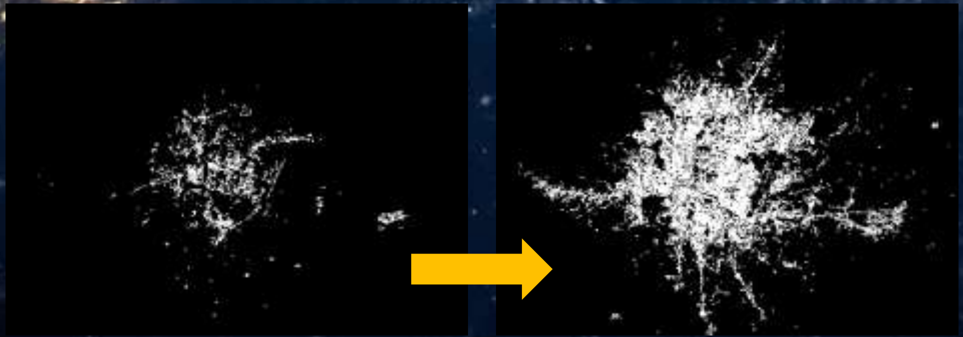
Athena Infonomics Brown Bag | November 19, 2020

SATELLITE DATA FOR DECISION MAKING

SEEING EARTH FROM 800KM ABOVE GROUND

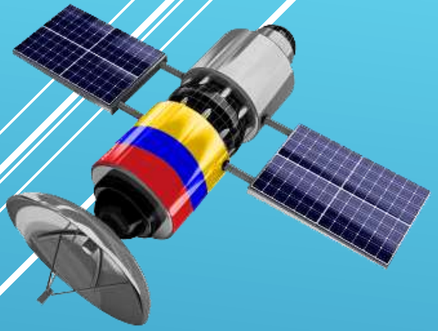
Assessing outcomes and impacts

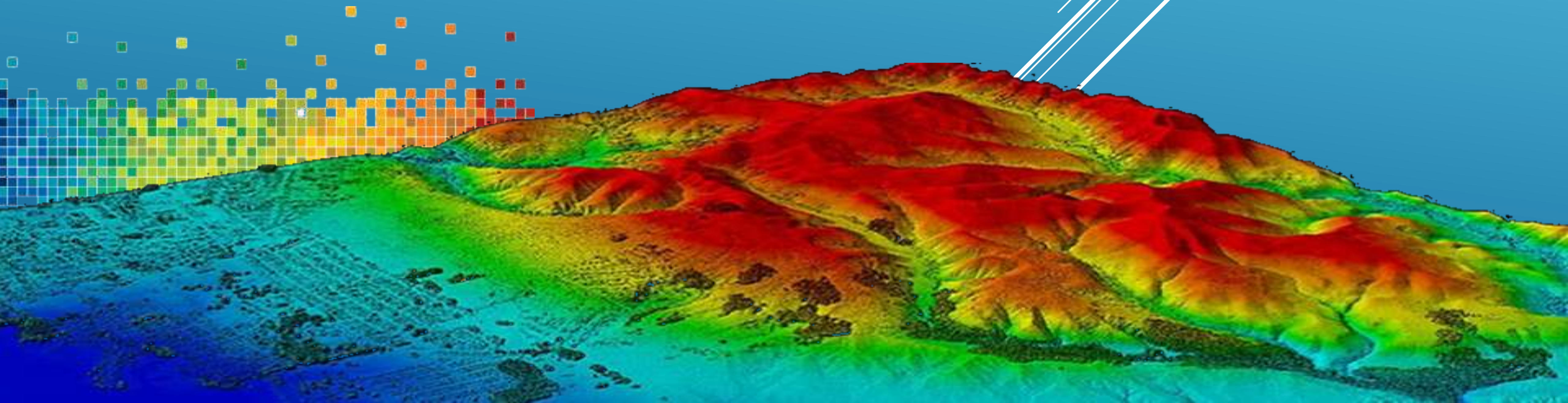
Ran Goldblatt, Ph.D.
Chief Scientist, New Light Technologies Inc.

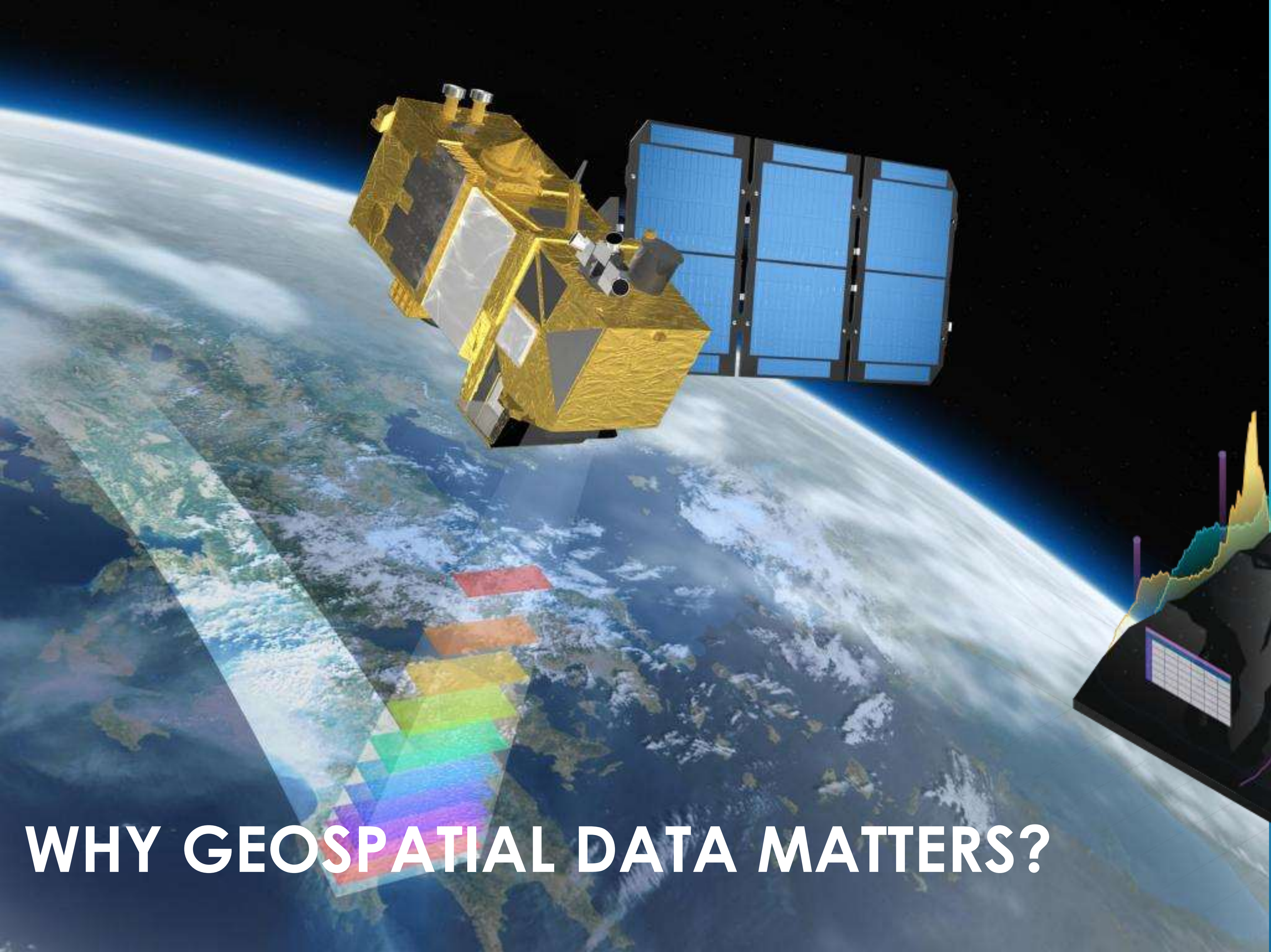


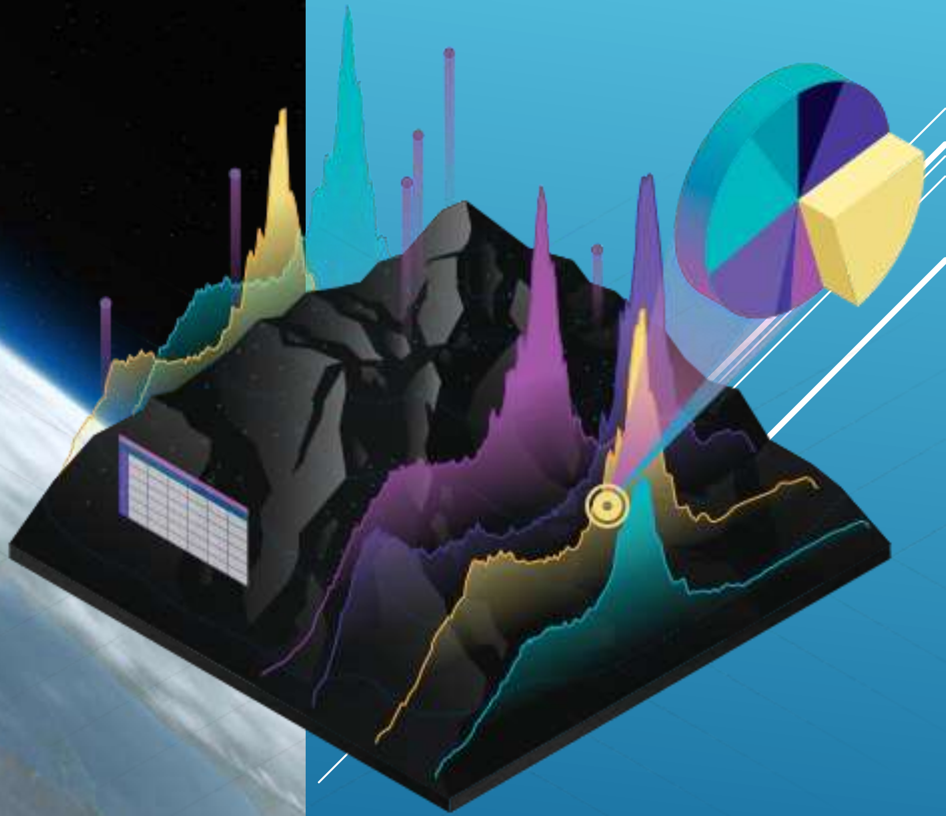
AGENDA

- What is geospatial data and why care about it?
- What is remotely sensed data?
- Using free satellite data to understand Earth
- Monitoring change on Earth from space
- Geospatial data for Impact Evaluation
- Recent innovations in geospatial analysis and satellite data





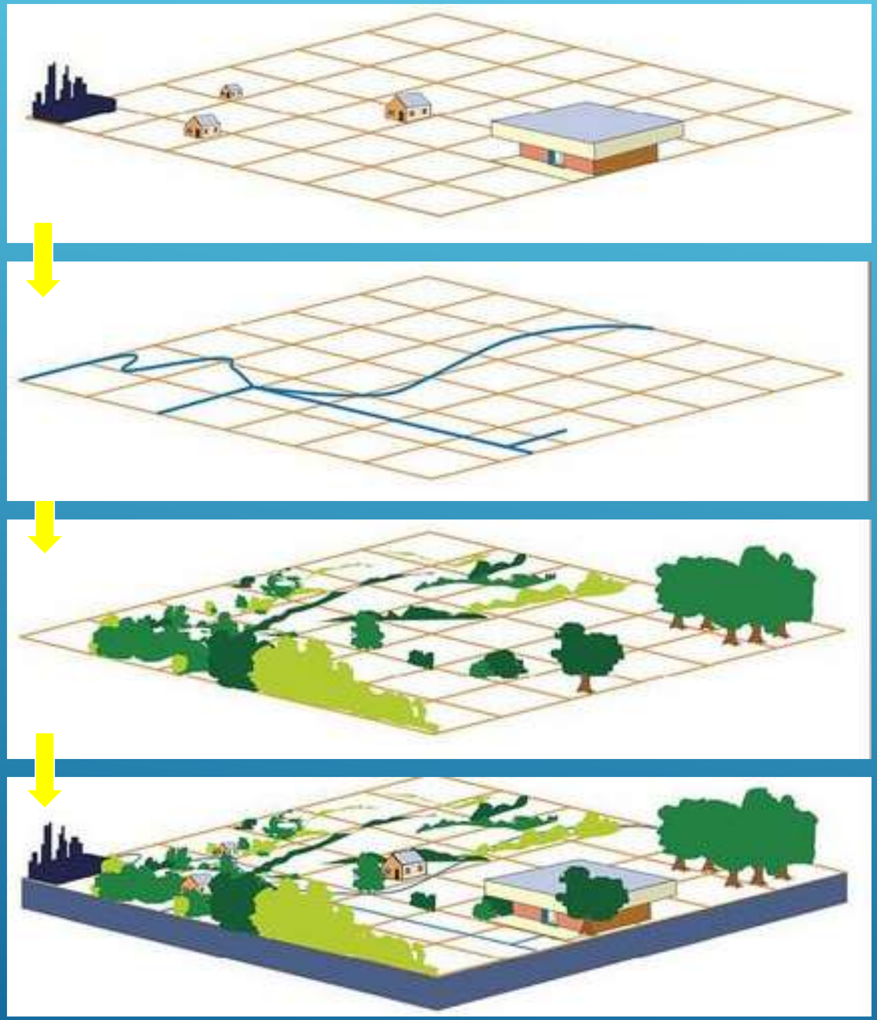




WHY GEOSPATIAL DATA MATTERS?

WHAT IS SPATIAL DATA?

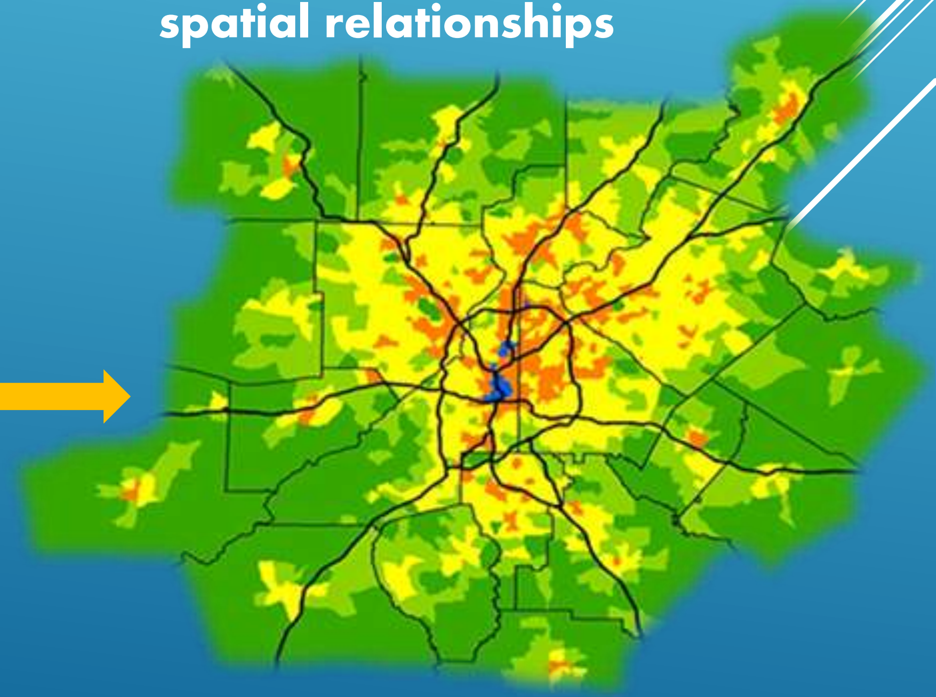
The real world



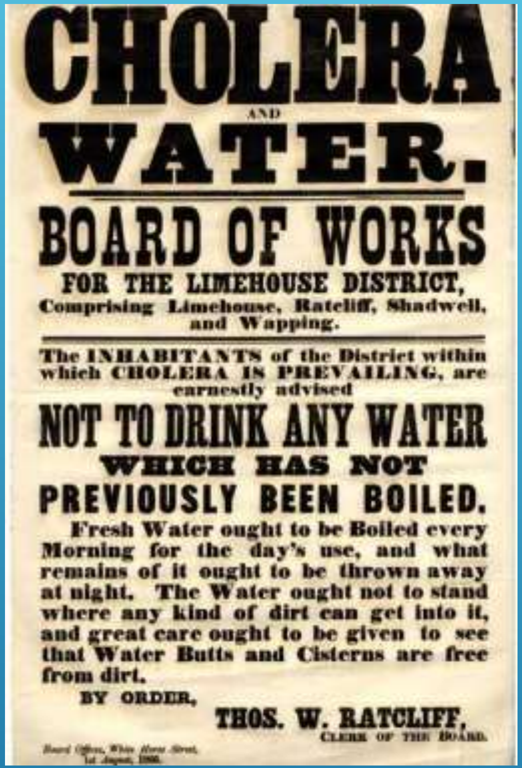
Entities that hold
spatial information

EMP_NUM	EMP_LNAME	EMP_FNAME	EMP_INITIAL	EMP_HIREDATE	ADDRESS	CITY	STA
101	News	John	G	11/8/1998	5430 17th Ave. SW	Seattle	WA
102	Senior	David	H	7/12/1987	104 58th Place SW	Everett	WA
103	Arbough	June	E	12/1/1994	1230 SW 150th St.	Burien	WA
104	Ramoras	Anne	K	11/15/1985	14206 greenbelt dr. east	sumner	WA
105	Johnson	Alice	K	2/1/1991	12002 SE 212nd Place	Kent	WA
106	Smithfield	William	<Null>	6/22/2002	11862 SE 157 PL	Renton	WA
107	Alonzo	Maria	D	10/10/1991	17725 NE 65th St A-135	Redmond	WA
108	Washington	Ralph	B	8/22/1989	5430 17th Ave SW	Seattle	WA
109	Smith	Larry	W	7/18/1995	2220 132nd Avenue SE	Bellevue	WA
110	Olenko	Gerald	A	12/11/1993	307 Northeast 65th Street	Seattle	WA
111	Wabash	Geoff	B	4/4/1989	15004 223rd St Se	Snohomish	WA
112	Smithson	Darlene	M	10/23/1992	11334 17th Avenue Northeast	Seattle	WA
113	Joenbrood	Delbert	K	11/15/1994	20629 SE 271st St.	Covington	WA
114	Jones	Annelise	<Null>	8/20/1991	21710 80th Ave. West	Edmonds	WA
115	Bawangi	Travis	B	1/25/1990	24455 Madura Drive Northeast	Kingston	WA
116	Pratt	Gerald	L	3/5/1995	1230 SW 150th St.	Burien	WA
117	Williamson	Angie	H	6/19/1994	1701 McDougall Ave.	Everett	WA
118	Frommer	James	J	1/4/2003	1919 96st SW #68	Lynnwood	WA

Understand
spatial relationships



Prior to the computerized maps:
Spatial analysis was limited to manual processing/interpretation.


CHOLERA
AND
WATER.
BOARD OF WORKS
FOR THE LIMEHOUSE DISTRICT,
Comprising Limehouse, Ratcliff, Shadwell, and Wapping.

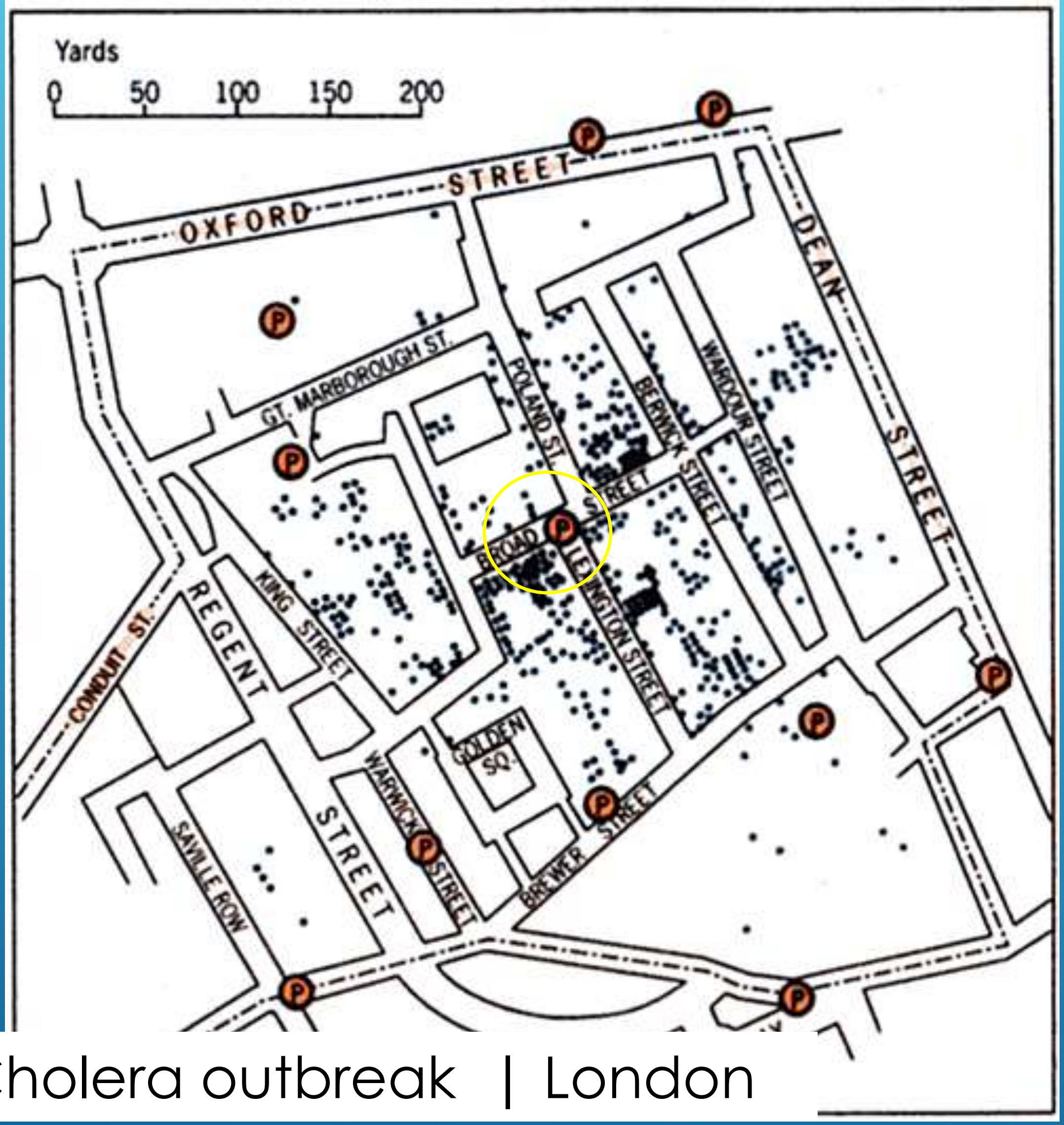
The INHABITANTS of the District within which CHOLERA IS PREVAILING, are earnestly advised

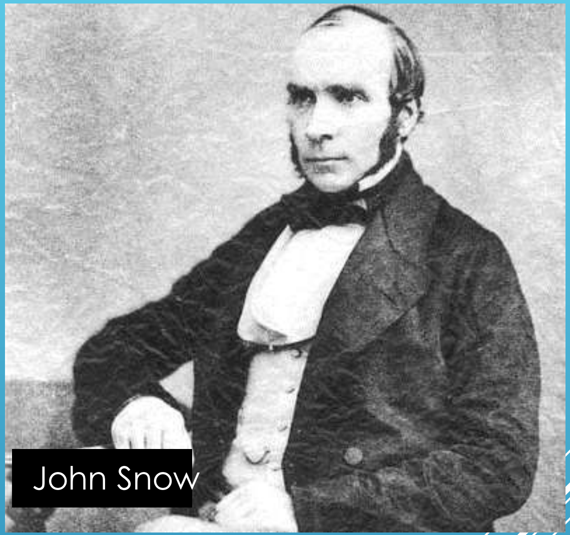
NOT TO DRINK ANY WATER
WHICH HAS NOT
PREVIOUSLY BEEN BOILED.

Fresh Water ought to be Boiled every Morning for the day's use, and what remains of it ought to be thrown away at night. The Water ought not to stand where any kind of dirt can get into it, and great care ought to be given to see that Water Butts and Cisterns are free from dirt.

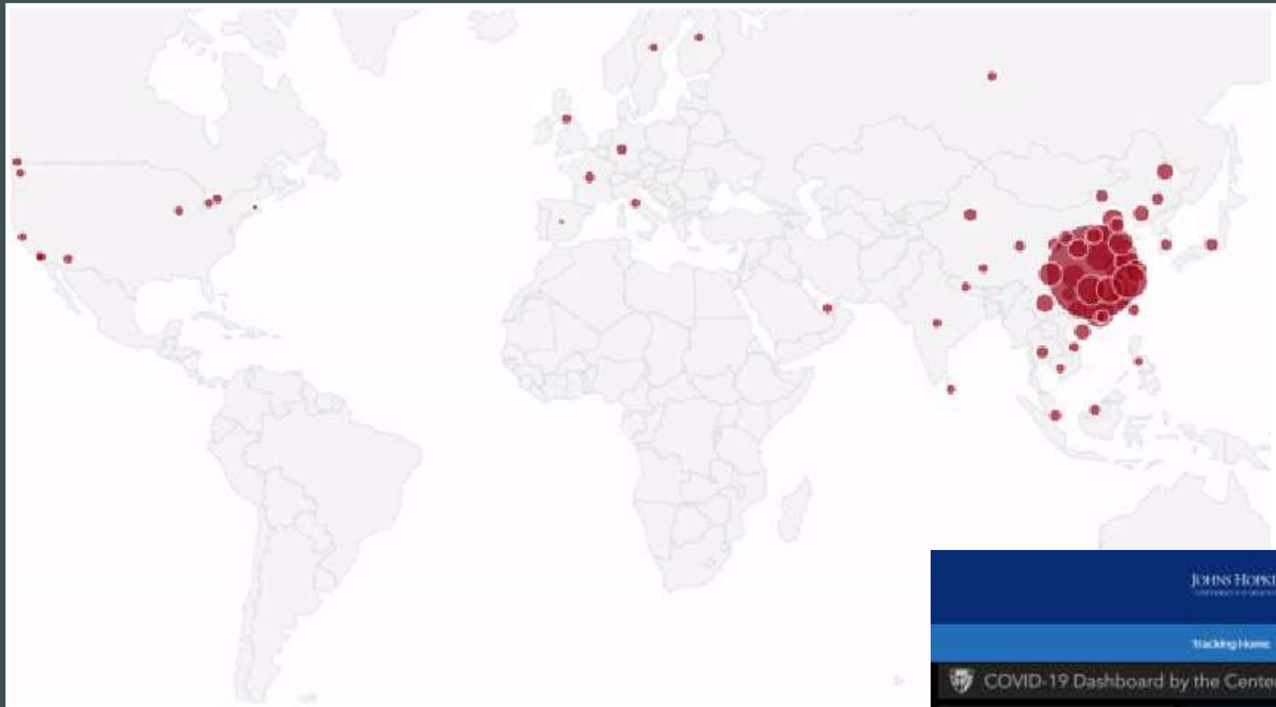
BY ORDER,
THOS. W. RATCLIFF,
CLERK OF THE BOARD.

1854




John Snow

- **1854**: mapping Cholera outbreak | London



Tracking COVID-19

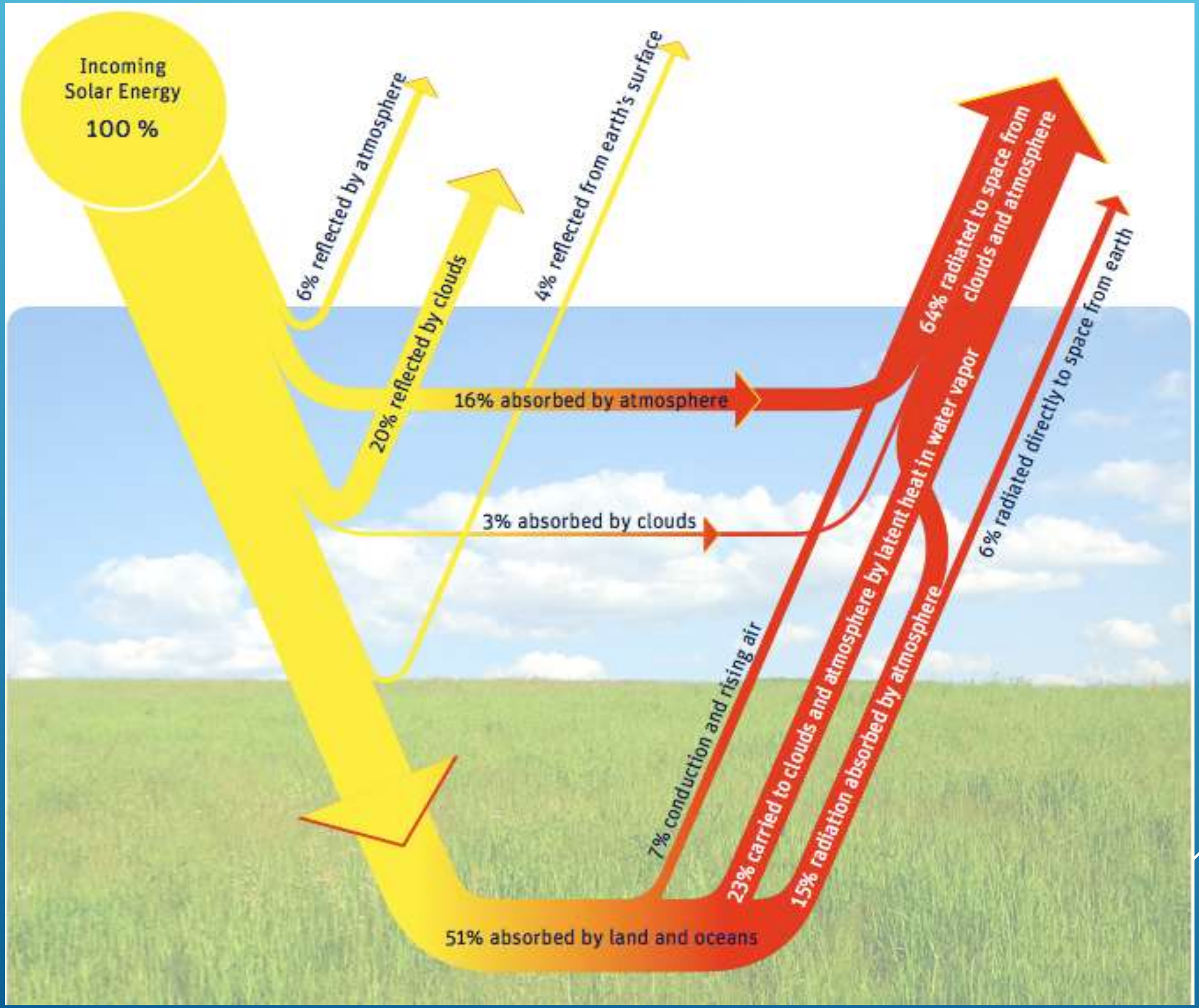
REMOTE SENSING

- The science of **IDENTIFYING**, **OBSERVING**, **COLLECTING** and **MEASURING objects without** coming into **direct contact** with them.

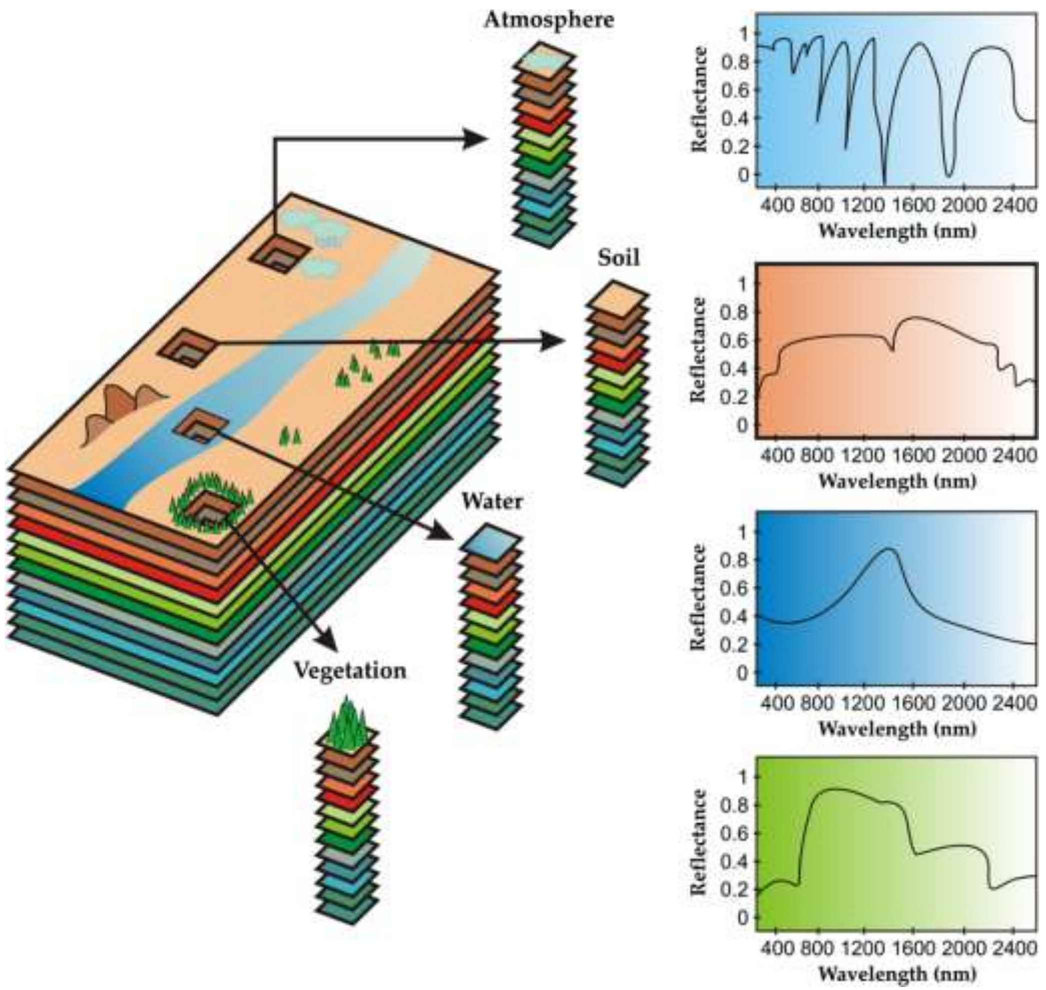
- Accomplished by humans and animals with the aid of **eyes**, or other **senses**.

- Satellites record the ***electromagnetic energy*** reflected or emitted from objects on Earth.

(PASSIVE) REMOTE SENSING - SATELLITES



The energy of the sun is **absorbed** or **scattered** through the atmosphere before it reaches earth.



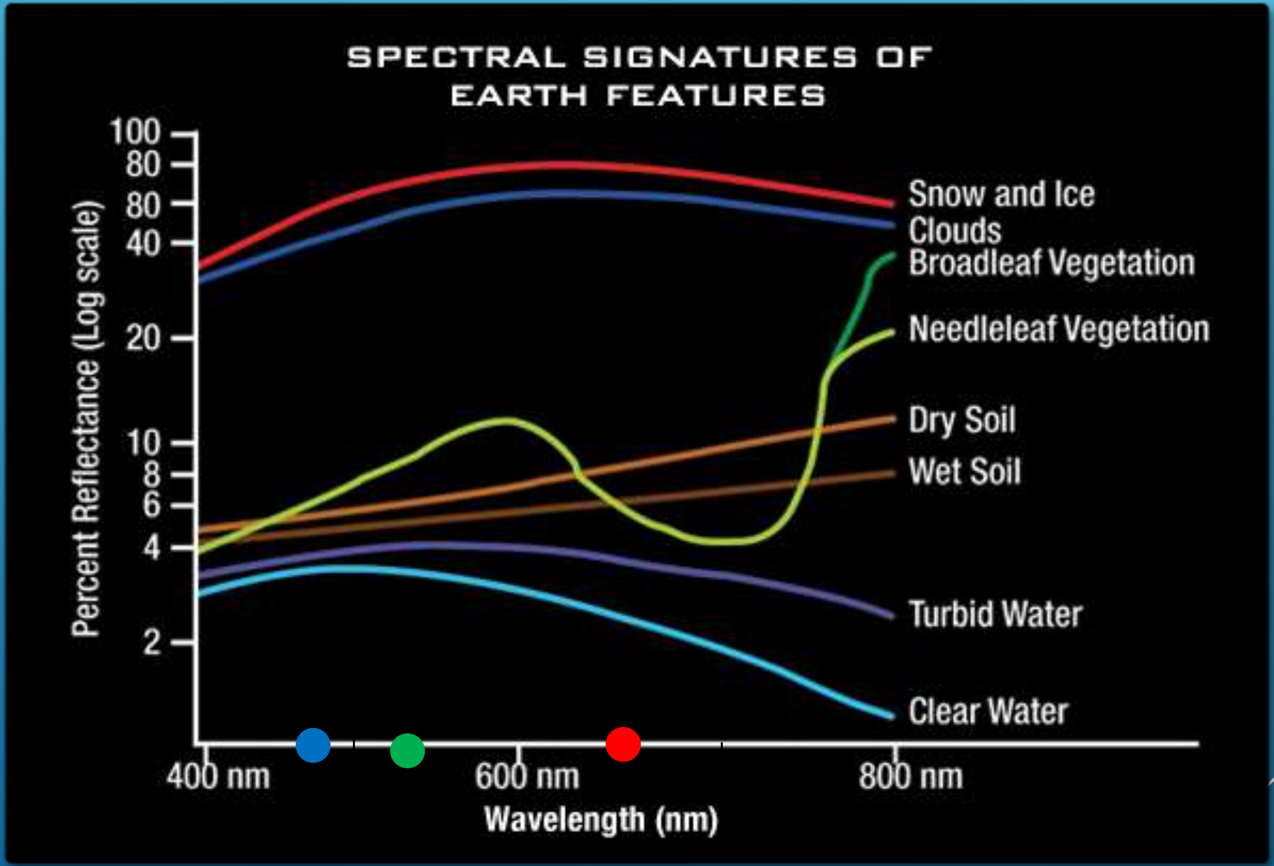
https://www.battelleecology.org/plot-spec-sig-python

RS: Learn about objects by studying the radiation **REFLECTED** and/or **EMITTED** by them.

Different types of land cover and land use on Earth have different characteristics

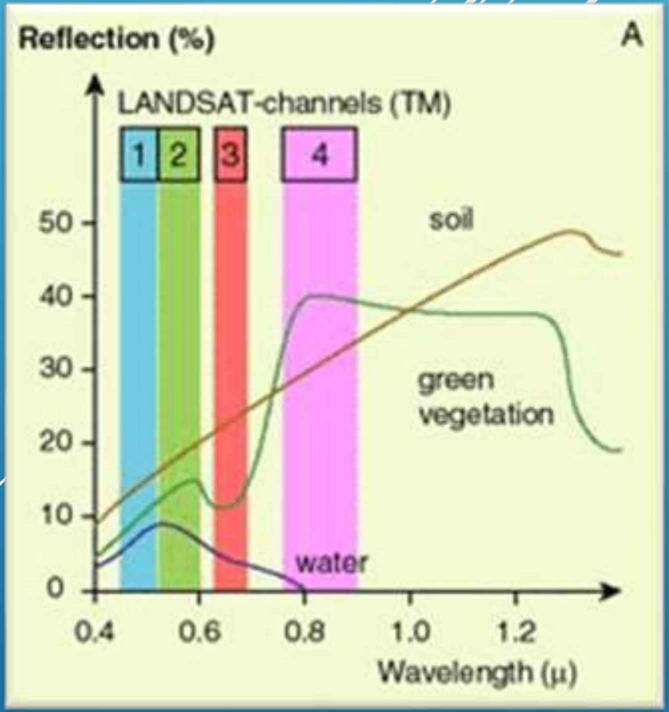
“Spectral Signature”:

“The unique distribution of reflected, emitted and absorbed radiation of an object”.

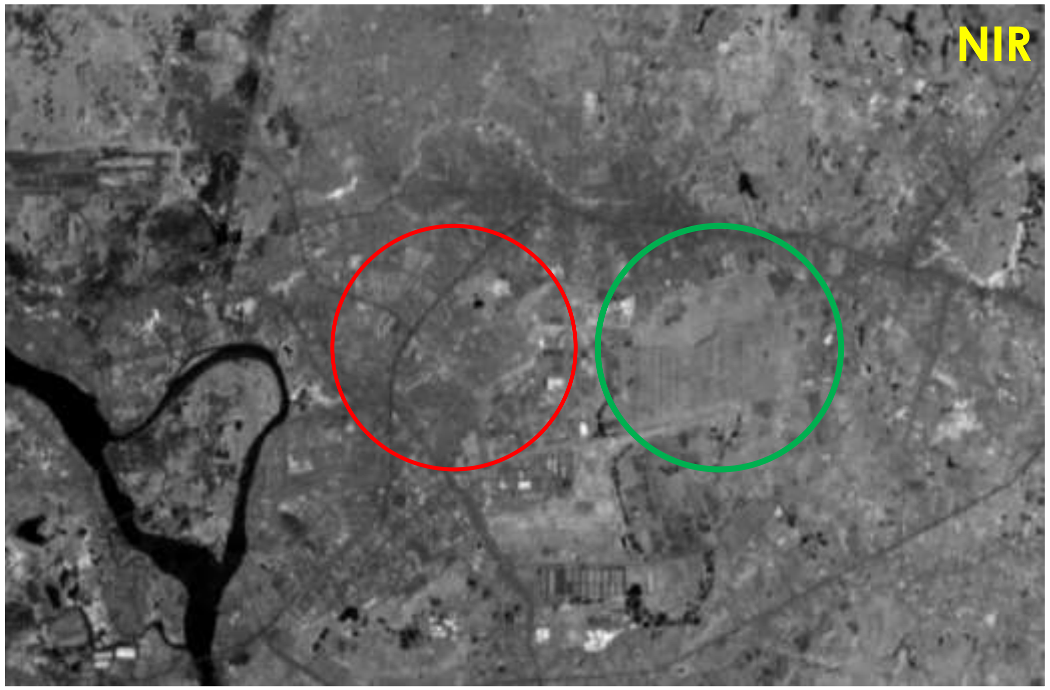


http://missionscience.nasa.gov/ems/09_visiblelight.html

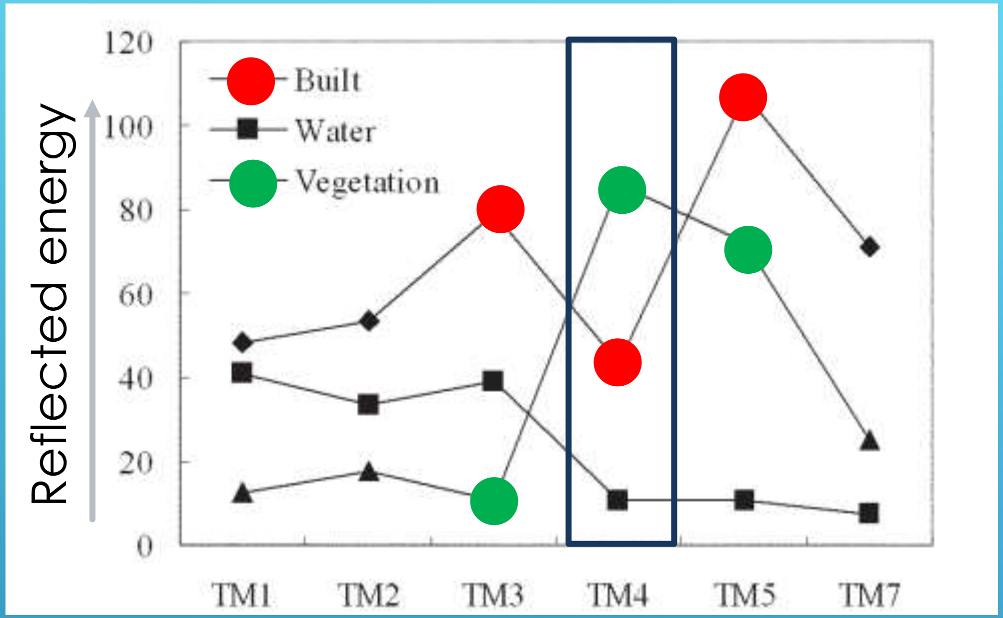
How much energy is reflected back



http://www.esa.int/

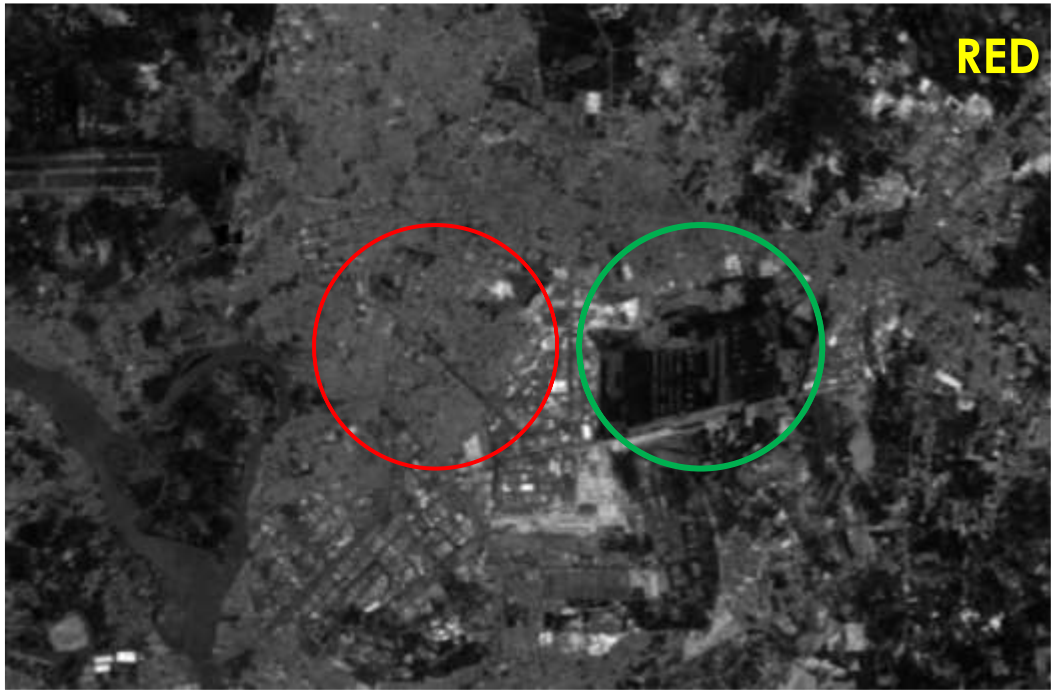


How much of the energy is reflected?

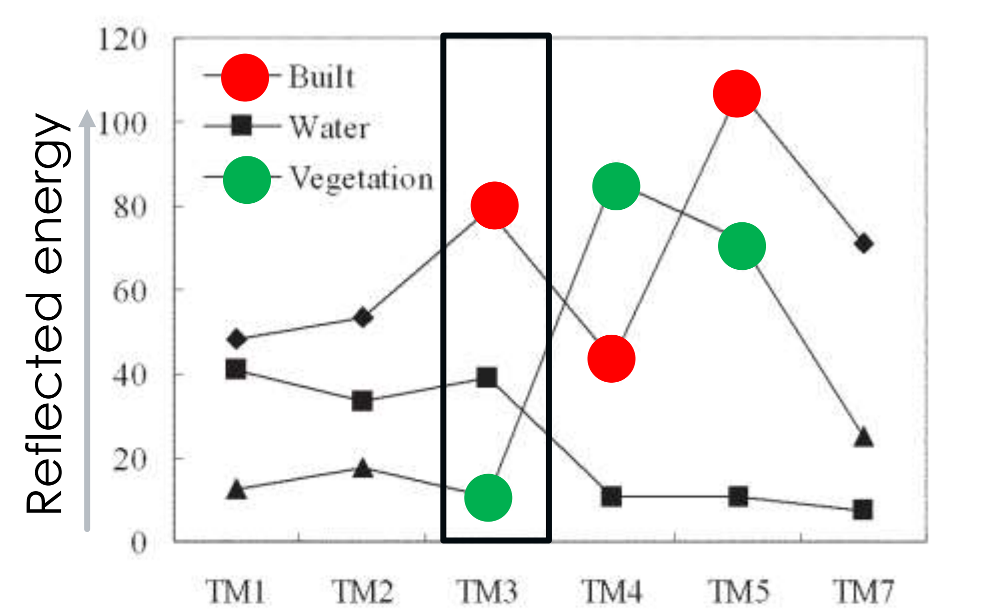


Xu, 2007

RED NIR MIR



How much of the energy is reflected?



Xu, 2007

RED NIR MIR

Spectral indices based on the spectral signature

NDVI

Normalized Difference Vegetation Index

NIR and RED bands

Red visible light is typically absorbed by a plant's chlorophyll; near-infrared is scattered by the leaf's mesophyll structure.

(NIR-RED) / (NIR+RED)

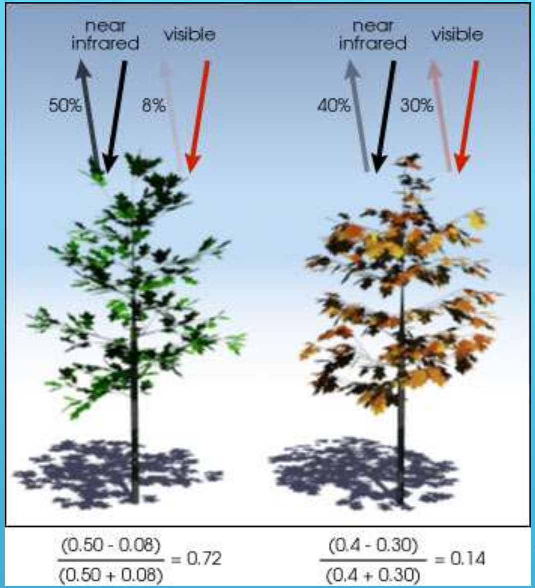
For a given object:

NDVI = (NIR — RED)/(NIR + RED)

H	L
Much is reflected	Much is absorbed

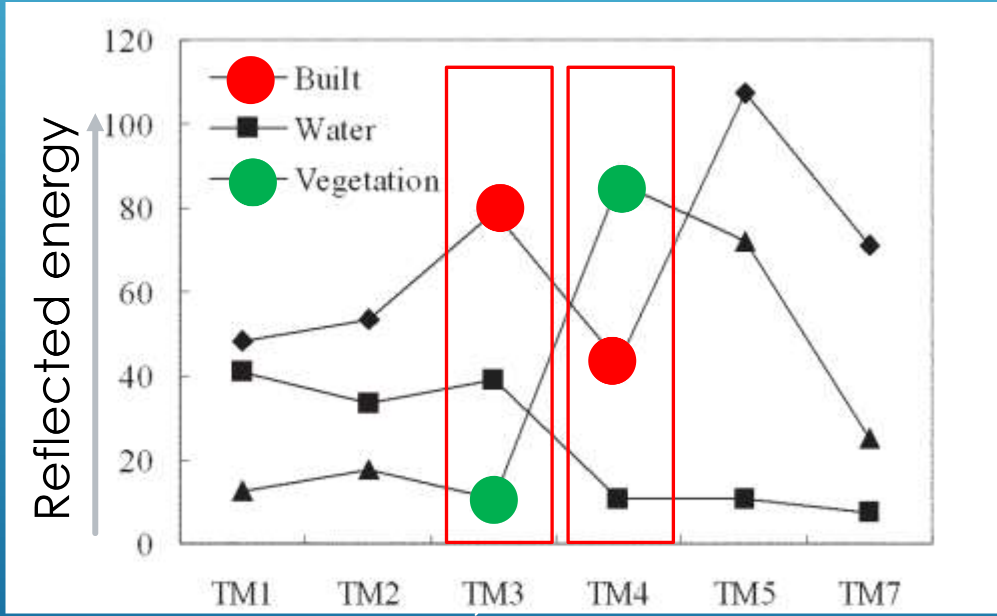
Index ranges from (-1) to (+1); however, no green leaves gives a value close to (0).
A zero means no vegetation and close to (+1) (0.8 - 0.9) indicates the highest possible density of green leaves

The bigger the difference between the near-infrared and the red reflectance, the more live vegetation there is.



earthobservatory.nasa

- Plants` chlorophyll **absorbs** the red light
- The leaves **reflect** the NIR light



Xu, 2007

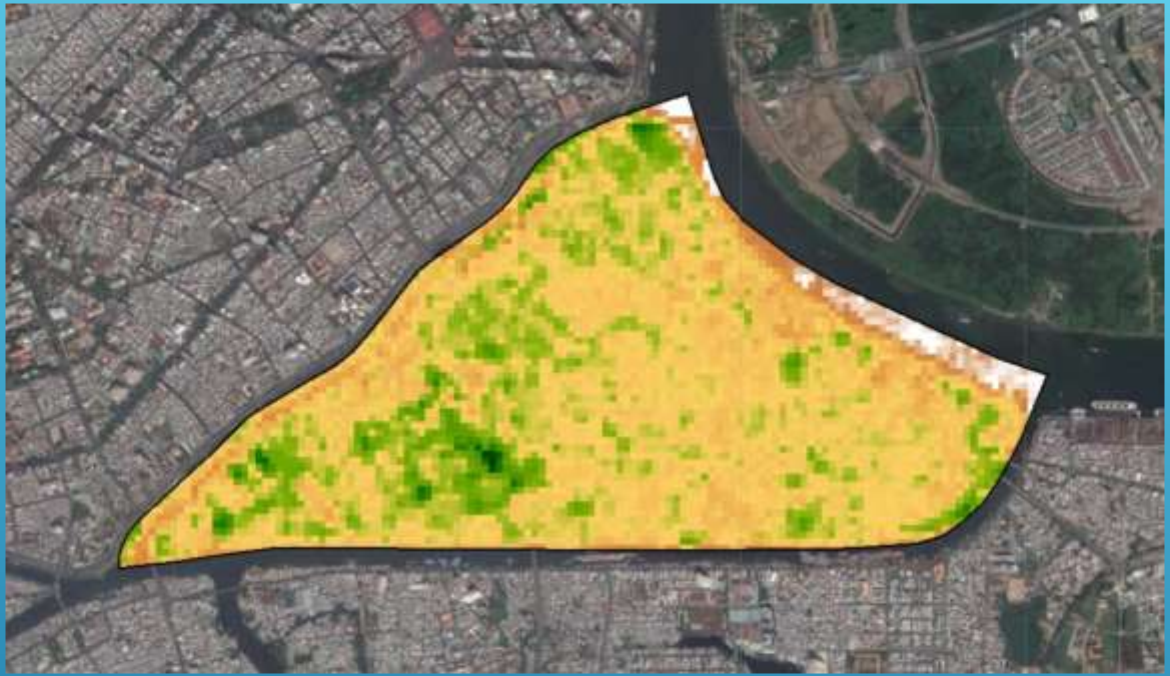
RED NIR MIR

intervention

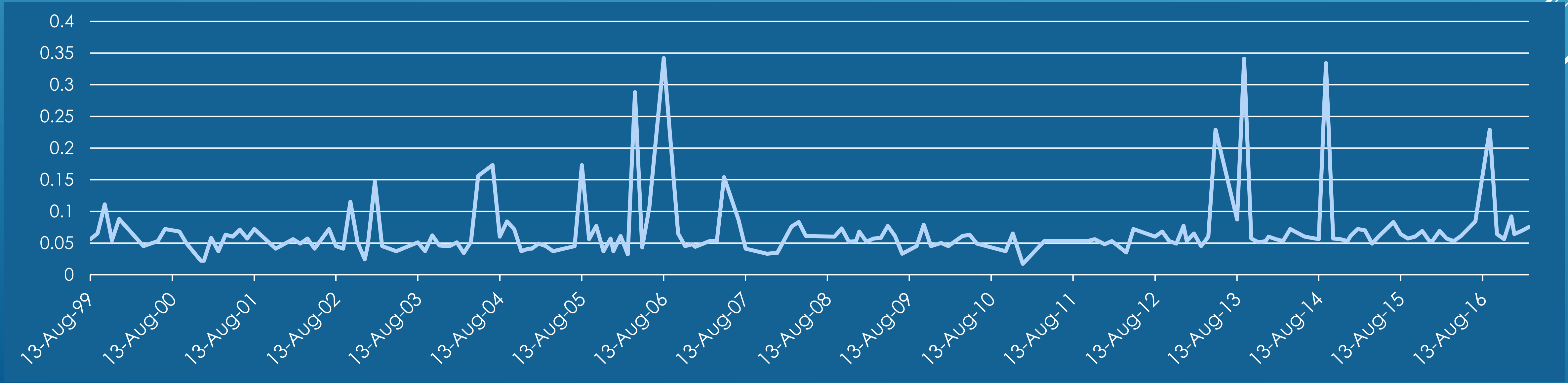
NDVI

Normalized Difference Vegetation Index

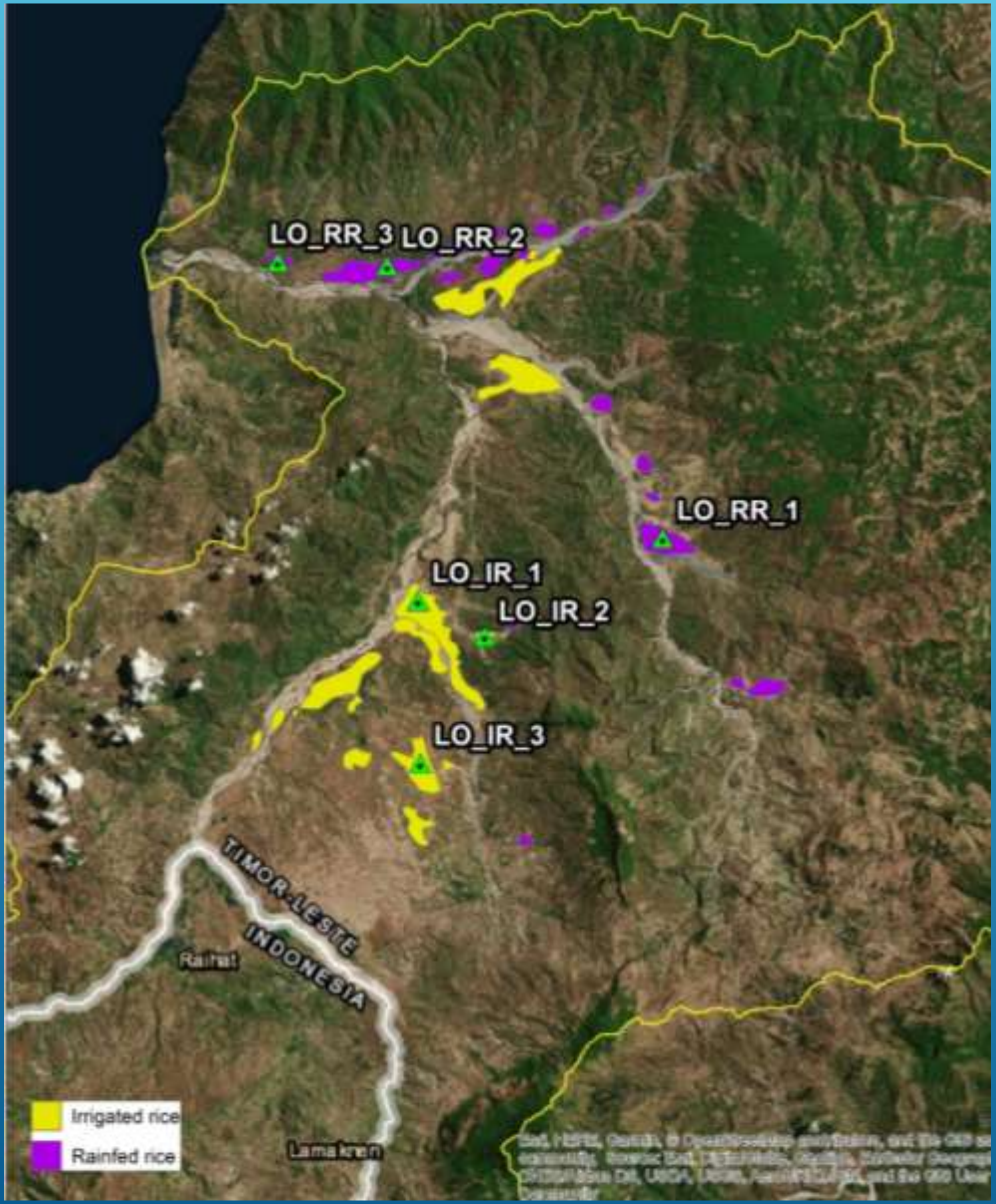
NDVI, 2000



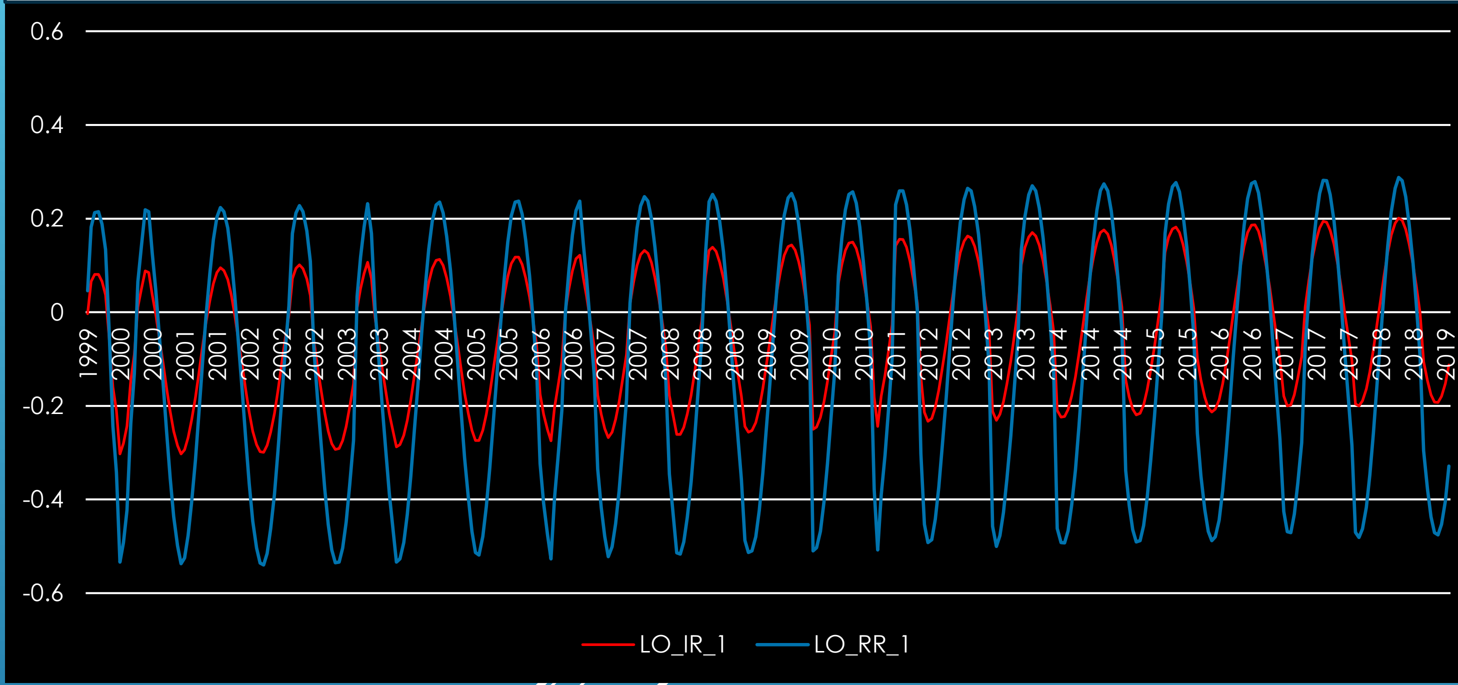
NDVI, 2016



MEASURING PRODUCTIVITY TRENDS



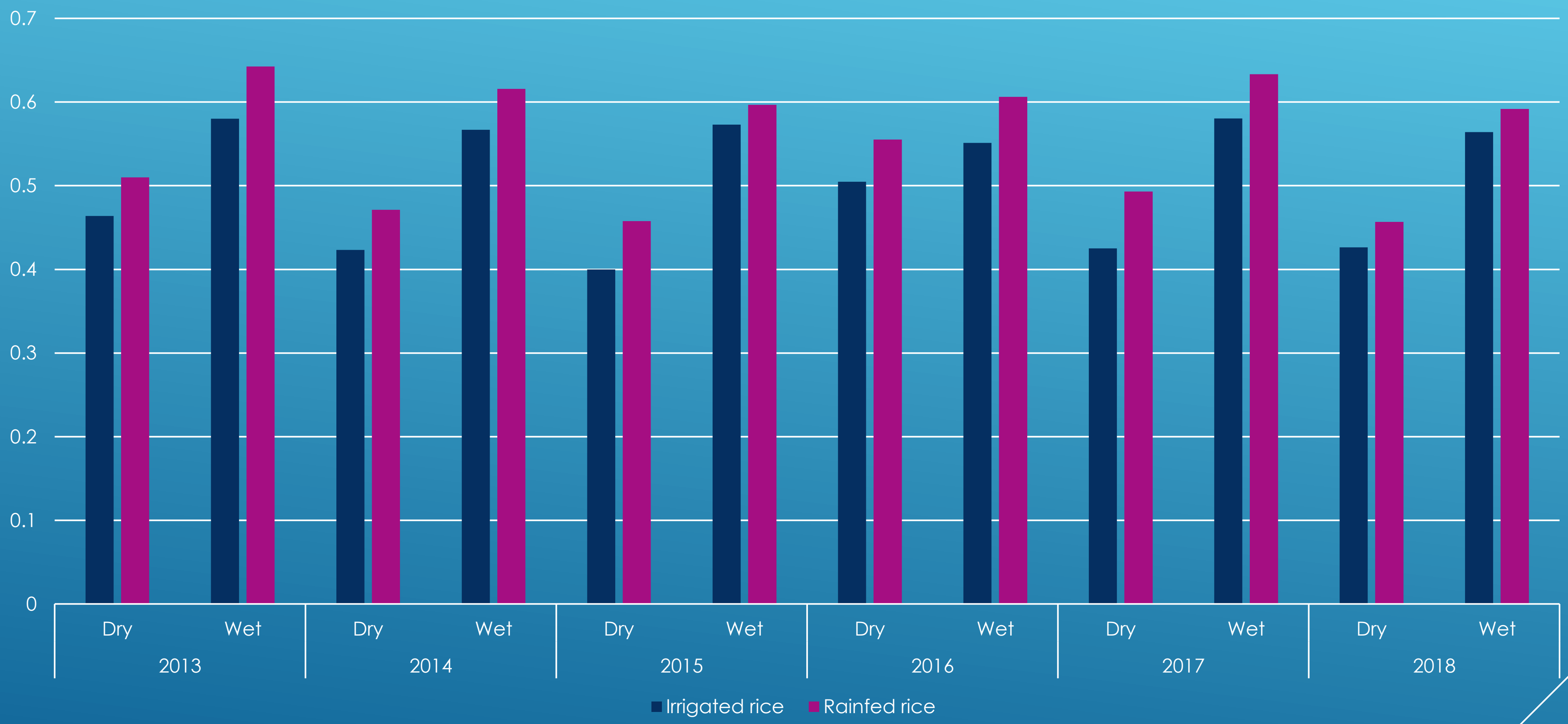
Productivity trends of irrigated vs. Rainfed agriculture plots



Irrigated rice field

Rainfed rice field

Average NDVI (irrigated vs. rainfed rice fields)



Case study: Timor-Leste (work funded by the World Bank)

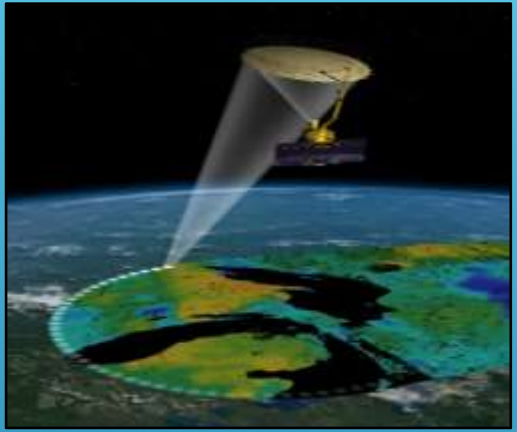
- **1,419 active satellites**, both government and private.
- **374** specifically for **Earth observation/science**

Tracking Earth in close to real-time!

"FIT FOR PURPOSE" TECHNOLOGIES

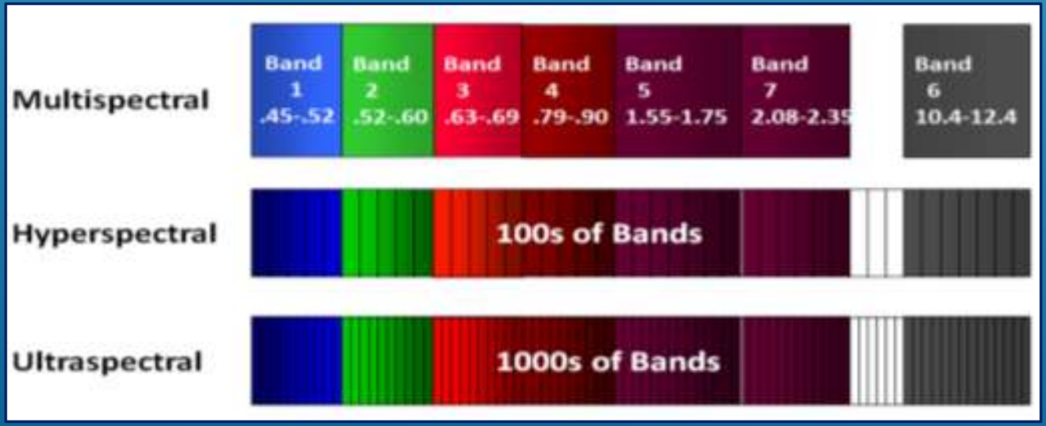
Spatial resolution

Temporal resolution

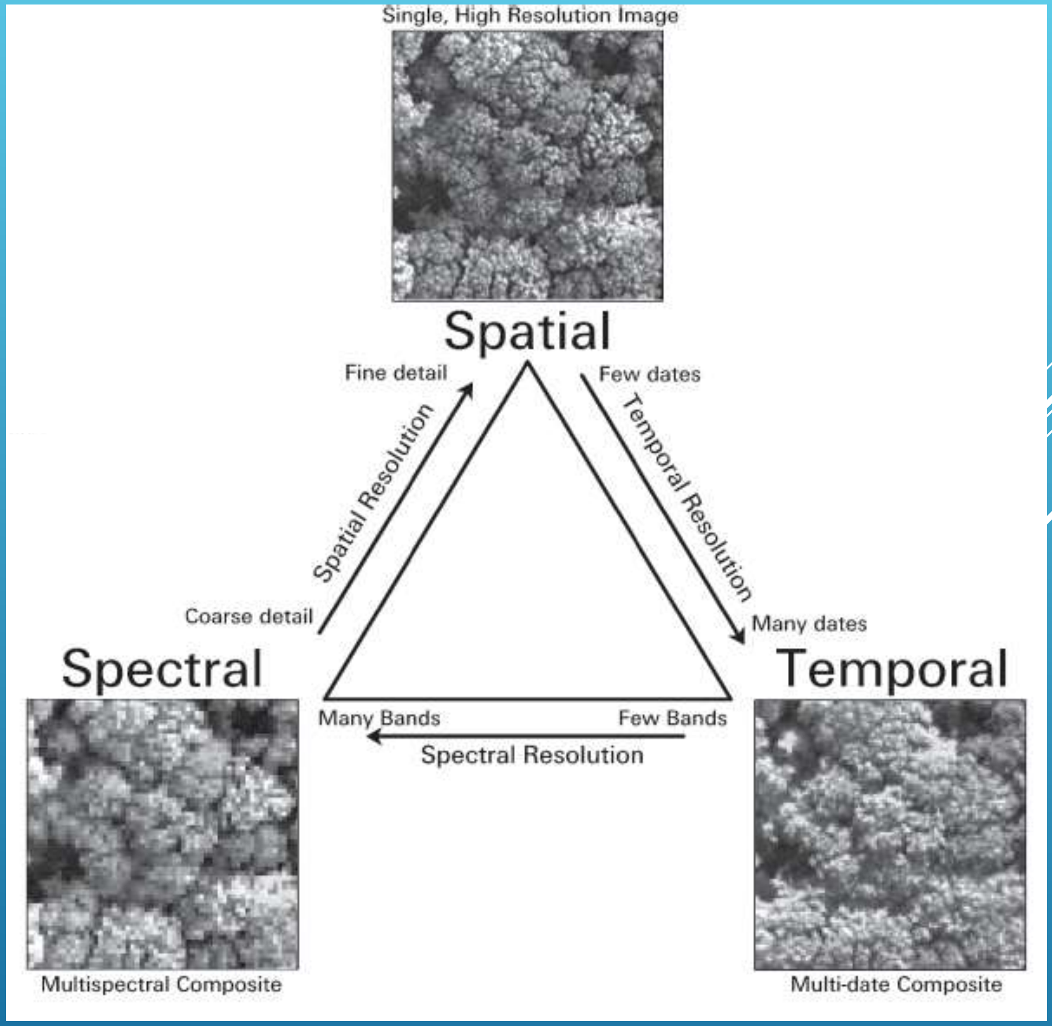


Many things to consider!

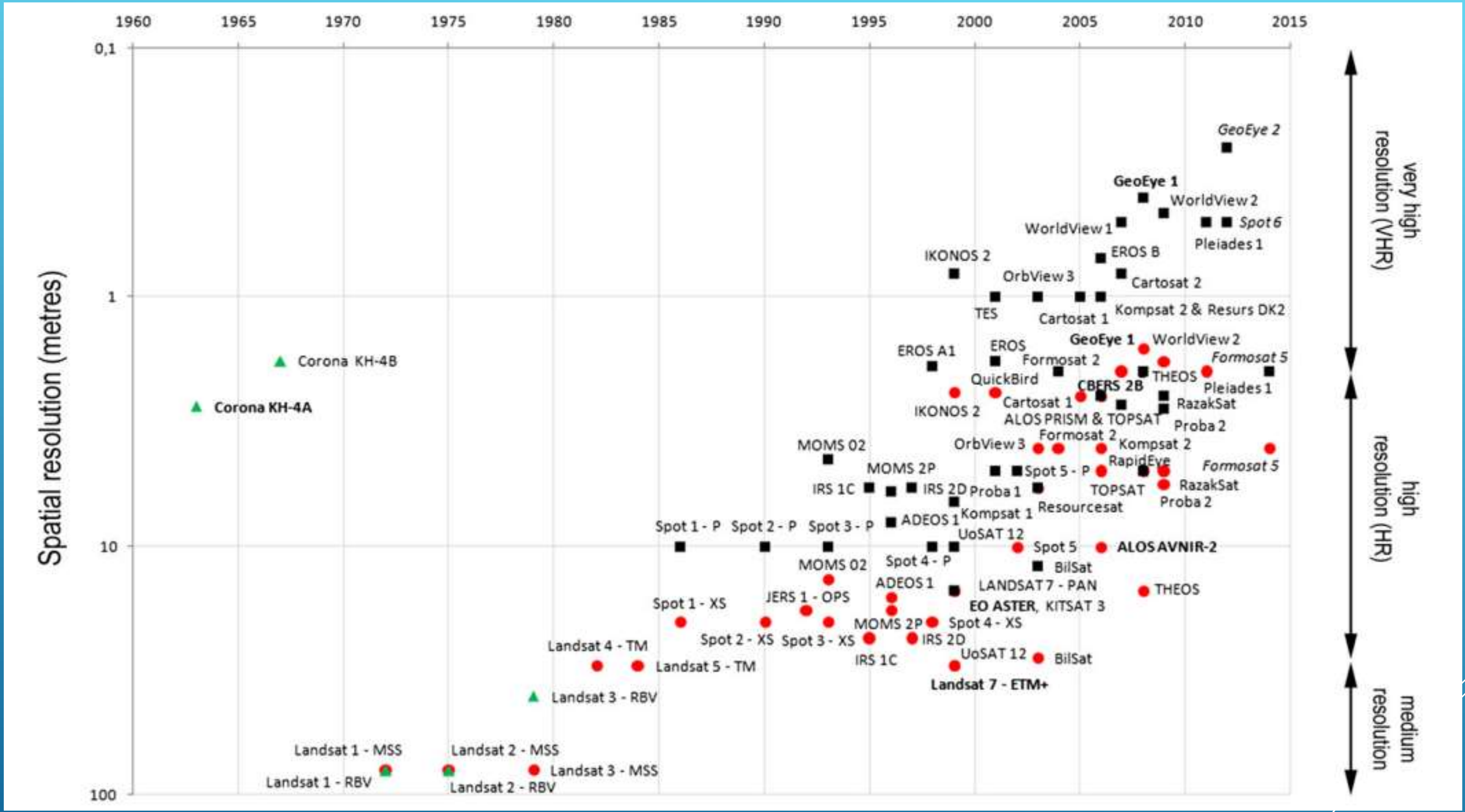
Spectral resolution



Price



Warner et al., 2009



The improvement of the spatial resolution of the remote sensing instruments (Deroin et al.)

Deroin, J. P., Téreygeol, F., Cruz, P., Guillot, I., & Méaudre, J. C. (2012). Integrated non-invasive remote-sensing techniques and field survey for the geoarchaeological study of the Sud Lípez mining district, Bolivia. Journal of Geophysics and Engineering, 9(4), S40-S52.

HIGH-RESOLUTION SATELLITE IMAGERY

https://arxiv.org/pdf/1805.09512.pdf

A CHANGE IN THE SATELLITE INDUSTRY

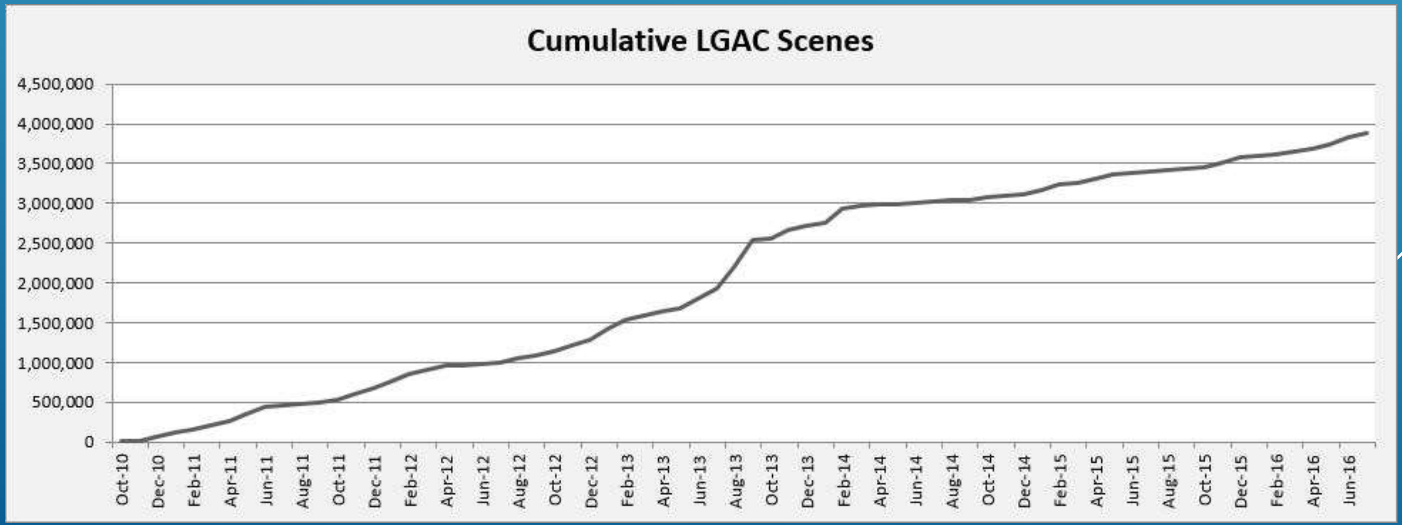
FROM *expensive*, *high-res*,
project specific satellite data TO
"Free", *medium-high* spatial resolution,
in *global scales*.

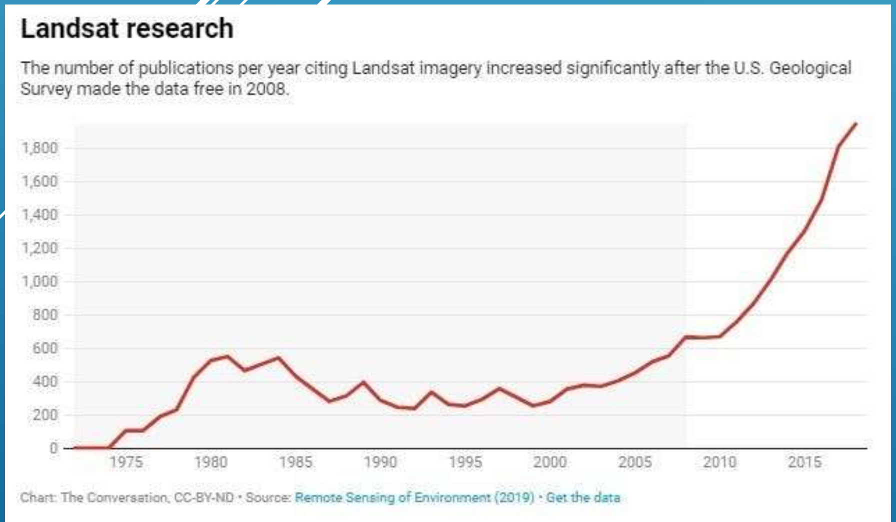
LANDSAT Mission - Mid 1960s:

US effort to develop and launch the first **civilian Earth observation satellite**.

The Earth Resources Technology Satellite – **Landsat.**

- Orbit altitude: 705 Km
- Revisit period: every 16 days
- Spatial resolution: >30m
- Spectral resolution: 8/11 bands





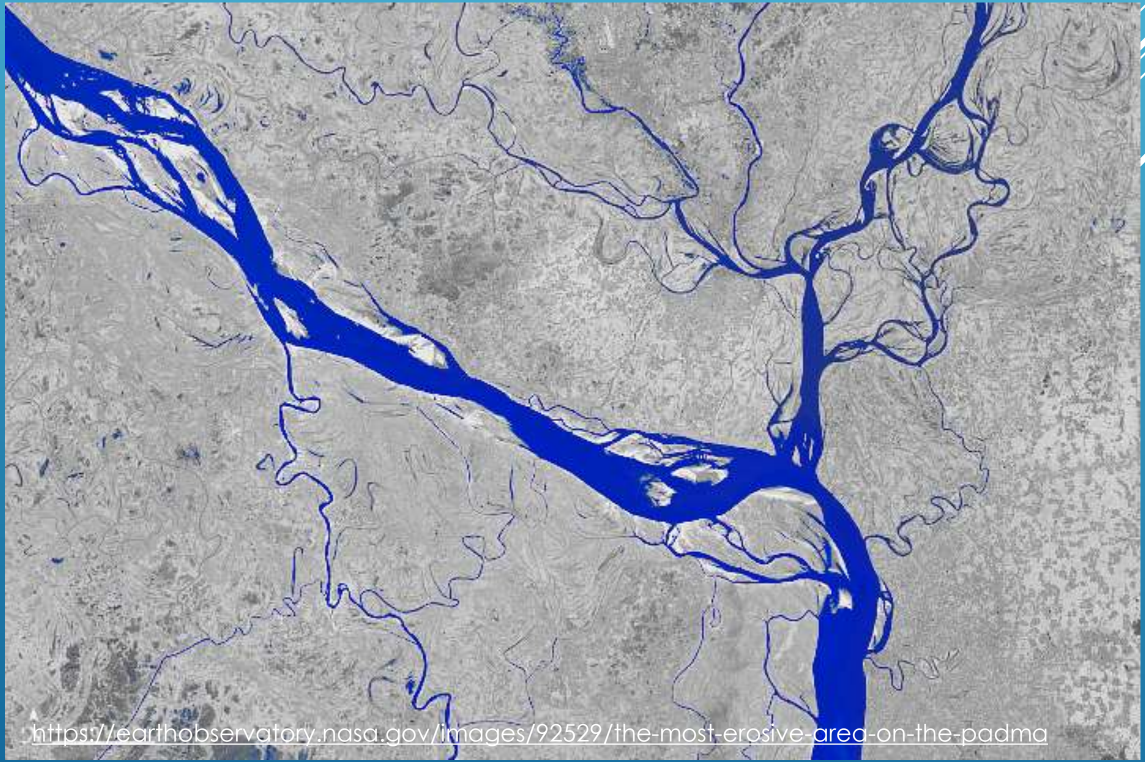
45 YEARS OF LANDSAT IMAGERY

https://directory.eoportal.org/web/eoportal/satellite-missions/content/-/article/landsat-8-ldcm

https://news.mongabay.com/2013/05/google-time-lapse-offers-view-of-earth-over-3-decades/

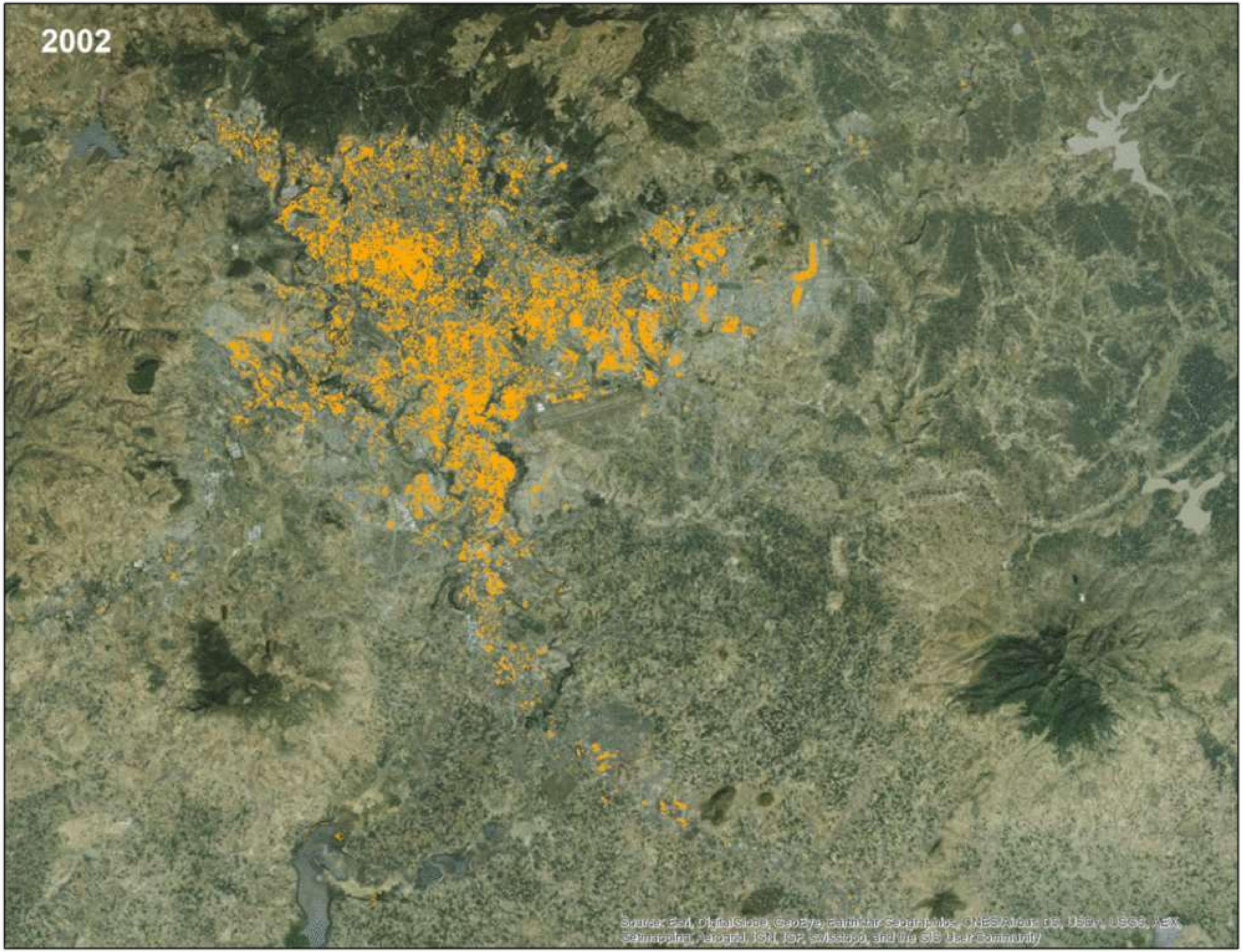
https://news.mongabay.com/

14 false-color images of the **Padma river** between 1988 and 2018 taken by the Landsat 5 and 8 satellites

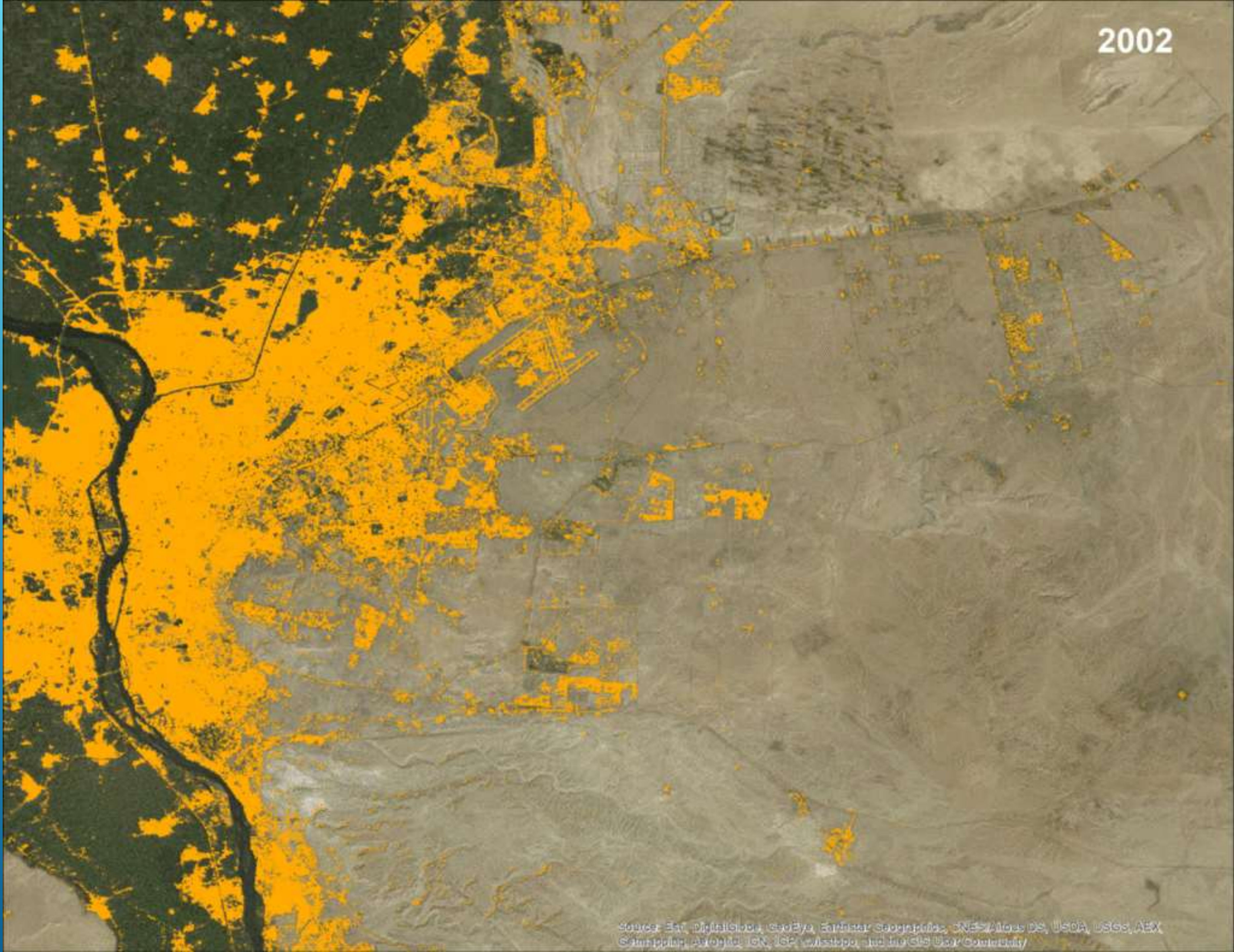


https://earthobservatory.nasa.gov/images/92529/the-most-erosive-area-on-the-padma

Addis Ababa, Ethiopia



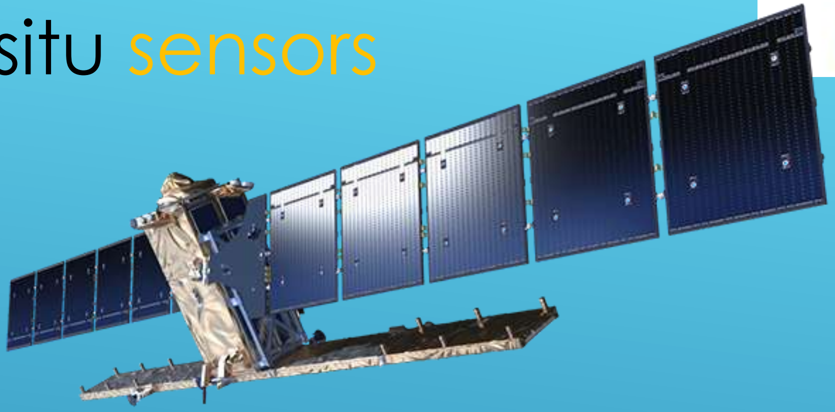
Cairo, Egypt



Copernicus Program (ESA)- 2010s:

Earth observation satellites and in-situ sensors

European Space Agency



Sentinel-2 (First launched: 6/2015)

Multispectral *high-resolution imaging*

- Revisit period: 5 days at equator
- Spatial resolution: 10m-30m
- Spectral resolution: 13 bands
- Includes 3 bands in the 'red edge' (e.g. determining vegetation state).

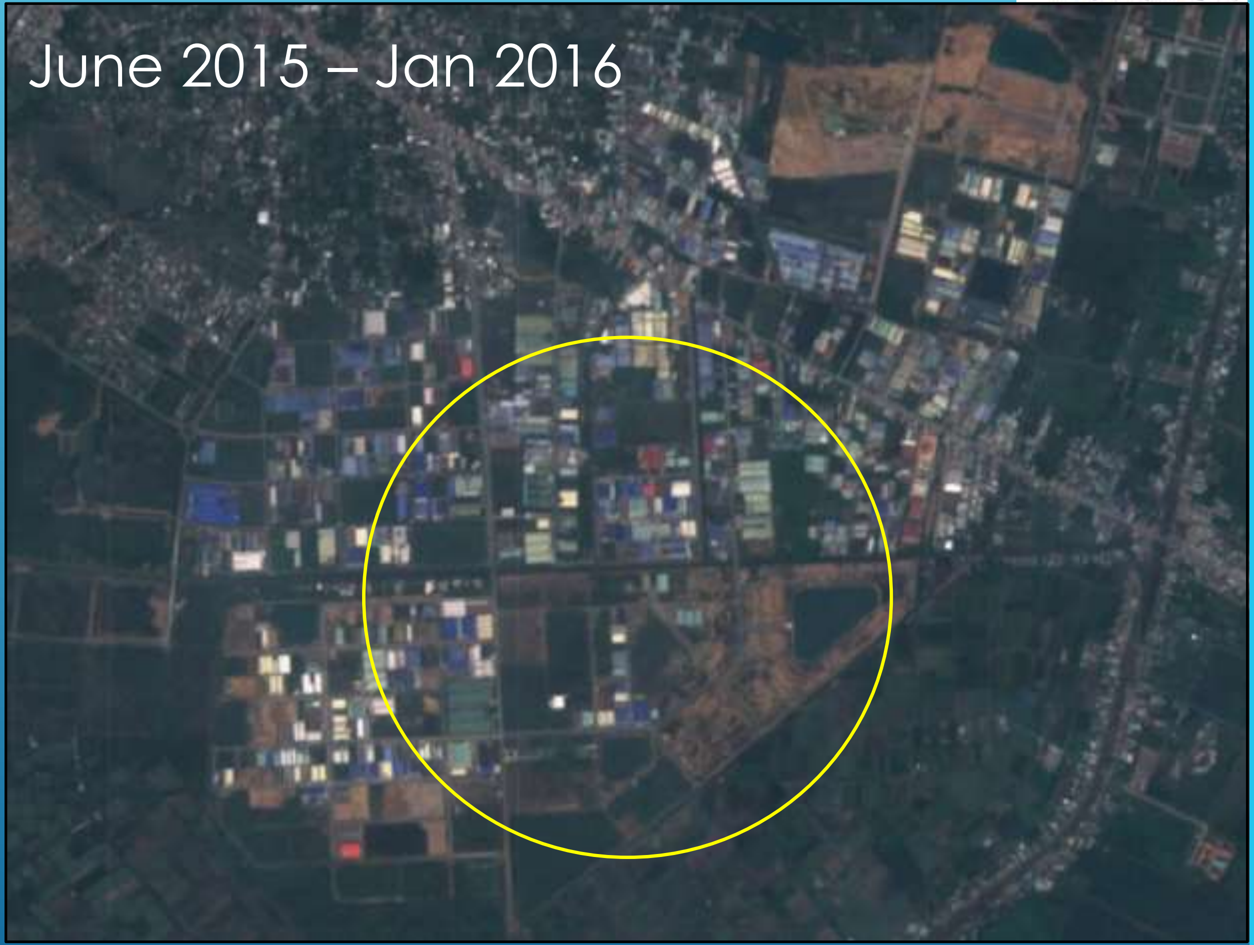
Sentinel-1 (First launched: 4/2014)

SAR imaging

- Revisit period: 6 days
- Spatial resolution: down to 5m
- Spectral band: C-band
- Land and ocean modes
- All-weather imaging of Earth's surface

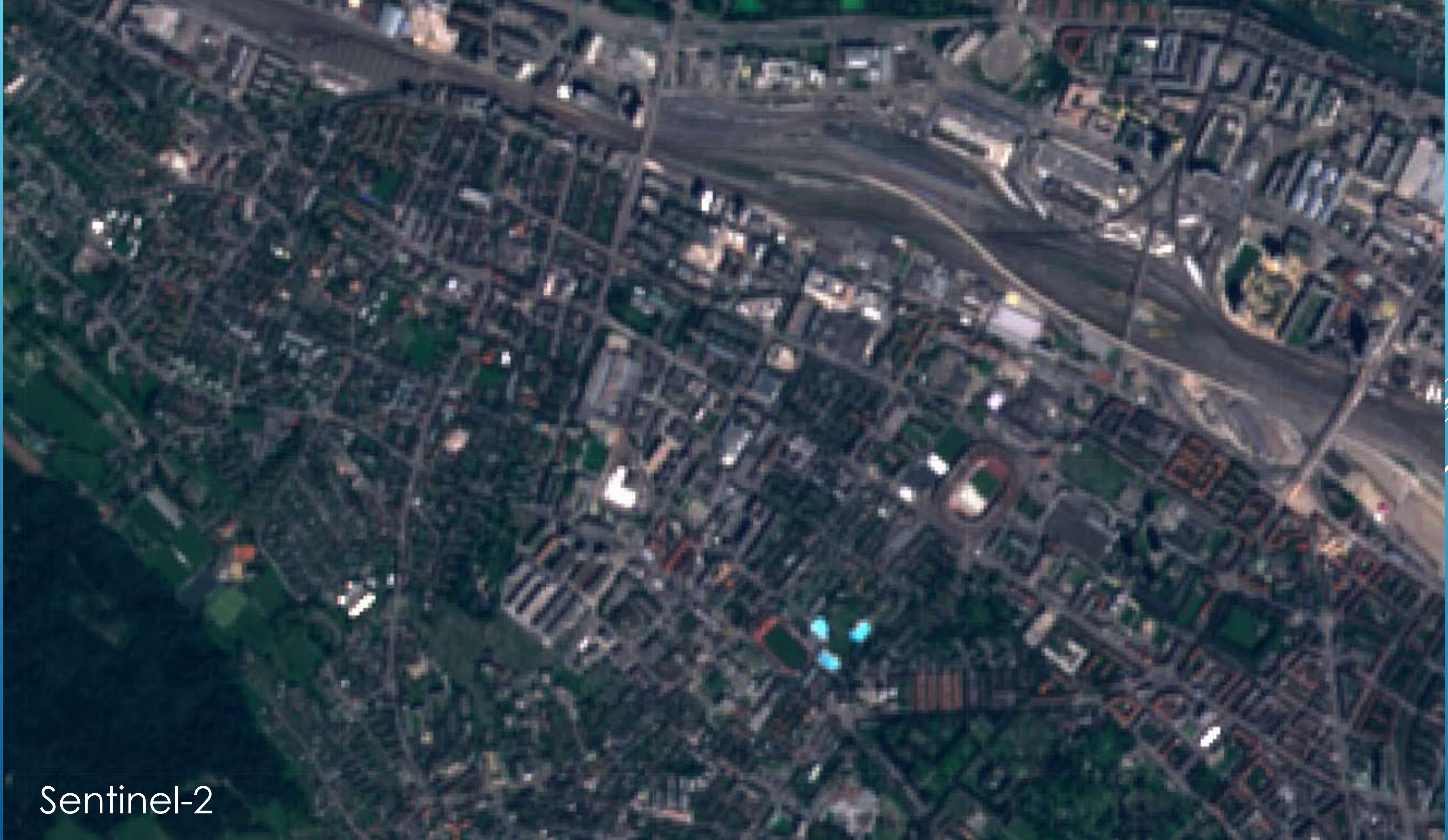
Sentinel-2

17 images from the Sentinel-2A satellite show a year of progress on the Third Bosphorus Bridge in Istanbul, Turkey
source:
http://www.esa.int/spaceinimages/Images/2016/08/Third_Bosphorus_Bridge_progress

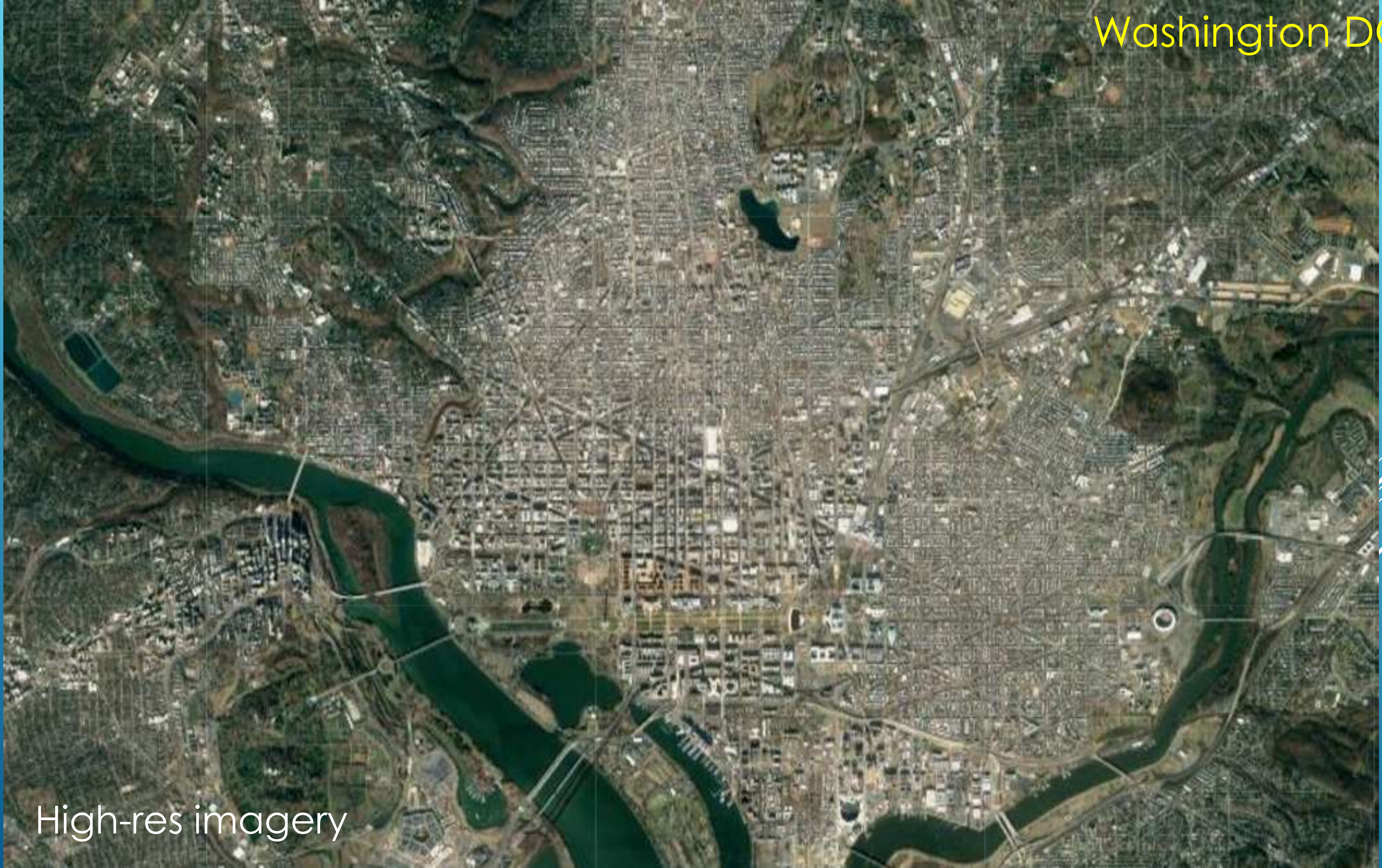


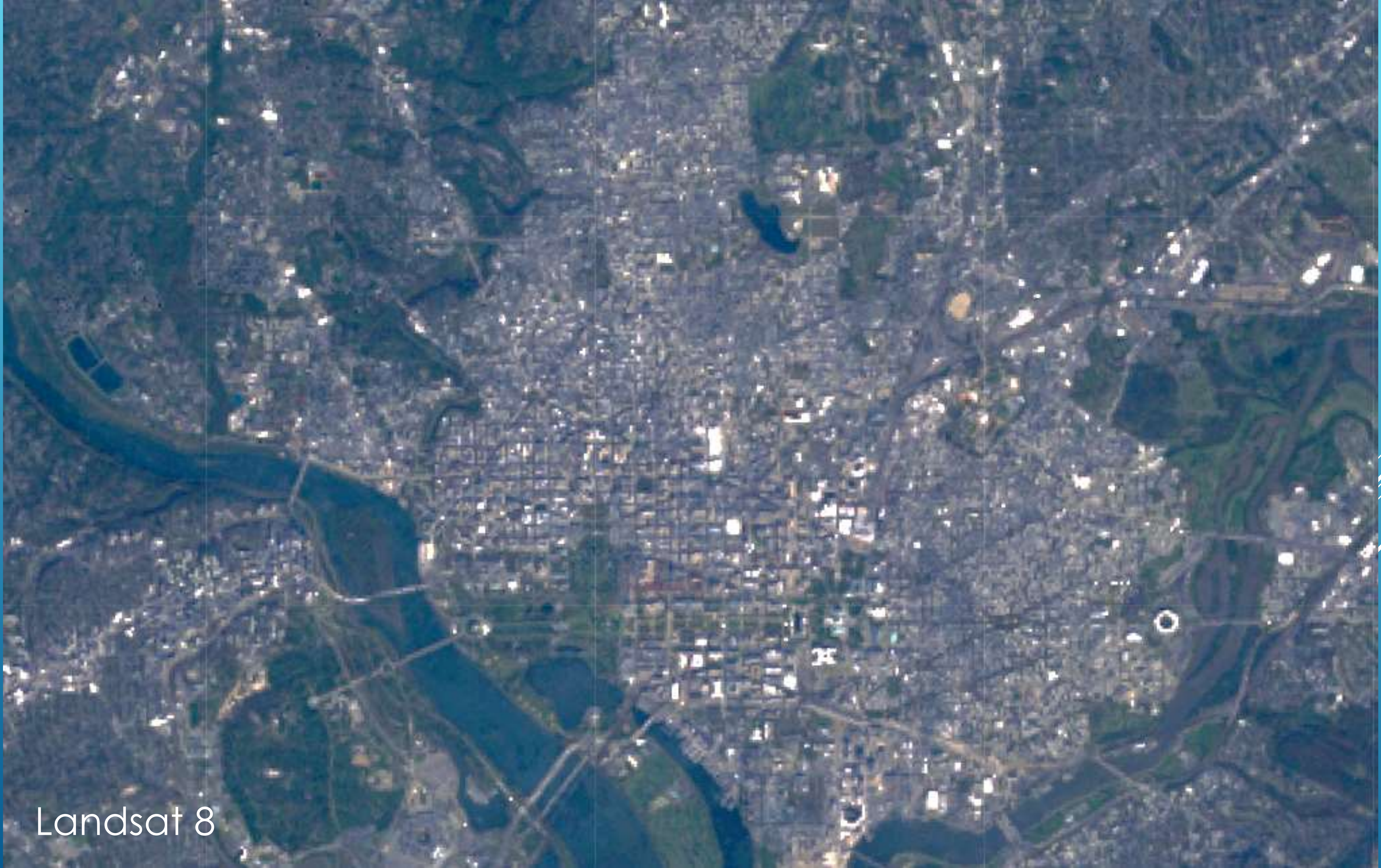
(Spatial) resolution matters…

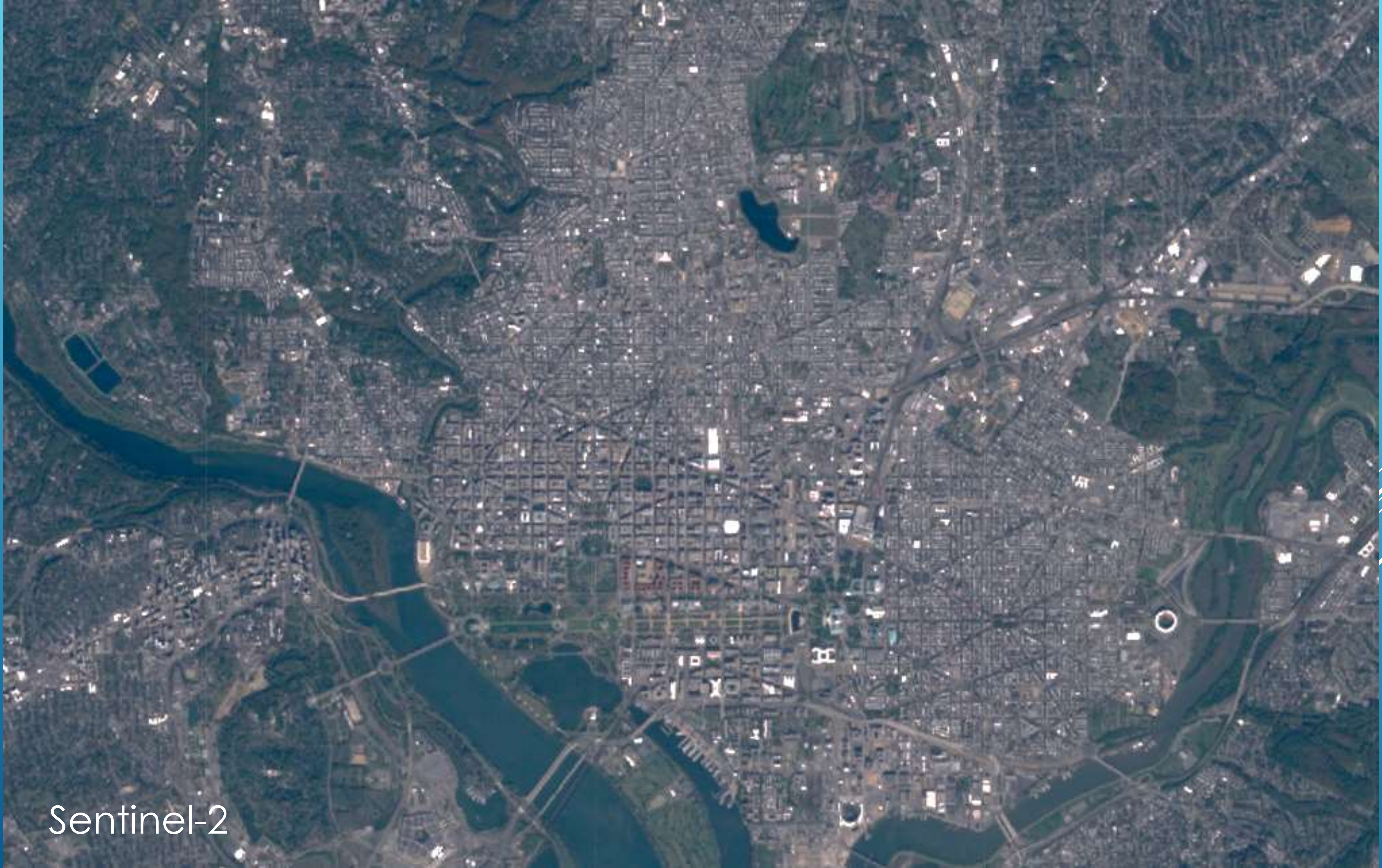
Landsat 8



Sentinel-2

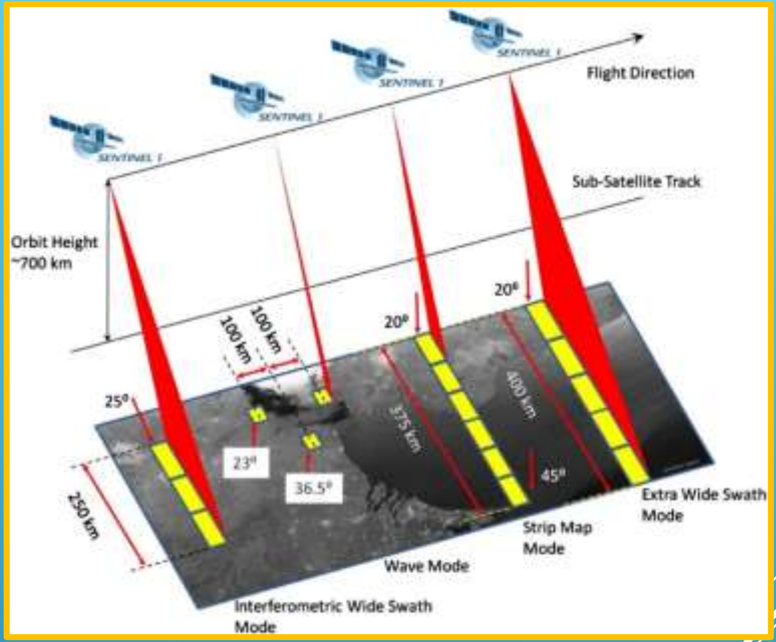

Washington DC
High-res imagery


Landsat 8

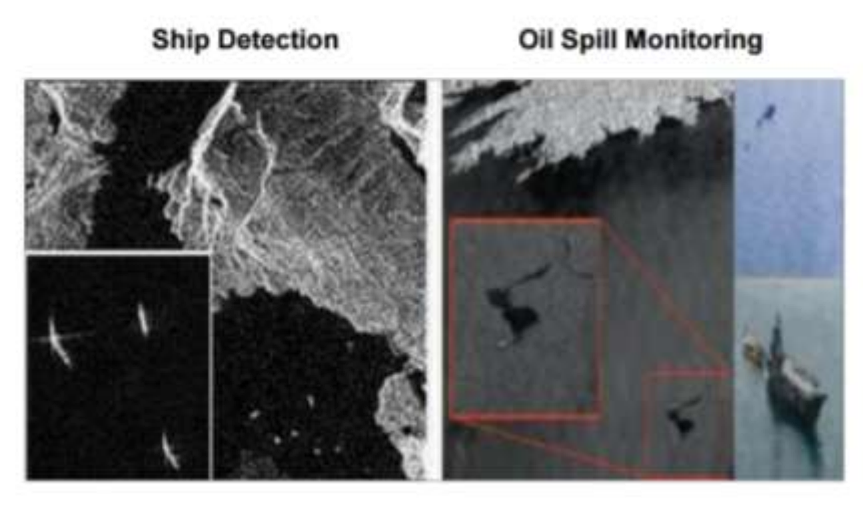

Sentinel-2

Sentinel-1: Applications

- Monitoring land deformation (detect changes occurring between acquisitions)
- Monitoring ground movement
- Monitoring landslides and volcanic uplift
- Direction, wavelength and heights of waves in open oceans



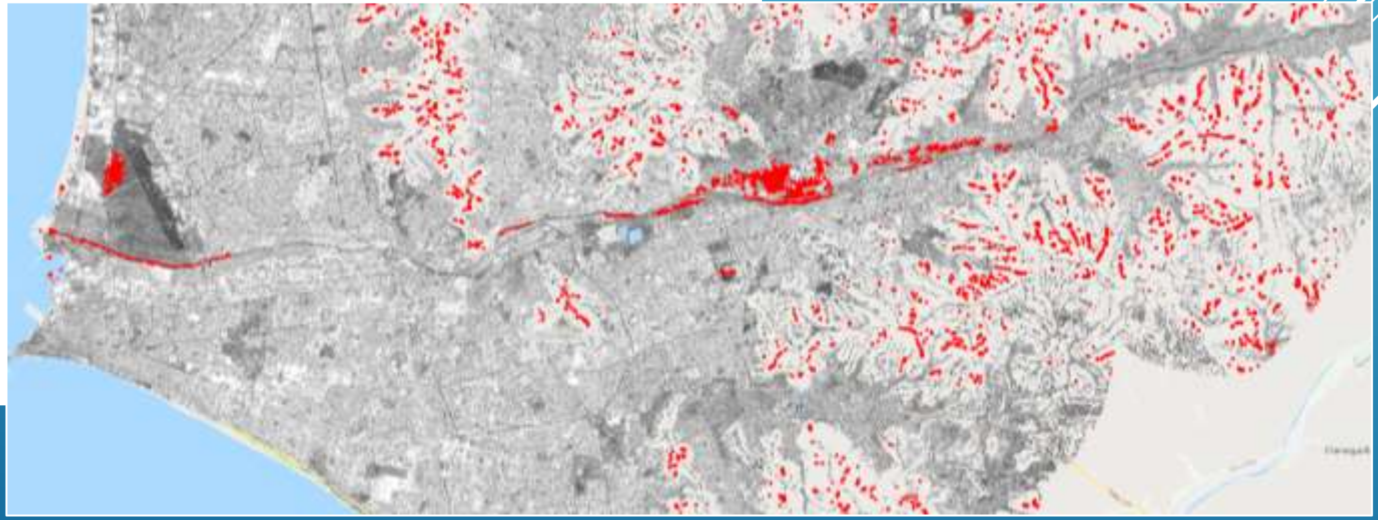
Iceberg detection



https://sentinel.esa.int

CAPTURED WITH SENTINEL-1

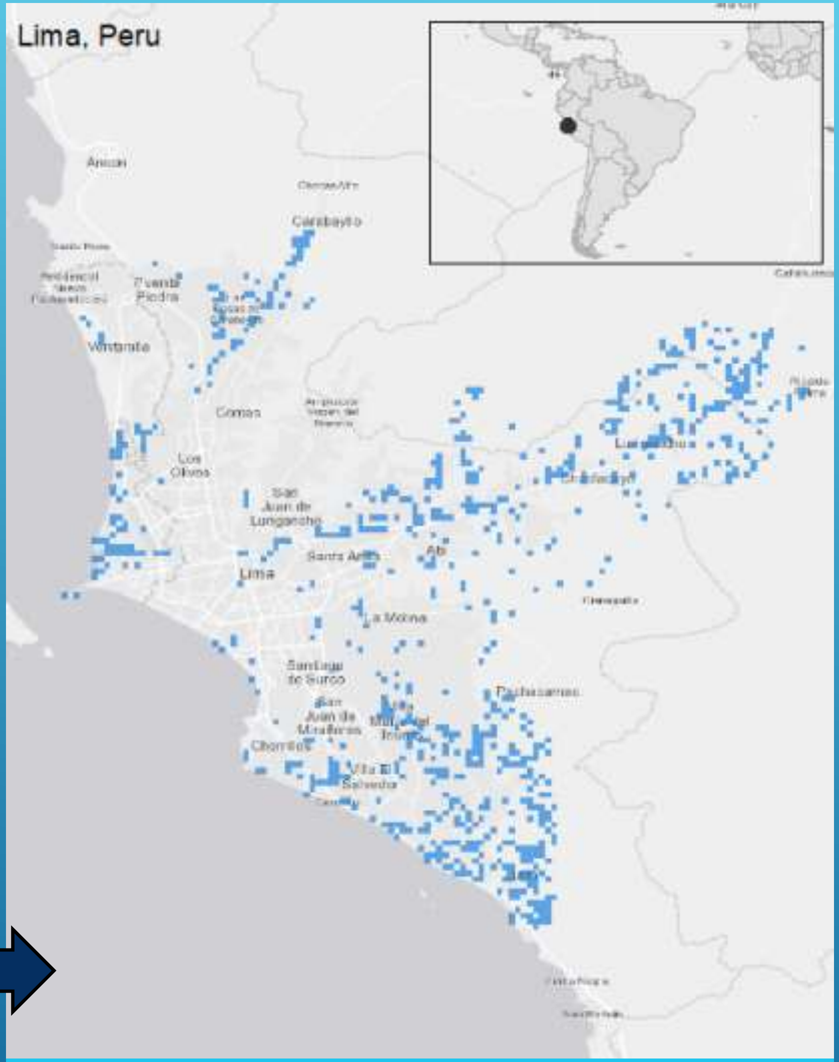
Lima, Peru. Flood event: March 2017



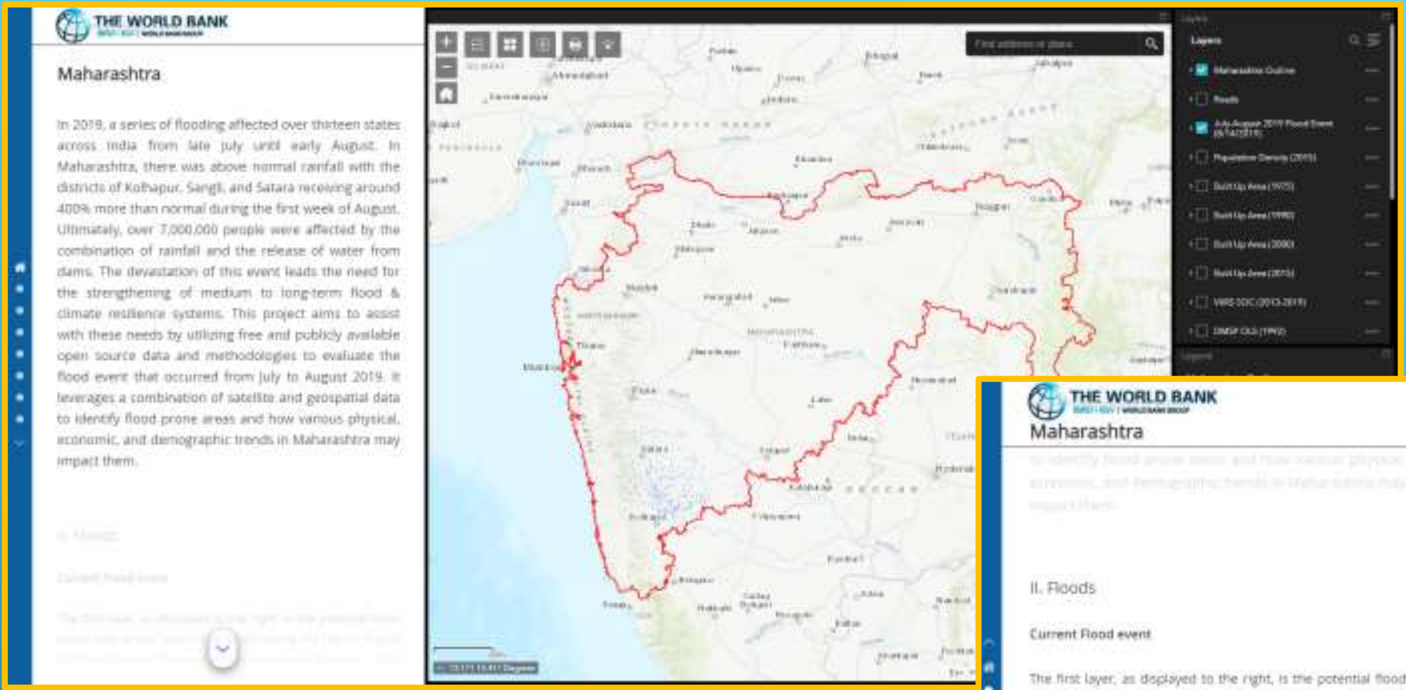
SAR backscatter change detection

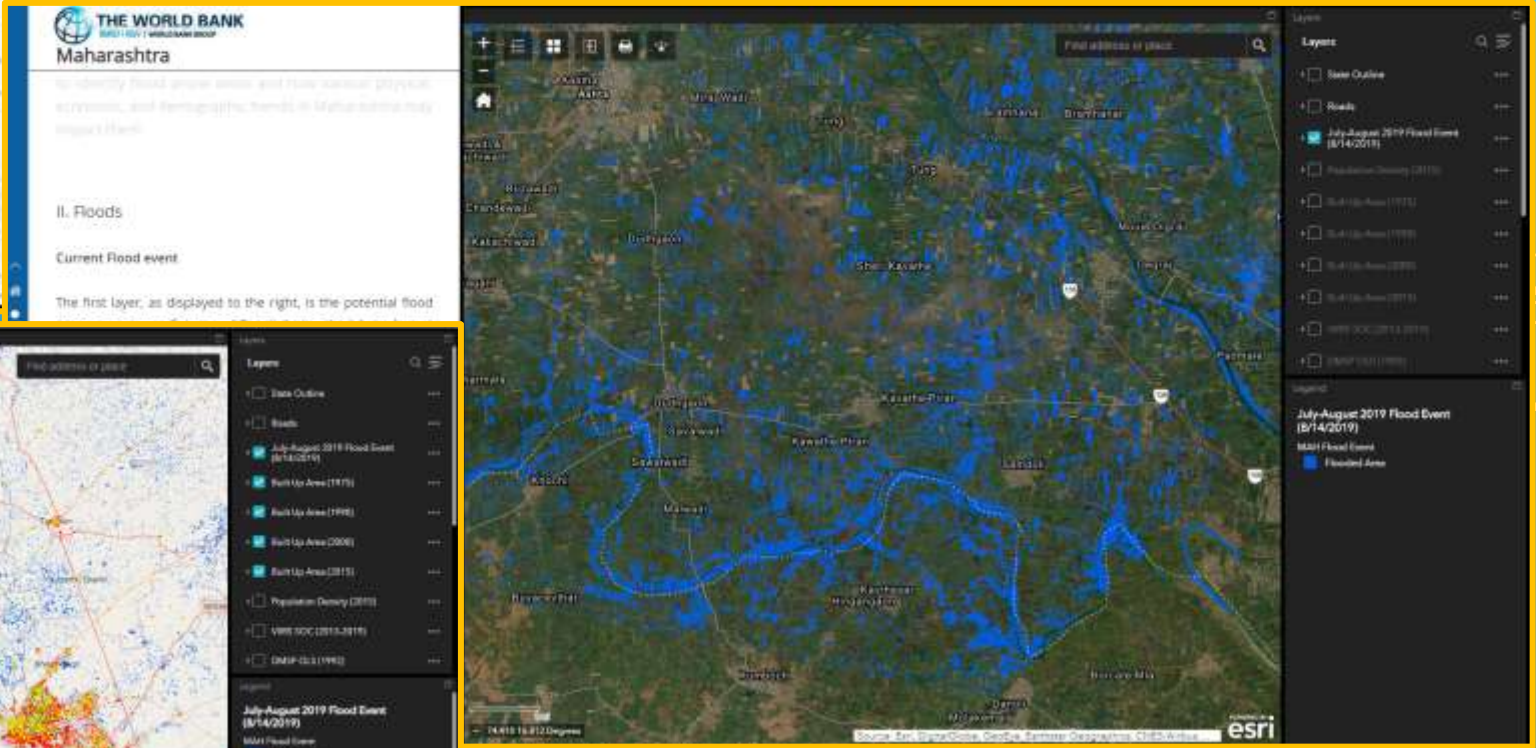
AGGREGATED FLOOD OCCURRENCE

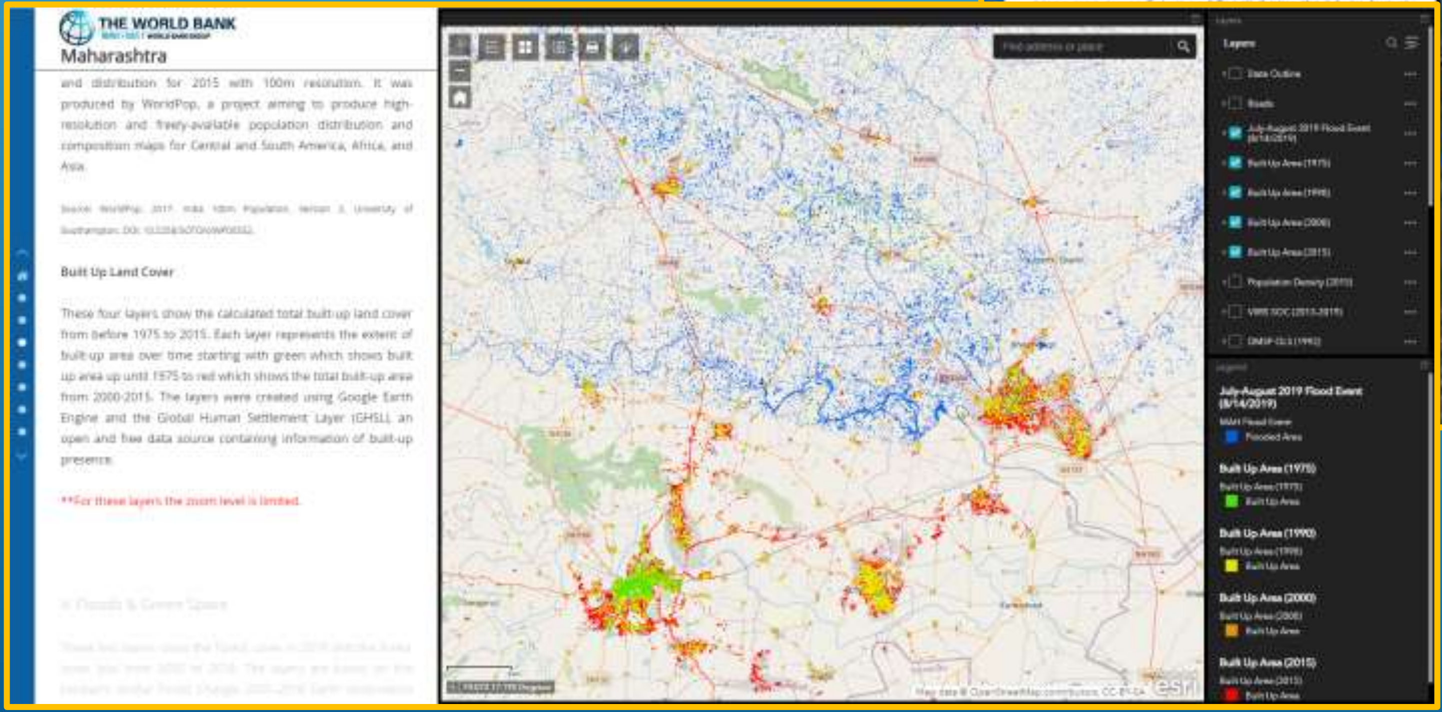
Flood occurrence (all events)



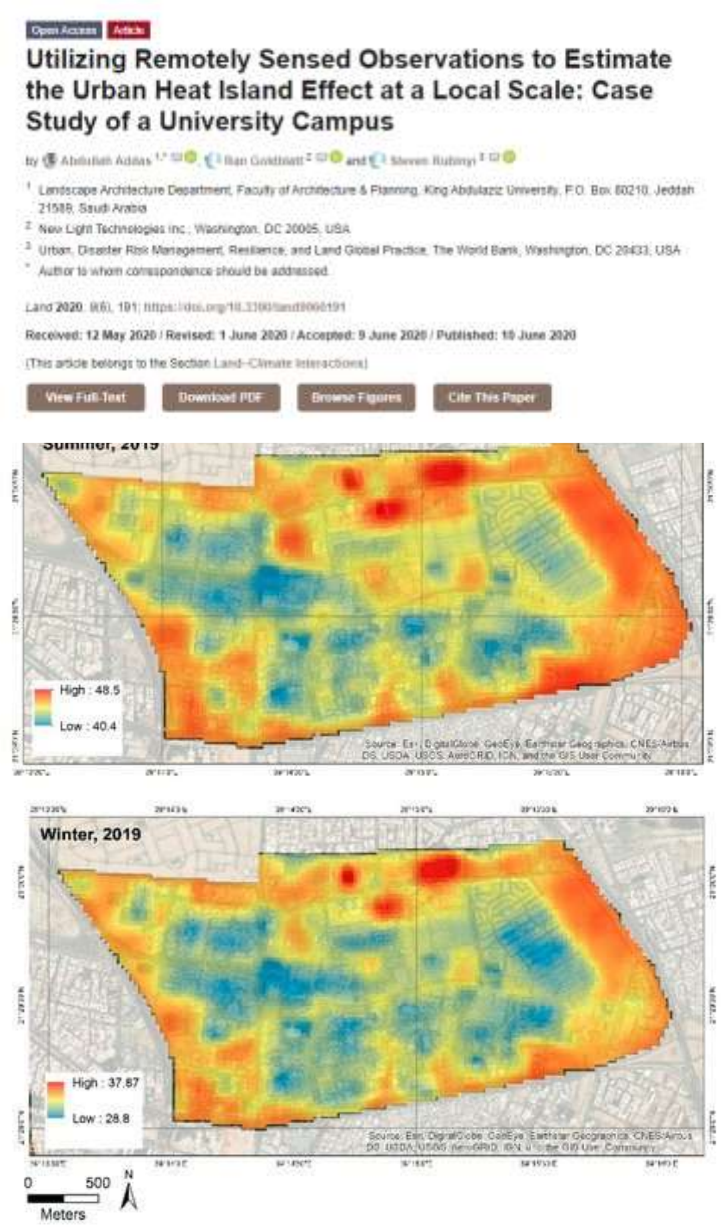
Clusters of frequent flooding


THE WORLD BANK
Maharashtra
In 2019, a series of flooding affected over thirteen states across India from late July until early August. In Maharashtra, there was above normal rainfall with the districts of Kolhapur, Sangli, and Satara receiving around 400% more than normal during the first week of August. Ultimately, over 7,000,000 people were affected by the combination of rainfall and the release of water from dams. The devastation of this event leads the need for the strengthening of medium to long-term flood & climate resilience systems. This project aims to assist with these needs by utilizing free and publicly available open source data and methodologies to evaluate the flood event that occurred from July to August 2019. It leverages a combination of satellite and geospatial data to identify flood prone areas and how various physical, economic, and demographic trends in Maharashtra may impact them.
Layers


THE WORLD BANK
Maharashtra
II. Floods
Current Flood event
The first layer, as displayed to the right, is the potential flood
Layers
State Outline
Roads
July-August 2019 Flood Event (8/14/2019)
July-August 2019 Flood Event (8/14/2019)
Flooded Area
esri


THE WORLD BANK
Maharashtra
and distribution for 2015 with 100m resolution. It was produced by WorldPop, a project aiming to produce high-resolution and freely-available population distribution and composition maps for Central and South America, Africa, and Asia.
Built Up Land Cover
These four layers show the calculated total built-up land cover from before 1975 to 2015. Each layer represents the extent of built-up area over time starting with green which shows built up area up until 1975 to red which shows the total built-up area from 2000-2015. The layers were created using Google Earth Engine and the Global Human Settlement Layer (GHSL), an open and free data source containing information of built-up presence.
**For these layers the zoom level is limited.
Layers
July-August 2019 Flood Event (8/14/2019)
Flooded Area
Built Up Area (1975)
Built Up Area (1990)
Built Up Area (2000)
Built Up Area (2015)
Built Up Area
esri

LAND SURFACE TEMPERATURE (LST)



Open Access | Article

Utilizing Remotely Sensed Observations to Estimate the Urban Heat Island Effect at a Local Scale: Case Study of a University Campus

by Abdullah Addas [1,*], Ran Goldblatt [2] and Steven Rubinyi [3]

[1] Landscape Architecture Department, Faculty of Architecture & Planning, King Abdulaziz University, P.O. Box 80210, Jeddah 21589, Saudi Arabia
[2] New Light Technologies Inc., Washington, DC 20005, USA
[3] Urban, Disaster Risk Management, Resilience, and Land Global Practice, The World Bank, Washington, DC 20433, USA
[*] Author to whom correspondence should be addressed.

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(This article belongs to the Section Land–Climate Interactions)

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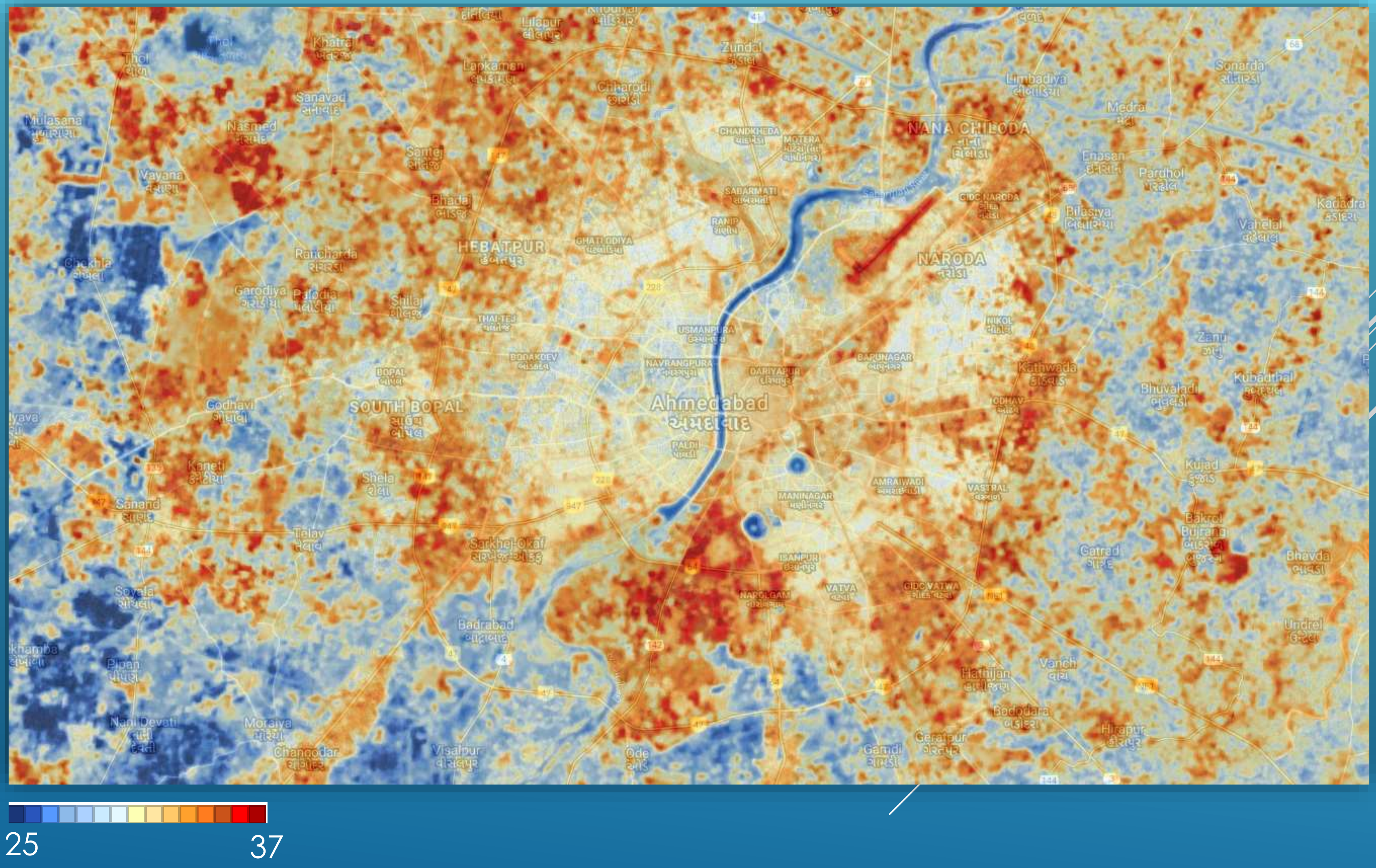


SATELLITES AS "BIG GEODATA" (VVV)

VOLUME

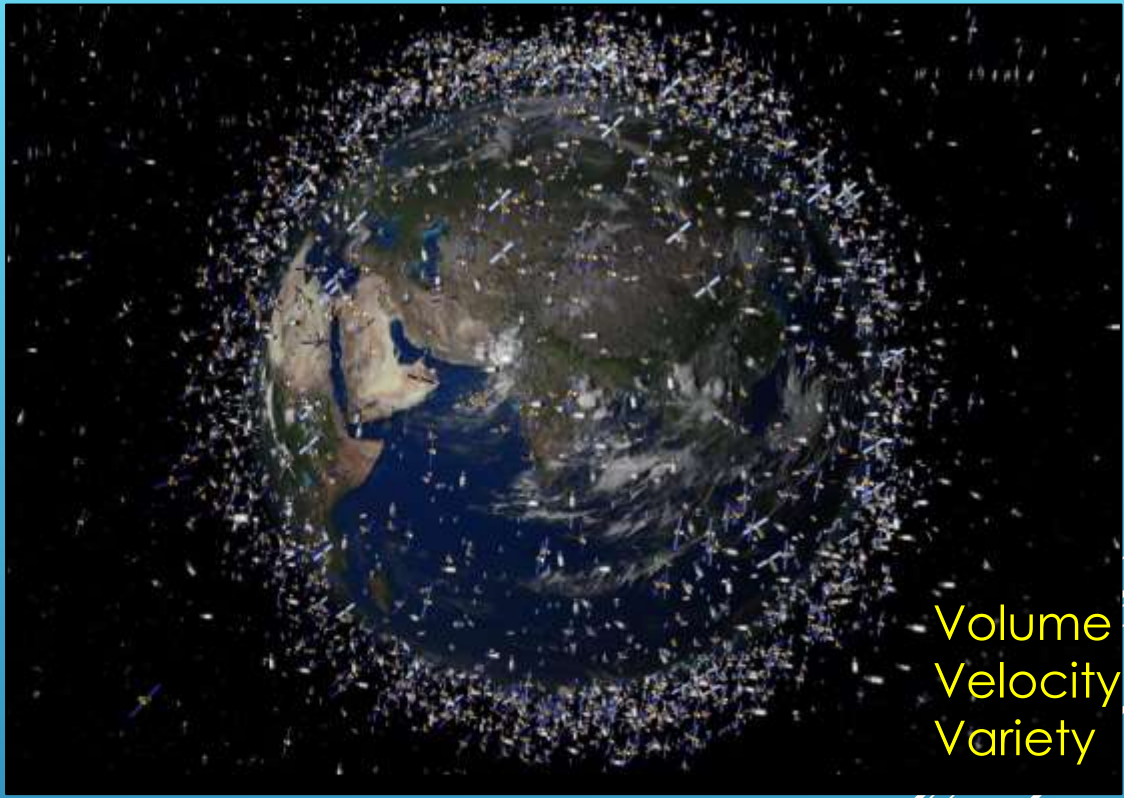
How much?

VELOCITY

How fast, how often?

VARIETY

What type of data?



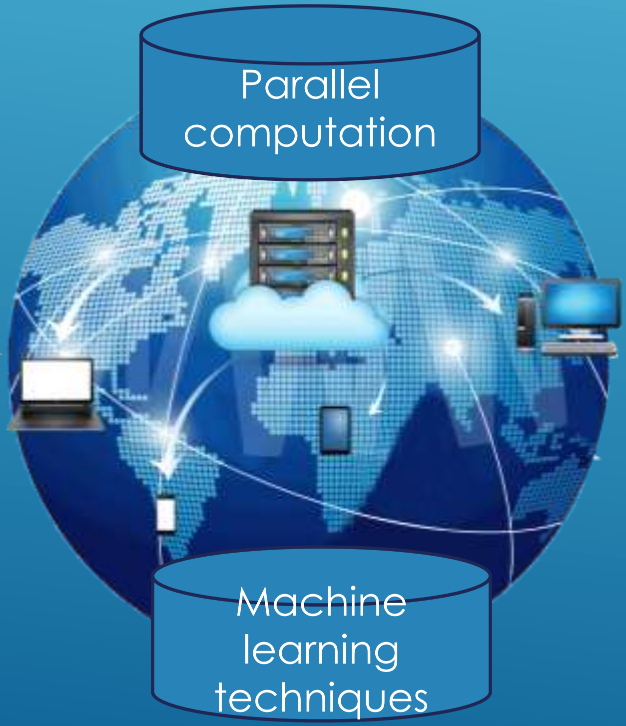
Capacity and Methods

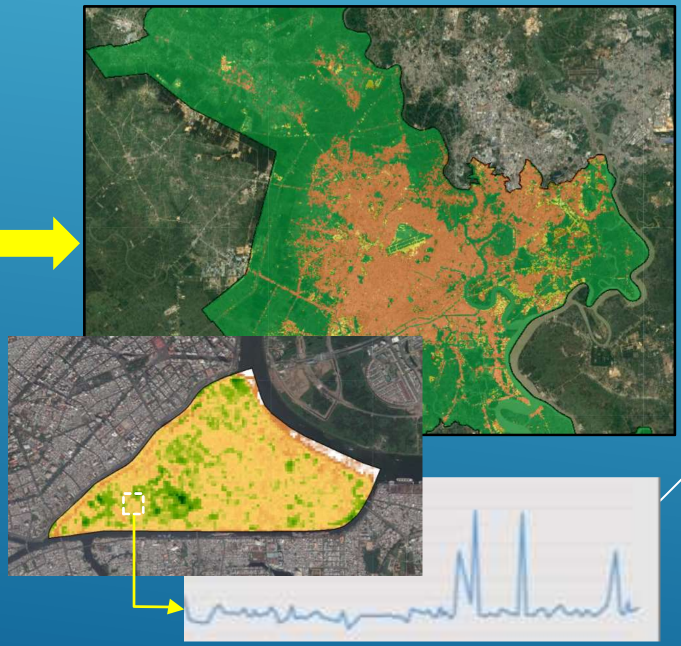
THE EMERGING CLOUD COMPUTATION

Scaling up the analysis across **SPACE** and **TIME**

Petabytes of Remote Sensing data

Your own data





Better decision mak

REMOTE SENSING AND MACHINE LEARNING

The domain of **MACHINE LEARNING** focuses on:
How machines learn rules from examples?

The goal:

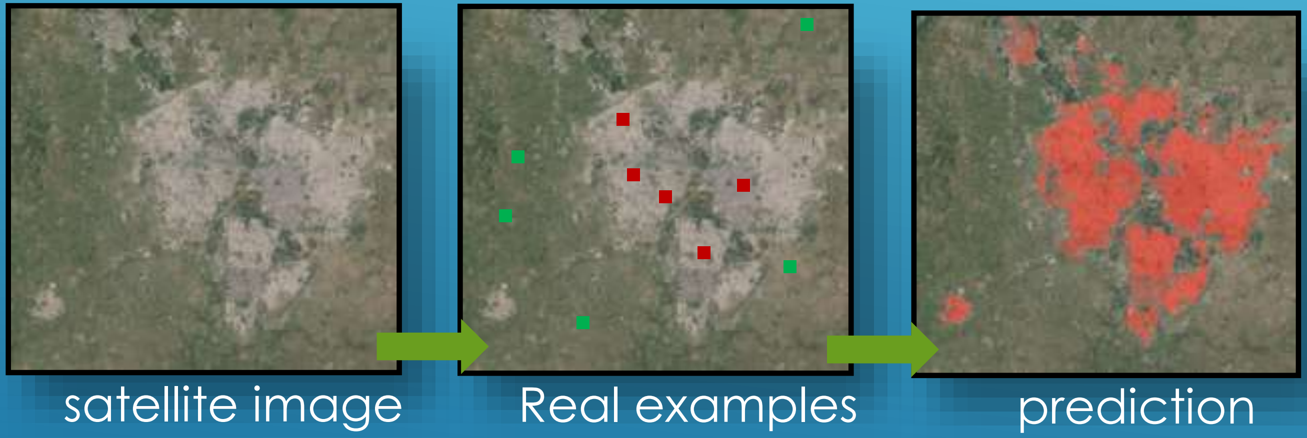
- Learn patterns from examples;
- Be able to generalize them to new examples.

Types of machine learning:
Unsupervised and supervised

- **Unsupervised**: find regularities, patterns and clusters in the data (beyond pure noise) according to some set of measurements.
- **Supervised**: learn from examples in an existing classification system, with explicit known output values (labels).

SUPERVISED MACHINE LEARNING

- **Example**: Supervised machine learning to detect urban areas
- Real examples ("ground truth data") are used to "teach" the classifiers about the characteristics (i.e. the unique spectral signature) of urban and not urban areas.
- Then, the classifiers predict which areas on the satellite image are urban.



remote sensing

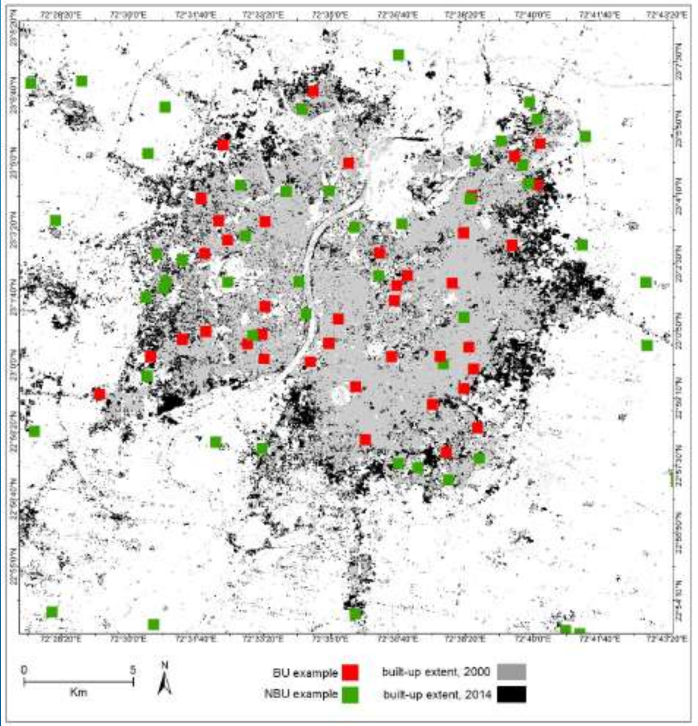
MDPI

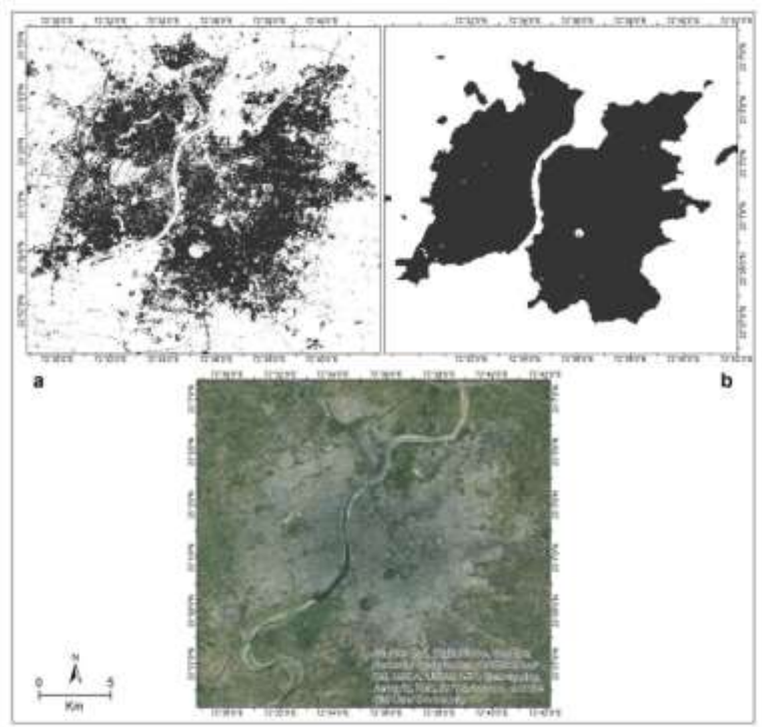
Article

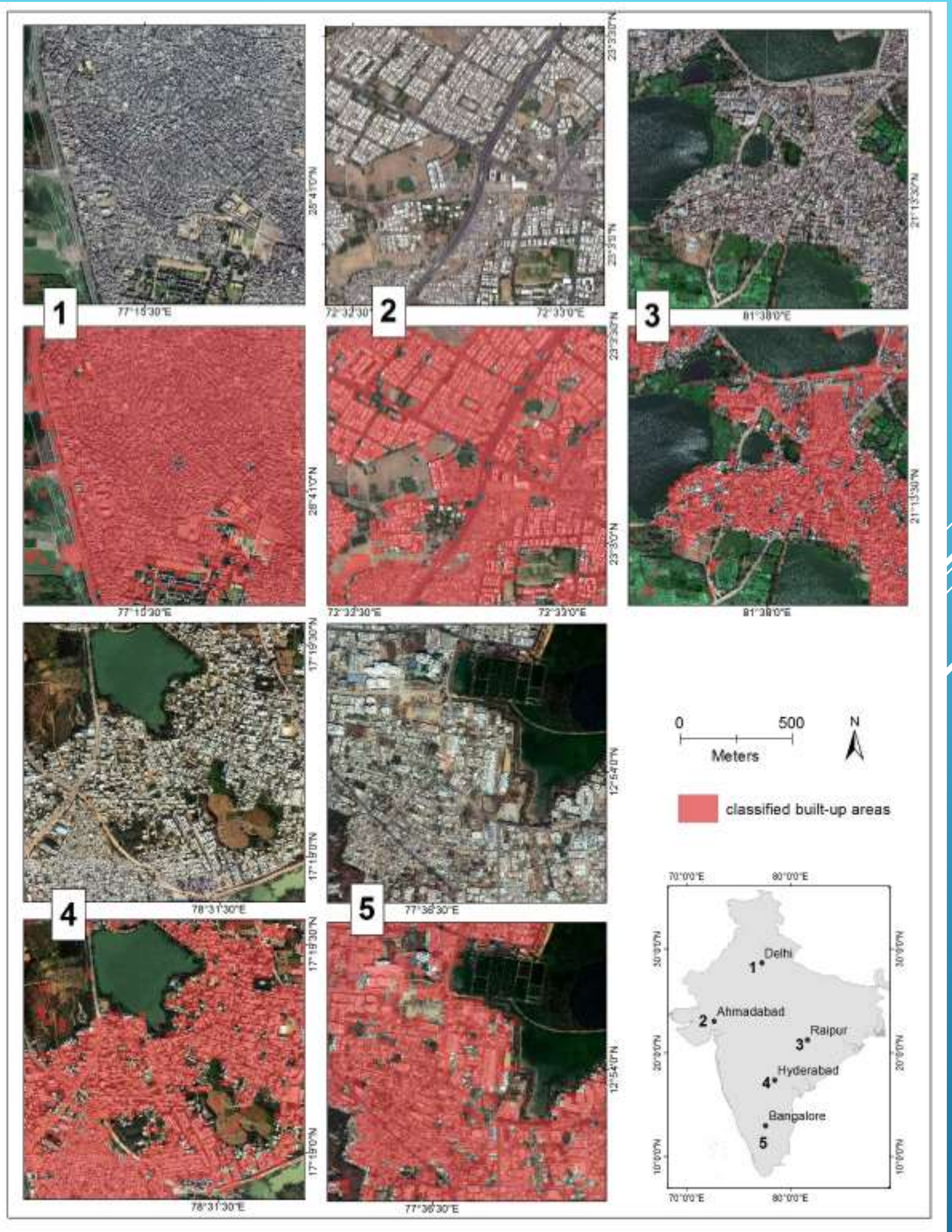
Detecting the Boundaries of Urban Areas in India: A Dataset for Pixel-Based Image Classification in Google Earth Engine

Ran Goldblatt [1,*], Wei You [2], Gordon Hanson [1] and Amit K. Khandelwal [3]

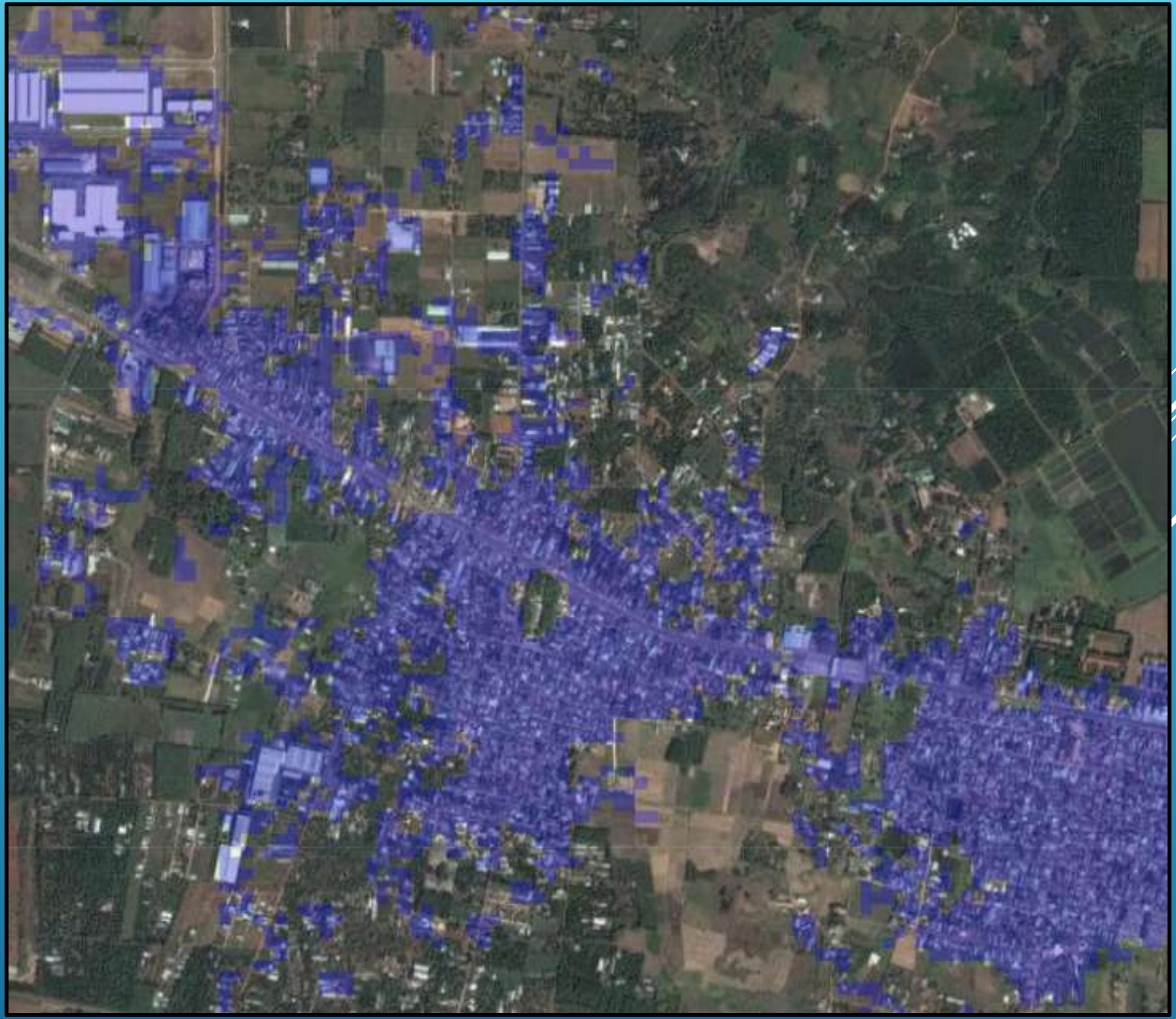
1 School of Global Policy and Strategy, University of California, San Diego, CA 92093, USA; gohanson@ucsd.edu
2 Department of Economics, University of California, San Diego, CA 92093, USA; wyou@ucsd.edu
3 Columbia Business School, Columbia University, New York, NY 10027, USA; ak2796@columbia.edu
* Correspondence: rgoldblatt@ucsd.edu; Tel.: +1-858-822-5087

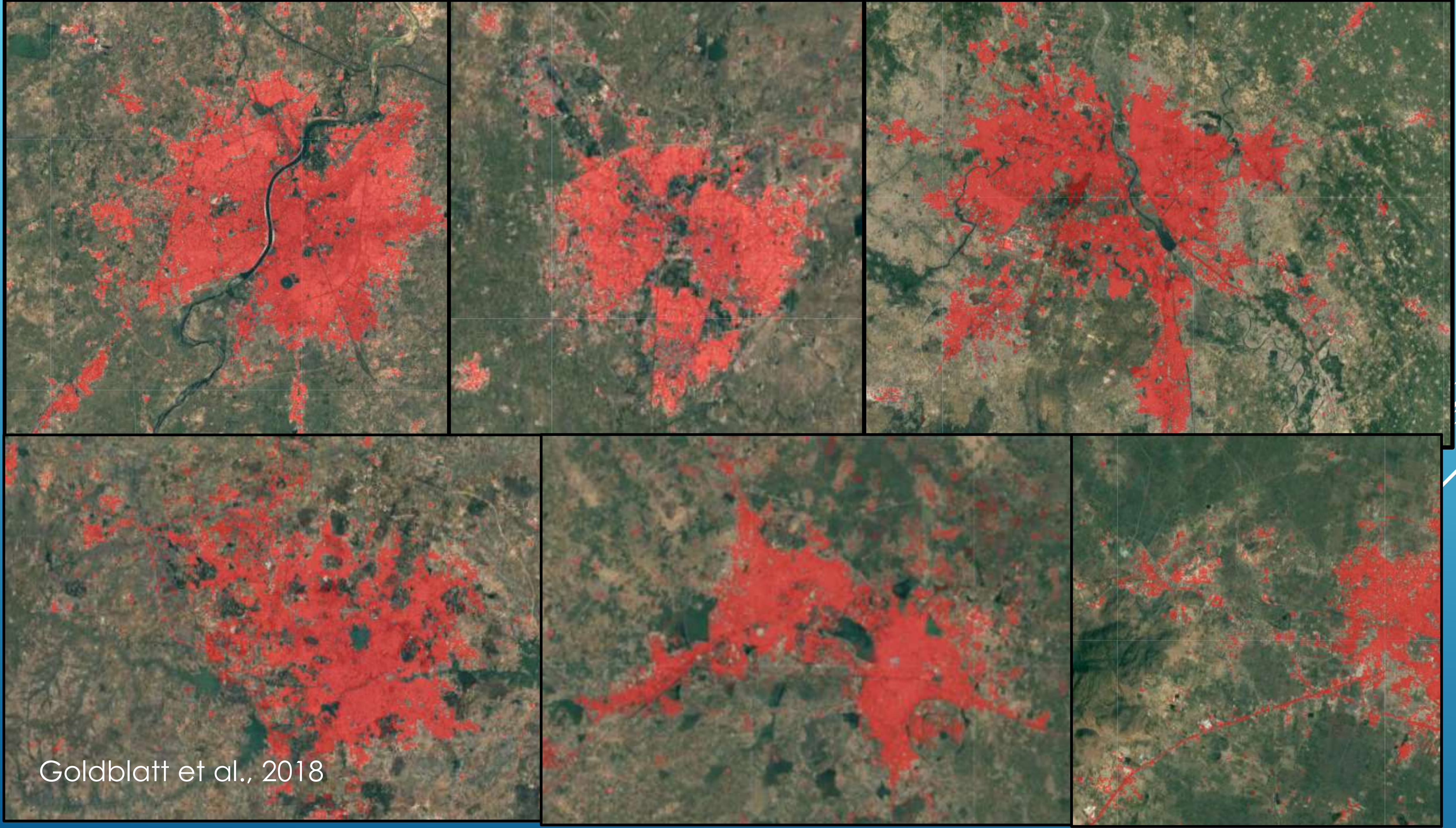






Built-up LC





Goldblatt et al., 2018

Remote Sensing of Environment 205 (2018) 253–275

Contents lists available at ScienceDirect

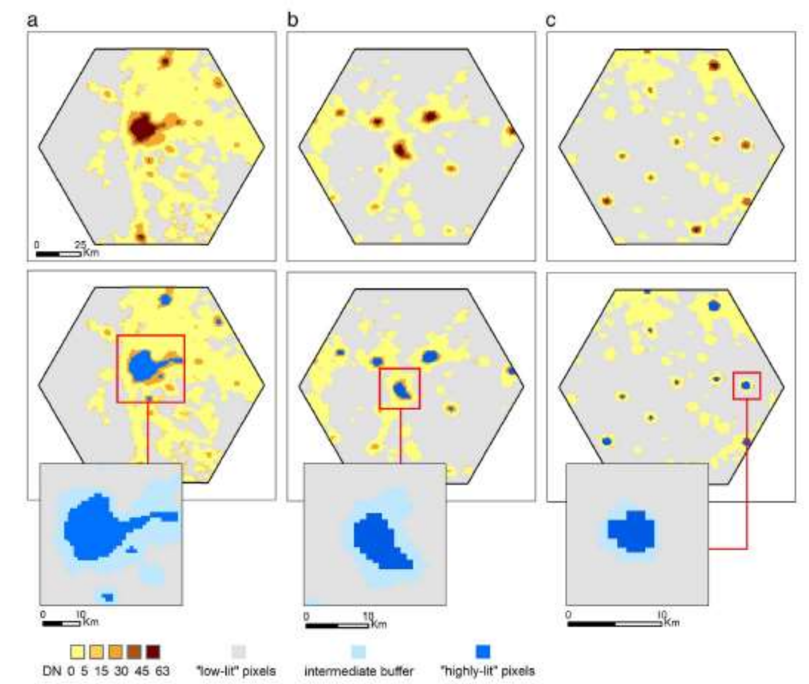
Remote Sensing of Environment

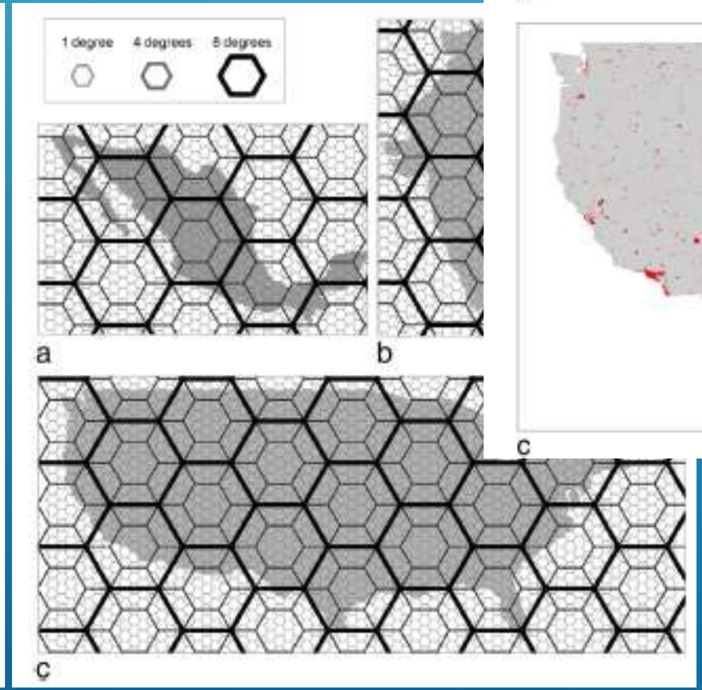
journal homepage: www.elsevier.com/locate/rse

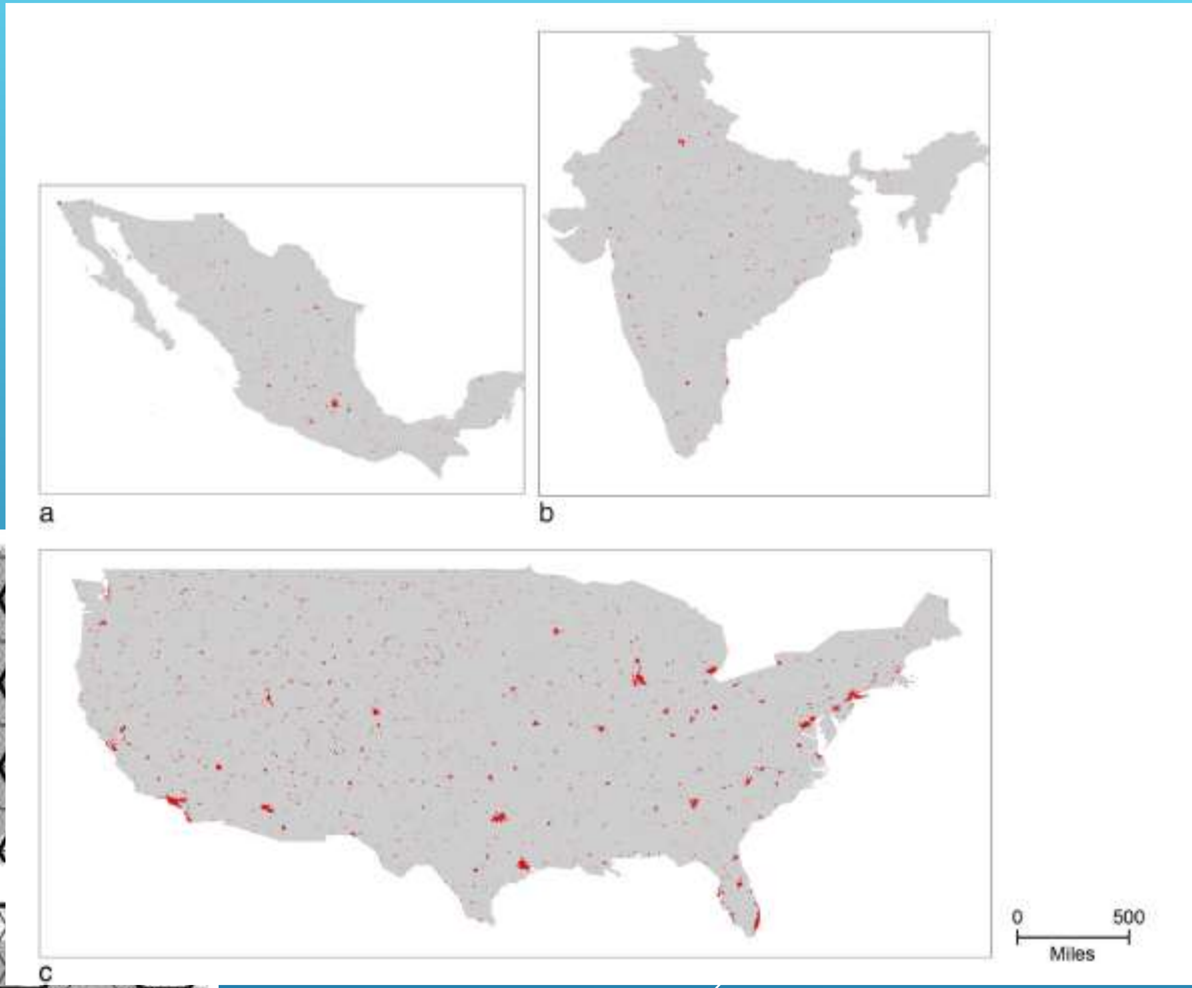
Using Landsat and nighttime lights for supervised pixel-based image classification of urban land cover

Ran Goldblatt[a,*], Michelle F. Stuhlmacher[b], Beth Tellman[b], Nicholas Clinton[c], Gordon Hanson[a], Matei Georgescu[b], Chuyuan Wang[b], Fidel Serrano-Candela[d], Amit K. Khandelwal[e], Wan-Hwa Cheng[b], Robert C. Balling Jr[b]

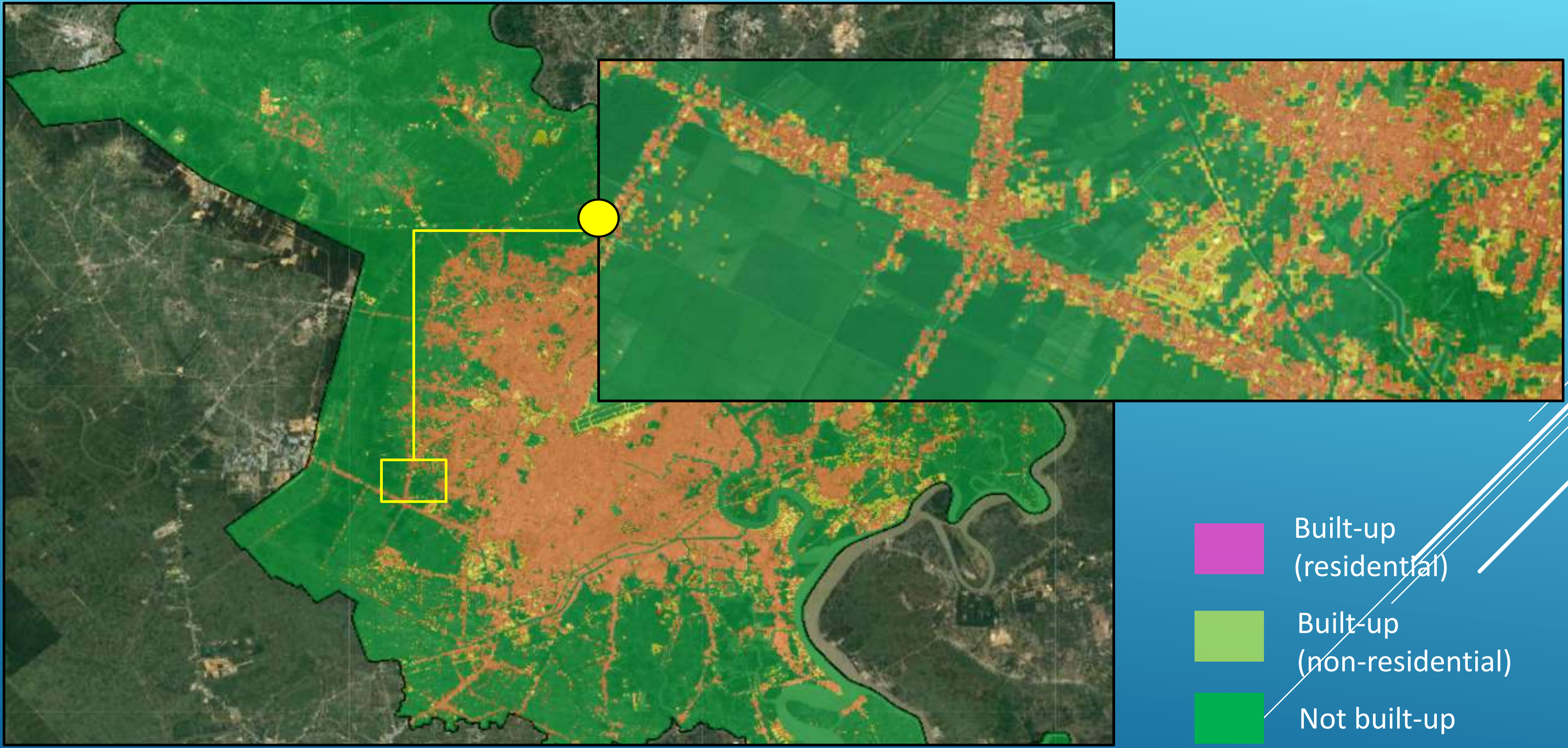
[a] School of Global Policy and Strategy, UC San Diego, 9500 Gilman Drive La Jolla, CA 92093-0519, USA
[b] School of Geographical Sciences and Urban Planning, Arizona State University, 976 S Forest Mall, Tempe, AZ 85281, USA
[c] Google, Inc., 1600 Amphitheatre Pkwy, Mtn. View, CA 94043, USA
[d] Laboratorio Nacional de Ciencias de la Sostenibilidad, Universidad Nacional Autónoma de México, Apartado Postal 70-275 Ciudad Universitaria, UNAM 04510 México, D.F. Circuito exterior s/n anexo al Jardín Botánico Exterior, Mexico
[e] Columbia Business School, Columbia University, New York, NY 10027, USA







“BUILT-UP” RESIDENTIAL AND NON-RESIDENTIAL



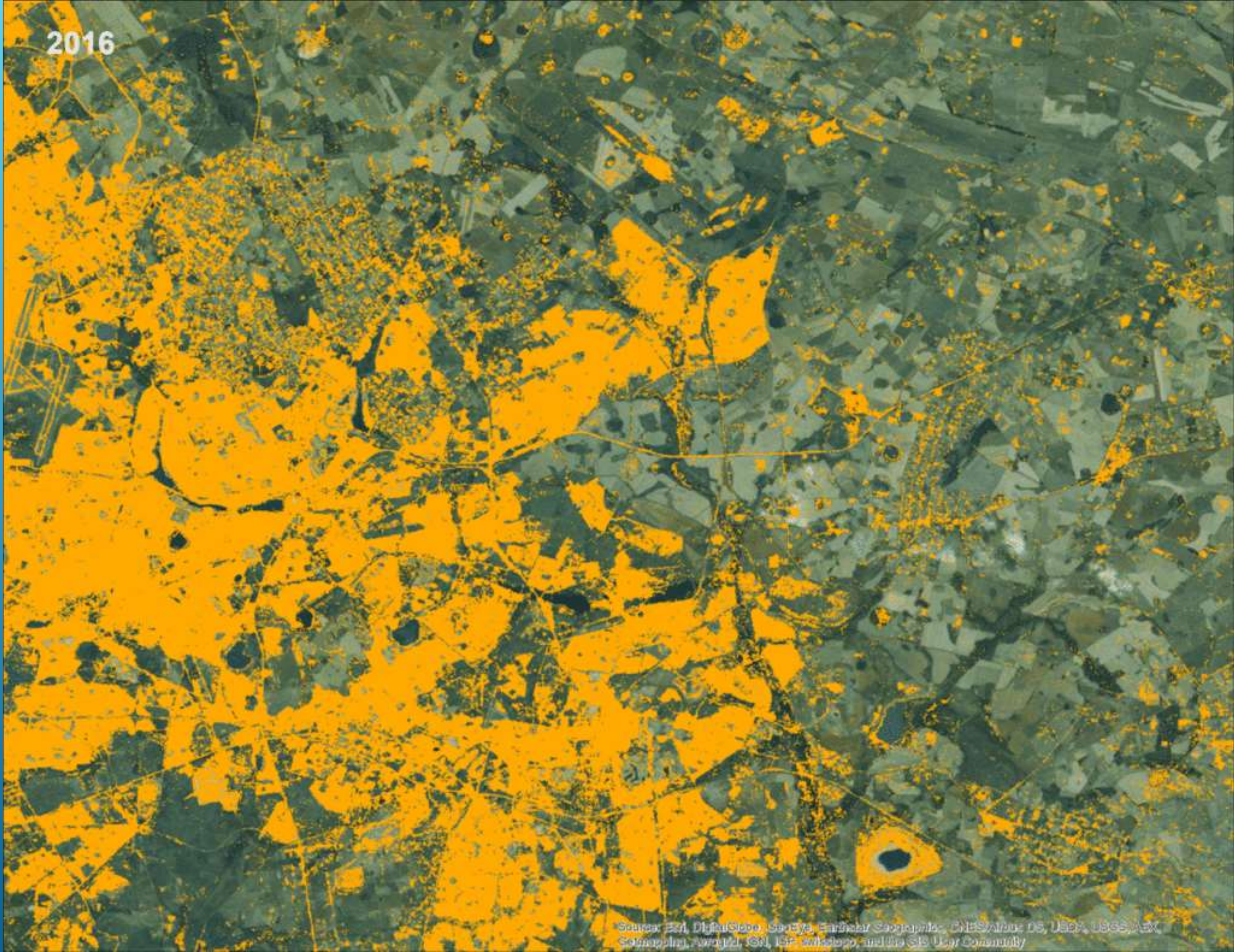
Built-up (residential)

Built-up (non-residential)

Not built-up

Ho Chi Minh City, Vietnam

Johannesburg, South Africa



HIGHER SPATIAL RESOLUTION

Increased spatial resolution allows us to detect individual buildings and structures.

This can potentially be used to estimate population size.

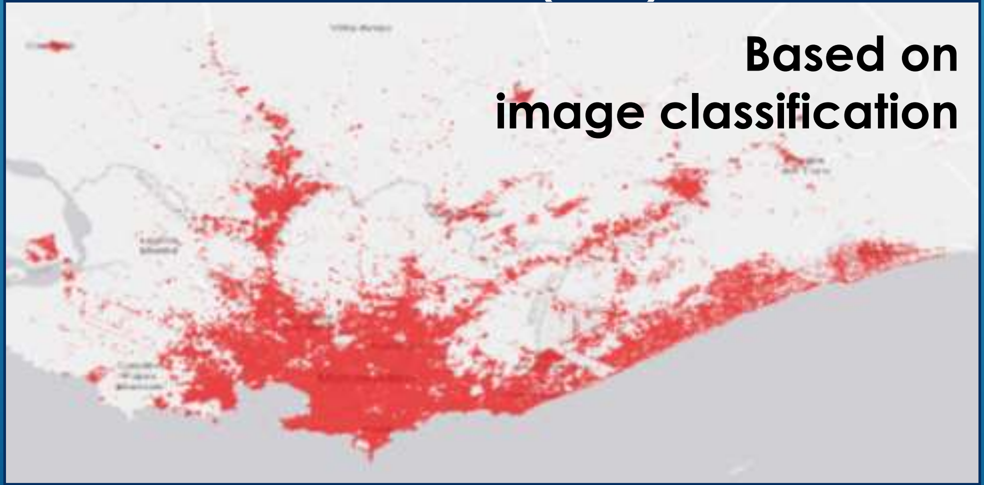
OPEN GREEN SPACES, VEGETATION / BUILT-UP RATIO

Data sources

Sentinel-2, Global Human Settlement Layer (GHSL)

GREEN SPACES

BUILT-UP LC (GHSL)



PERCENT GREEN / BUILT-UP

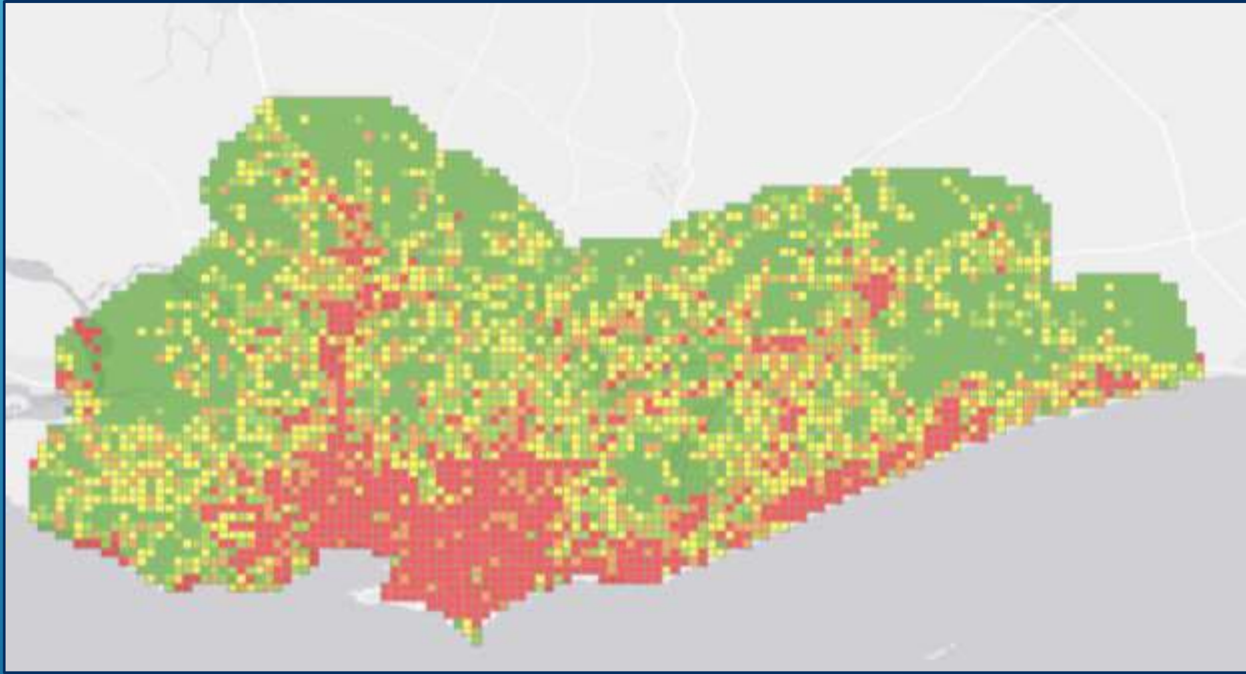
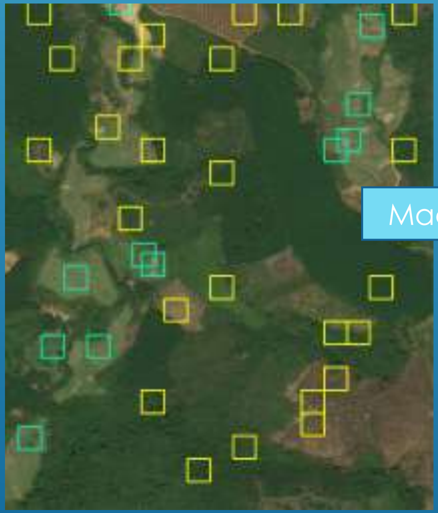


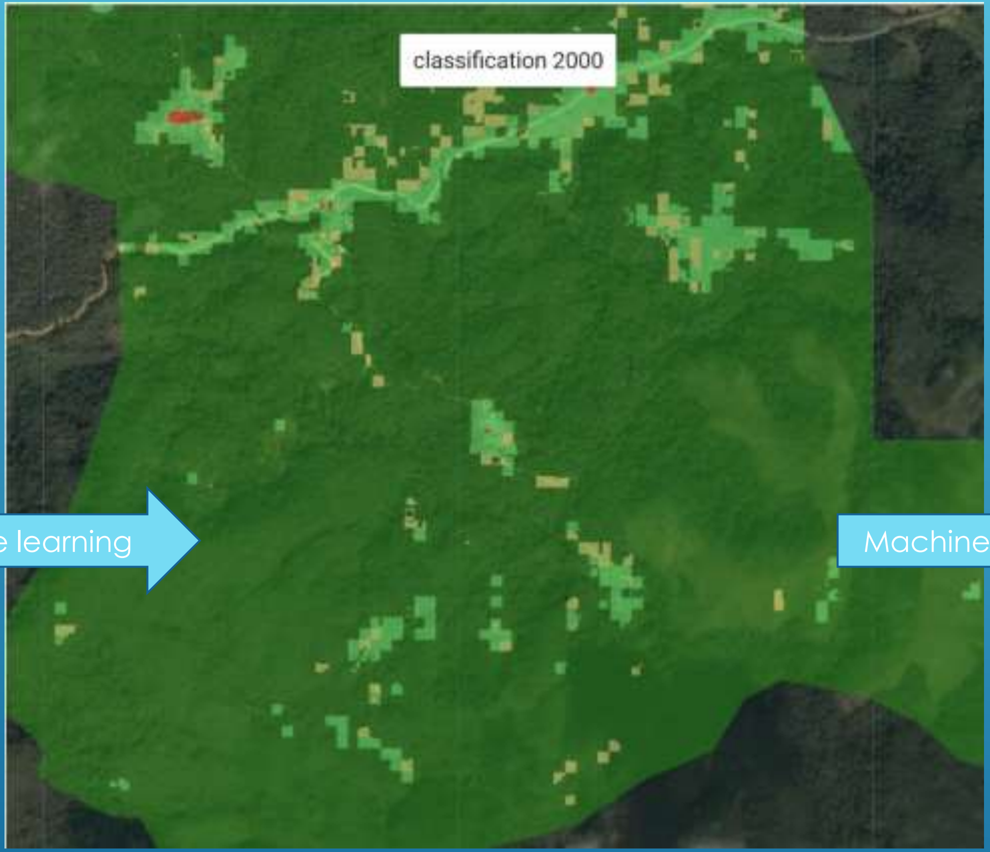
IMAGE CLASSIFICATION OF **LAND USE AND LAND COVER**

An automated and easy-to-use methodology for mapping annual land cover changes

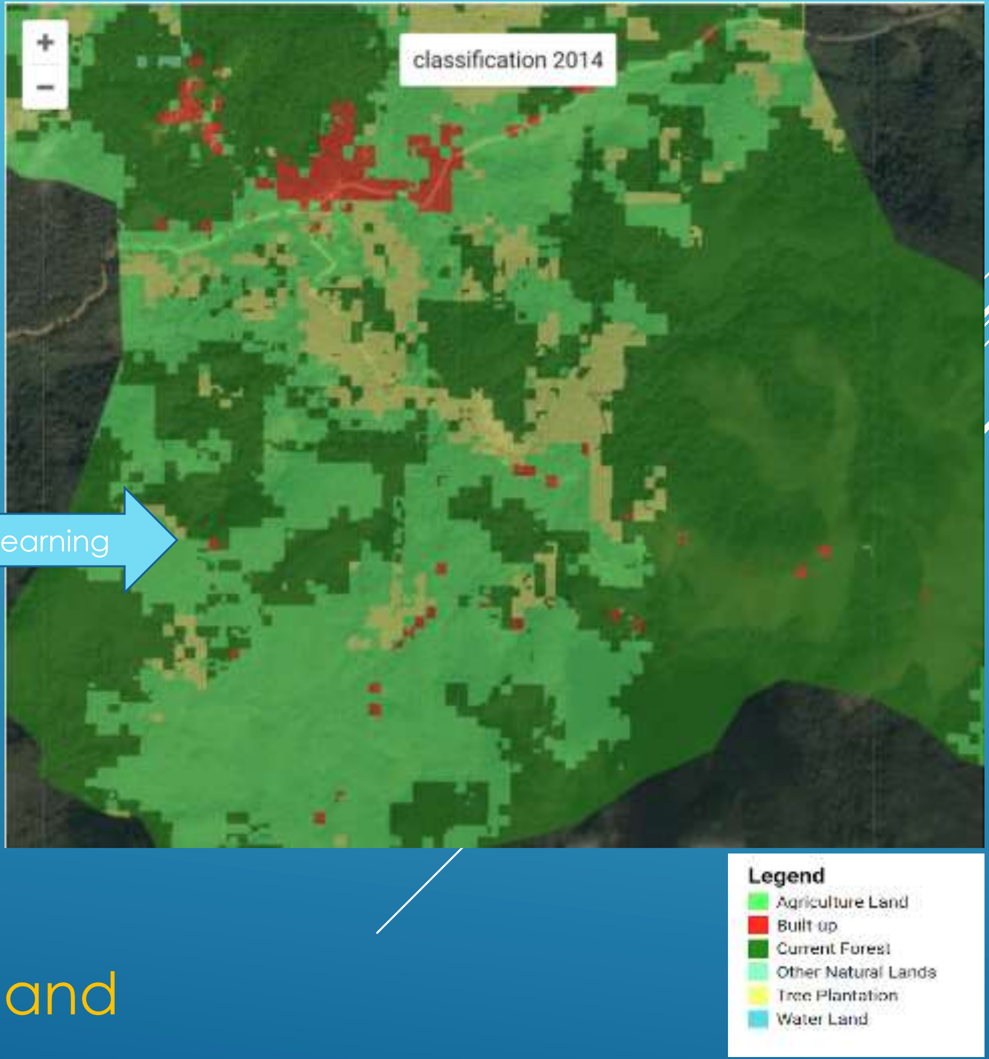


Several thousands of hand-labeled examples

Machine learning



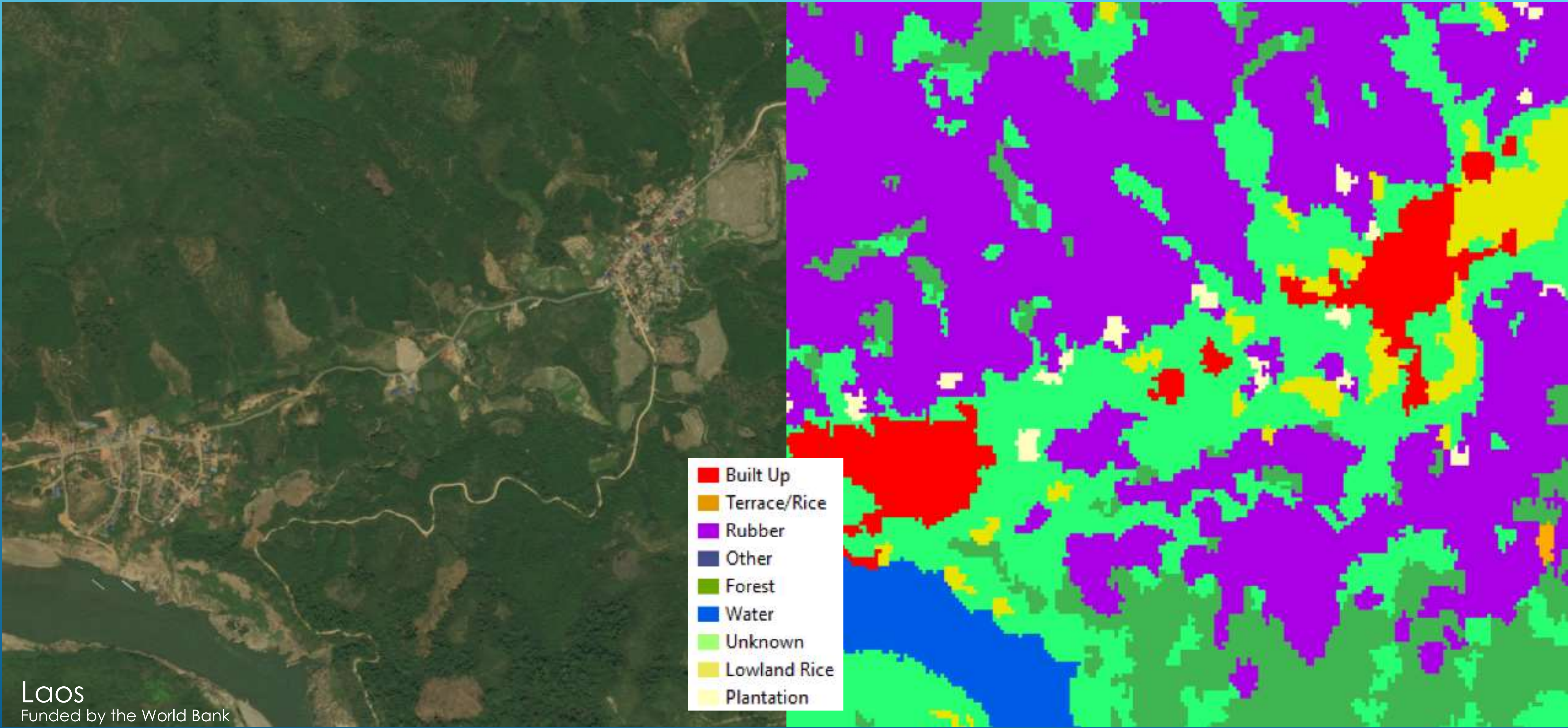
Machine learning



Conversion from
natural forest cover to agriculture land

SENTINEL-2 CLASSIFICATION

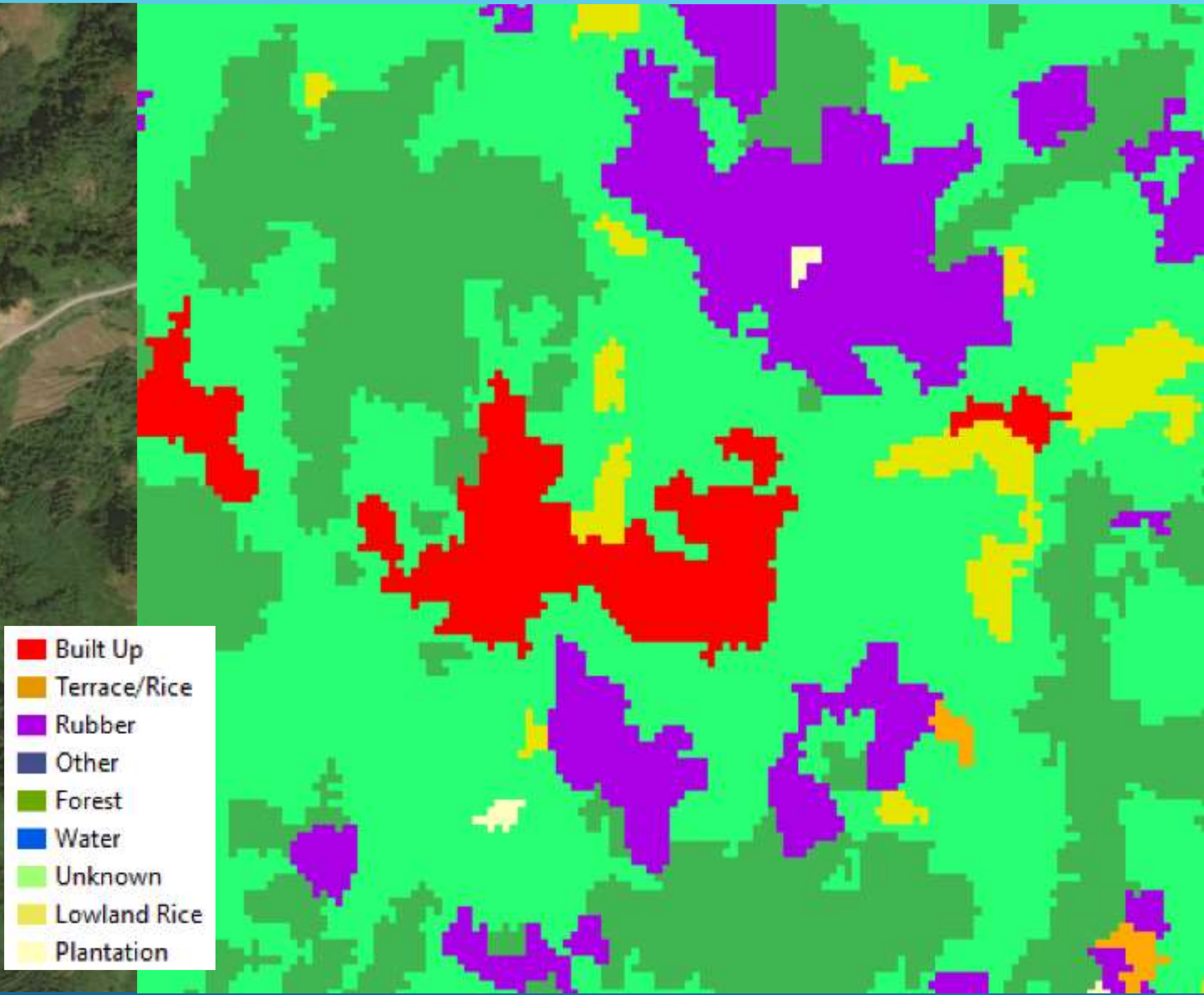
Accurate high-resolution classification map representing land cover based on Sentinel-2 imagery from 2016



Google Satellite Basemap for reference (2019)

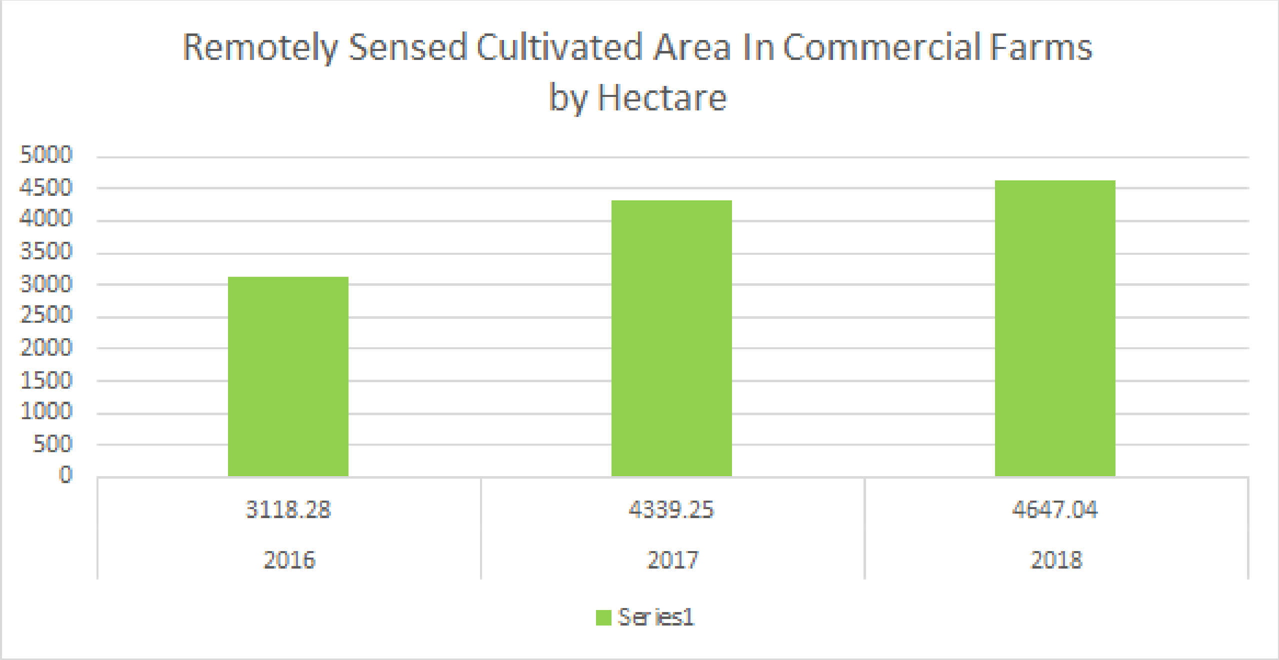
SENTINEL-2 CLASSIFICATION

Accurate high-resolution classification map representing land cover based on Sentinel-2 imagery from 2016



Google Satellite Basemap for reference (2019)

Cultivated Hectares By Year Using Sentinel-2

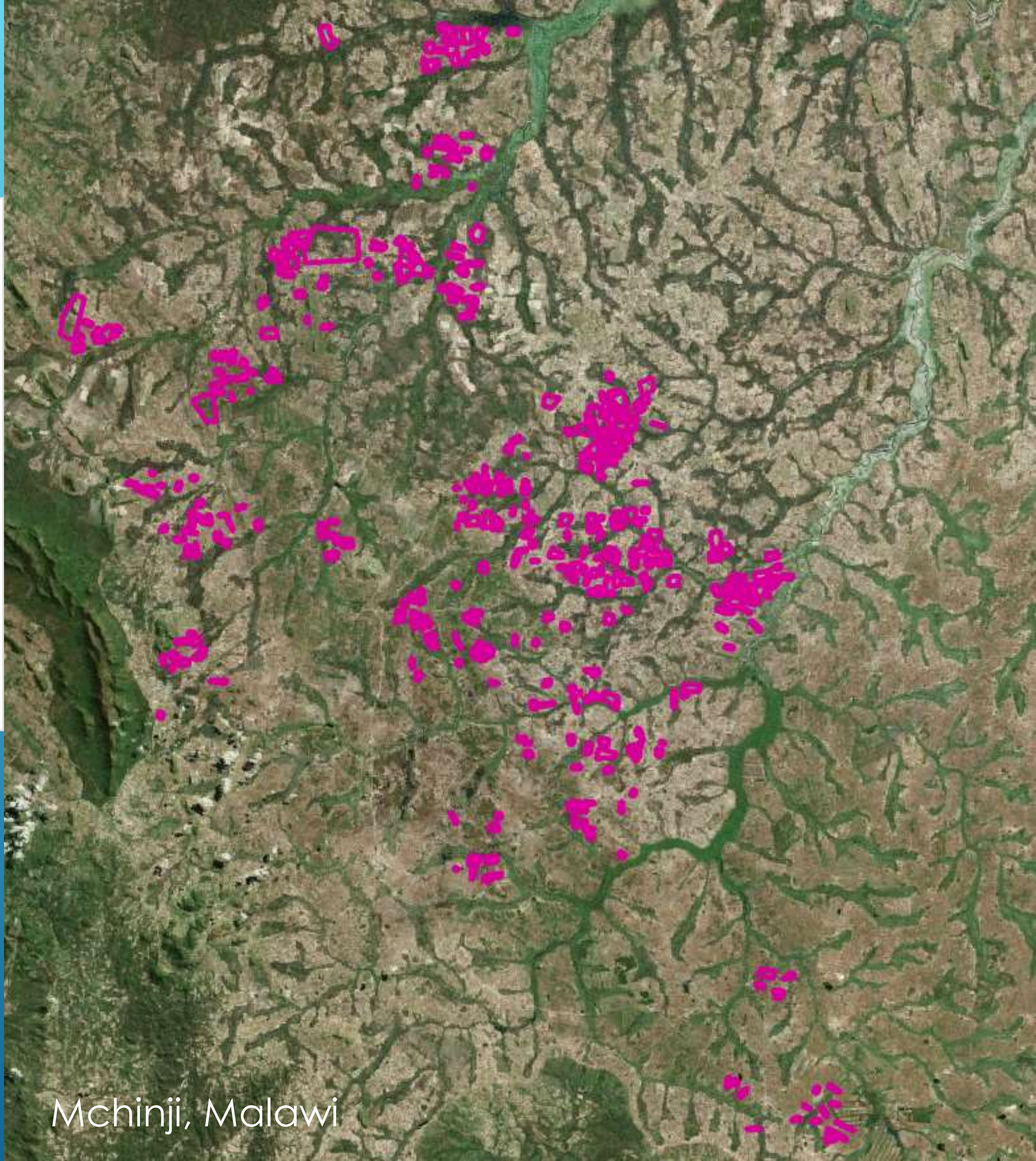


Mean cultivated area by percent

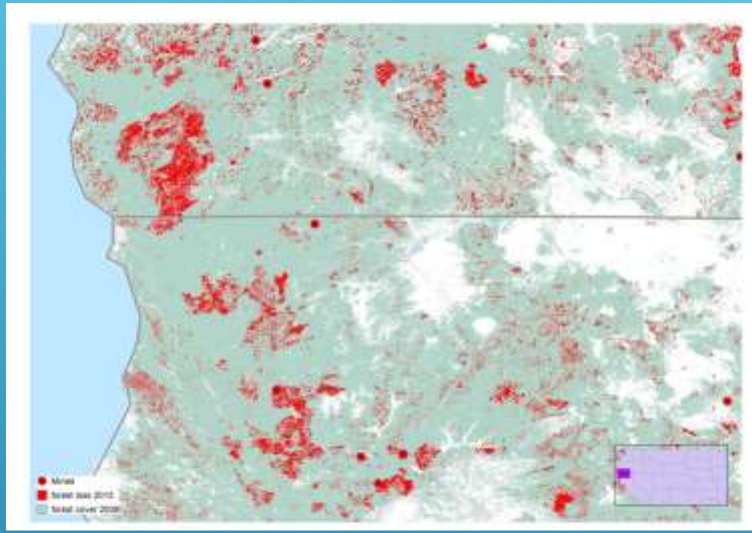
2016: 36.05

2017: 49.11

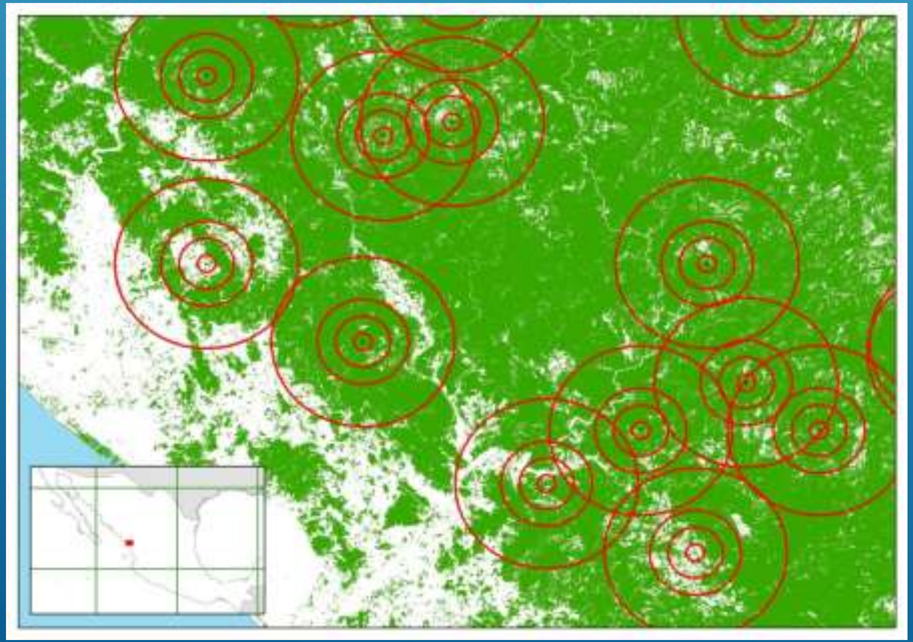
2018: 54.41

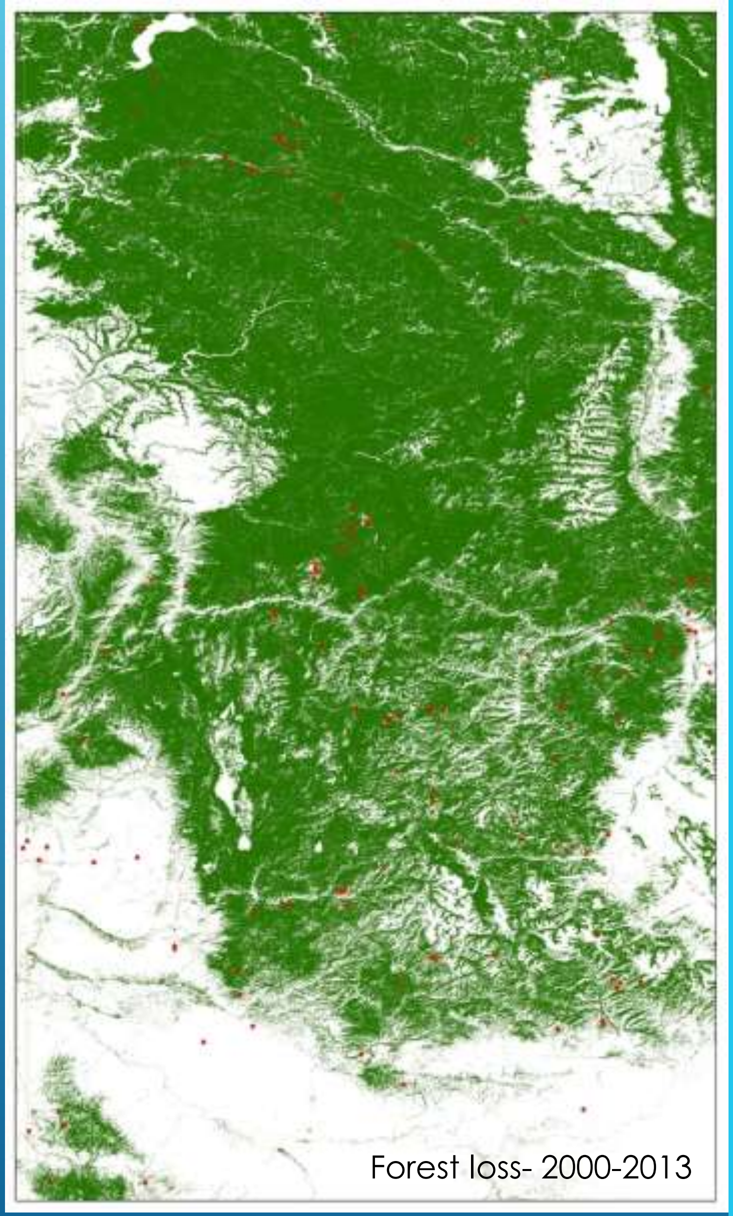


Forest cover and mining activity



Forest loss- 2013



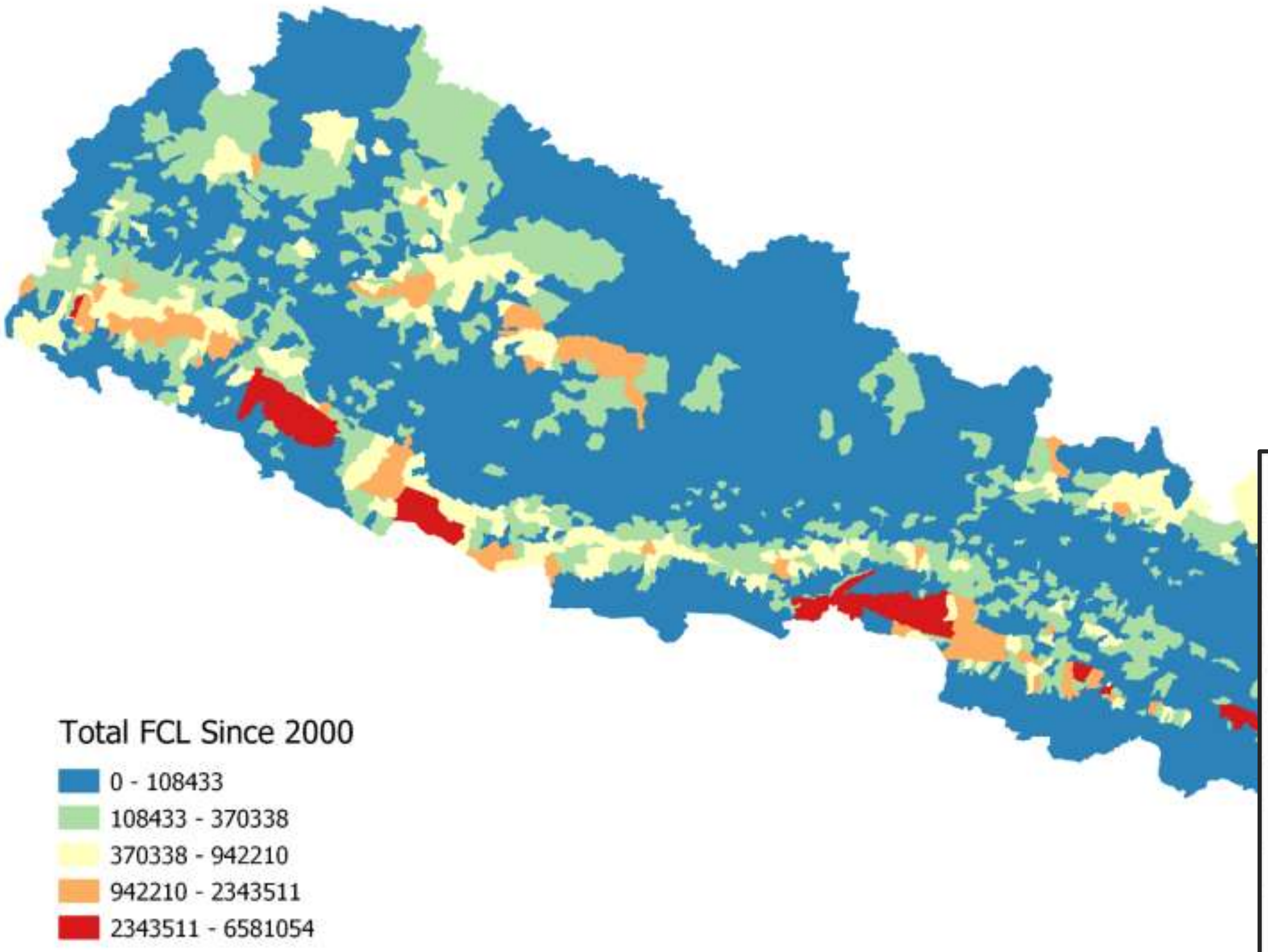


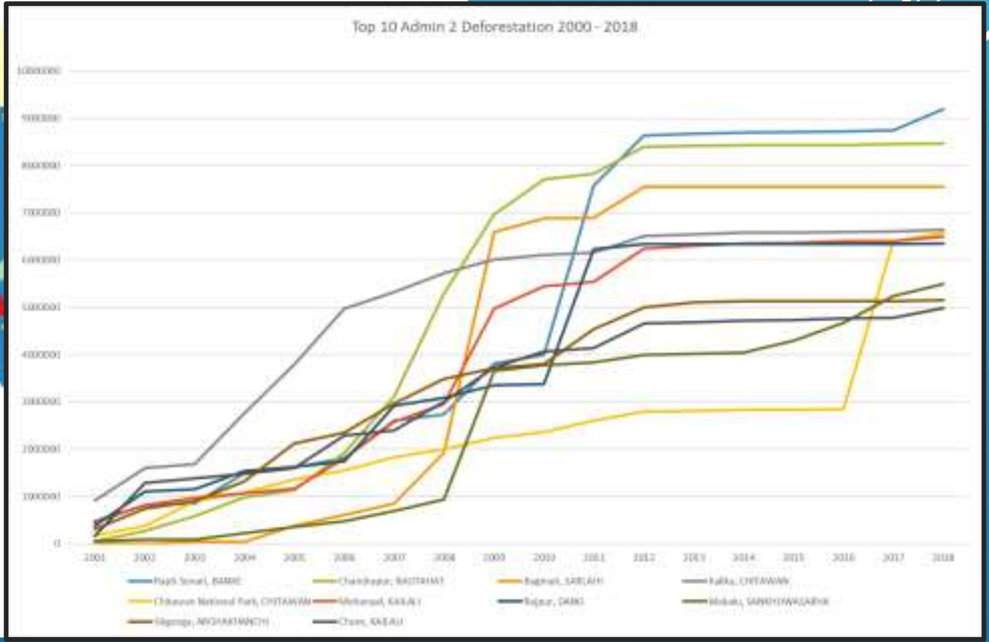
Forest loss- 2000-2013

Nepal Total Forest Cover Loss Since 2000 Administrative District 3

Description: Cumulative forest cover loss per sqm per Admin Level 3 from 2000-2018.

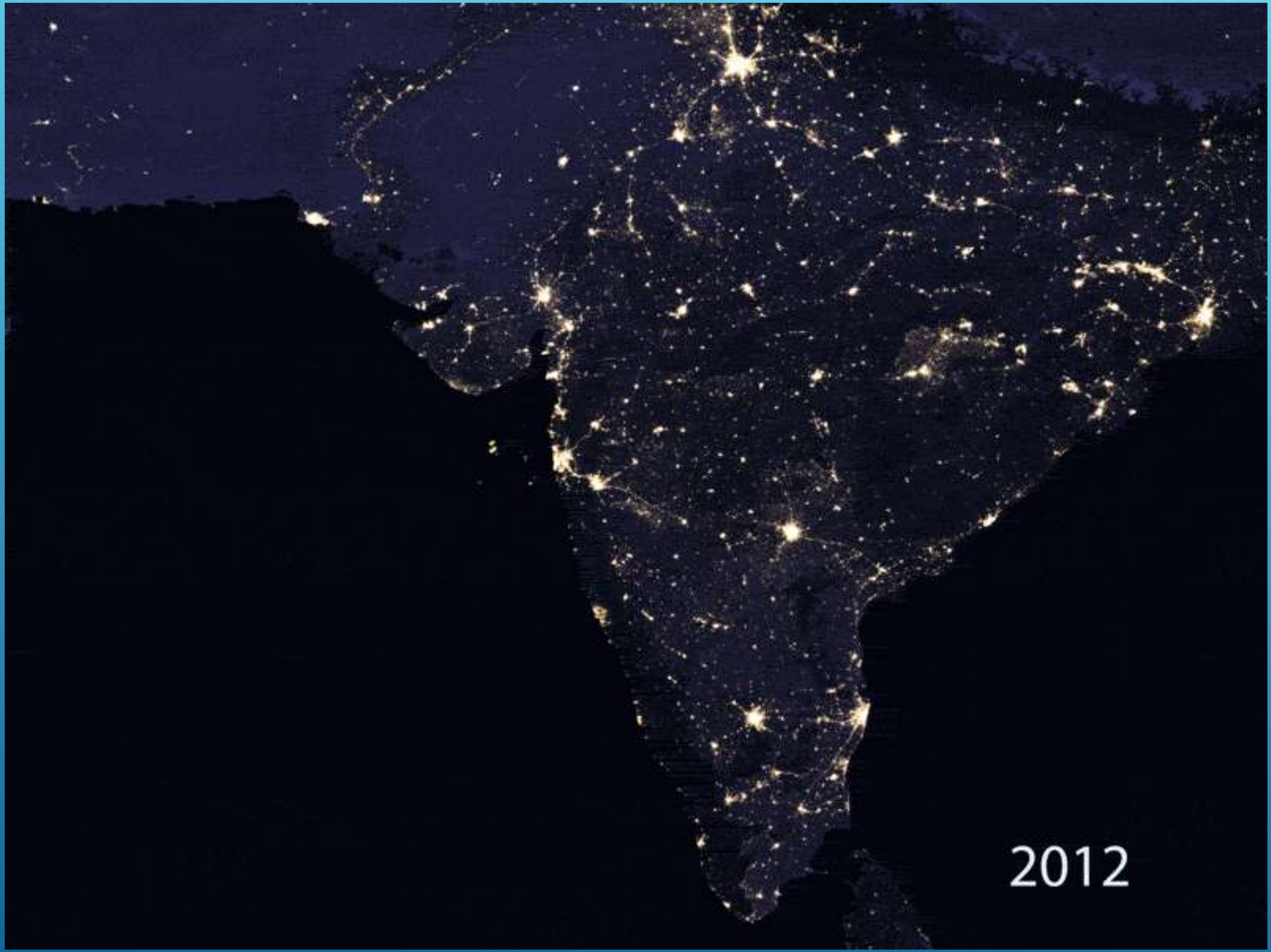
Significant forest cover loss in this period occurred close to the southern border (visualized in orange and red).



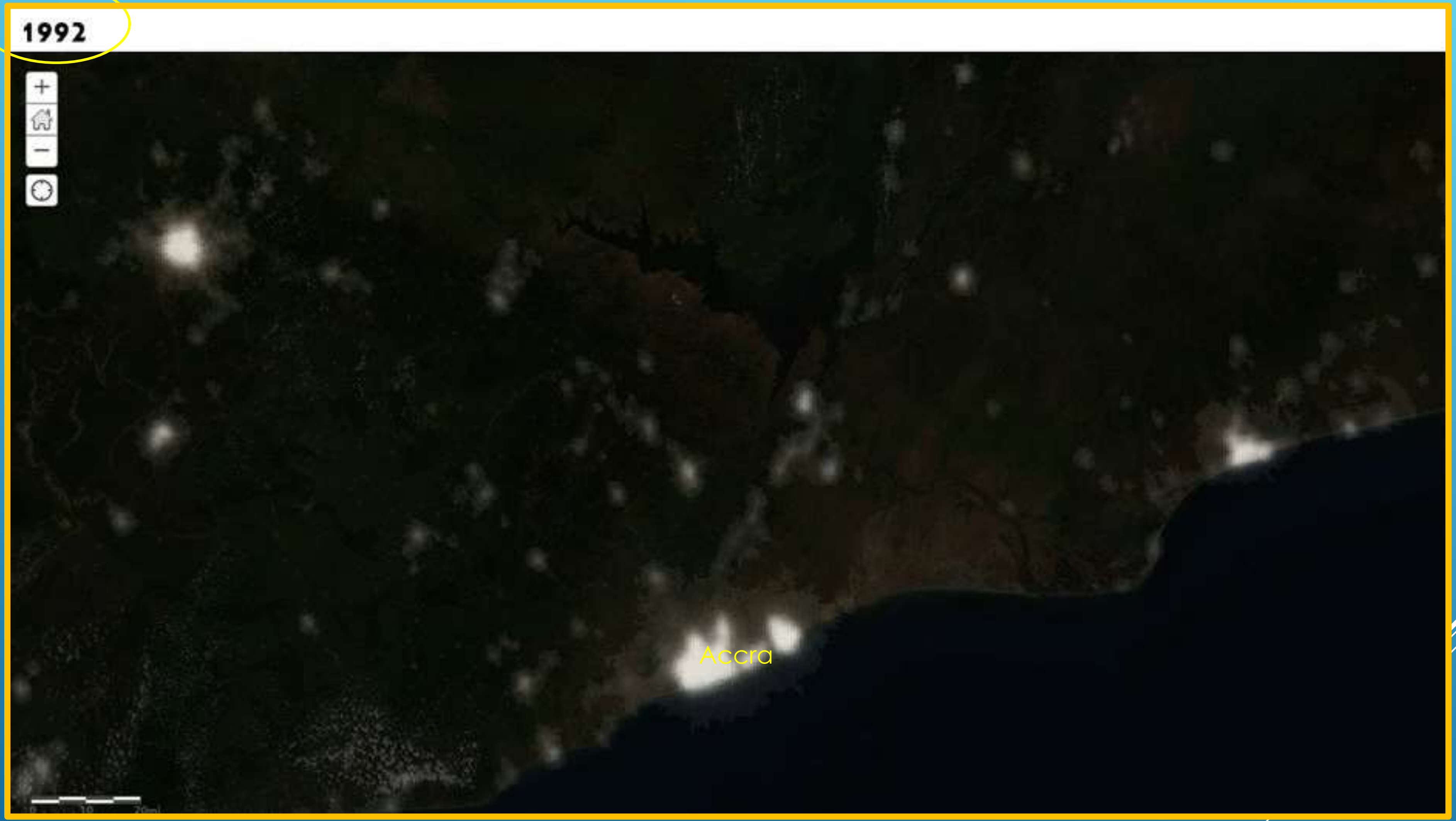


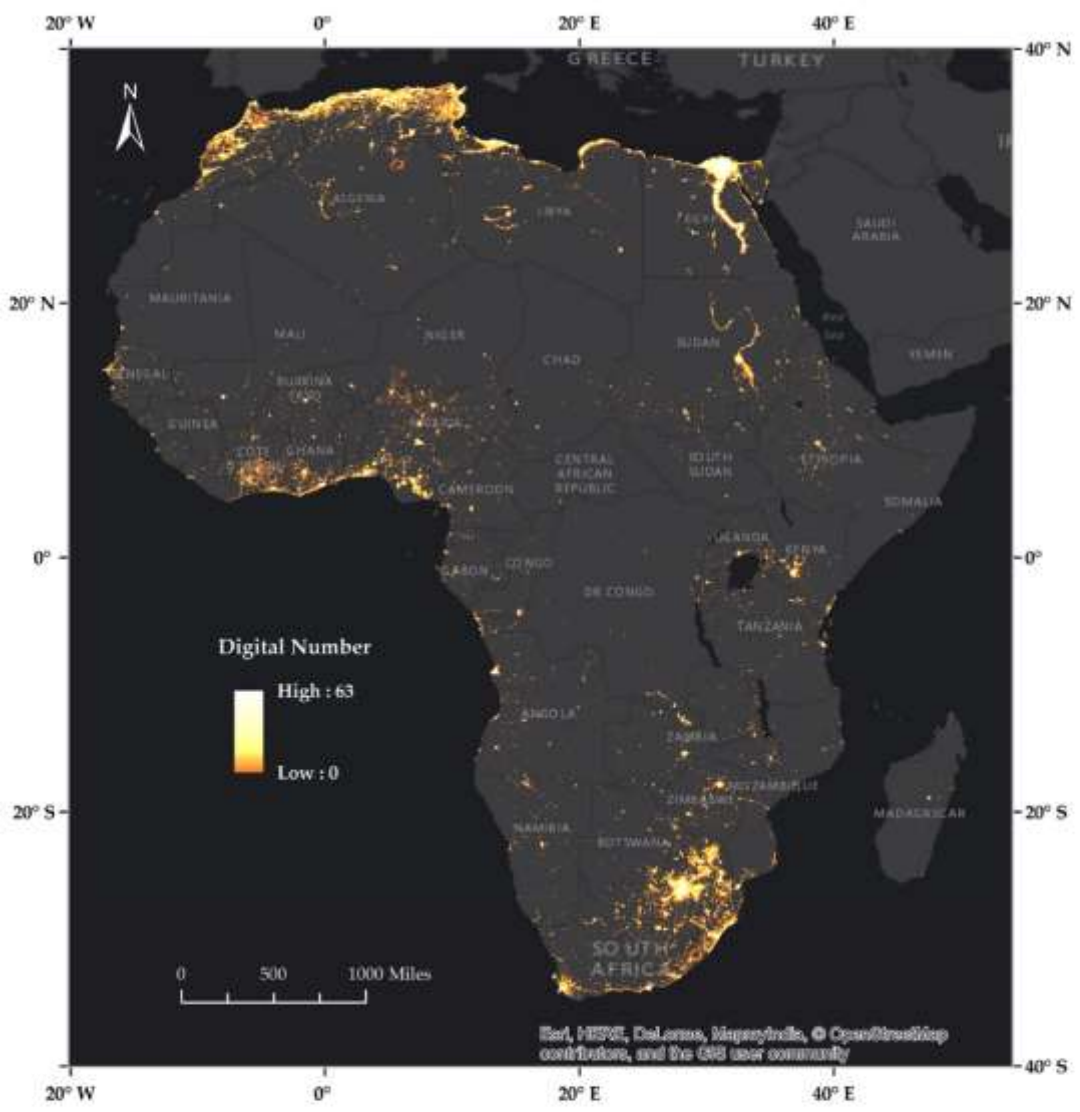
Funded by the World Bank


Google
India night light
Google Search
I'm Feeling Lucky

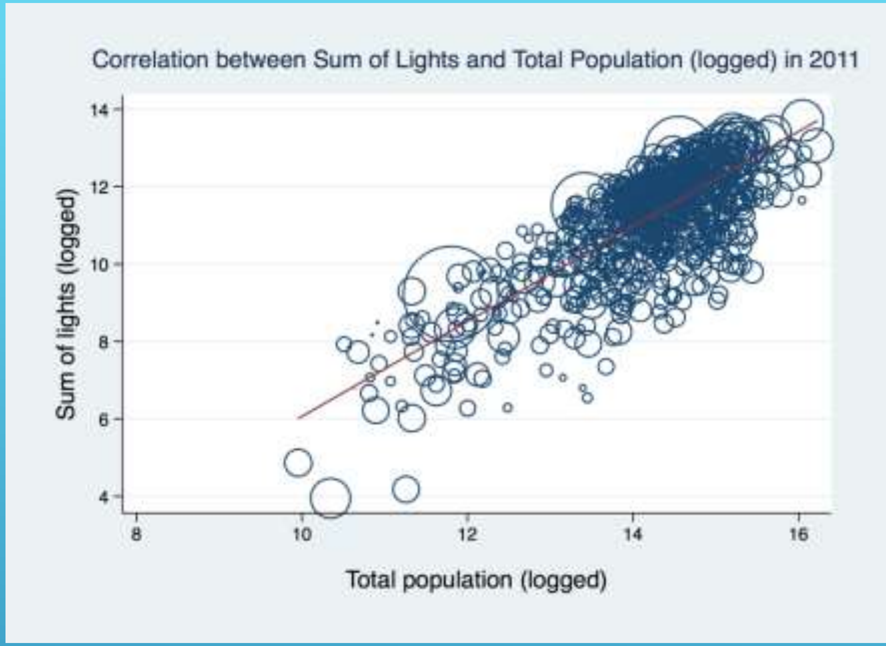

2012

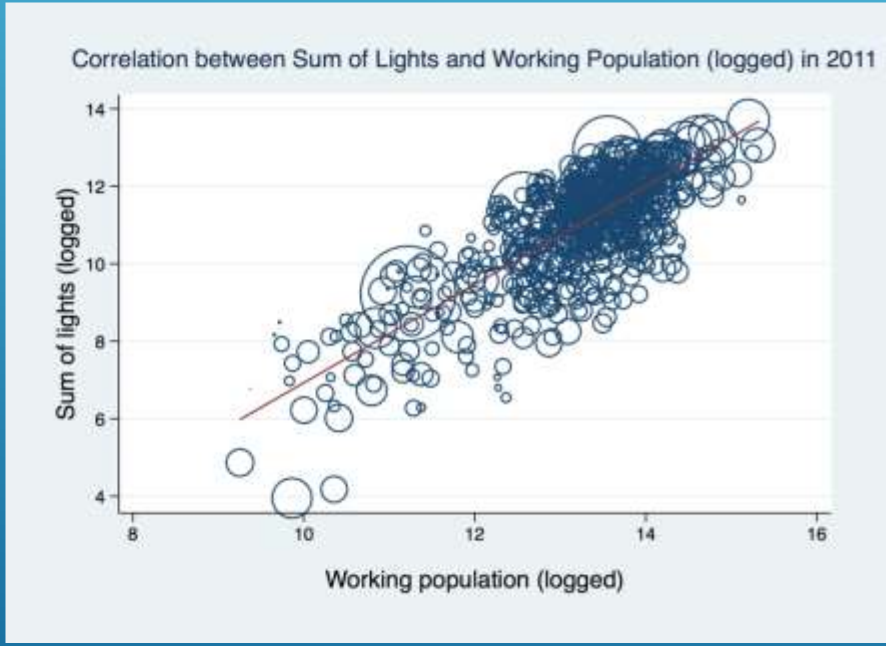
Changes in nighttime lights, Ghana



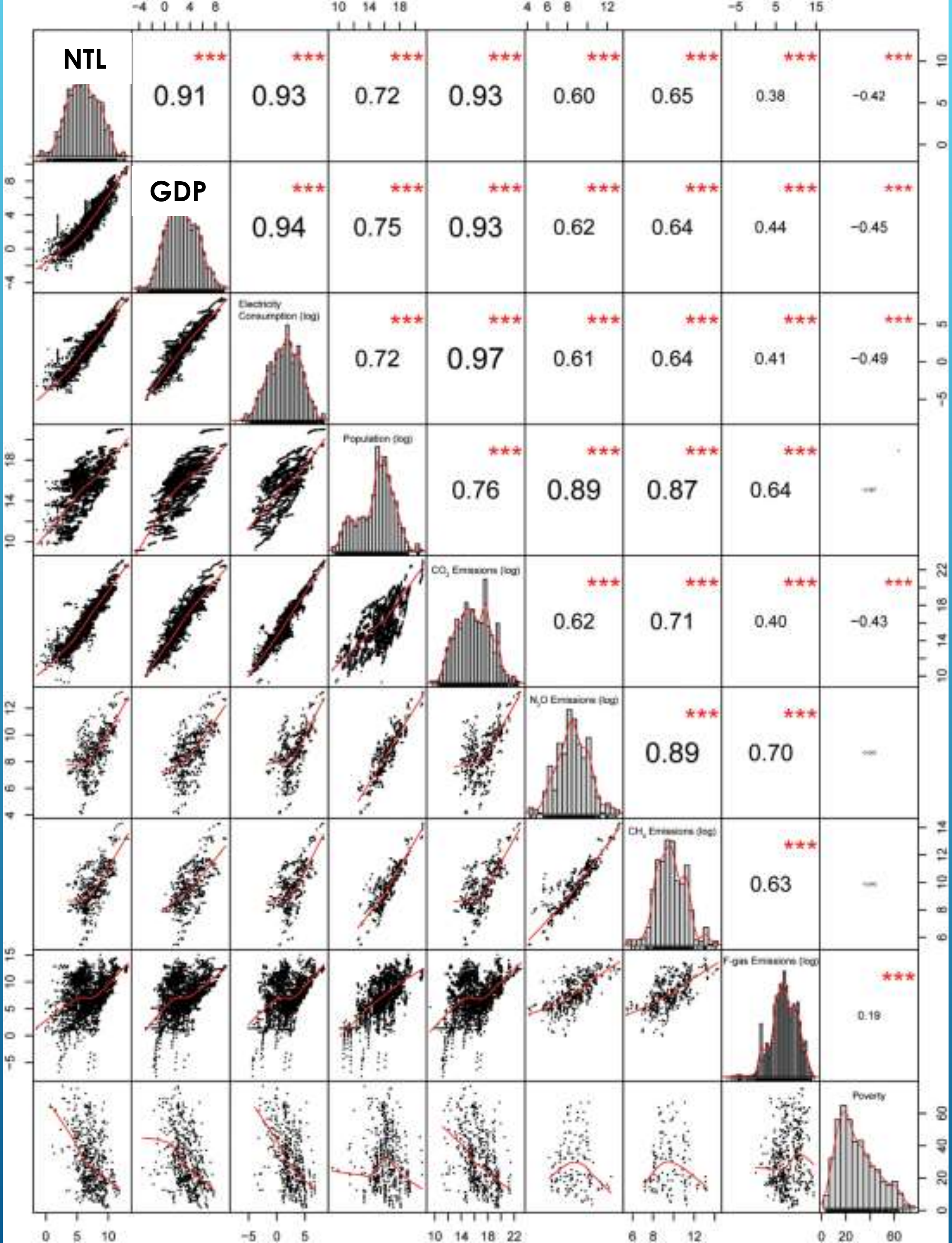


Savory et al., 2017





Henderson et al., 2017



Night-time lights: A global, long term look at links to socio-economic trends

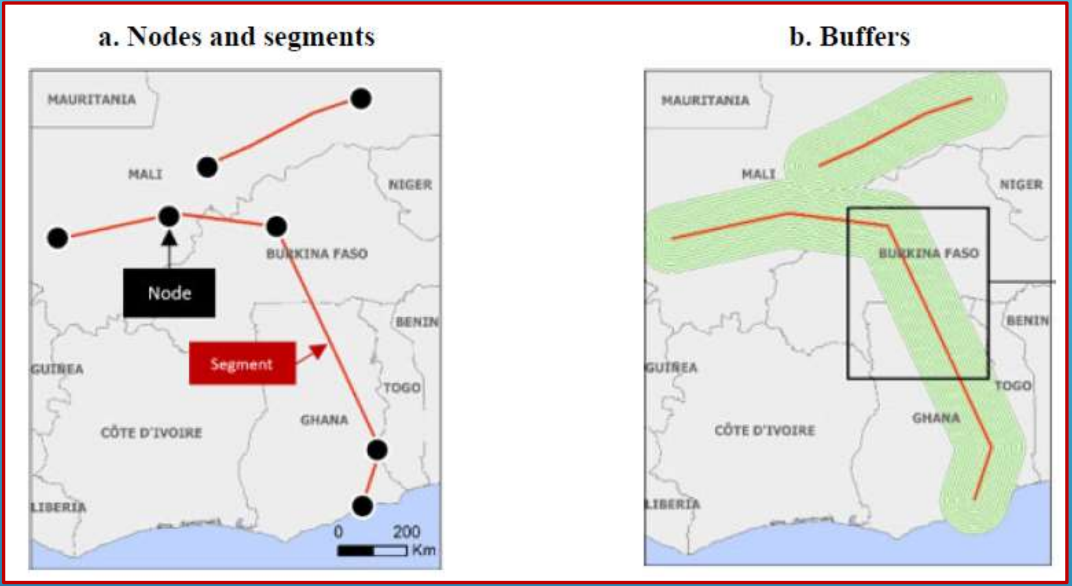
Jeremy Proville, Daniel Zavala-Araiza, Gernot Wagner

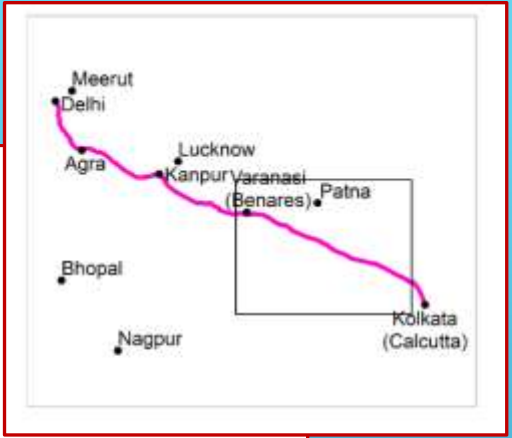
Published: March 27, 2017 • https://doi.org/10.1371/journal.pone.0174610

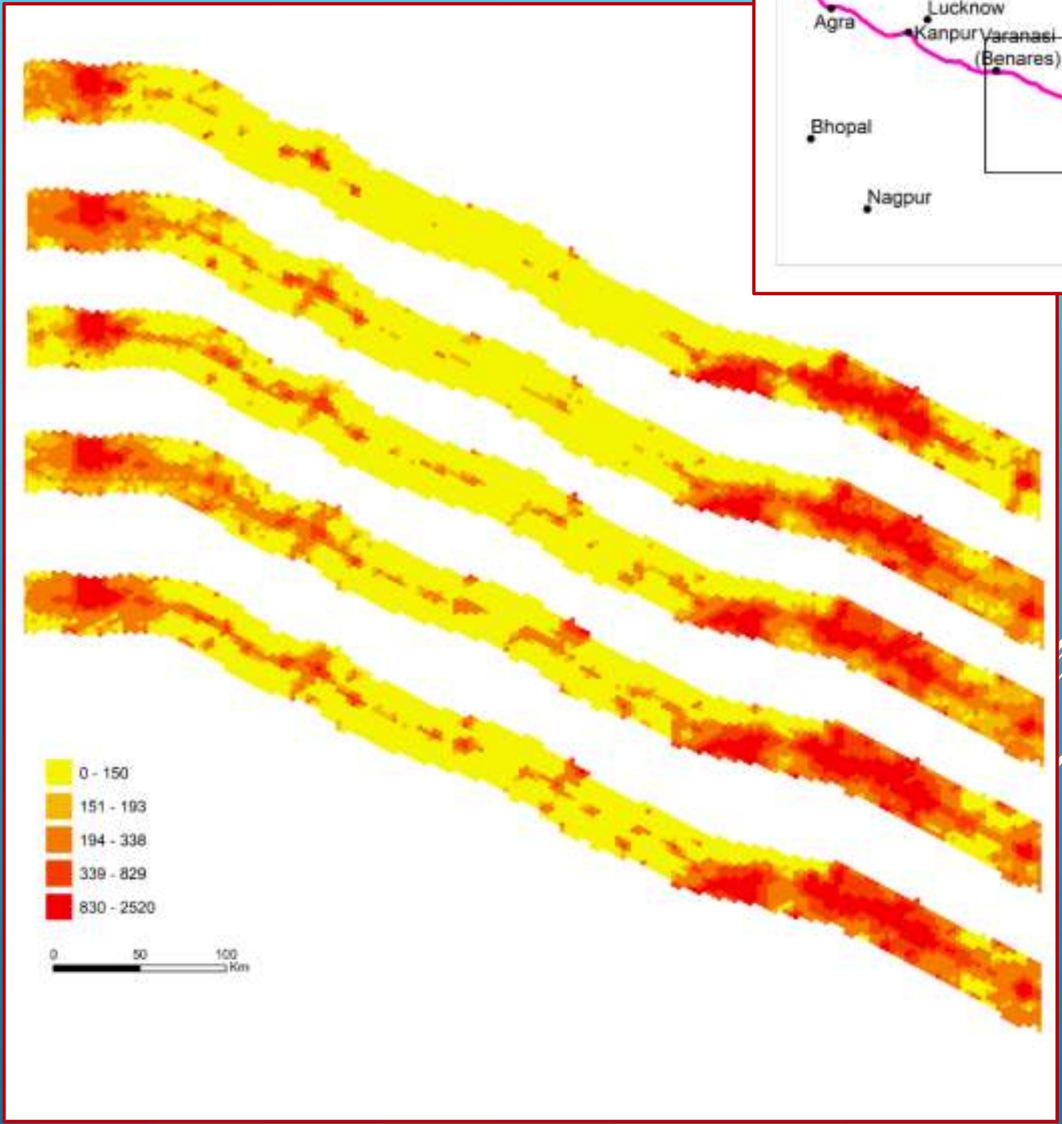
Correlation between area lit and a collection of socio-economic indicators.

The matrix shows links between logarithms of Area Lit, GDP, Electric Power Consumption, Population, CO2 Emissions, N2O Emissions, CH4 Emissions, F-gas Emissions, and non-log Poverty Headcount Ratio, respectively. Numbers on the top-right side of the matrix denote Pearson's r values (font size ∝ value), and stars represent significance level (***, $p < 0.05$).

THE **ECONOMIC BENEFITS** OF INFRASTRUCTURE INVESTMENT







1995

2000

2005

2010

2012

Funded by the World Bank

Journal of Urban Economics xxx (xxxx) xxx

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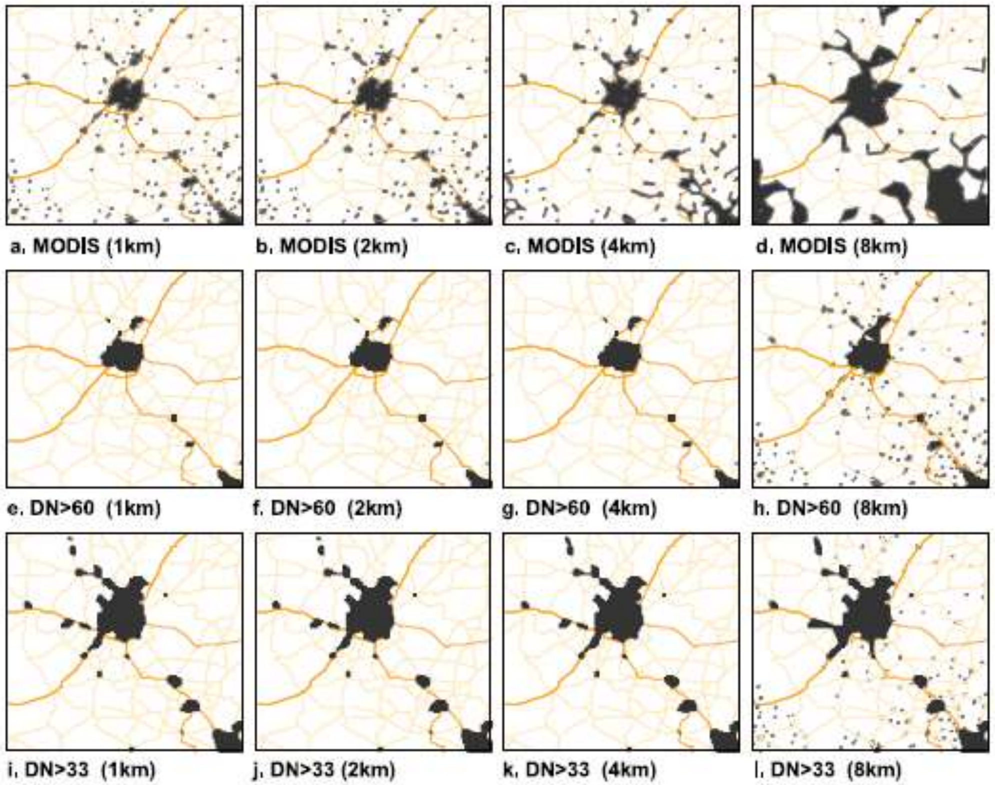
Detecting urban markets with satellite imagery: An application to India☆

Kathryn Baragwanath[a], Ran Goldblatt[b], Gordon Hanson[c,*], Amit K. Khandelwal[d]

[a] UCSD, United States
[b] New Light Technologies, United States
[c] UCSD & NBER, United States
[d] Columbia GSB & NBER, United States



Working paper

Detecting urban markets with satellite imagery

An application to India

Kathryn Baragwanath Vogel
Ran Goldblatt
Gordon Hanson
Amit K. Khandelwal

March 2019

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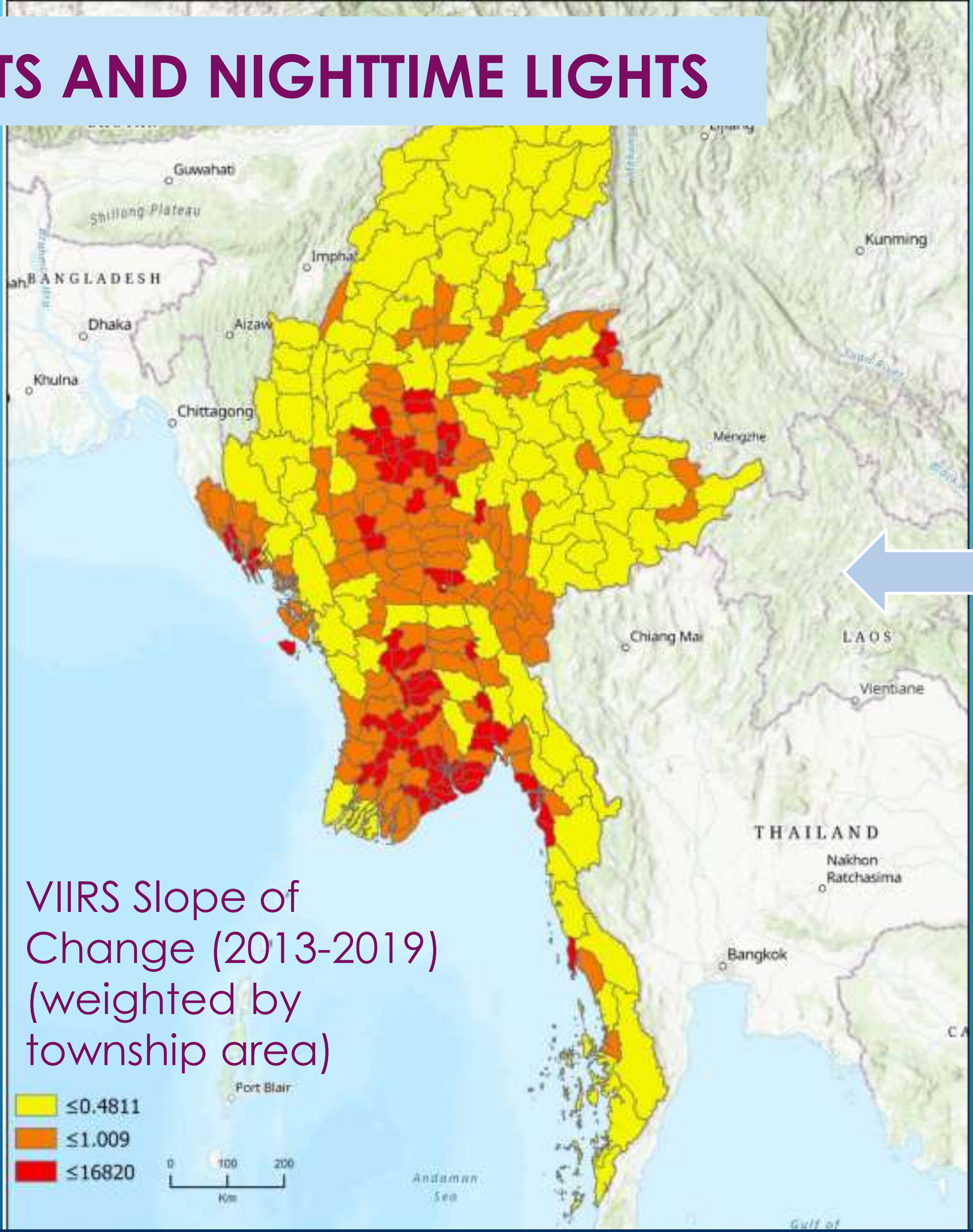
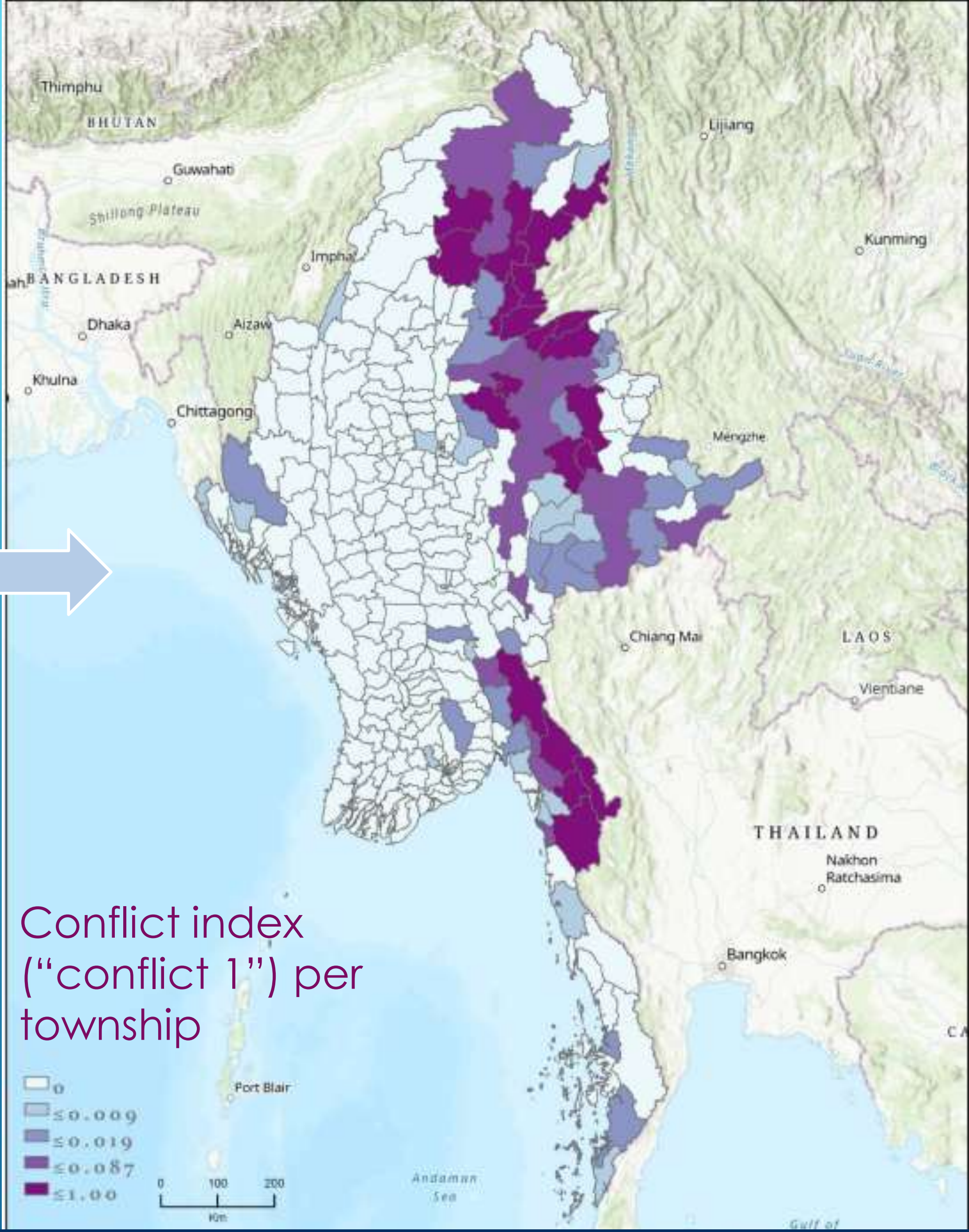
CONFLICTS AND NIGHTTIME LIGHTS

Myanmar



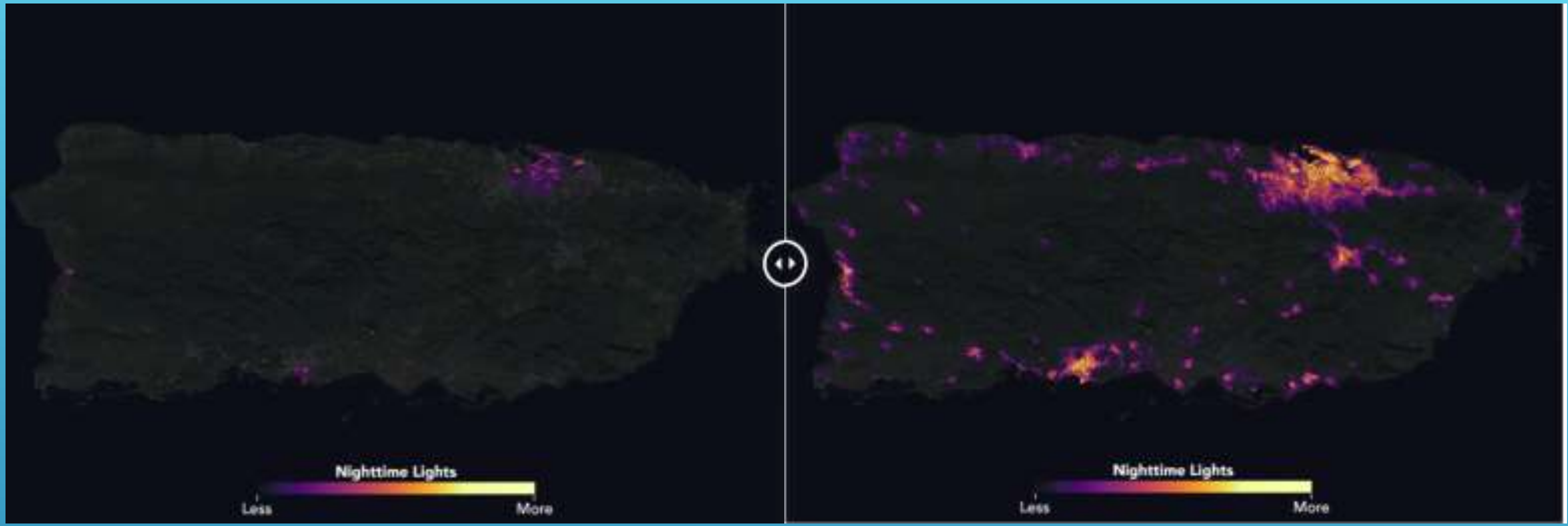
VIIRS Slope of Change (2013-2019) (weighted by township area)

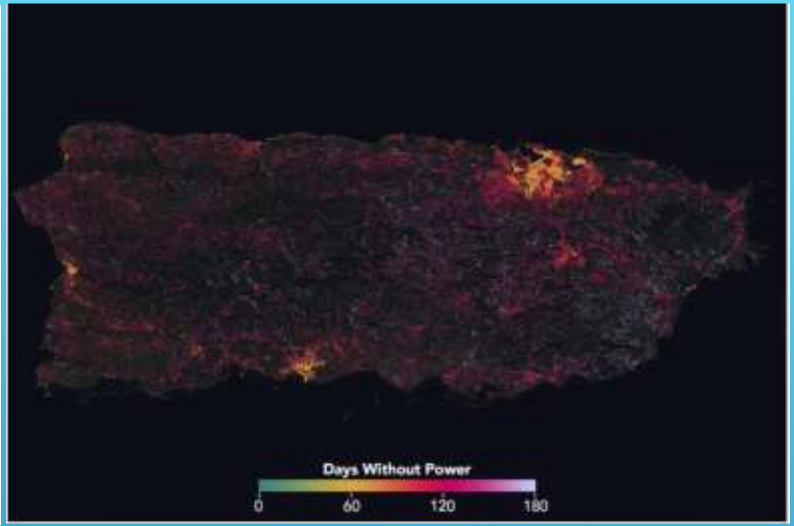


Conflict index ("conflict 1") per township

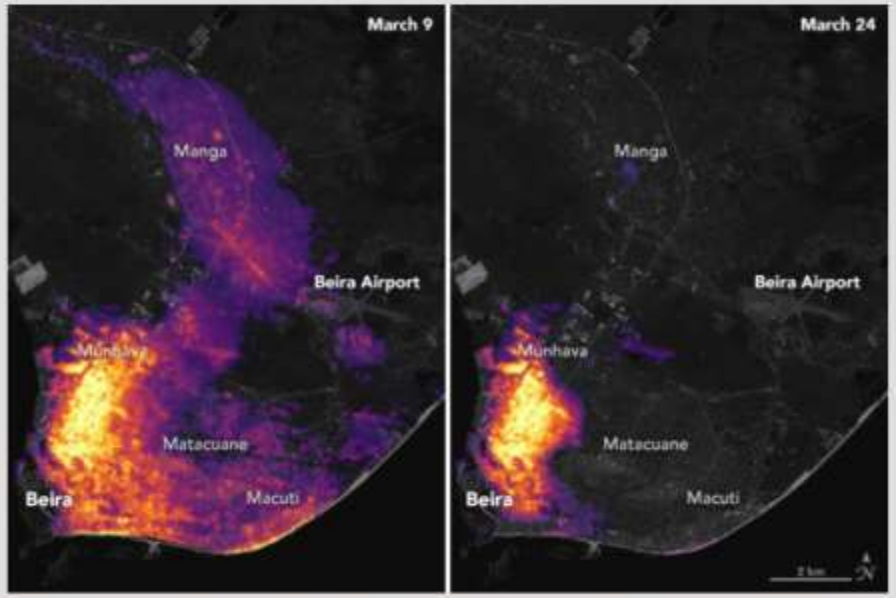
Funded by the World Bank

Recover post Hurricane Maria

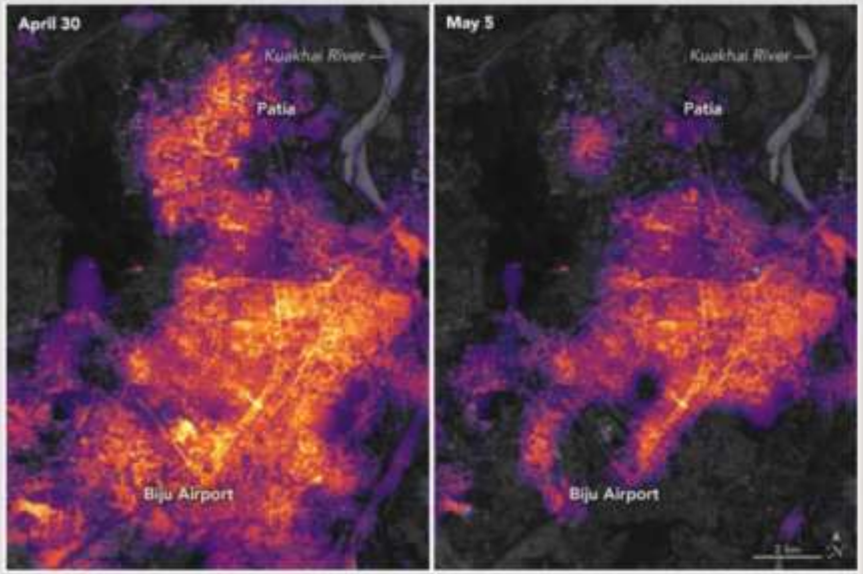




https://earthobservatory.nasa.gov/images/144371/night-lights-show-slow-recovery-from-maria



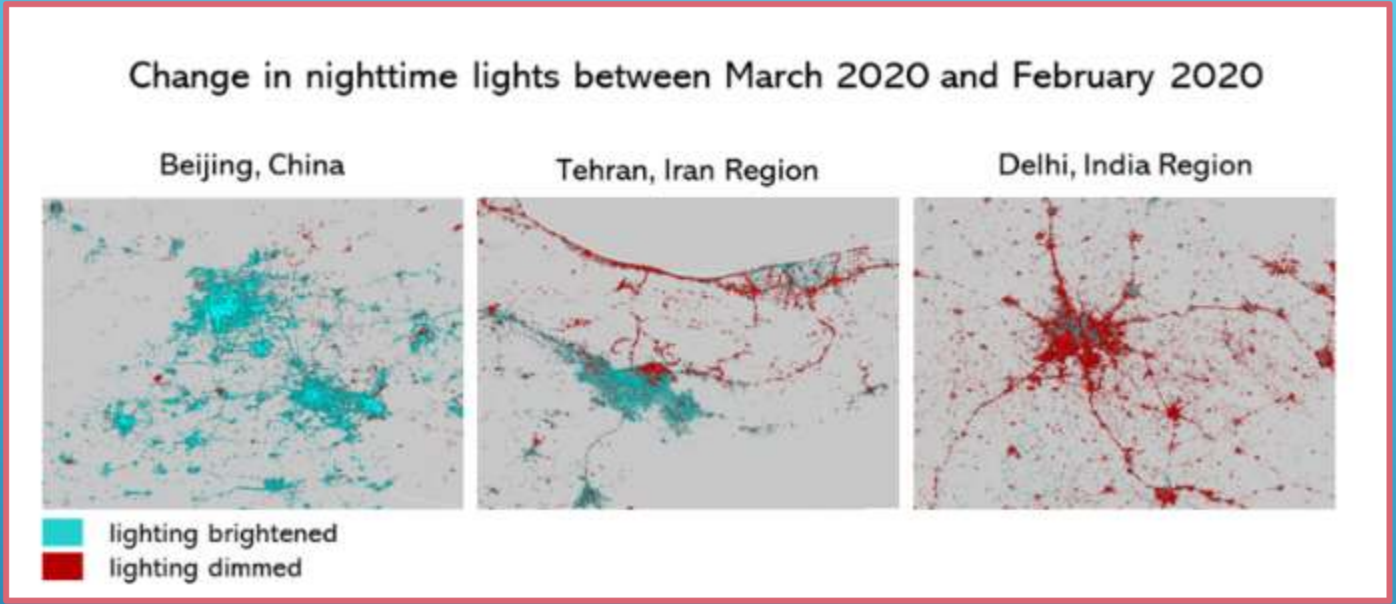
VIIRS Black Marble imagery of Mozambique comparing before (March 9th, 2019) and after (March 24th, 2019) flood impacts from Cyclone Idai.



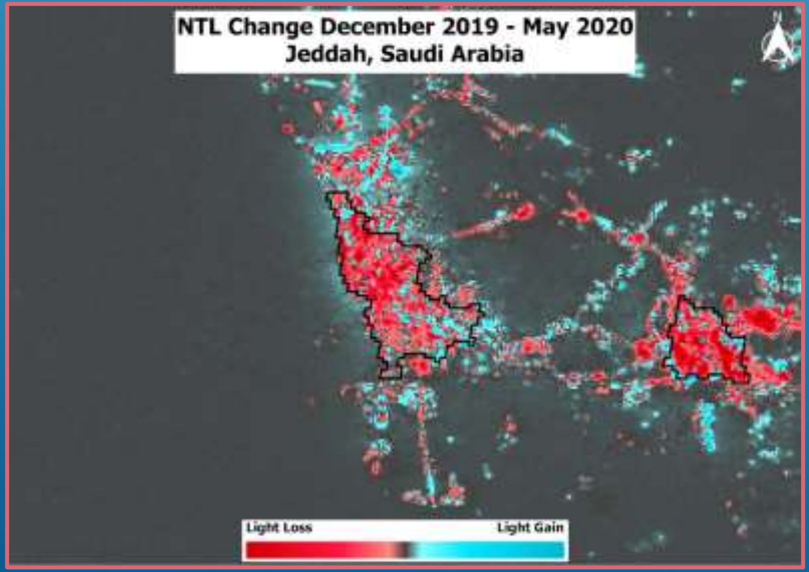
VIIRS Black Marble imagery of nighttime lights in Bhubaneswar India, comparing April 30th and May 5th 2019. Credit: NASA Earth Observatory, Ranjay Shrestha / NASA GSFC

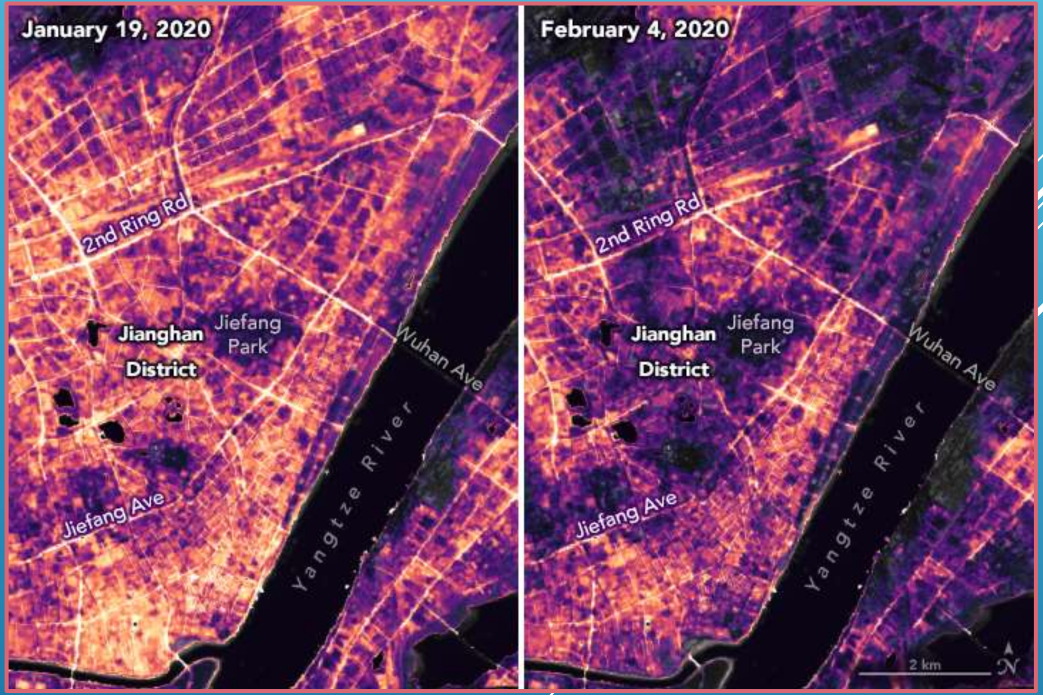
Black Marble data

THE ECONOMIC IMPACTS OF COVID-19

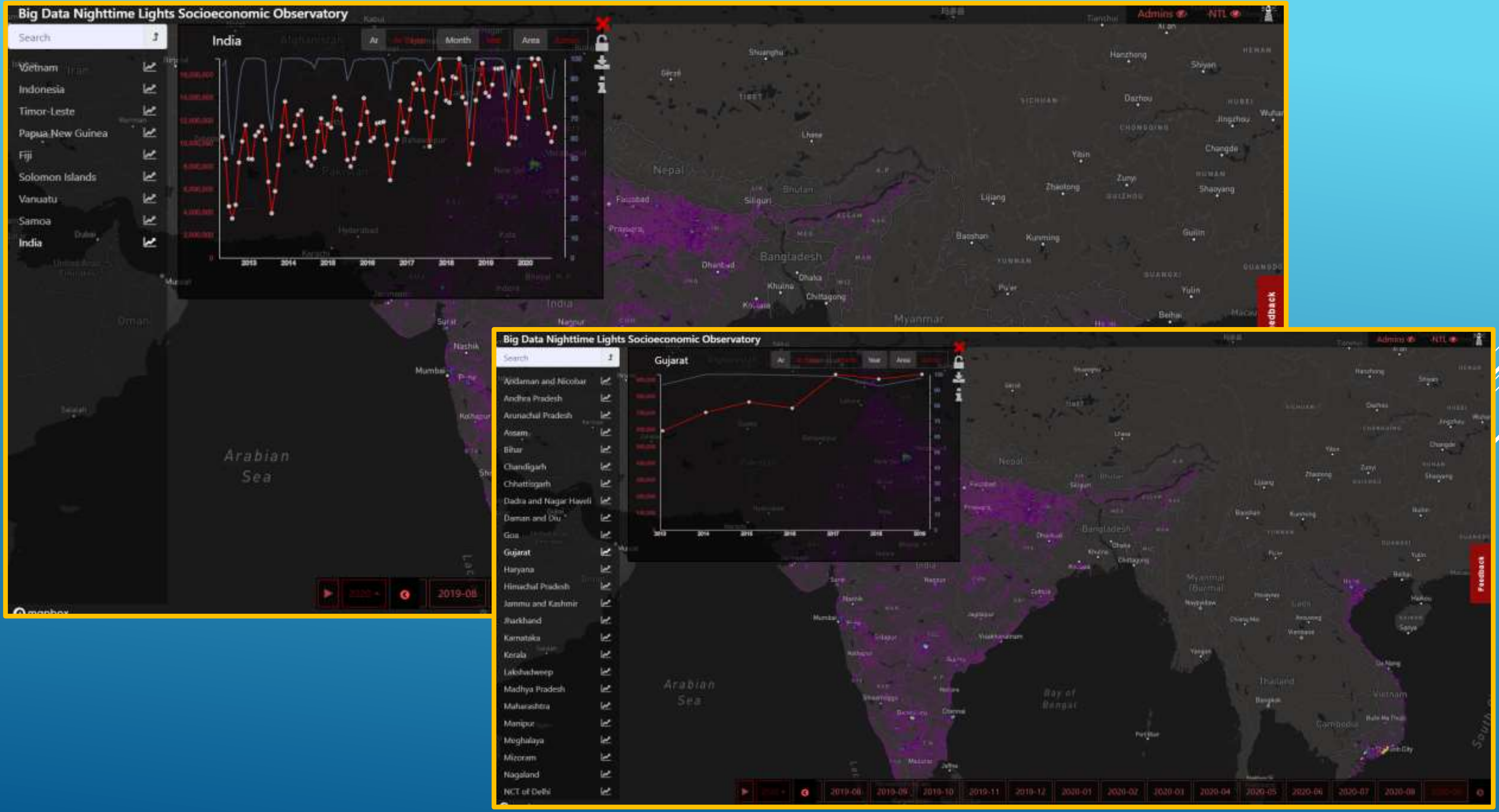


Changes in the intensity of nighttime lights can be used to illustrate pace of recovery. These images show changes in nighttime lights between March 2020 and February 2020. Cyan = lighting brightened, Red = lighting dimmed. Source: Elvidge et al., 2020. The Payne Institute for Public Policy.





Changes in activity around the city of Wuhan, China, between January 19 and February 4, 2020, as observed by nighttime lights. Source: NASA's Goddard Space Flight Center (GSFC) and Universities Space Research Association (USRA).


Big Data Nighttime Lights Socioeconomic Observatory
Search
India
Month
Area
Vietnam
Indonesia
Timor-Leste
Papua New Guinea
Fiji
Solomon Islands
Vanuatu
Samoa
India
2013
2014
2015
2016
2017
2018
2019
2020
Admins
NTL
Arabian Sea
Oman
Nepal
Bhutan
Bangladesh
Myanmar
2019-08
Big Data Nighttime Lights Socioeconomic Observatory
Search
Gujarat
Year
Area
Andaman and Nicobar
Andhra Pradesh
Arunachal Pradesh
Assam
Bihar
Chandigarh
Chhattisgarh
Dadra and Nagar Haveli
Daman and Diu
Goa
Gujarat
Haryana
Himachal Pradesh
Jammu and Kashmir
Jharkhand
Karnataka
Kerala
Lakshadweep
Madhya Pradesh
Maharashtra
Manipur
Meghalaya
Mizoram
Nagaland
NCT of Delhi
Arabian Sea
Bay of Bengal
Nepal
Bangladesh
Thailand
Vietnam
Cambodia
2019-08
2019-09
2019-10
2019-11
2019-12
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
Feedback

THANK YOU!

New Light Technologies

Ran Goldblatt, Ph.D.
Chief Scientist
New Light Technologies Inc.

ran.goldblatt@nltgis.com

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December 10-11, 2020

Geo4Dev Workshop 2020

On December 10th-11th, CEGA's Geospatial Analysis for Development (Geo4Dev) Initiative will host an online symposium to showcase cutting-edge tools, datasets, and applications of geospatial data for global development research, followed by a hands-on workshop for those interested in building or honing their skills in this space. The convening will formally launch the new Geo4Dev website–an open-access hub for geospatial data, research, and tools–as well as the newest Nighttime Lights dataset, developed for public use by the National Oceanic and Atmospheric Administration (NOAA).

Please register for the symposium and workshop by clicking on the orange button below, and direct any questions you have to info@geo4.dev.

Click Here to Register for the Geo4Dev Workshop

EXTRA

REMOTE SENSING ANALYSIS FOR **IMPACT EVALUATION**

How can satellite data help improve IEs?

➢ **Measuring outcomes of interventions**

Examples: Measuring economic growth, GDP, poverty, wealth, infrastructure quality, population distribution, land productivity, ground water.

➢ **Constructing (unbiased) comparison groups**

Comparing units based on relevant pre-program characteristics or based on spatial discontinuity. Satellites continuously collect data (both temporally and spatially), thus data is **not susceptible to self-selection bias** like other sources of big data.

➢ **Long term impacts**

Collecting several years of pre- and post-program data through face-to-face survey is expensive and, in many cases, infeasible. With satellite data it is possible to **collect pre- and post-program data**, including **follow-up data**, without the need for going to the field.

→ Allowing measurement of long-term program impacts, which can help analyze how the impacts evolve over time and how long they last.

Overcoming analytical challenges

- **Assessing pre-program trends**

Quasi-experimental designs require pre-program similarity between the treatment and the control group (levels and distribution), often for several years before the program. **Historical satellite imagery** makes it possible to **evaluate parallel trend assumptions**.

- **Controlling for covariates**

Not controlling for confounding factors often leads to an ***omitted variable* bias**.
With satellite data it is possible to **control for local time-varying factors** through a **fixed effects approach** at the level of individual pixels and for time-invariant factors according to the **reflectance characteristics of individual pixels**.

- **Heterogeneous Effects**

IEs often measure the **average treatment effect** for an **entire treatment group** rather than heterogeneous effects for **sub-groups** (largely due to the data availability). Satellite data allows researchers to **estimate heterogeneous effects** based on **observable baseline conditions** such as population density at the cell-level, etc. with sufficient power for sub-group analysis.

Overcoming analytical challenges (cont.)

- **Robustness analyses**

Satellite data can help conduct robustness analyses by allowing for the **identification of multiple comparison groups** that would have been expensive or infeasible through traditional data collection methods. Similarly, **placebo tests can be conducted through testing the treatment effect** on the treated for an arbitrary pre-program date.

- **External validity and generalizability**

Satellite data are available not only for the program area, but also for the **country/regional context**. This allows evaluation of the external validity of the results by considering the broad spatial context.

Overcoming logistical challenges

- **Cost of data collection**

A fundamental challenge of IEs is the cost of survey data collection, which can reach up to USD 400k (according to 3ie). The survey alone can cost up to USD 200k. In comparison, the cost of a desk-based impact evaluation with free satellite data would be around USD 150k.

- **Retrospective, desk-based evaluation**

Historical time series satellite data allows retrospective assessment of programs already implemented and in most cases the evaluation can be implemented remotely.

TO SUMMARIZE

- Satellite data is revolutionizing how understand Earth
- Free satellite data is increasingly available at high spatial, spectral and temporal resolutions
- Cloud based computational platforms allows one to scale the analysis across space and time
- AI and ML approaches allows to translate the collected data into meaningful information that can be used for an informed decision making.
- Increasingly, sources of geospatial data and satellite imagery are being utilized to support and improve the process of IEs.