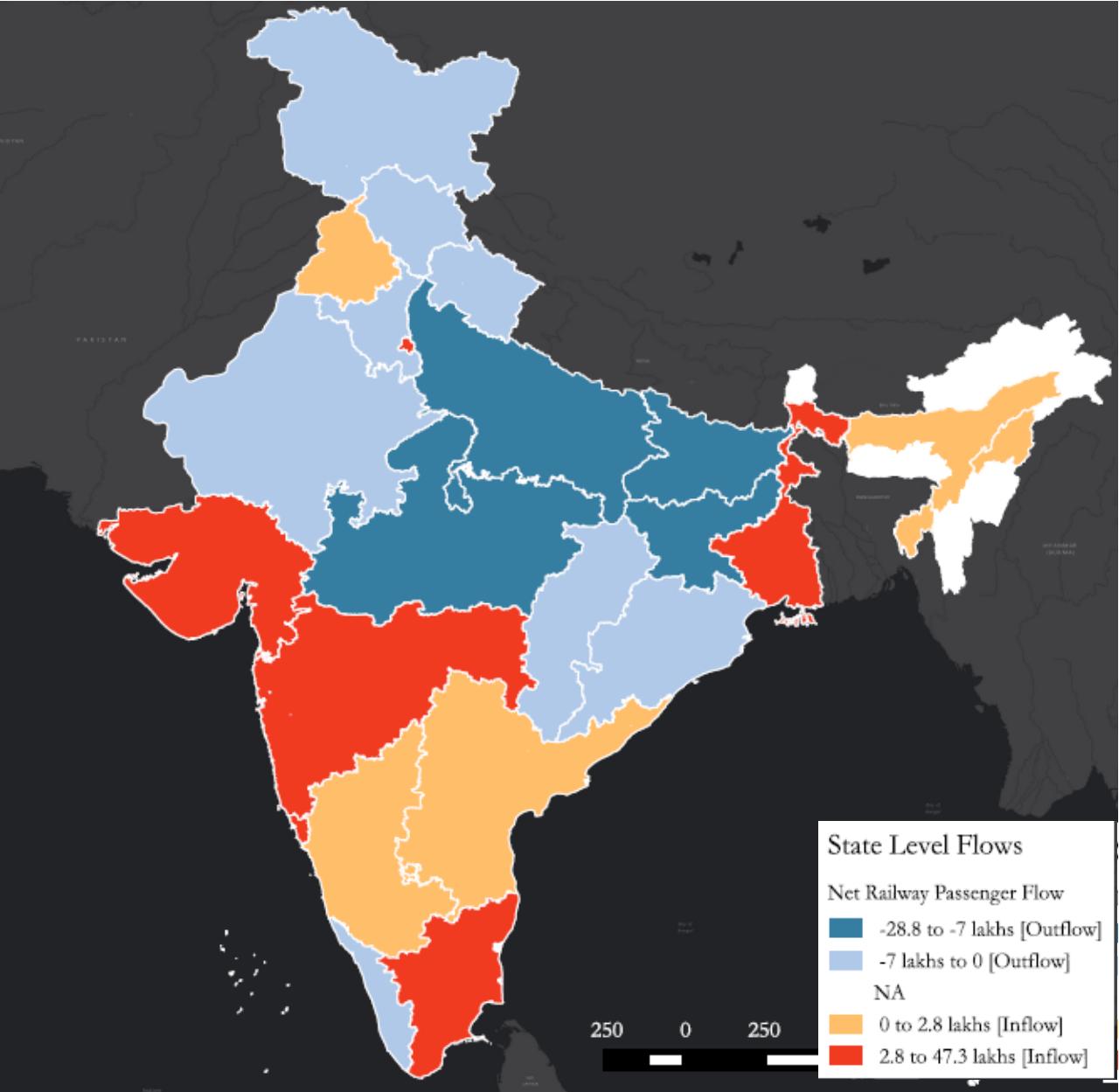
# Migration I: Motivation



# Migration II: Dynamic



# Migration III: Railway Passenger Traffic



# Section II. B: Public Policy

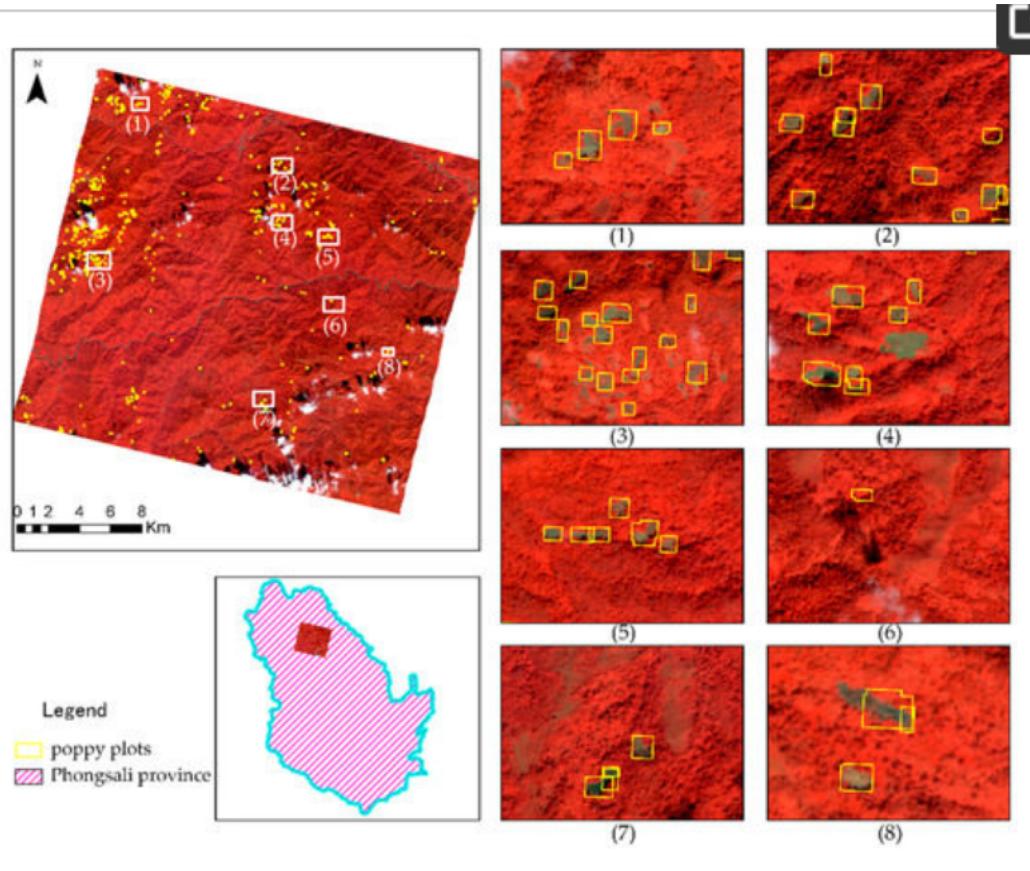
*Applications: Under research & external*

# Active Projects I Tin (Rooftops)

Poverty assessment: Census roof-top



# Active Projects III: Opium & Conflict



Source: Yiu, Tian, 2018 Myanmar

- More than 90% of illicit heroin globally, and more than 95% of the European supply
- Provides about 400,000 jobs in Afghanistan
- Area: Helmand, South Kandahar

*FIN*



*follow up*

email: [pkhare@uchicago.edu](mailto:pkhare@uchicago.edu), [parthakhare@gmail.com](mailto:parthakhare@gmail.com)

website: <https://parthkhare.github.io/>