Future of Food

Addressing Food & Water Security Via Recent Advances In Machine Learning

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Google DeepMind India
Jun 2025


Allow myself to introduce...

Chocolates for answering
my questions

OR

Asking good questions

Agenda

Climate Change
- Science & Facts
- Google’s Climate Strategy

Food & Agriculture
- Context
- Problem Selection

AnthroKrishi
- Capabilities
- How to - data, model and evaluate
- Realize Impact

How can you solve similar problems ?
- Remote Sensing - A Crash Course

Engagement opportunities

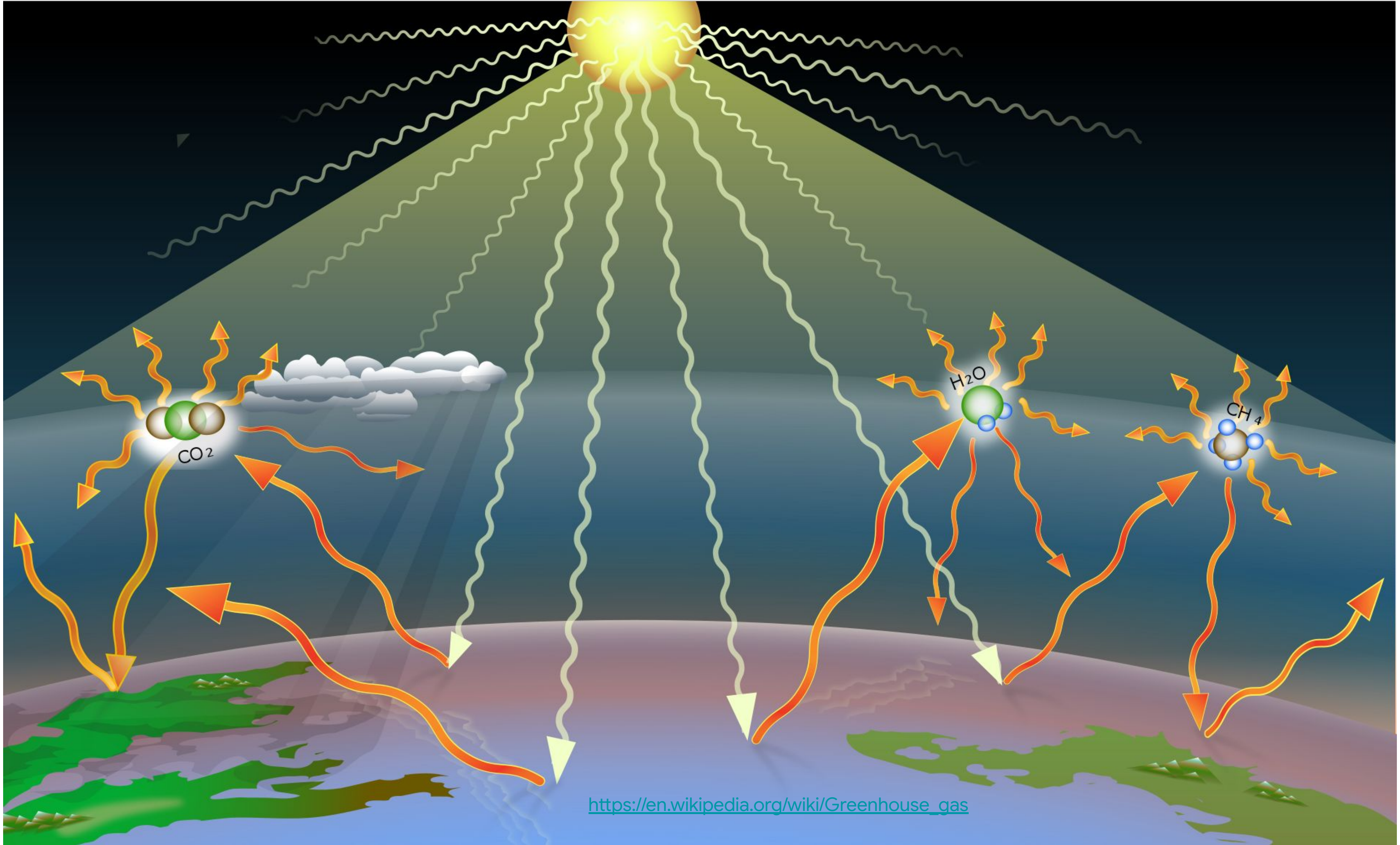
Basic Science & Facts

CLIMATE SCIENCE BASICS:

1. It's warming.
2. It's us.
3. We're sure.
4. It's bad.
5. We can fix it.

(Thanks to Dr. Kimberly Nicholas for putting it so simply).

350.org



https://en.wikipedia.org/wiki/Greenhouse_gas

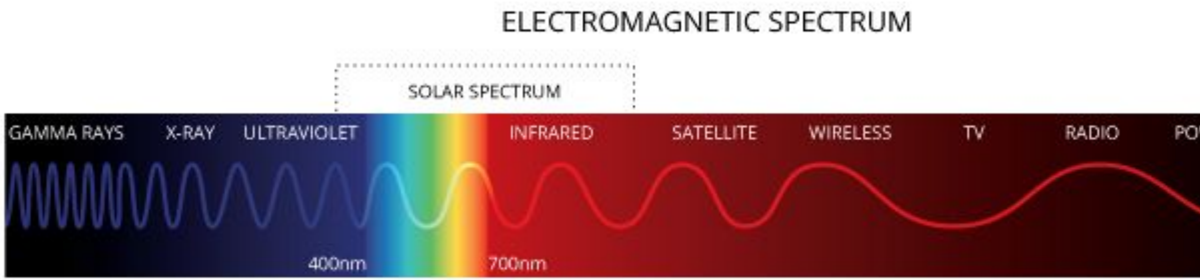
Atmosphere and Sunlight

https://uwpcc.ocean.washington.edu/

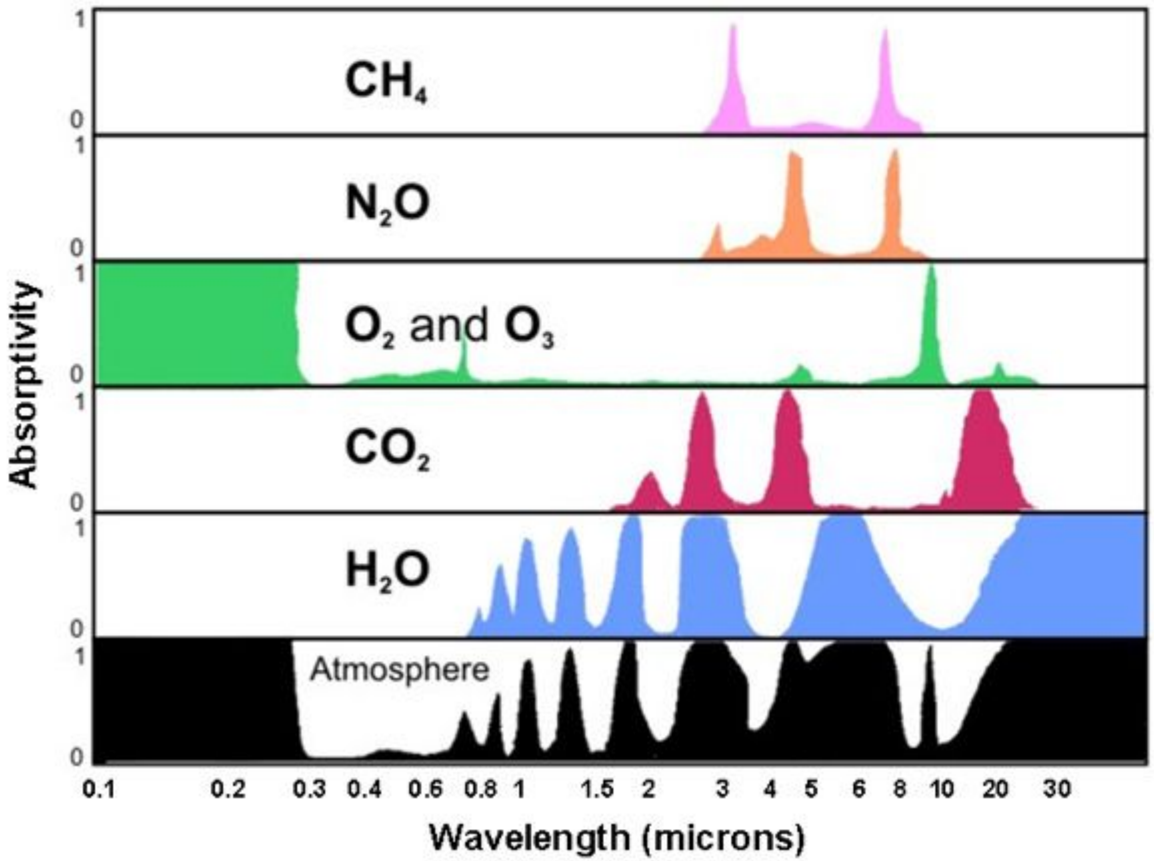
How does the greenhouse effect work?

N_2 (78% of atmosphere)
O_2 (21% of atmosphere)
Ar (0.9% of atmosphere)
H_2O (variable, 0-1%)
CO_2 (0.04% of atmosphere)
CH_4 (0.00018% of atmosphere)

Which do you think are greenhouse gases?
What is the difference between greenhouse and non-greenhouse gases?



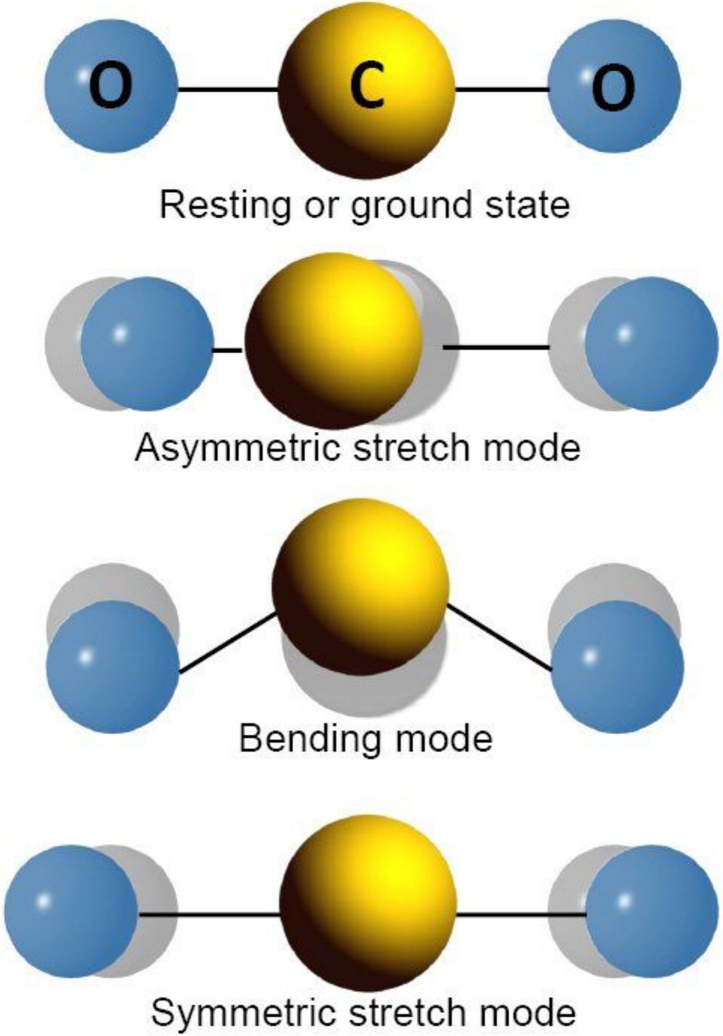
Absorption

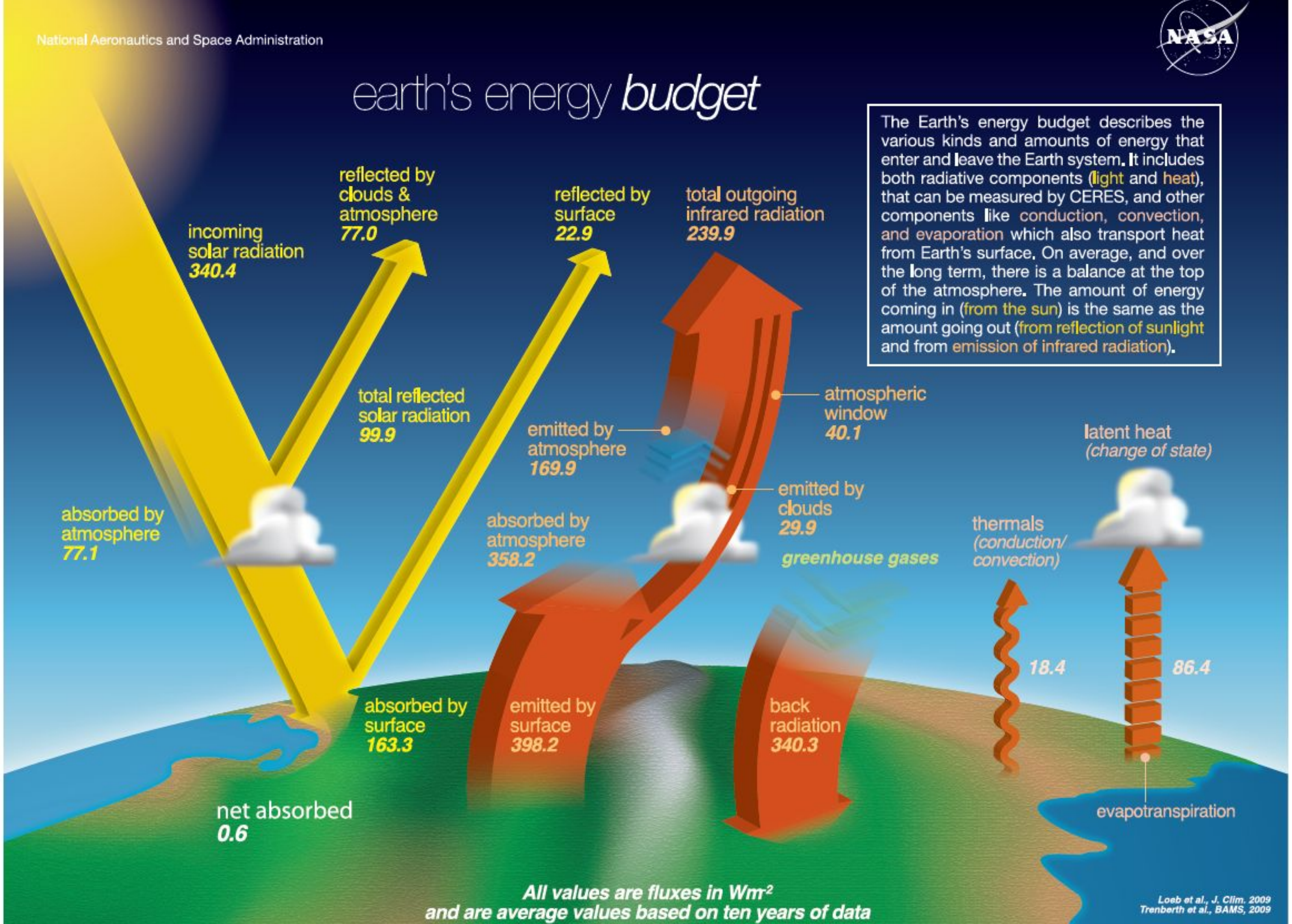


https://www.geoexpro.com/articles/2020/08/recent-advances-in-climate-change-research-part-viii-how-carbon-dioxide-absorbs-earth-s-ir-radiation

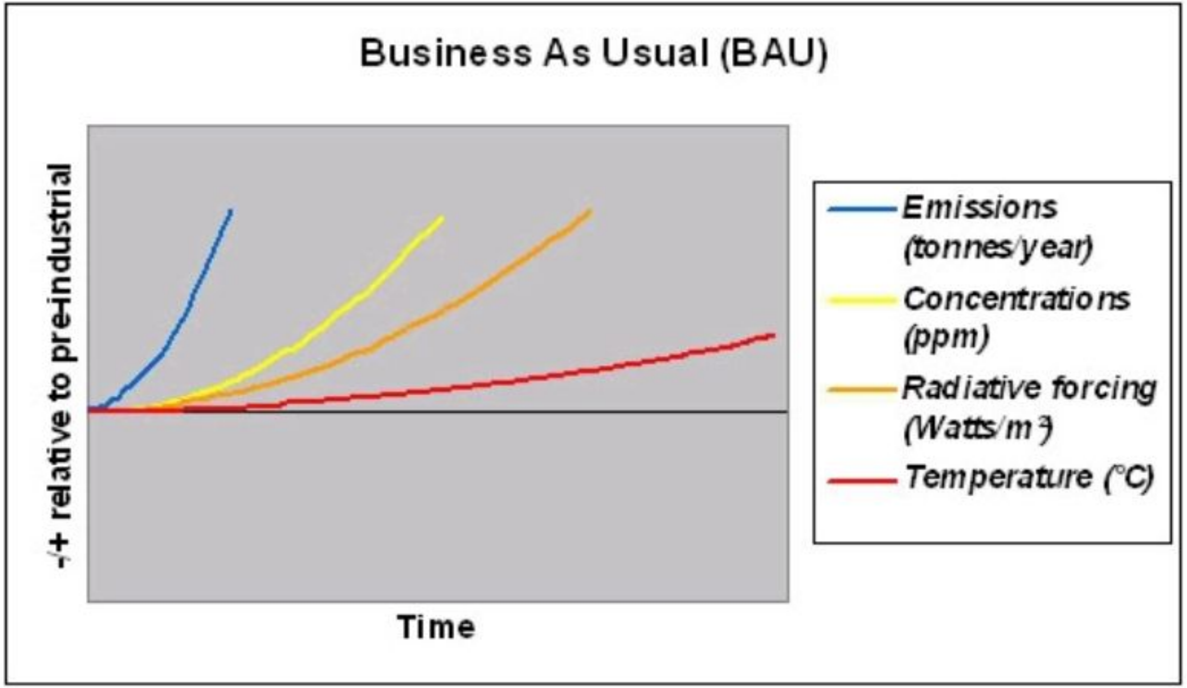
CO_2 details

https://www.geoexpro.com/articles/2020/08/recent-advances-in-climate-change-research-part-viii-how-carbon-dioxide-absorbs-earth-s-ir-radiation



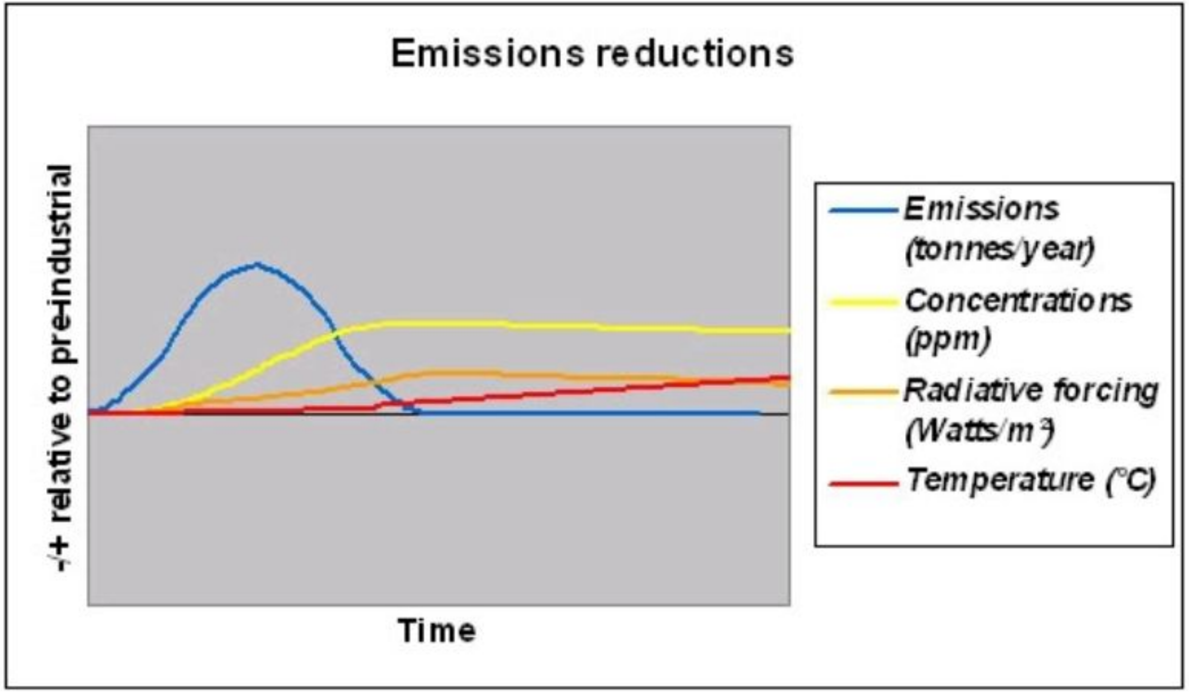

National Aeronautics and Space Administration
NASA
earth's energy budget
The Earth's energy budget describes the various kinds and amounts of energy that enter and leave the Earth system. It includes both radiative components (light and heat), that can be measured by CERES, and other components like conduction, convection, and evaporation which also transport heat from Earth's surface. On average, and over the long term, there is a balance at the top of the atmosphere. The amount of energy coming in (from the sun) is the same as the amount going out (from reflection of sunlight and from emission of infrared radiation).
incoming solar radiation 340.4
reflected by clouds & atmosphere 77.0
reflected by surface 22.9
total outgoing infrared radiation 239.9
total reflected solar radiation 99.9
emitted by atmosphere 169.9
atmospheric window 40.1
latent heat (change of state)
absorbed by atmosphere 77.1
absorbed by atmosphere 358.2
emitted by clouds 29.9
greenhouse gases
thermals (conduction/ convection)
18.4
86.4
absorbed by surface 163.3
emitted by surface 398.2
back radiation 340.3
evapotranspiration
net absorbed 0.6
All values are fluxes in Wm²
and are average values based on ten years of data
Loeb et al., J. Clim. 2009
Trenberth et al., BAMS, 2009

Radiative Forcing



http://www.darkoptimism.org/2008/09/03/climate-science-translation-guide/

Radiative Forcing



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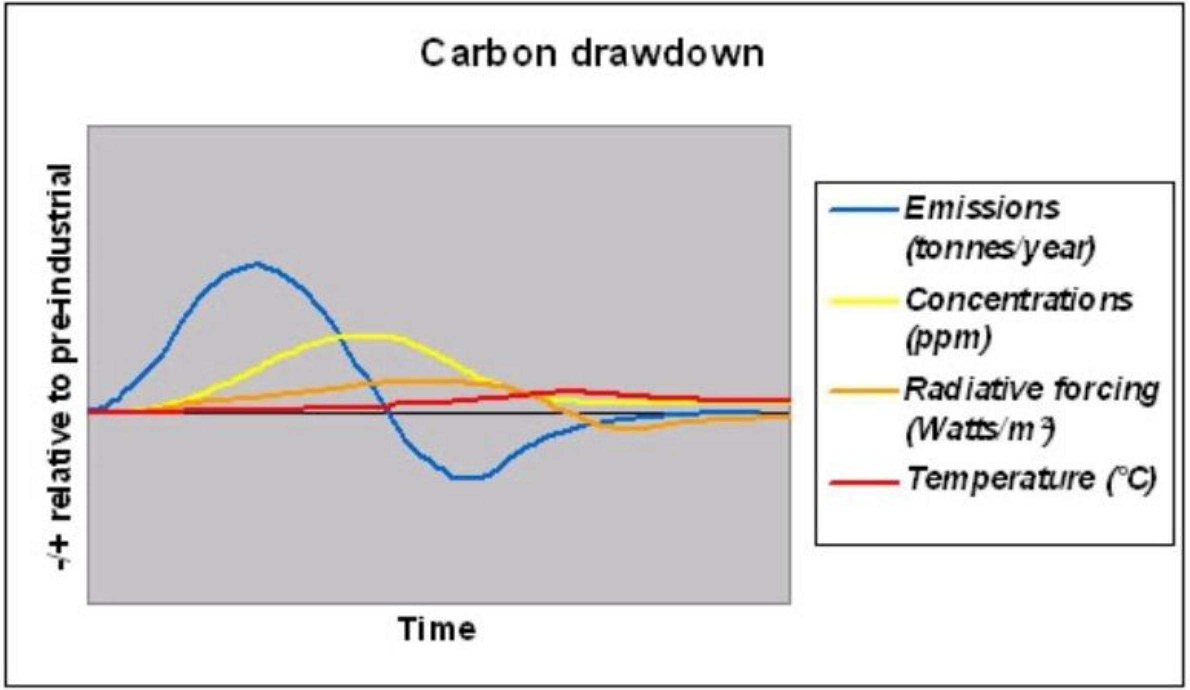
Radiative Forcing

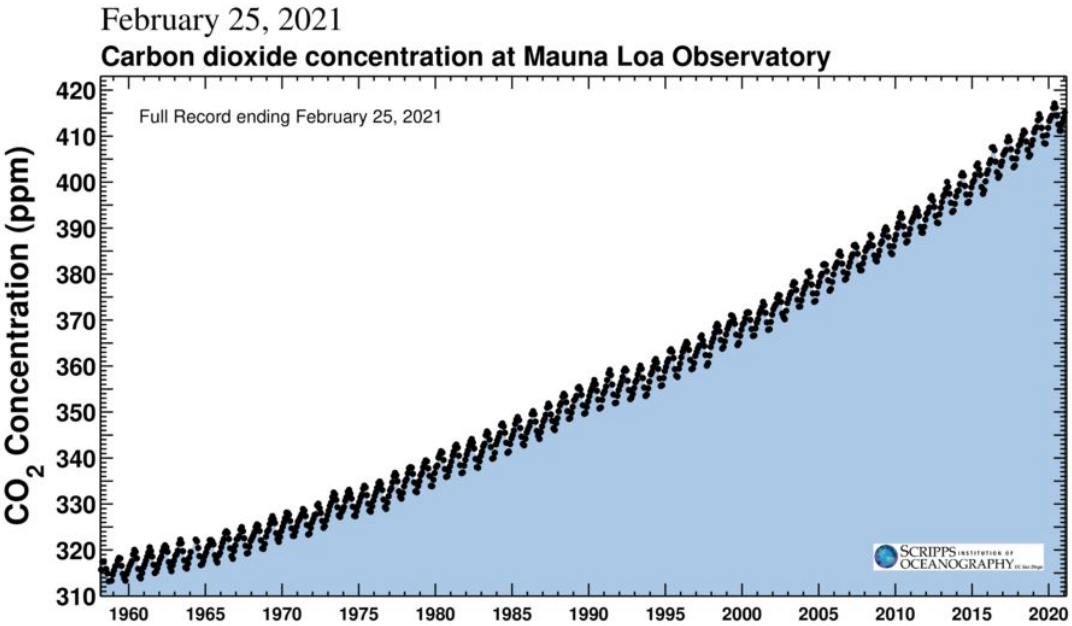


http://www.darkoptimism.org/2008/09/03/climate-science-translation-guide/

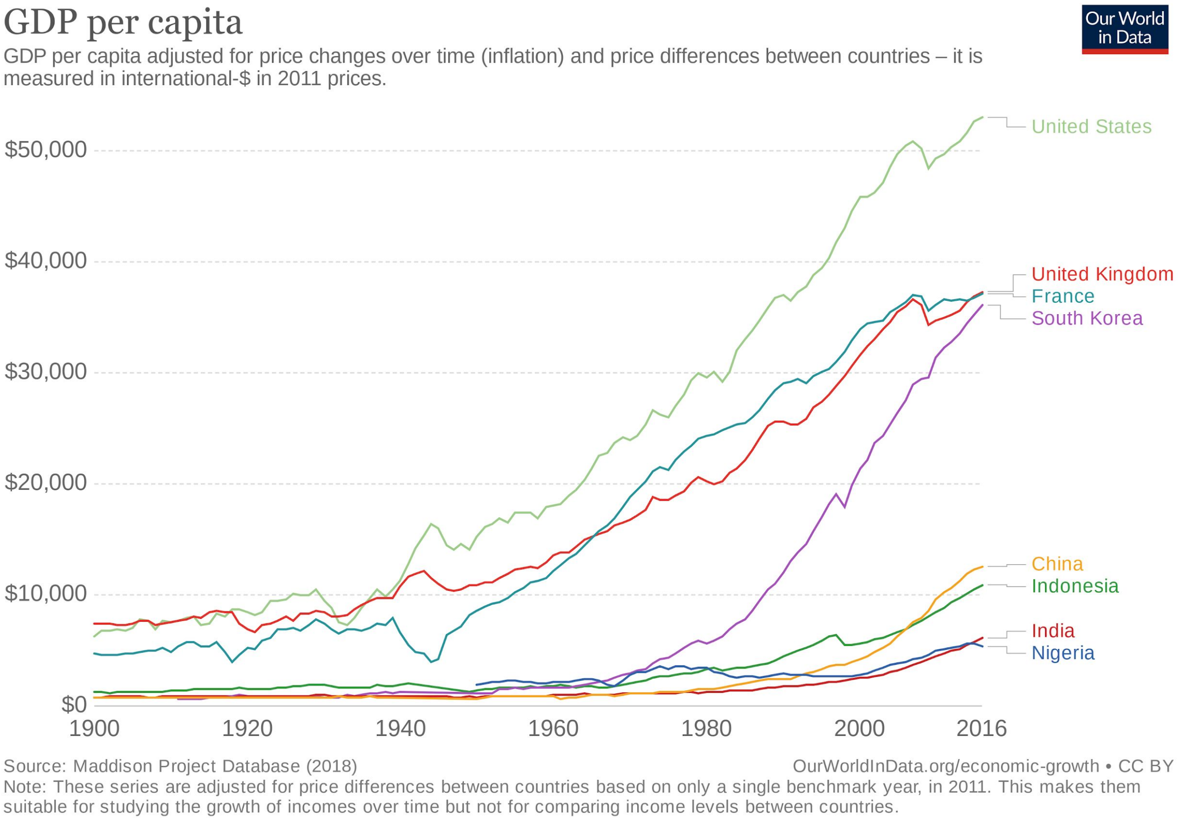
Keeling Curve

Broad consensus about climate change occuring and being human caused.

Urgent need to act with all speed and at scale.

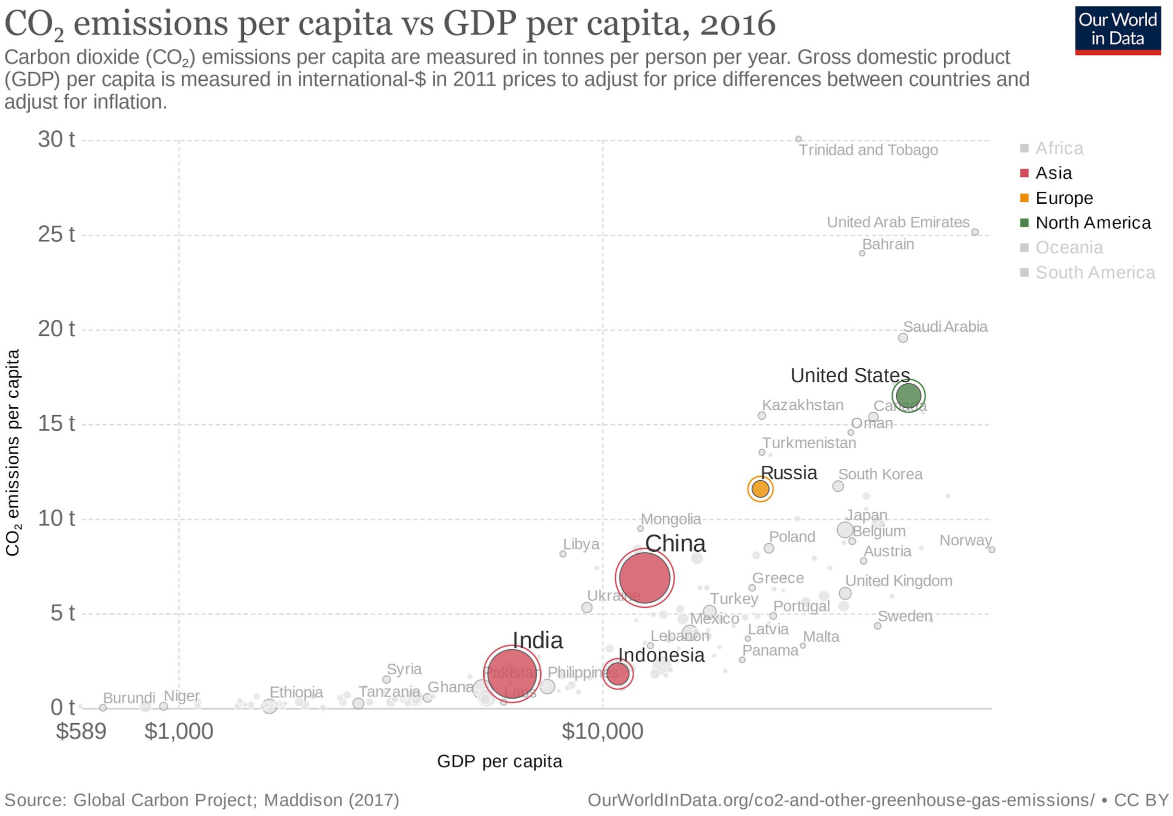


Good



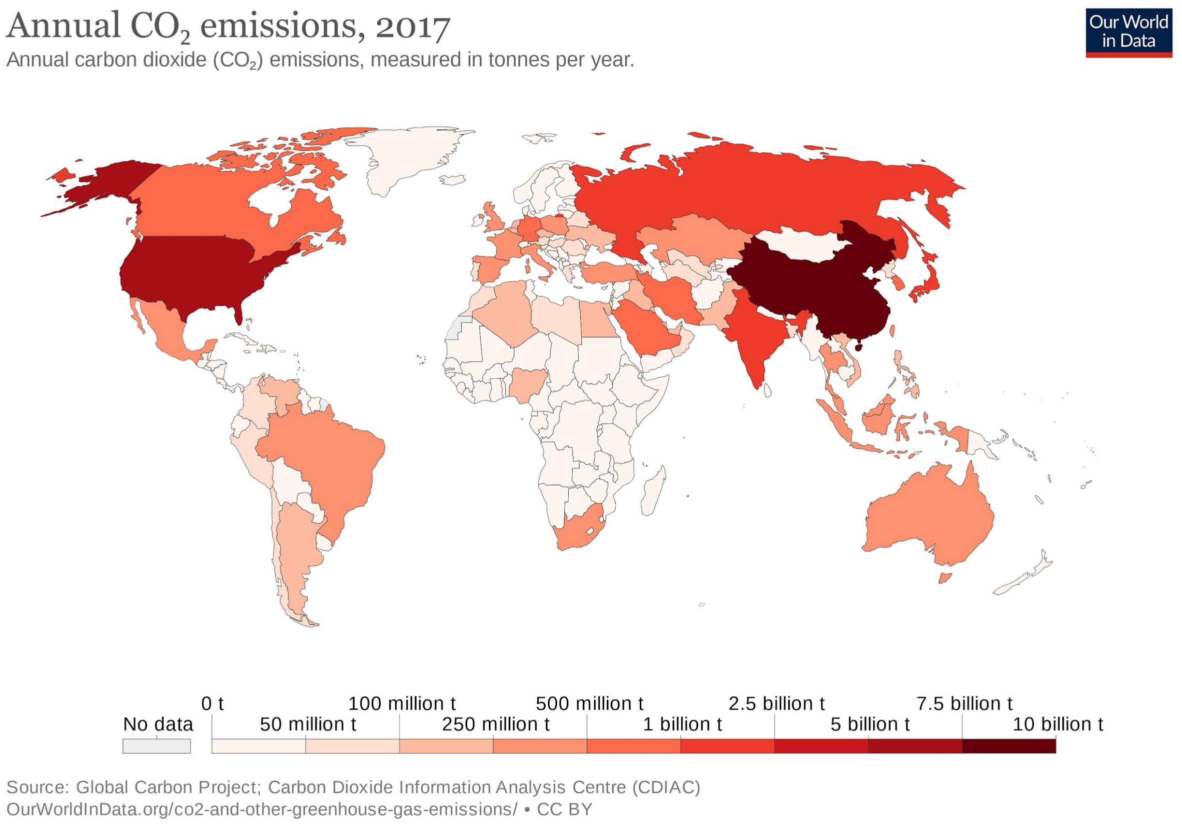
https://ourworldindata.org/

Unfortunate



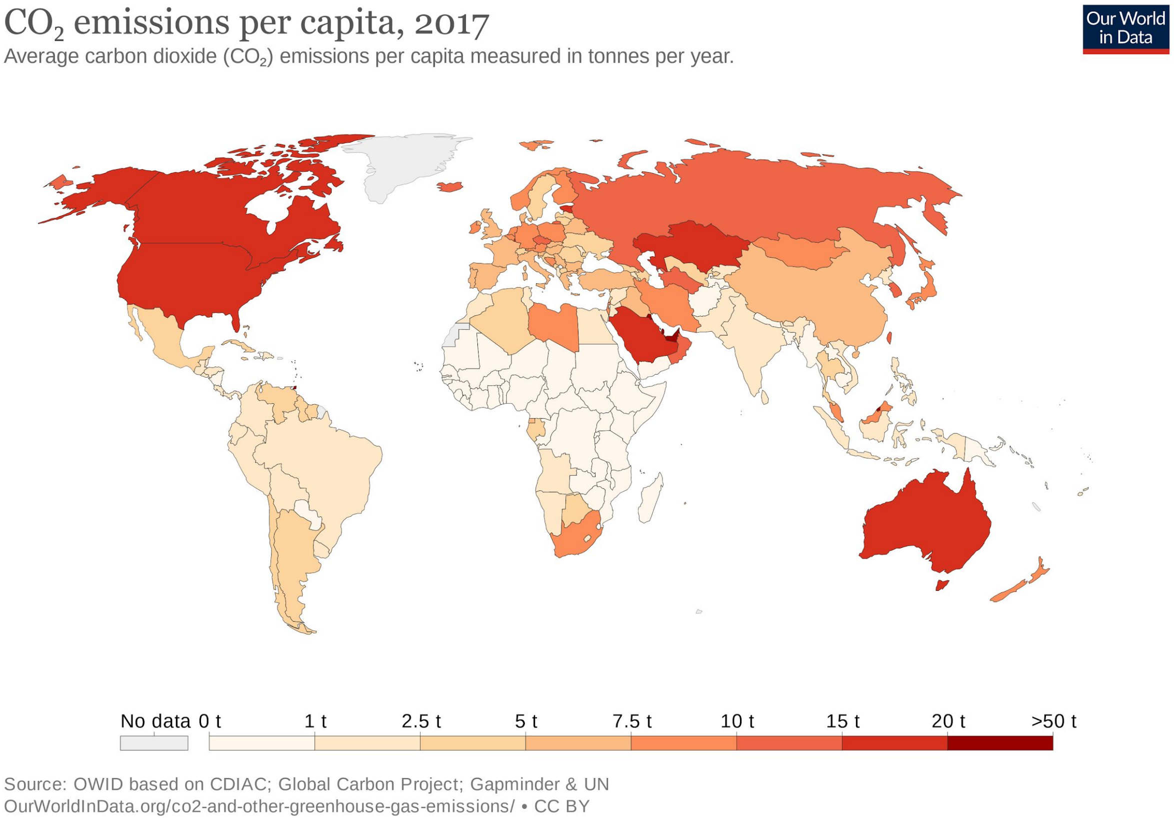
https://ourworldindata.org/

Bad



https://ourworldindata.org/

Ugly



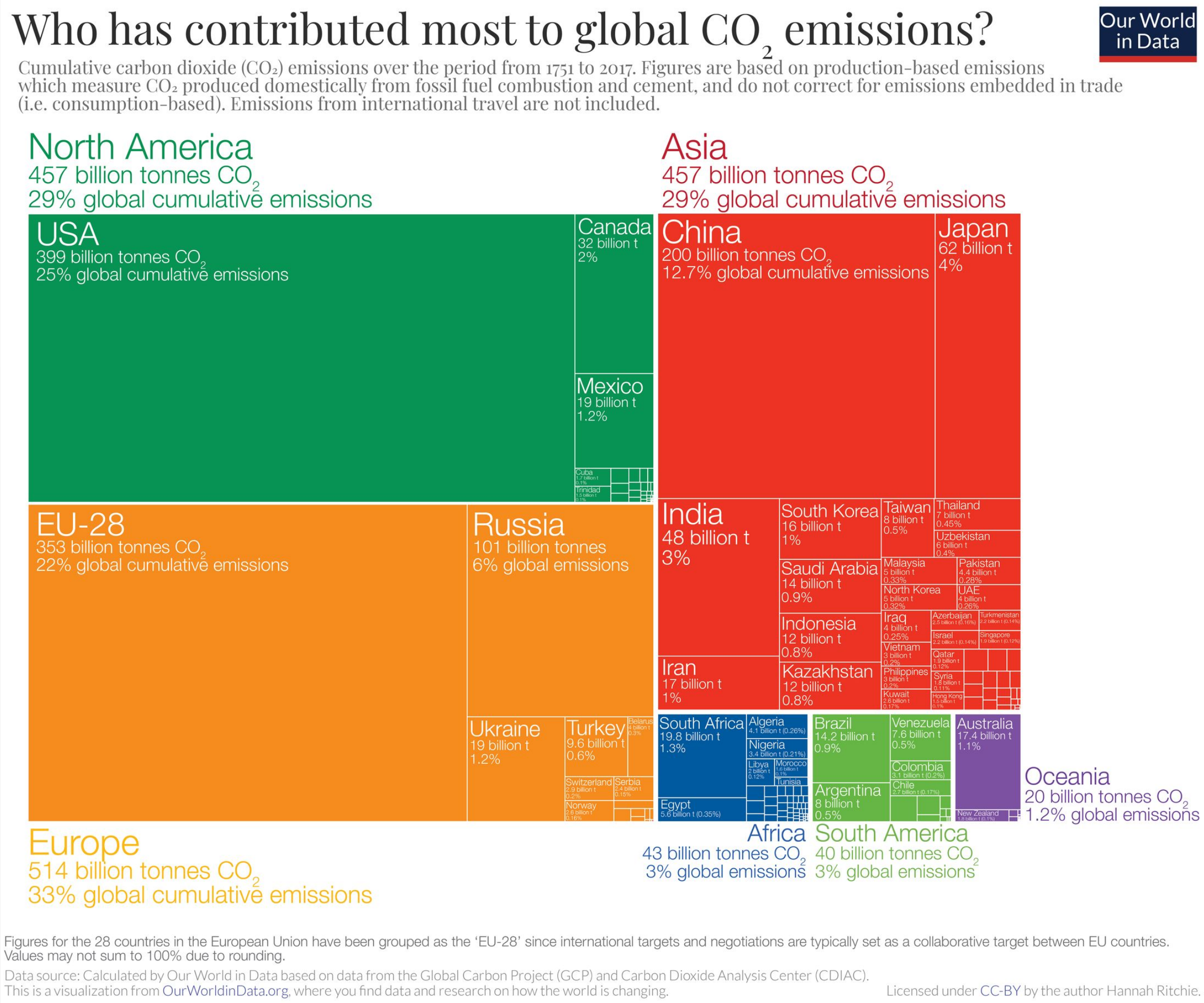
https://ourworldindata.org/

Global Carbon Budget (Cumulative Emissions 1850- 2016)

USA and EU have disproportionately emitted CO_2

Most citizens in the Global South, still live a pre-industrialized lifestyle.

https://ourworldindata.org/



UNFCCC

Article 3

Signed by all UN parties in 1992

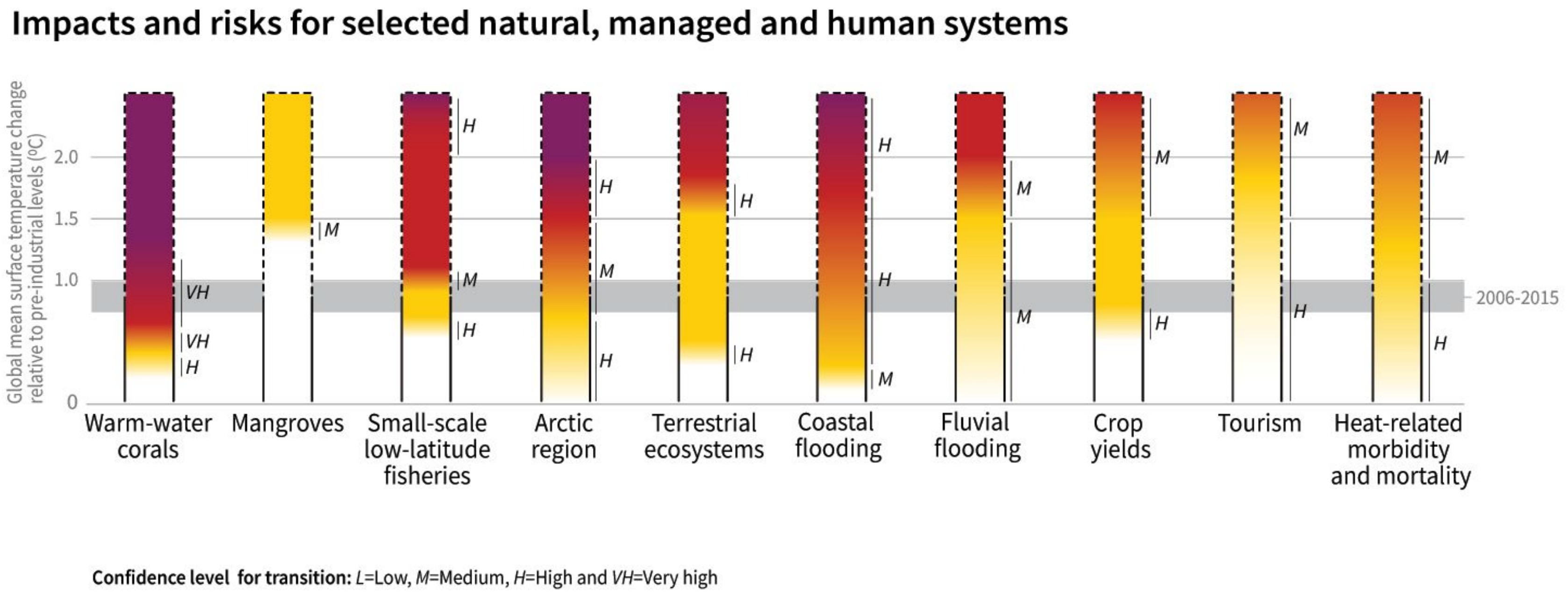
https://unfccc.int/resource/docs/convkp/conveng.pdf

1. The Parties should protect the climate system for the benefit of present and future generations of humankind, **on the basis of equity and in accordance with their common but differentiated responsibilities and respective capabilities.** Accordingly, the developed country Parties should take the lead in combating climate change and the adverse effects thereof.

2. The specific needs and special circumstances of developing country Parties, especially those that are particularly vulnerable to the adverse effects of climate change, and of those Parties, **especially developing country Parties, that would have to bear a disproportionate or abnormal burden under the Convention, should be given full consideration**

Ferrari

- 3 friends buy a Ferrari.
- 2 rich friends take it for a ride and wreck it.
- And then ask the poor friend to pay to fix it.



Purple = Very high risks of severe impact and significant irreversible persistent climate related hazards.
Red = Servere widespread impacts.
Yellow = Impact detectable and attributable to climate change.

Credit : https://www.ipcc.ch/sr15/

At 2.0°C, **10 million will be displaced** due to sea level rise vs 1.5°C.

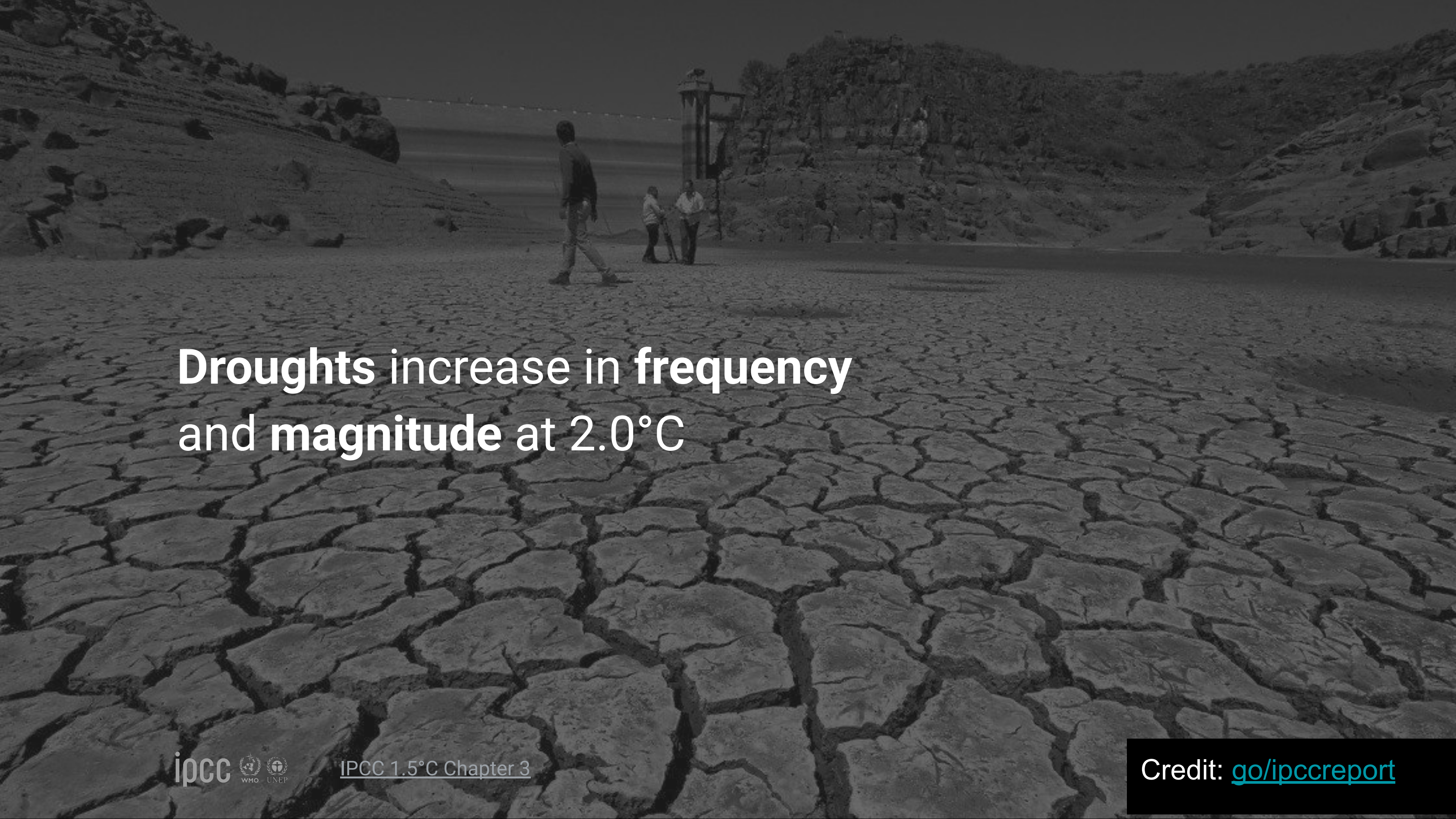
100s of millions will be forced into extreme poverty.

Risks are unevenly distributed and are generally **greater for disadvantaged people and communities** in countries at all levels of development.

Credit: go/ipccreport, https://www.ipcc.ch/report/ar5/syr/

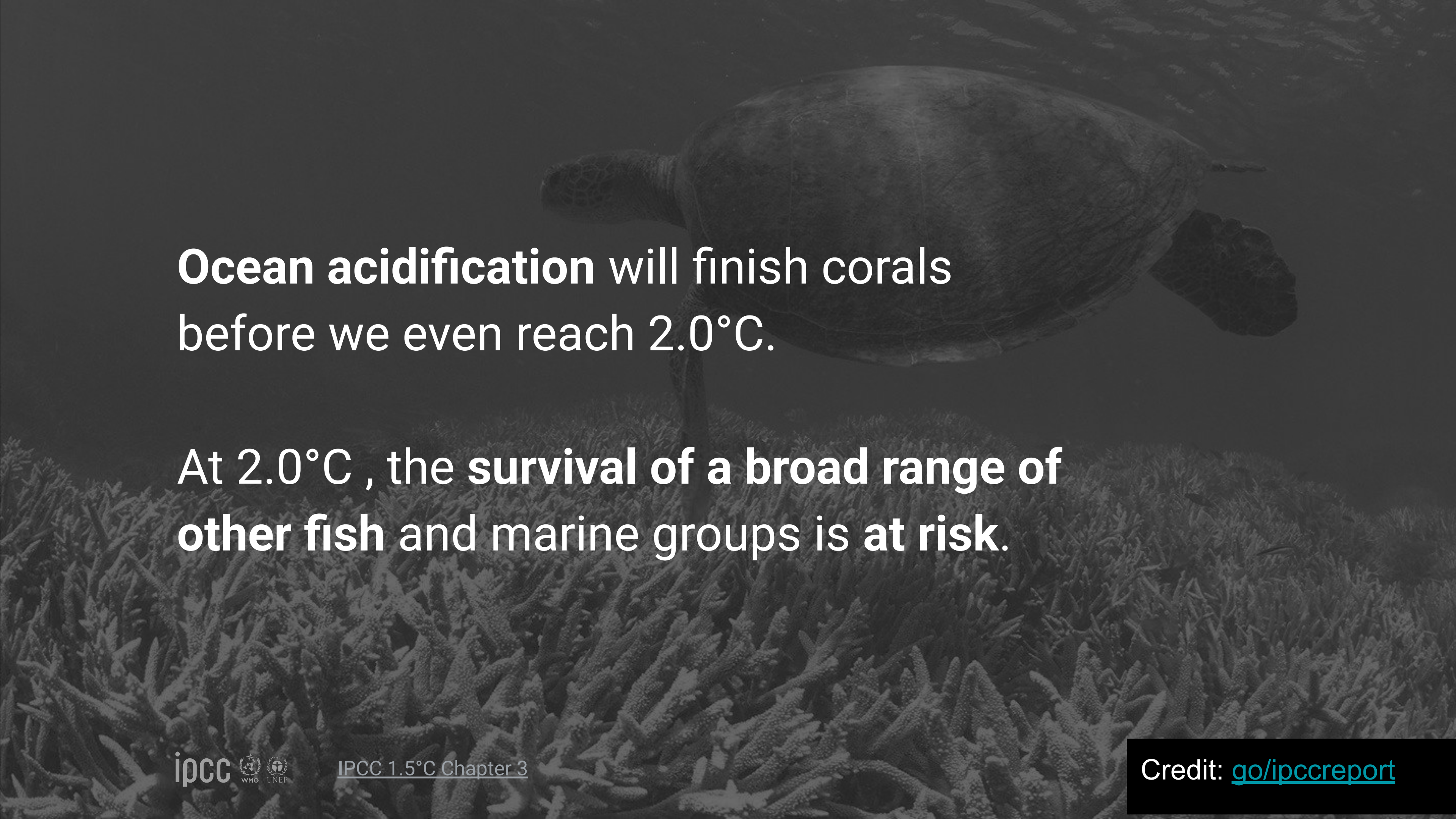
Credit: go/ipccreport

2017, Cape Town, Gamka Dam during “Day Zero” drought


Droughts increase in **frequency**
and **magnitude** at 2.0°C
IPCC 1.5°C Chapter 3
Credit: go/ipccreport

Credit: go/ipccreport

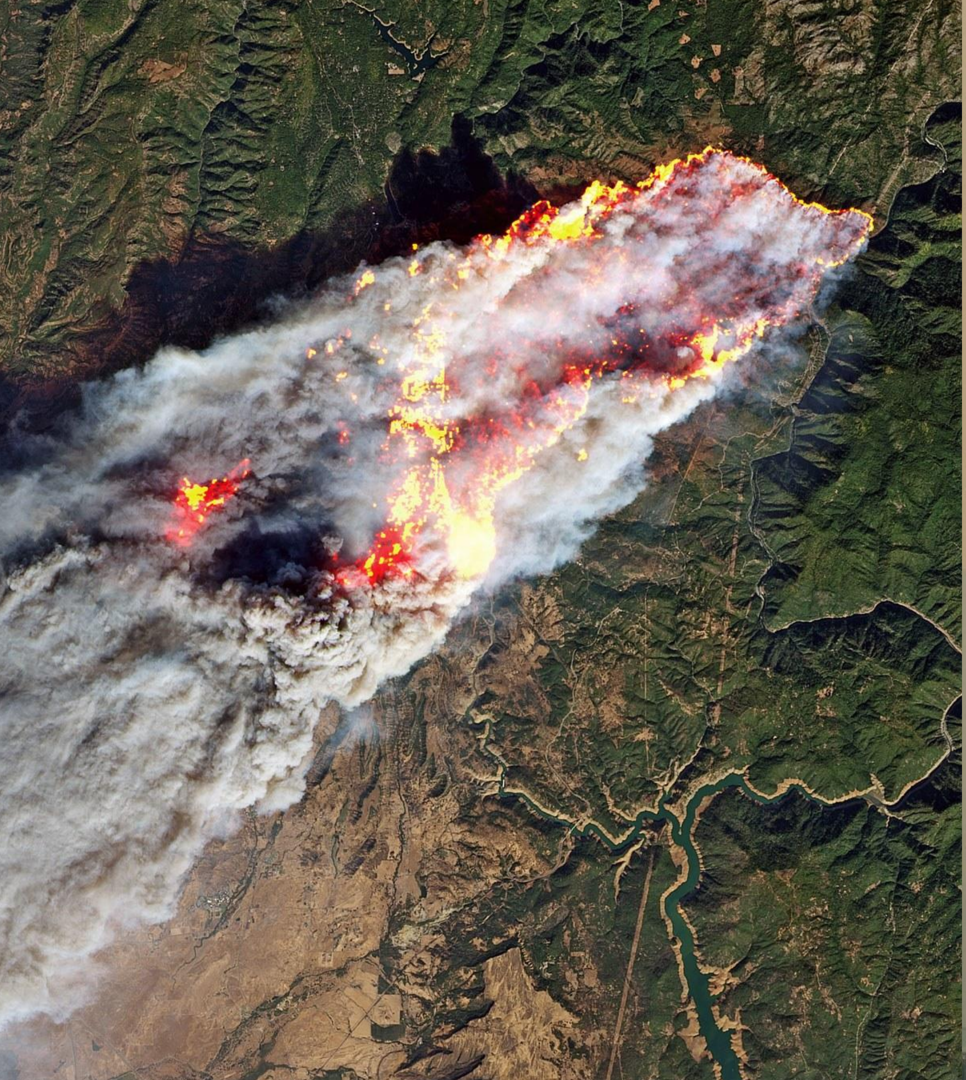
Turtle swims over bleached coral at Heron Island, Great Barrier Reef


Ocean acidification will finish corals before we even reach 2.0°C.
At 2.0°C , the **survival of a broad range of other fish** and marine groups is **at risk**.
ipcc
WMO UNEP
IPCC 1.5°C Chapter 3
Credit: go/ipccreport

Credit: go/ipccreport

At 2.0°C we risk crossing environmental **tipping points**, including **ice shelf collapse** and **runaway warming** feedback loops.

If these points are crossed, cutting emissions will be too little, too late.



2018, San Francisco during Camp Fire

Credit: go/ipccreport

Credit: go/ipccreport

2018 Camp Fire aftermath

Wildfires are a new normal at 2.0°C.

ipcc WMO UNEP

A.1, IPCC 1.5C Summary for Policymakers

Credit: go/ipccreport

All of these effects compound.
Increased vulnerabilities to
energy, food, and water at 2.0°C
will overlap temporally and spatially,
creating cascade failure risks.

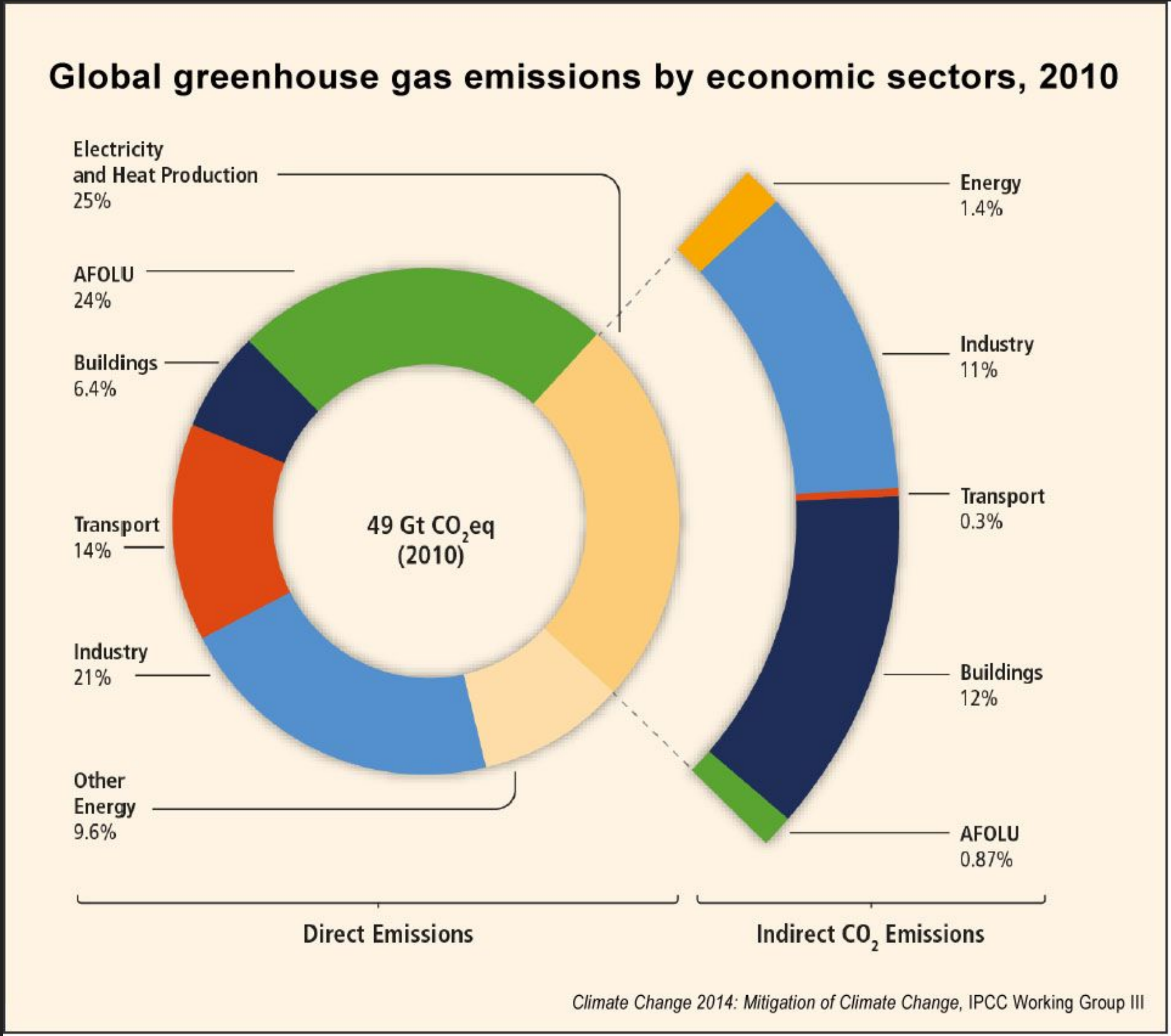
Eyes on the prize

Adaptation and mitigation are complementary strategies for reducing and managing the risks of climate change.

Many options can help address climate change, but no single option is sufficient by itself, and single points of failure are not ideal either.

BEWARE of DISTRACTIONS
QUANTIFY EVERYTHING

Credit : https://www.ipcc.ch/



Three Pillars

All three are equally important.

Not always, but usually policy precedes finance, and finance precedes technology.

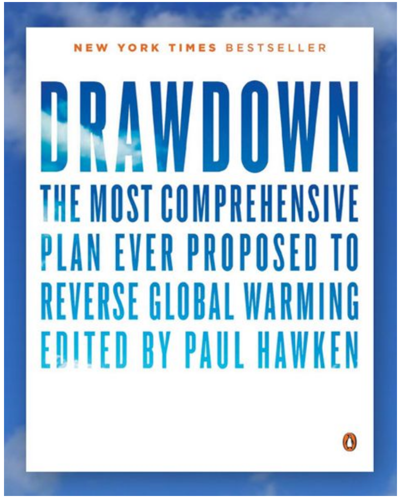
POLICY FINANCE TECHNOLOGY

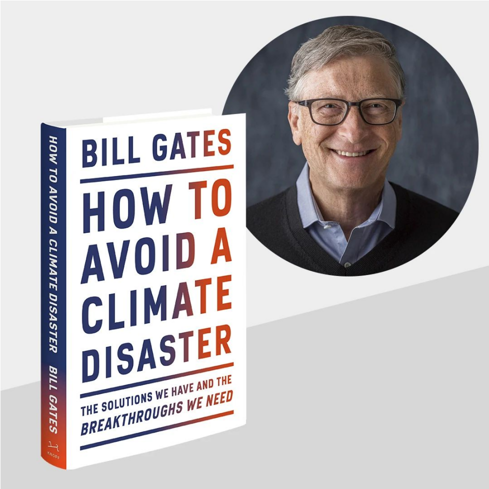
Necessity is the mother of invention

TECHNOLOGY!

Complete Decarbonization of every sector is URGENT

There is STRONG BUSINESS case for investing in climate solutions





- Deploy existing technology **Rapidly**.
- Fund **Research** for tomorrow's needs (example: sequestration, energy storage)
- Make the transformation of society **Equitable**

Complete Decarbonization

India's double burden

The science is clear - we need complete decarbonization.

India is still developing, vast majority of citizens are still getting out of the poverty trap.

India needs to be a model of doing both at the same time - Achieve development while reducing carbon impact.
<u>No other country has done this before</u>

“Western” Lifestyle

- Disproportionate consumption of resources needs to be reduced by the rich countries.

- Rich countries need to help poor countries **LEAPFROG** carbon based backbone.
  - No electricity to solar and wind.
  - No cars to EVs.
  - Plant based “meats” diet.

- If Poor countries adopt a traditional “western lifestyle” we have no hope!

Google's Climate Strategy


2019
2020
2021
2022

Carbon neutral since 2007.
Carbon free by 2030.

Carbon free electricity by 2030.

Single-use-plastic free* by 2030.

All electric kitchen by 2030.

Cut food waste in half for each Googler by 2025.

Send zero food waste to landfill by 2025.

Replenish 120% of the water we consume by 2030.

Net-zero across all operations and value chains by 2030.

*ONLY for own operations & food program

Our ambitious 10-year strategy for carbon goes far beyond our own operations.

LEADING AT GOOGLE

Go beyond carbon neutrality for our operations.

SUPPORTING PARTNERS

Empower partners (nonprofits, researchers, policymakers, etc.) with the tech they need to scale up carbon solutions.

ENABLING EVERYONE

Through our products (core products, consumer hardware), we offer helpful ways for everyone to be part of the solution.

LEADING AT GOOGLE

GOOGLE'S APPROACH

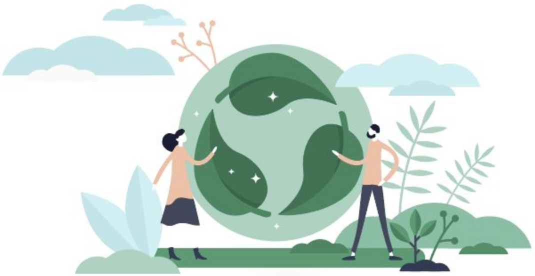
DATA CENTERS

CARBON-FREE ENERGY

SUSTAINABLE WORKPLACES

DEVICES & SERVICES

EVOLUTION OF ENERGY SUSTAINABILITY



WHAT IS CARBON NEUTRAL?

The carbon we emit through operations is **offset with renewable energy purchases** and carbon credits.

WHAT IS CARBON FREE?

On an hourly basis, in every location, we'll **run on carbon free energy** (CFE) sources.

WHAT IS 100% RENEWABLE?

The electricity we use on an annual and global basis is **matched with renewable energy purchases.**

GOOGLE'S ENERGY JOURNEY

Offsetting Emissions since 2007

Google has purchased in enough high-quality carbon offsets and renewable energy to bring our net operational emissions to zero.

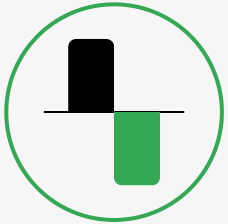
Reducing Emissions since 2017

Google has matched its global, annual electricity use with wind and solar purchases. However, our facilities still rely on carbon-based power in some places and times.

Eliminate Emissions by 2030

Google intends to match its operational electricity use with nearby (on the same regional grid) carbon-free energy sources in every hour of every year.

CARBON NEUTRALITY
since 2007



100% RENEWABLE ENERGY
since 2017

24/7 CARBON-FREE ENERGY
by 2030

SUPPORTING PARTNERS

GOOGLE'S APPROACH

SUSTAINABILITY BONDS

IMPACT CHALLENGE

NEW SCALABLE TECHNOLOGIES

ENABLING EVERYONE

GOOGLE'S APPROACH

GOOGLE HOTELS

GOOGLE FLIGHTS

GOOGLE MAPS

NEST THERMOSTAT

GOOGLE SEARCH

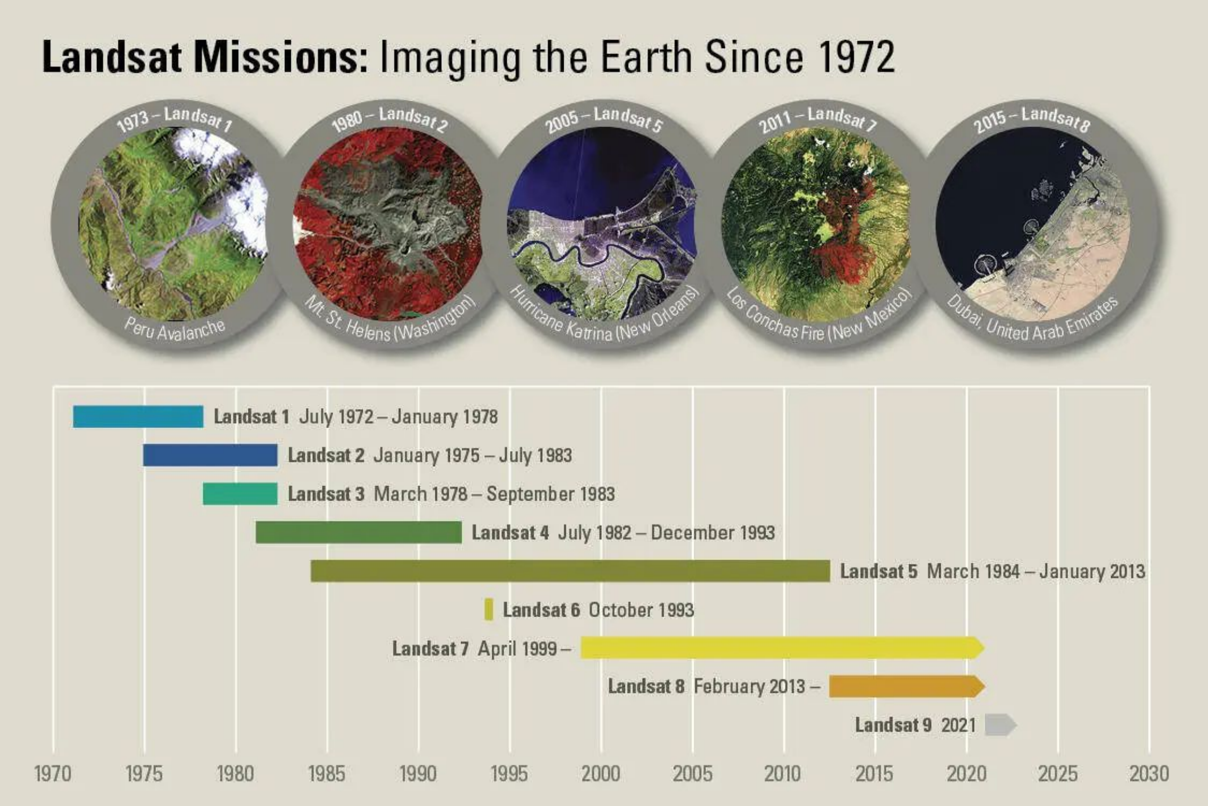
GOOGLE SHOPPING

Remote Sensing

A crash course

Earth Observation

NASA's Landsat mission has been the workhorse of remote sensing for almost 50 years.

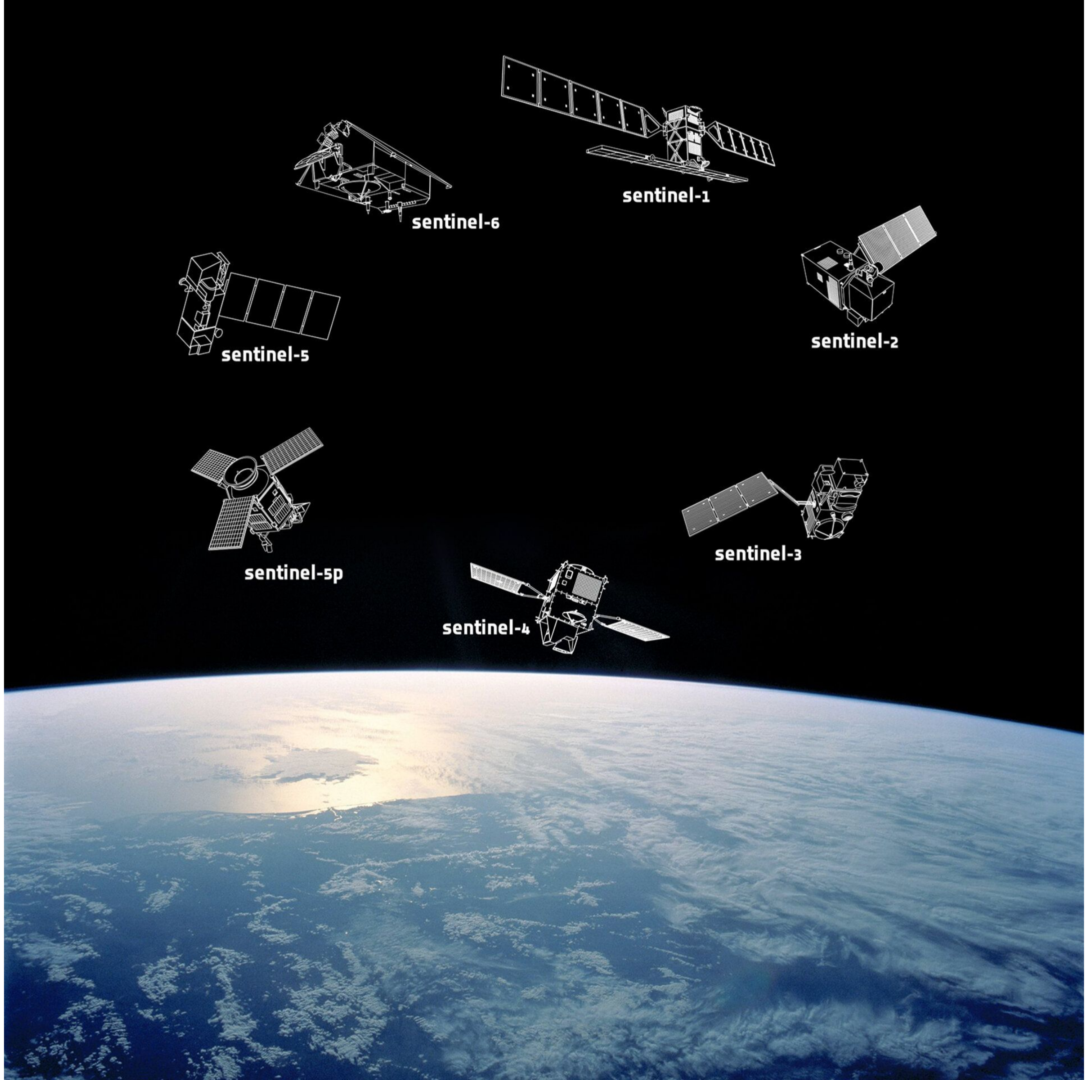


https://gisgeography.com/landsat/

Sentinel (Copernicus)

Sentinel program by ESA is a fan favorite, and most likely to be part of any remote sensing researcher’s toolkit.

https://www.esa.int/Applications/Observing_the_Earth/Copernicus/The_Sentinel_missions



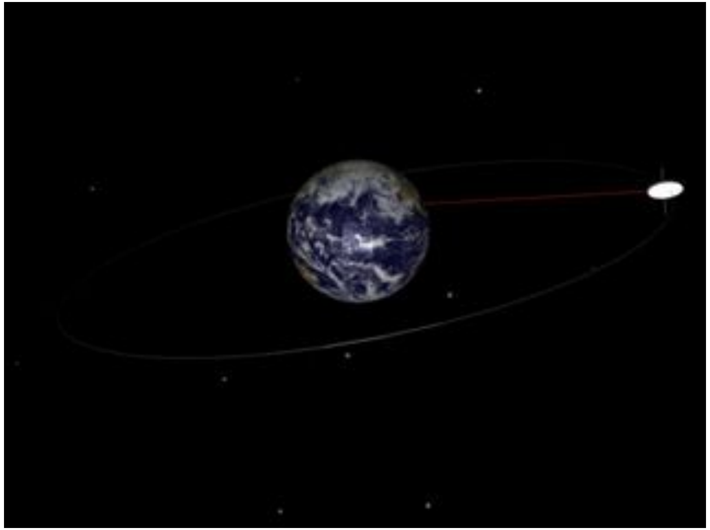
Orbits

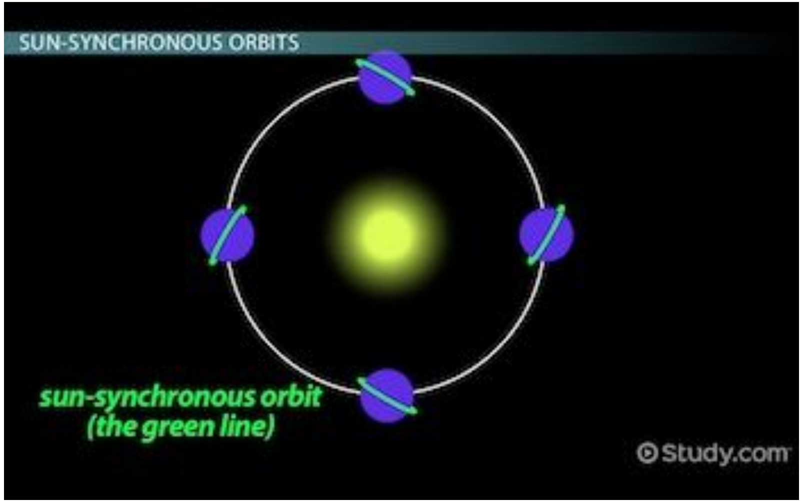
Orbits are destiny for satellites.

Most EOS satellites are in sun-synchronous orbit.

Geosynchronous orbit is useful for real time data access.

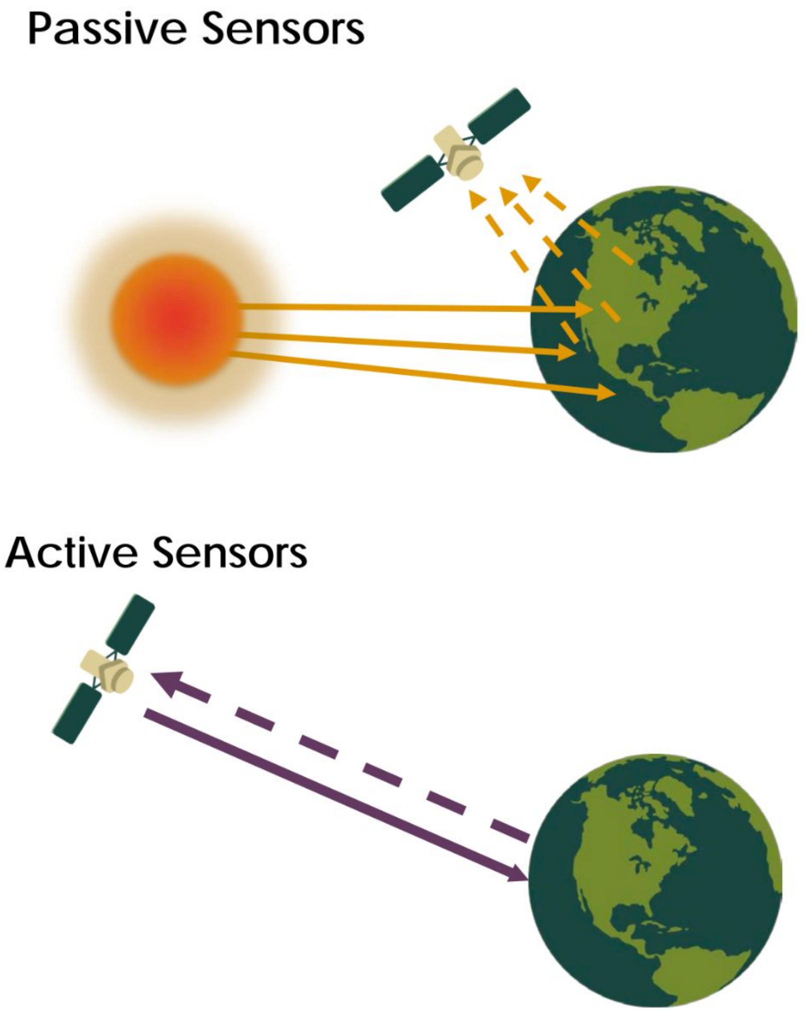
https://upload.wikimedia.org/wikipedia/commons/b/b0/Geosynchronous_orbit.gif
https://study.com/academy/lesson/sun-synchronous-orbit-vs-geostationary-orbit.html





Types of Sensors

Most satellite sensors are passive.



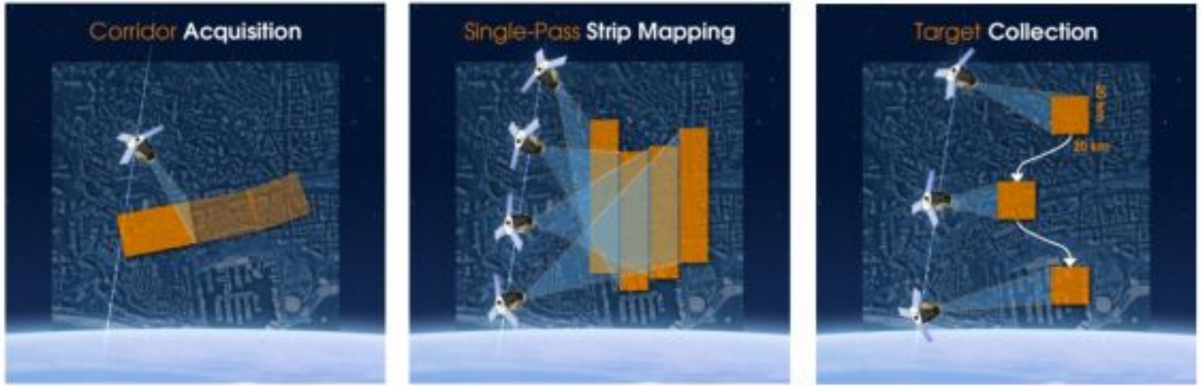
https://earthdata.nasa.gov/learn/backgrounders/remote-sensing

Spatial Resolution

https://earthdata.nasa.gov/learn/backgrounders/remote-sensing

Temporal Resolution

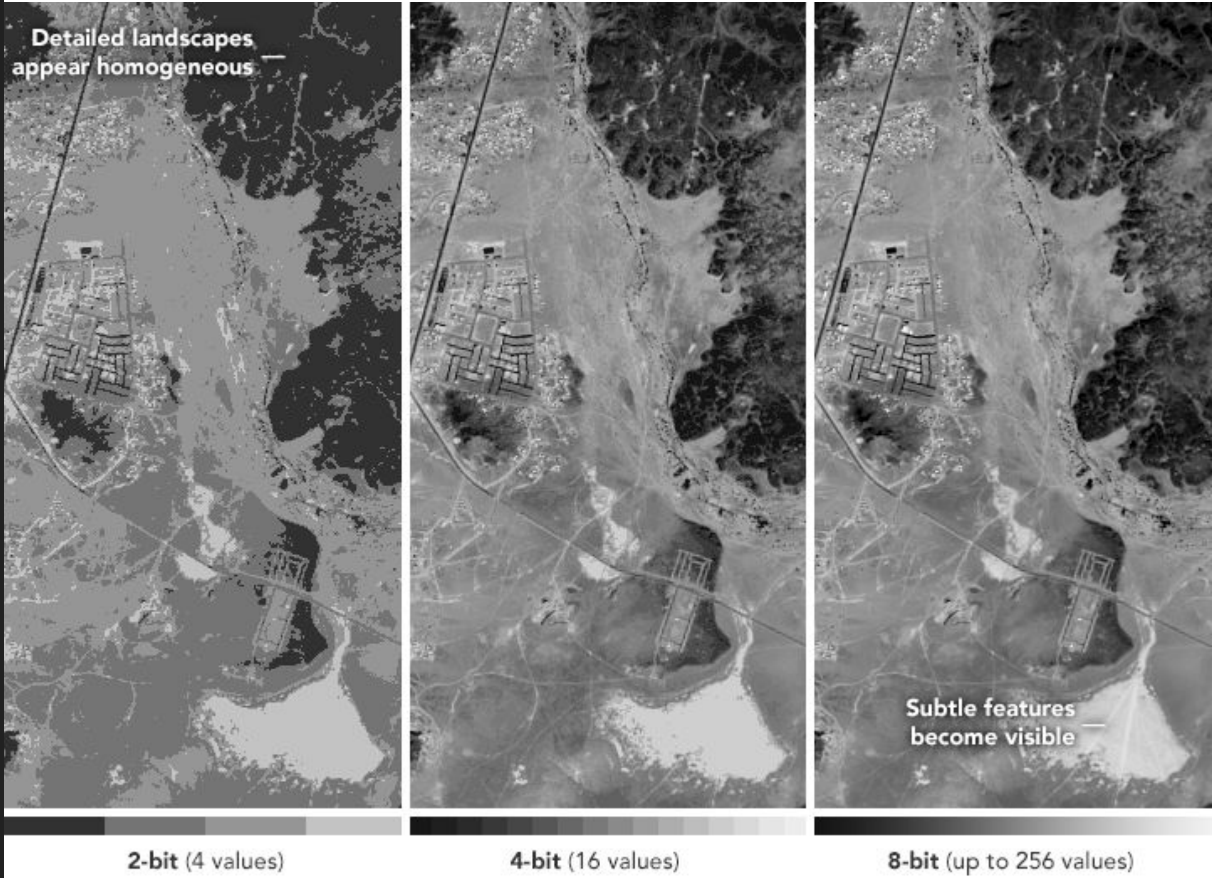
Orbit and acquisition technique determines revisit, but a constellation of identical satellites can increase revisit frequency.



https://www.intelligence-airbusds.com/imagery/constellation/
https://earthdata.nasa.gov/learn/backgrounders/remote-sensing

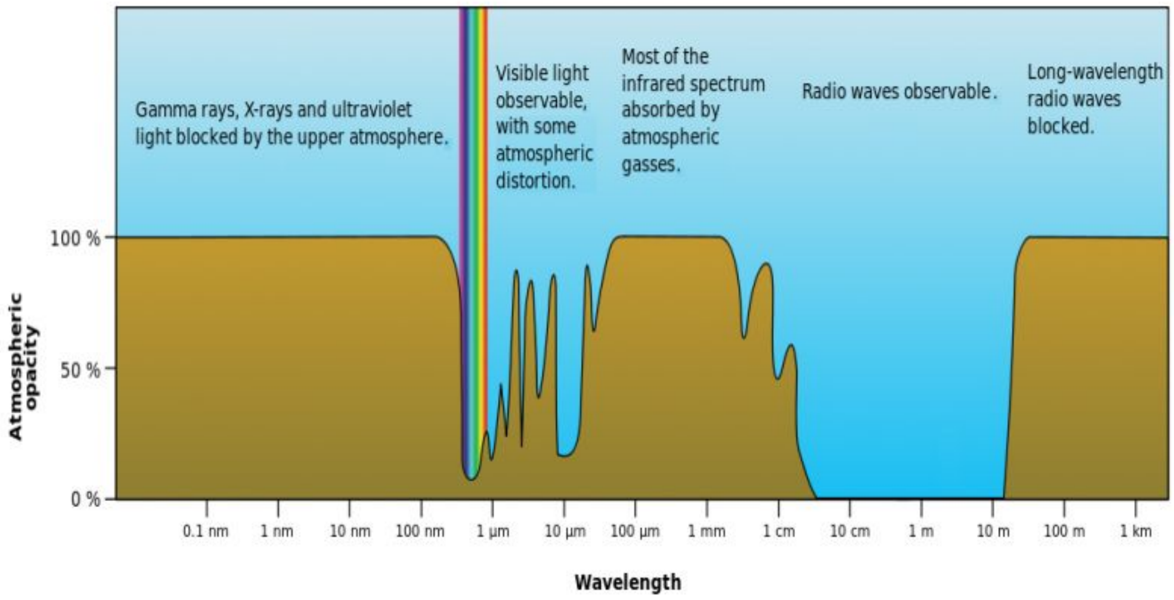
Radiometric Resolution

bits per pixel

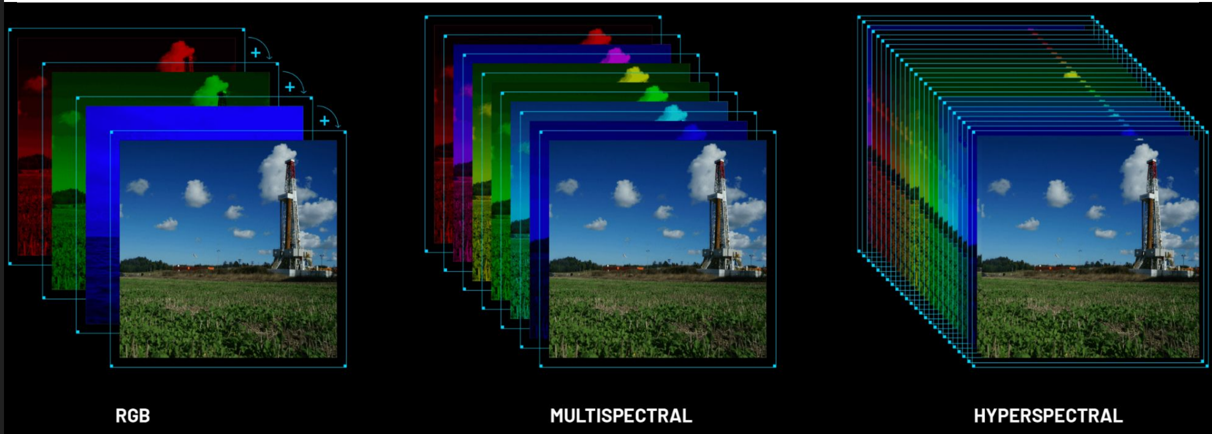


https://earthdata.nasa.gov/learn/backgrounders/remote-sensing

Spectral Resolution



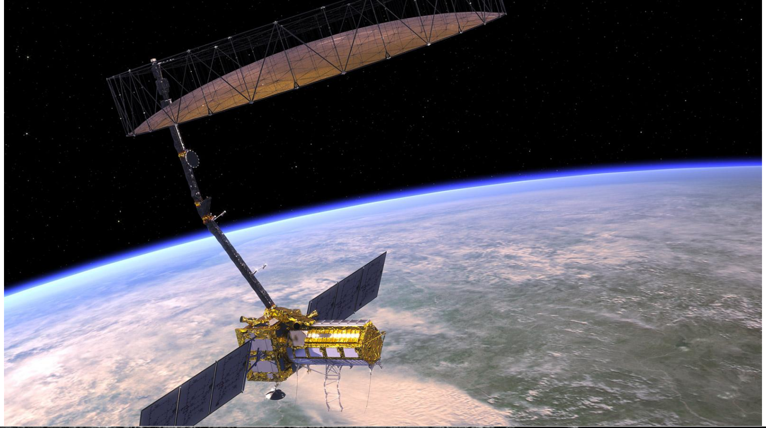
Width of EM spectrum being observed per band, and total range of observation.

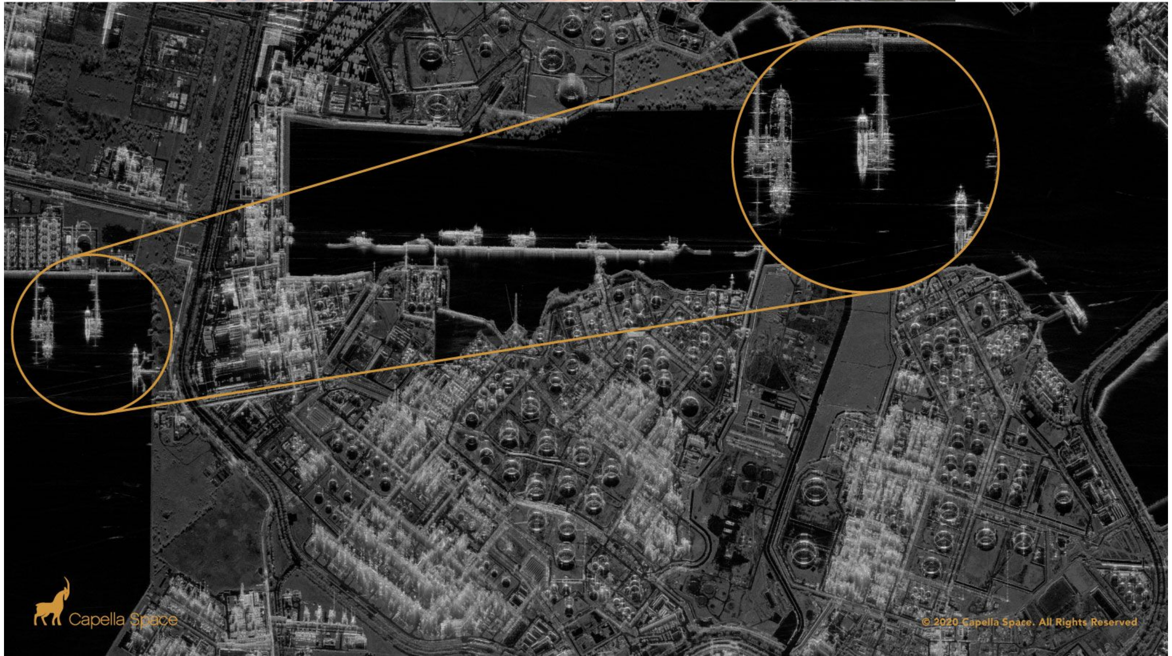


https://www.pixxel.space/technology
https://earthdata.nasa.gov/learn/backgrounders/remote-sensing

Synthetic aperture radar

NISAR, first collaboration between NASA and ISRO, will be the most expensive earth observation satellite.

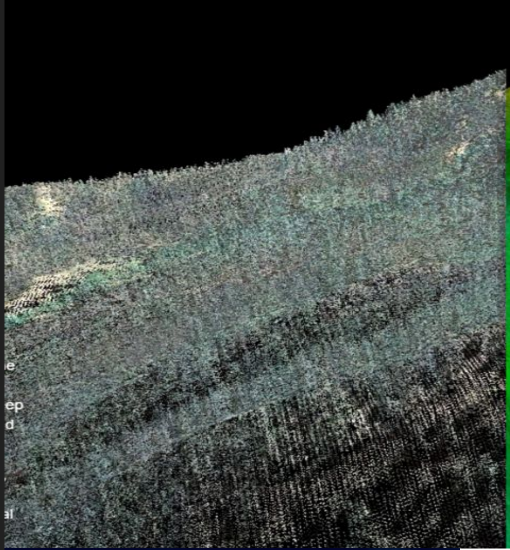


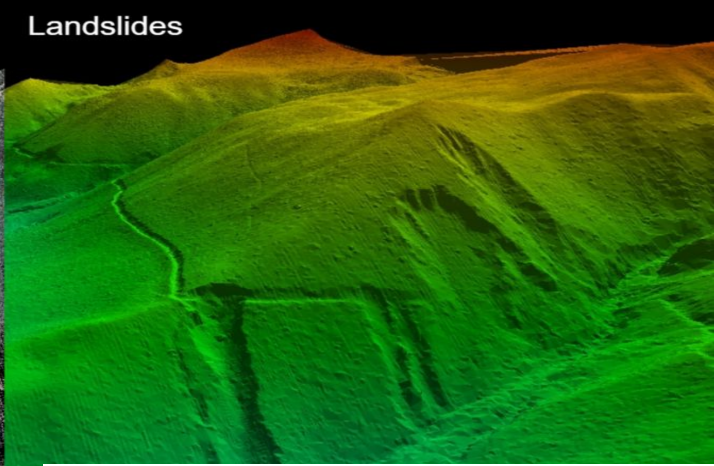


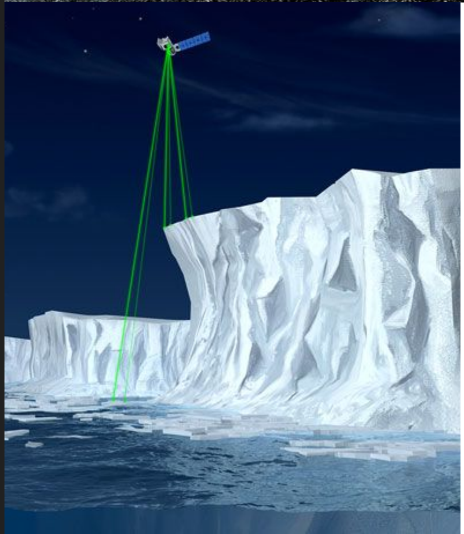
https://nisar.jpl.nasa.gov/
https://www.capellaspace.com/

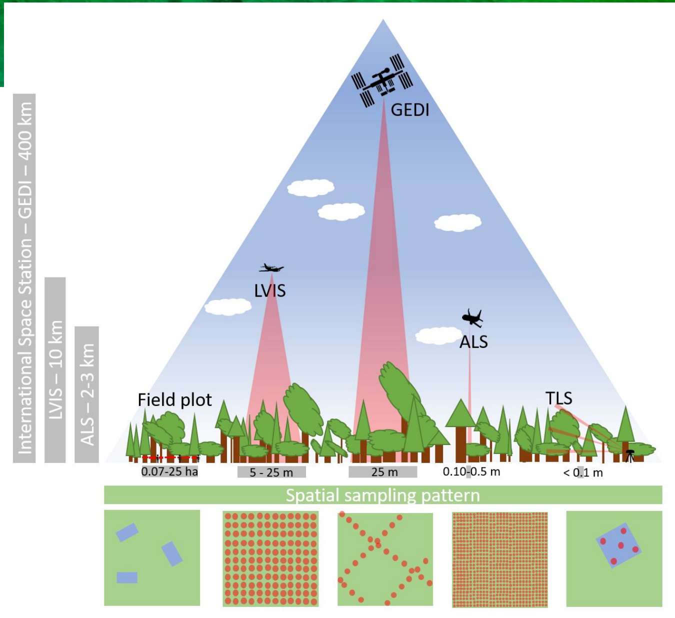
LIDAR

GEDI is the latest LIDAR satellite that has been used in innovative ways.









https://www.usgs.gov/media/images/lidar-point-cloud-vs-bare-earth-dem
https://www.sps-aviation.com/experts-speak/?id=527&h=LiDAR-Satellites

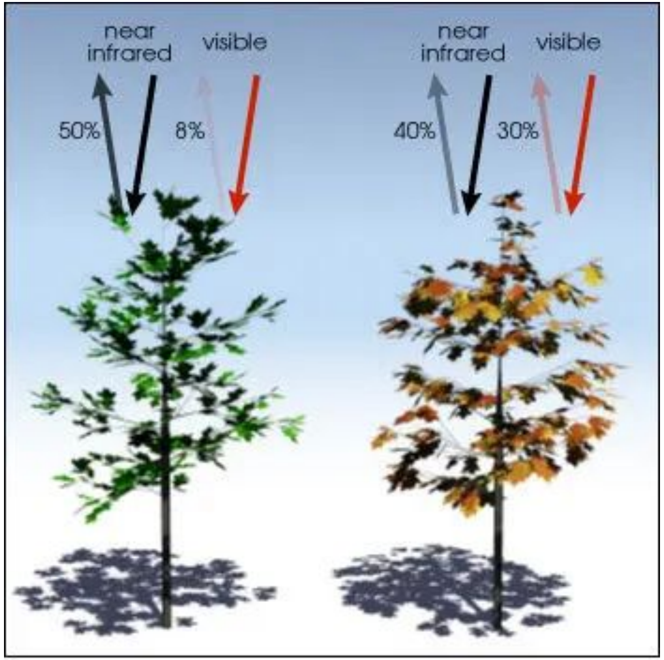
Vegetation Indices

NDVI is the most popular vegetation index that measures chlorophyll content (plant health).

Quite useful for analytical modeling.

https://gisgeography.com/ndvi-normalized-difference-vegetation-index/

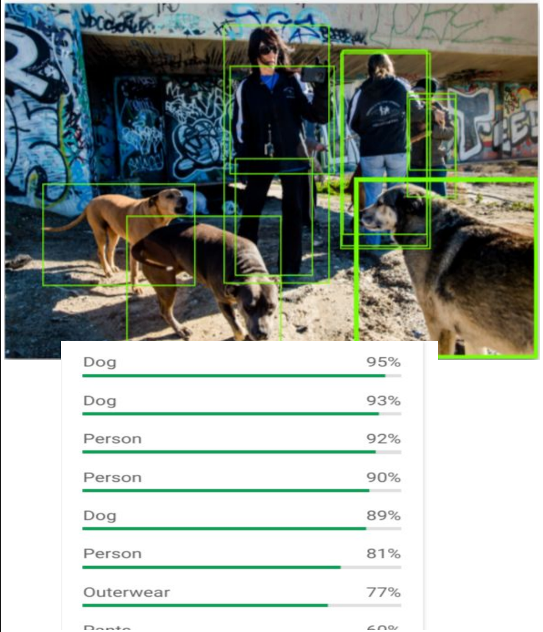
$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

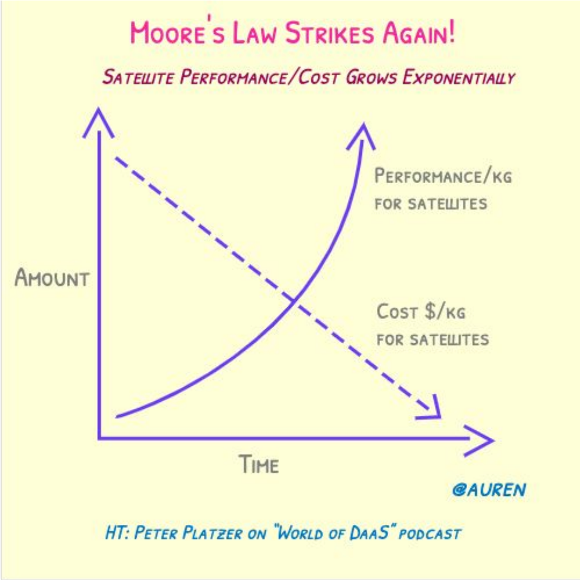


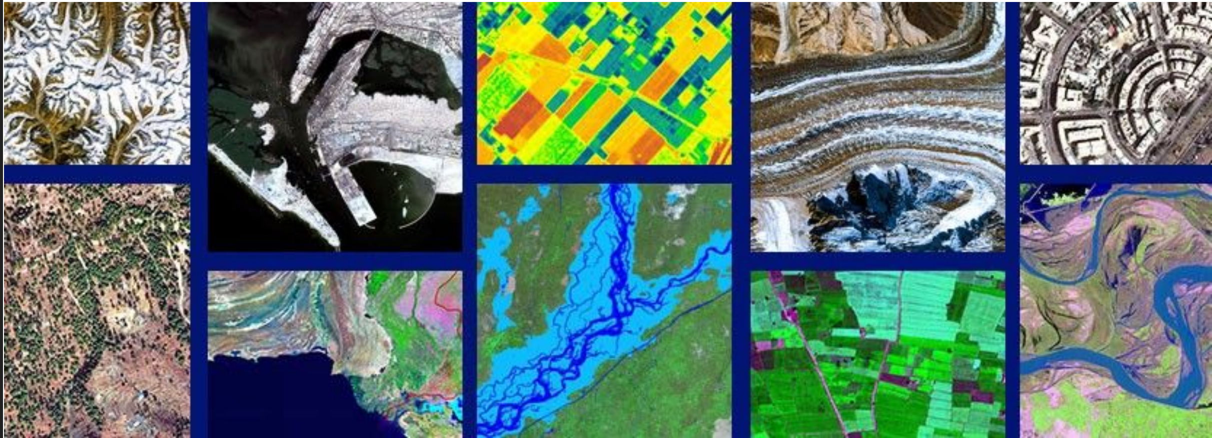
$$\frac{(0.50 - 0.08)}{(0.50 + 0.08)} = 0.72 \qquad \frac{(0.4 - 0.30)}{(0.4 + 0.30)} = 0.14$$

ML / AI & Remote Sensing

Golden age of GIS is here
Cost of new data is falling, while quality and quantity is rapidly increasing.







https://www.safegraph.com/blog/moores-law-strikes-the-satellite-industry
https://iremkomurcu.medium.com/deep-learning-in-remote-sensing-74b3b6233bae

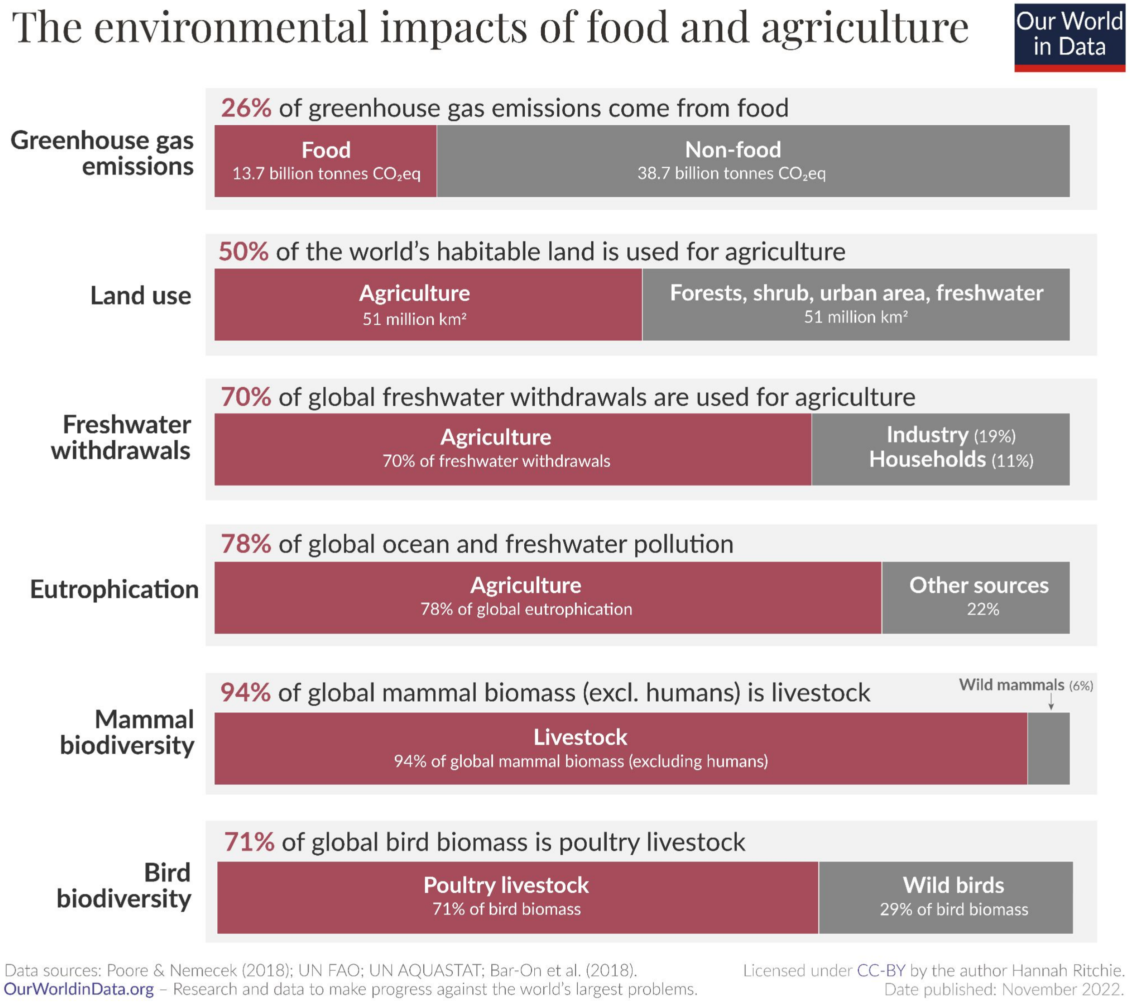
Food & Agriculture

Mitigation

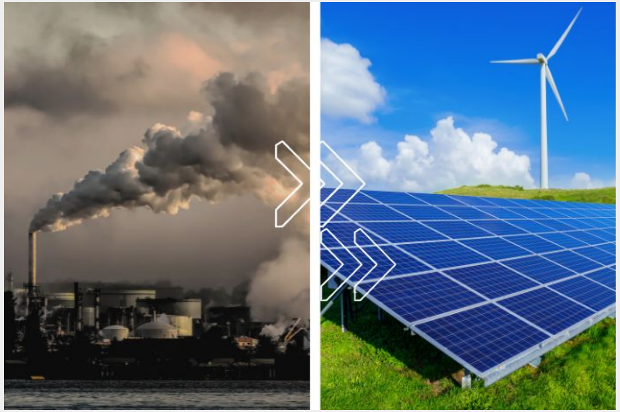
Food & Water Security (Adaptation)

Air & Water Pollution

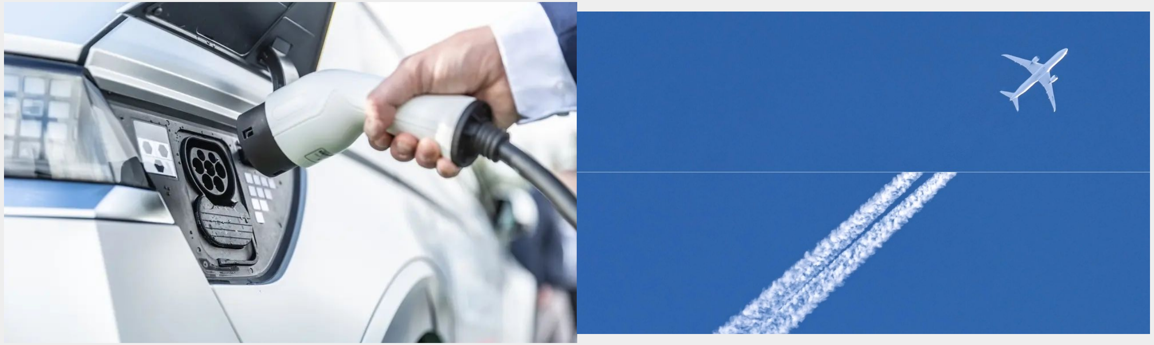
Nature & Biodiversity



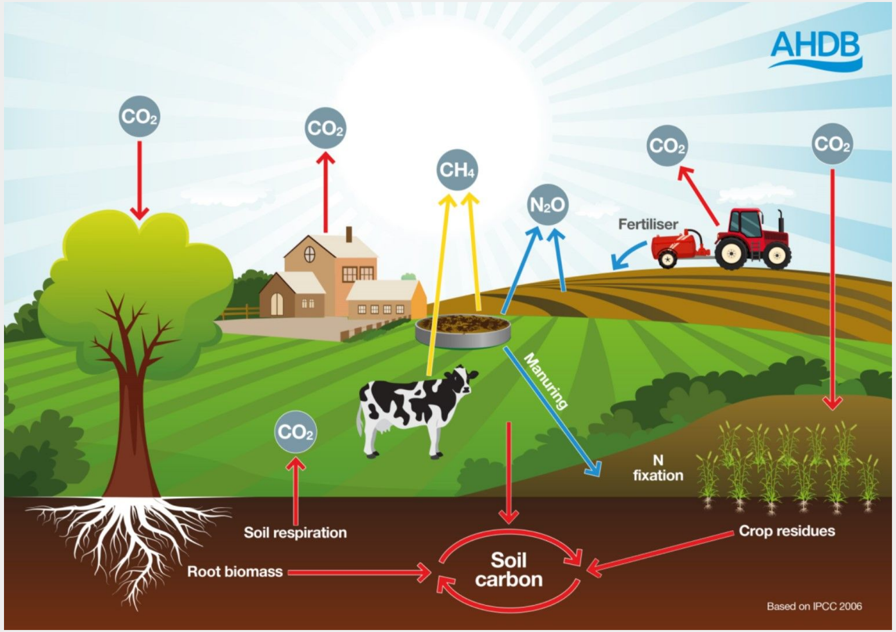
Energy



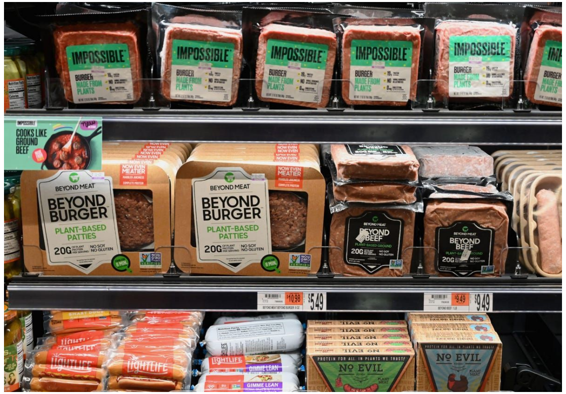
Transportation

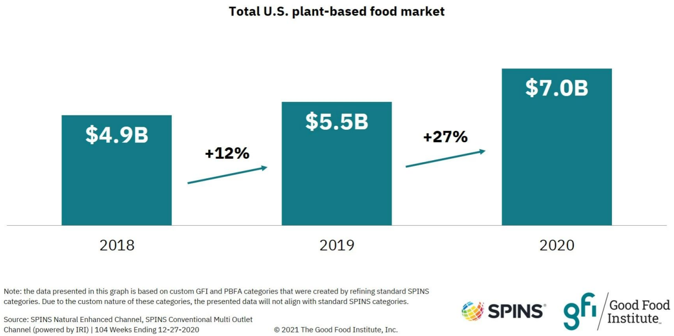


Agriculture is a hard to abate sector.
There are no clear solutions that scale.

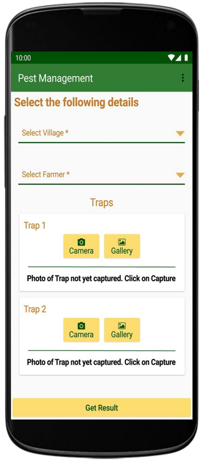


Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Demand Management	Increase plant based diets	No	No
	Faux Meats	No	No

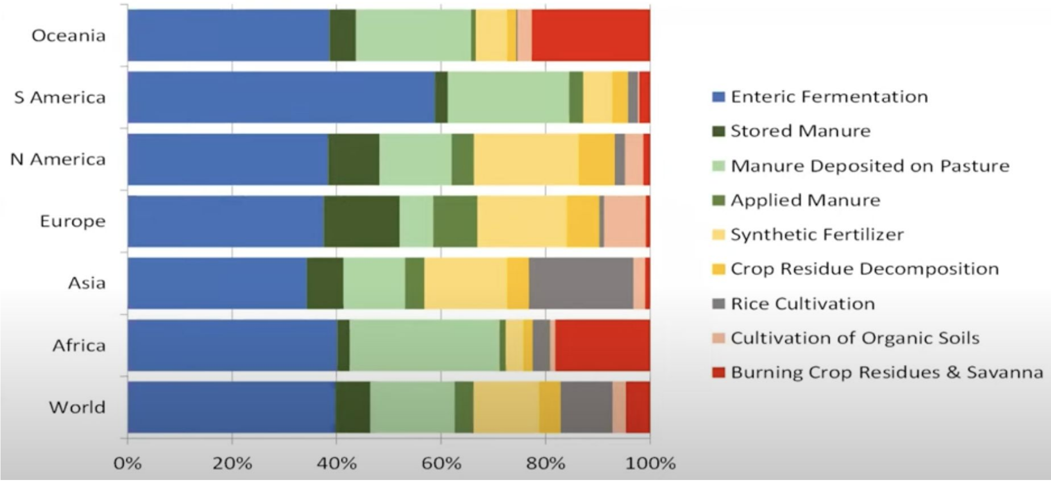


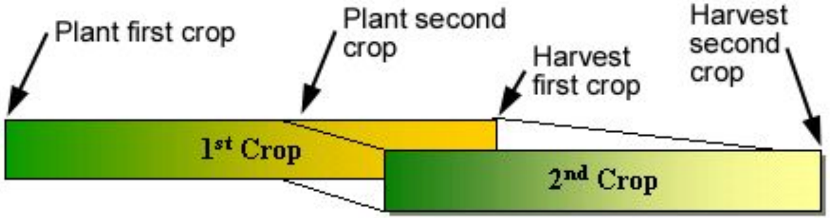


Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Supply Management	Yield Improvements	Yes	Yes
	Pest & Disease detection	Yes	Yes
	Reduce food waste - improve supply chain	Yes	Yes (Data availability is a challenge)
	Reduce food waste - Identify food spoilage	Yes	Maybe

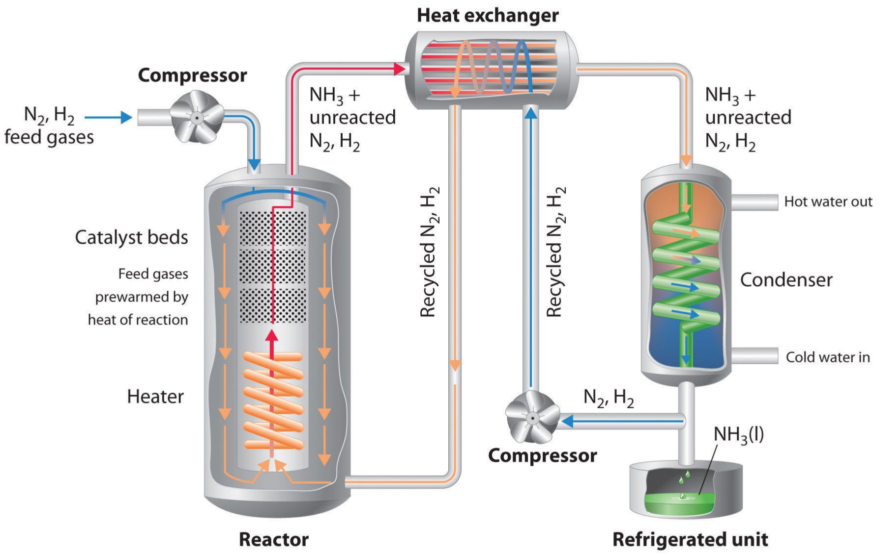


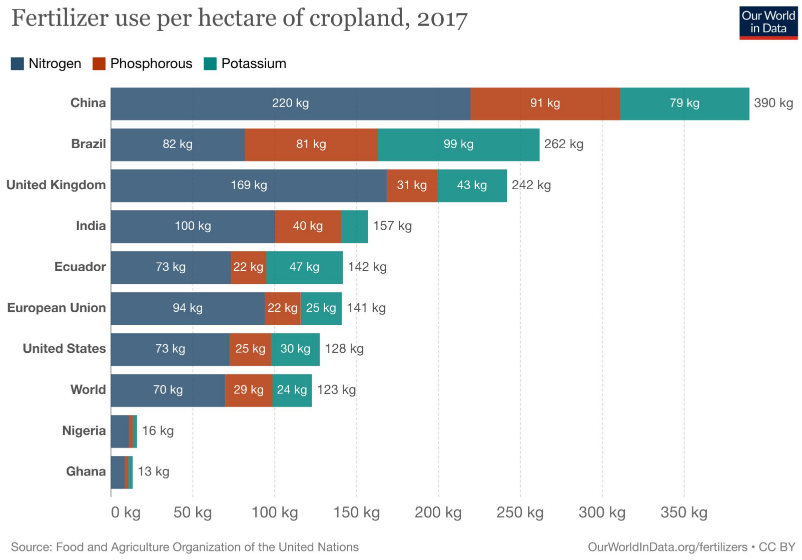
Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Change Ag Practices	Livestock management - diet additives / manure management	No	Maybe
	Non flooded rice production	Maybe	Yes
	Agroforestry / Intercropping	Yes	Yes
	Crop Residue Management	Maybe	Yes
	Agrivoltaics	Maybe	Maybe



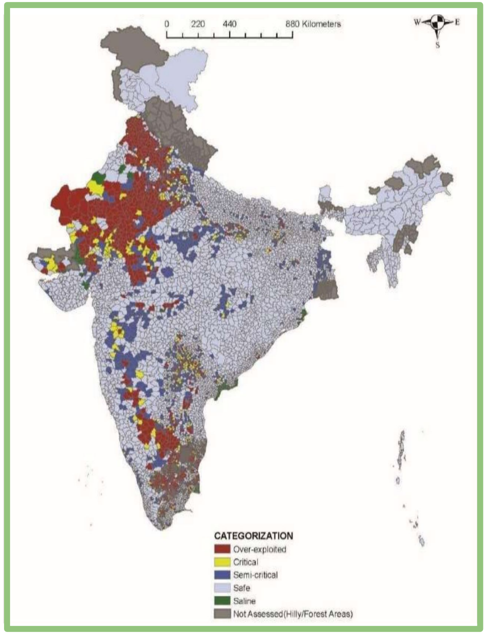


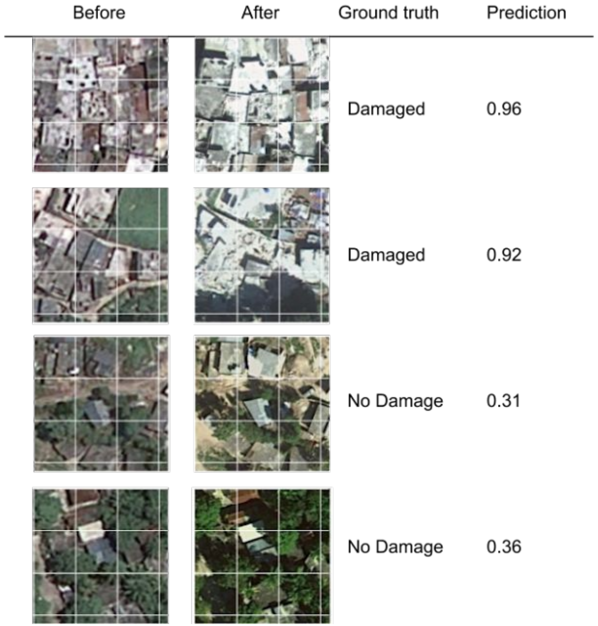
Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Reduce Resource Intensity	Precision Chemical inputs	Yes	Maybe
	Hydroponics	No	Yes
	Vertical farming	Yes	No





Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Climate Adaptation	Irrigation optimization	Yes	Yes
	Rainwater harvesting	No	Yes
	Crop Flood damage assessment	Yes	Yes





Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Soil Health & Soil Carbon Sequestration	Regenerative Agriculture	Yes	Yes
	Perennial Grain Crops	Maybe	Yes

Category	Intervention	AI/ML Transformational Potential	Applicable in the Global south ?
Genetically modified crops	Genetically modified crops	Yes	Yes

Crop	Method	Target gene	Stress/trait	Reference
Biotic Stress				
A. thaliana/ N. benthamiana	NHEJ	dsDNA of virus (A7, B7, and C3 regions)	Beet severe curly top virus resistance	Ji et al., 2015
A. thaliana	NHEJ	*elF(iso)4E*	Turnip mosaic virus (TuMV) resistance	Pyott et al., 2016
N. benthamiana	NHEJ	BeYDV	Bean yellow dwarf virus (BeYDV) resistance	Baltes et al., 2015
N. benthamiana	NHEJ	ORFs and the IR sequence sDNA of virus	Tomato yellow leaf curl virus (TYLCV) and Merremia mosaic virus (MeMV)	Ali et al., 2015
Rice	NHEJ	*OsERF922* (ethylene responsive factor)	Blast Resistance	Wang F. et al., 2016
Rice (IR24)	NHEJ	*OsSWEET13*	Bacterial blight disease resistance	Zhou et al., 2015
Bread wheat	NHEJ	*TaMLO-A1*, *TaMLO-B1*, and *TaMLOD1*	Powdery mildew resistance	Wang et al., 2014
Cucumber	NHEJ	*elF4E* (eukaryotic translation initiation factor 4E)		Chandrasekaran et al., 2016
			Cucumber vein yellowing virus (CVYV), Zucchini yellow mosaic virus (ZYMV), and Papaya ring spot mosaic virus type-W (PRSV-W)	
Abiotic stress				
Maize	HDR	*ARGOS8*	Increased grain yield under drought stress	Shi et al., 2017
Tomato	NHEJ	*SlMAPK3*	Drought tolerance	Wang et al., 2017
A. thaliana	NHEJ	*UGT79B2, UGT79B3*	Susceptibility to cold, salt, and drought stresses	
A. thaliana	HDR	*MIR169a*	Drought tolerance	Zhao et al., 2016
A. thaliana	NHEJ	*OST2* (OPEN STOMATA 2) (AHA1)	Increased stomatal closure in response to abscisic acid (ABA),	Osakabe et al., 2016
Rice	HDR, NHEJ	*OsPDS, OsMPK2, OsBADH2*	Involved in various abiotic stress tolerance	Shan et al., 2013
Rice	NHEJ	*OsMPK5*	Various abiotic stress tolerance and disease resistance	Xie and Yang, 2013
Rice	NHEJ, HDR	*OsMPK2, OsDEP1*	Yield under stress	Shan et al., 2014
Rice	NHEJ	*OsDERF1, OsPMS3, OsEPSPS, OsMSH1, OsMYB5*	Drought tolerance	Zhang et al., 2014
Rice	NHEJ	*OsAOX1a, OsAOX1b,OsAOX1c, OsBEL*	Various abiotic stress tolerance	Xu et al., 2015
Rice	NHEJ	*OsHAK-1*	Low cesium accumulation	Cordones et al., 2017
Rice	NHEJ	*OsPRX2*	Potassium deficiency tolerance	Mao et al., 2018
Nutritional and other Traits				
Rice	NHEJ	*25604 gRNA for 12802 genes*	Creating genome wide mutant library	Meng et al., 2017
Maize	NHEJ	*ZmIPK1A ZmIPK andZmMRP4*	Phytic acid synthesis	Liang et al., 2014
Wheat	HDR	*TaVIT2*	Fe content	Connorton et al., 2017
Soybean	NHEJ	*GmPDS11* and *GmPDS18*	Carotenoid biosynthesis	Du et al., 2016
Tomato	NHEJ	*Rin*	Fruit ripening	Ito et al., 2015
Potato	HDR	*ALS1*	Herbicide resistance	Butler et al., 2016
Cassava	NHEJ	*MePDS*	Carotenoid biosynthesis	Odipio et al., 2017

- Deeper roots to drawdown more carbon
- Reflect more sunlight (albedo adjustment)
- Adaptation to droughts and floods
- Faster growth and increased yields
- Disease / pest resistance
- Drawing down / reducing emissions of Nitrous oxide

There are no silver bullets in climate change

We need all of the above.
But *How to invest ?*

Deep need for a underpinning digital layer to experiment, measure, monitor and support data driven decision making.

AnthroKrishi

Digitizing agriculture for targeted data driven allocation of resources & services

Agriculture in India

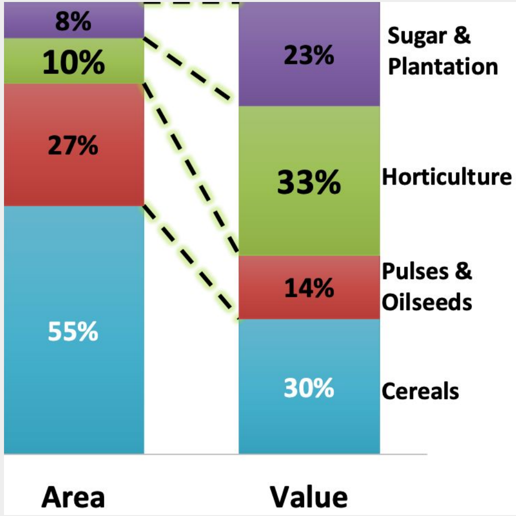
16%	43%	60%
Agriculture is only 16% of country's gross GDP	Agriculture employees 43% of the population	Groundwater is critically low in 60% of the districts (counties)

- Chronic low yields

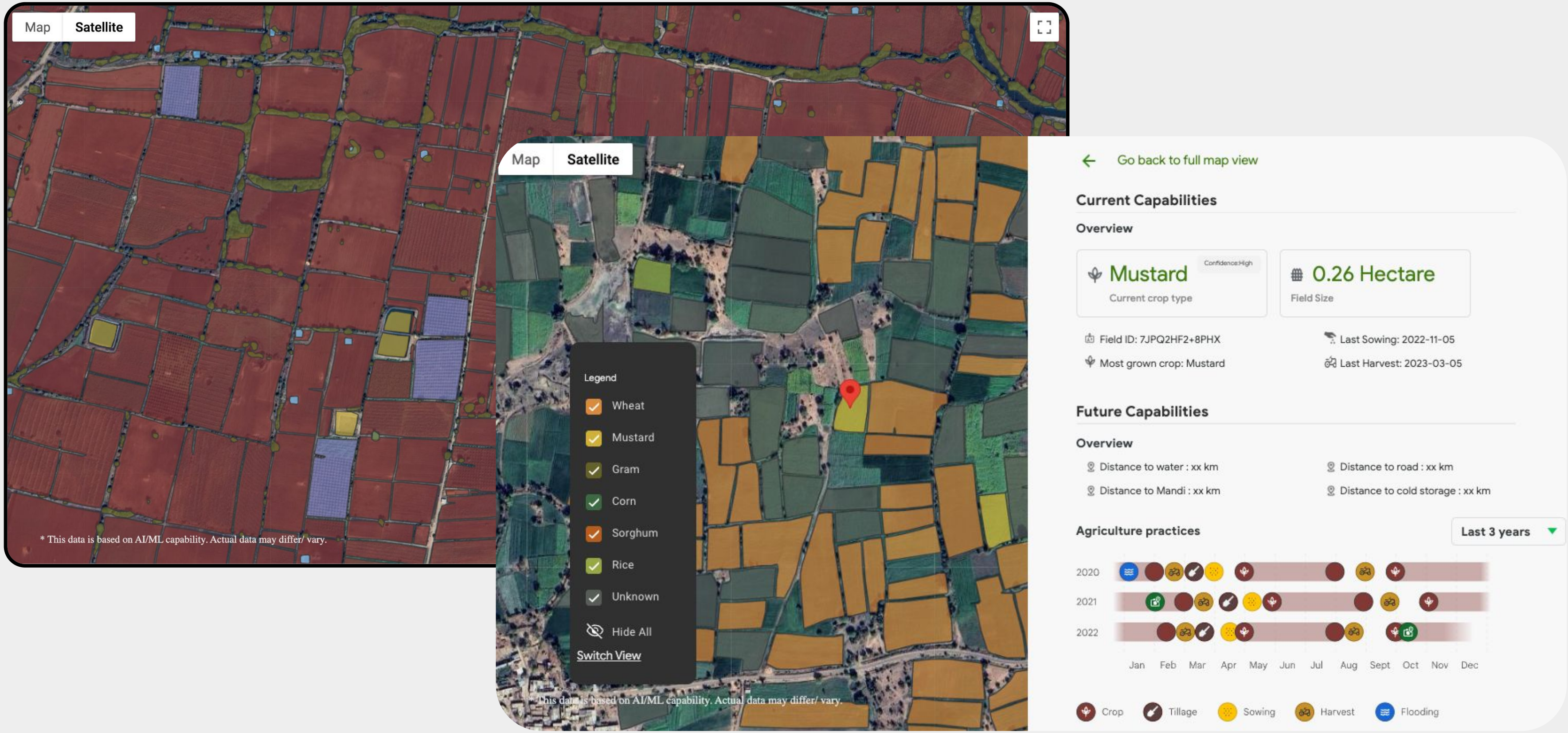
- 82% land ⇒ 44% value

- Solutions need to be COST EFFECTIVE and SIMPLE

- **Investments, Policy and Technology are hitting a transformational inflection point**



Commodity	Average yield (tonnes per hectare, 2017)	Most productive country (tonnes per hectare, 2017)	
Rice	3.85	9.82	Australia
Buffalo milk	2.00[74]	2.00[74]	India
Cow milk	1.2[74]	10.3[74]	Israel
Wheat	2.8	8.9	Netherlands
Cotton (Lint + Seeds)	1.6	4.6	Israel
Mangoes, guavas	6.3	40.6	Cape Verde
Fresh Vegetables	13.4	76.8	United States
Chicken meat	10.6	20.2	Cyprus
Potatoes	19.9	44.3	United States
Banana	37.8	59.3	Indonesia
Sugar cane	66	125	Peru
Maize	1.1	5.5	Nicaragua
Oranges			
Tomatoes	19.3	55.9	China
Chick peas	0.9	2.8	China
Okra	7.6	23.9	Israel
Soybeans	1.1	3.7	Turkey
Hen eggs	0.1[74]	0.42[74]	Japan
Cauliflower and Broccoli	0.138[74]	0.424[74]	Thailand
Onions	16.6	67.3	Ireland

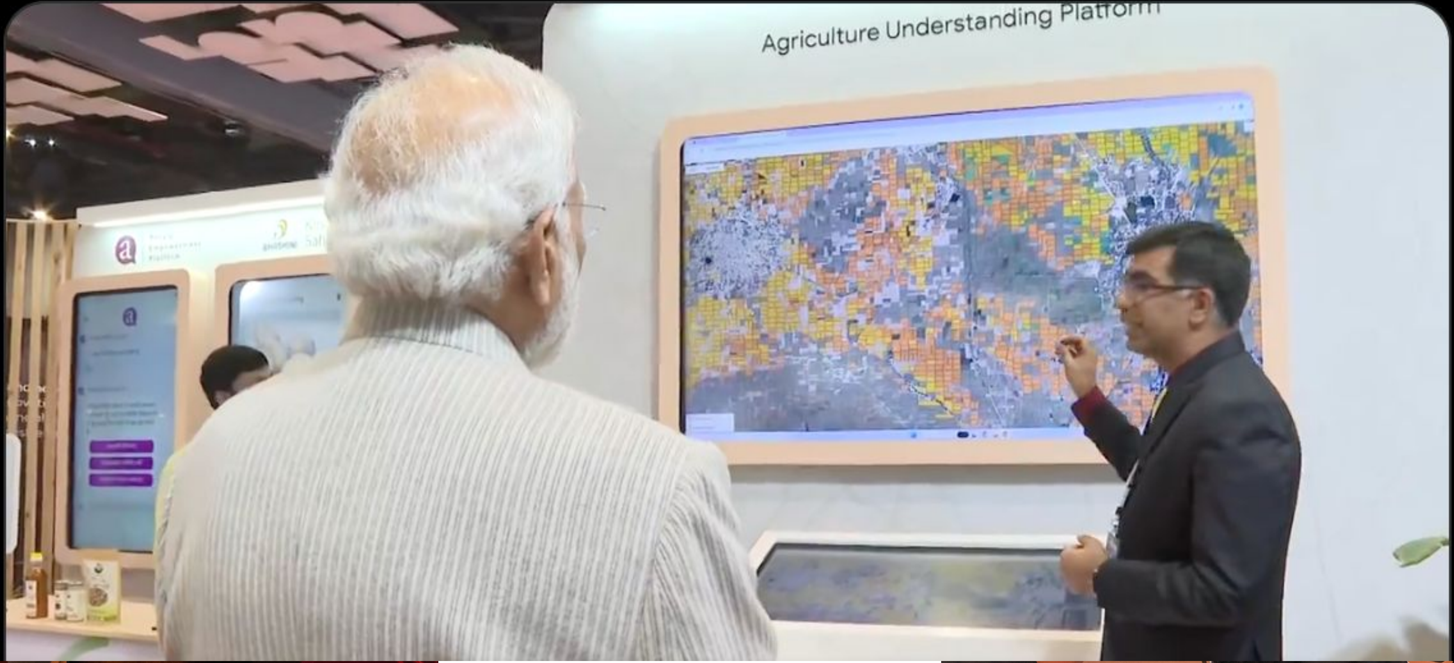


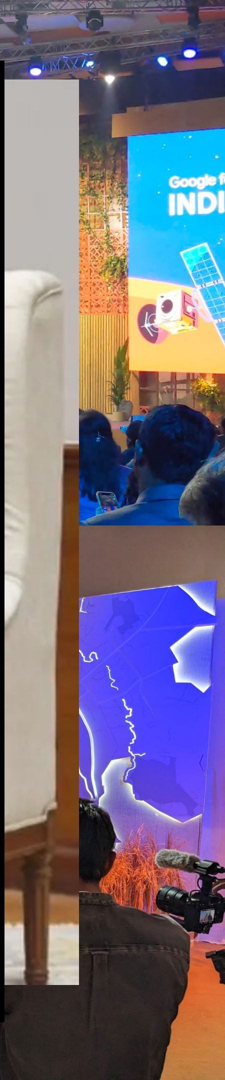
Brief - Organize the agricultural information at an individual farm field level

Demo

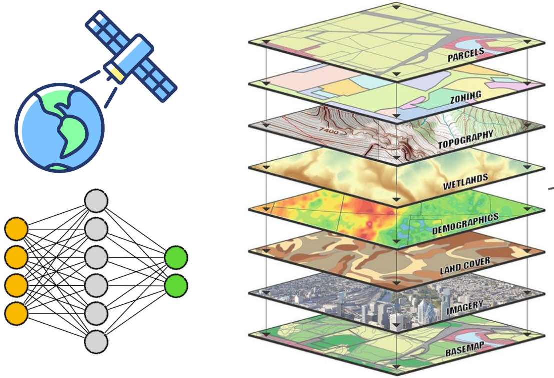
Narendra Modi
@narendramodi

Highlights from a memorable Global Partnership on Artificial Intelligence Summit, which reaffirms the importance of AI for a better planet.





Engagement model



Generate map layers using public and private overhead imagery, that is entirely PII free

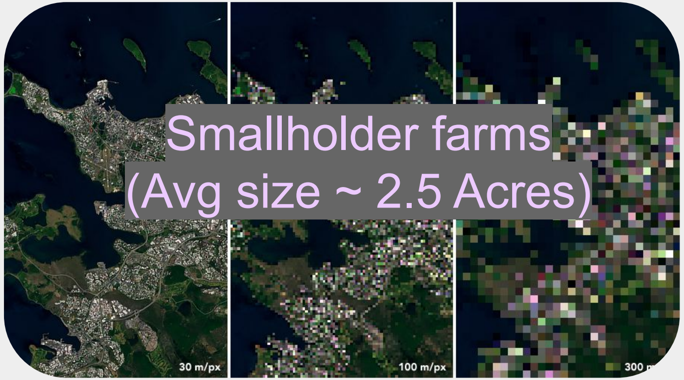
Govt appointed vendors validate and link Google's satellite derived field level insights with farmers.

Government can now target, track and monitor interventions, and be data driven in decision making


How was I gonna do it?

GeoFMs & Types of Earth Observation resolutions

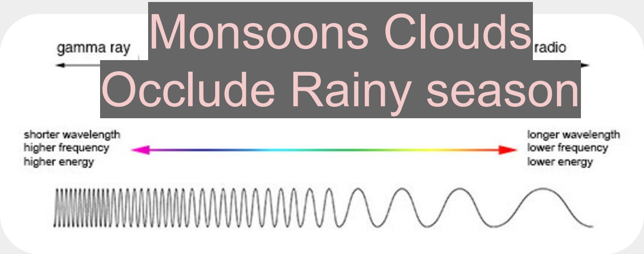
Spatial



Understanding & interpreting data across all of these resolutions is the core challenge for GeoFMs

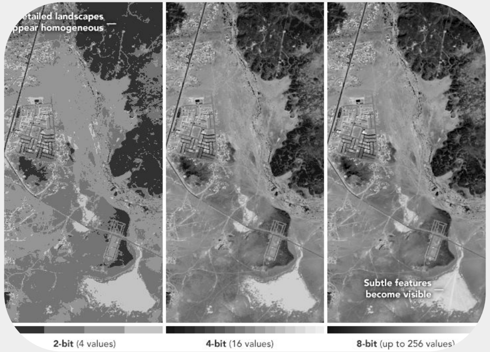
Temporal

Spectral



AnthroKrishi pushes on Spatial, Temporal and Spectral simultaneously.

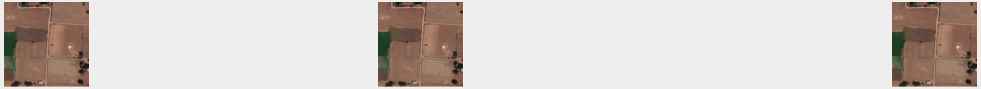
Radiometric



TIME

10m
Satellite
Weekly

30cm
Satellite
Annual



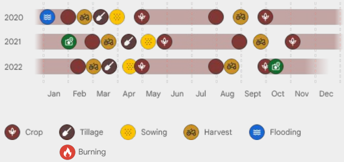
StreetView
Every 3 to 6
years

Weather
Continuous

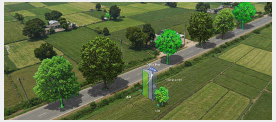
Modeling challenge: Heterogeneity in data modalities, resolution and frequency

Street View + Satellite (+ Weather?)

30x Super Resolution Segmentation (Latent Diffusion)
Multi Task (Segmentation & Crop Classification)



Event Detection



Tree Volume
(Carbon stock)
measurement

Yield Prediction

Classification

Segmentation

Key challenge

- Lack of large and public datasets
- Fragmented benchmarks and metrics

- Collect and clean labeled data
- Understand the domain, and create internal benchmarks for iterative improvement

These are common challenges for India and Global South!

Our Solutions

Agricultural Landscape Understanding [ALU]

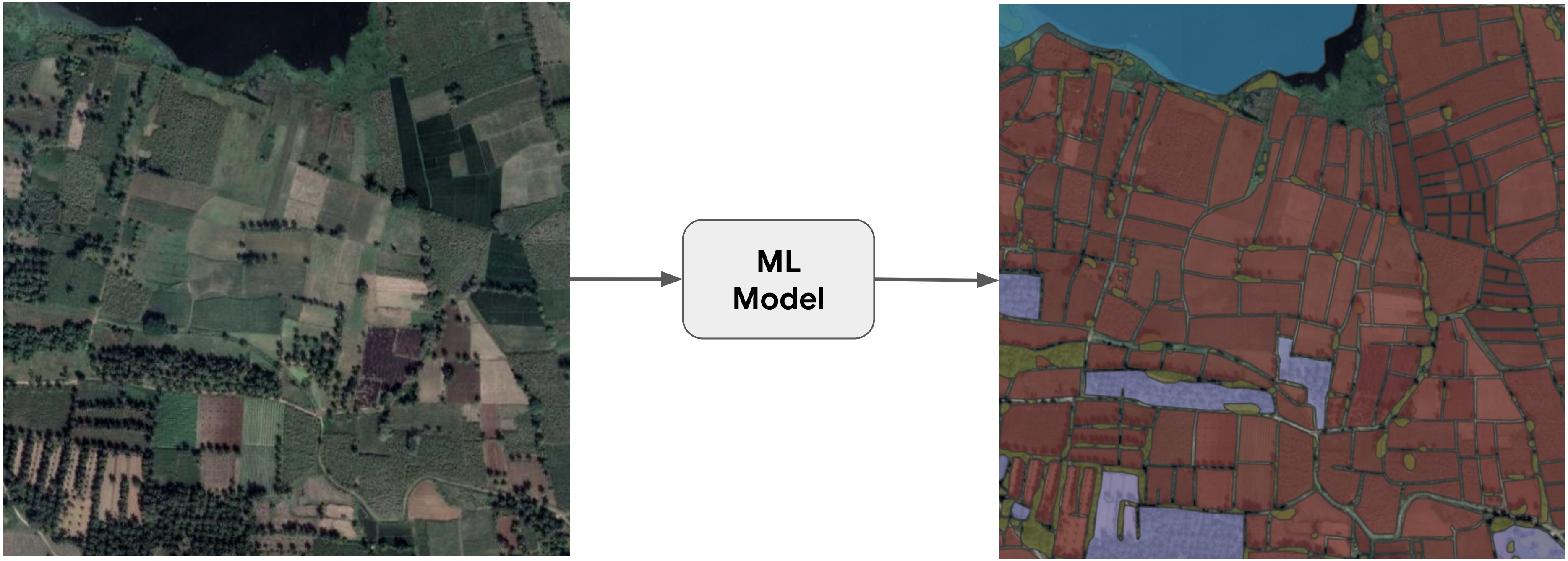
1. Panoptic Segmentation *High Res Sat Images → Fields, wells, ponds, trees...* API Launched	2. Superresolution for Segmentation *Low Res Sat + High Res Sat Reference → Field boundaries* New latent diffusion based model

Agricultural Monitoring and Event Detection [AMED]

3. Crop Type Classification *ALU + Low Res Sat → Crop Type* API to be launched soon	4. Satellite Super Cross Fusion *Low Res Sat + Street View (during training) → features for classification & other tasks* Model development ongoing

Data challenges .... Algorithmic challenges

Agricultural Landscape Understanding



Agricultural Landscape is complex

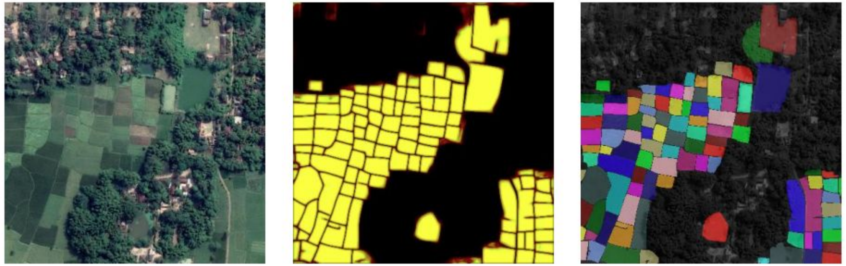
Digitizing landscape is fundamental to targeting

Agricultural Landscape Understanding

Problem

Delineate boundaries of multiple agricultural classes from Very High Resolution (VHR) Satellite Images

Panoptic Segmentation Problem



Given an input satellite image we generate multi-class semantic segmentation and instance segmentation for each layer

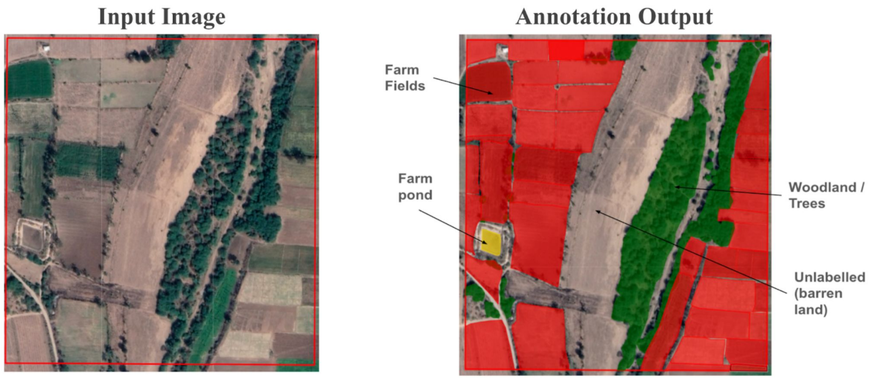
Challenges

- Insufficient labelled datasets
  - Unsuitable for smallholder farms
  - No labels for non-field classes

Layer	Classes
Ground	Fields, farm ponds, other water bodies
Well	Dug wells
Tree	Trees, woodlands
Cloud	Opaque, transparent cloud

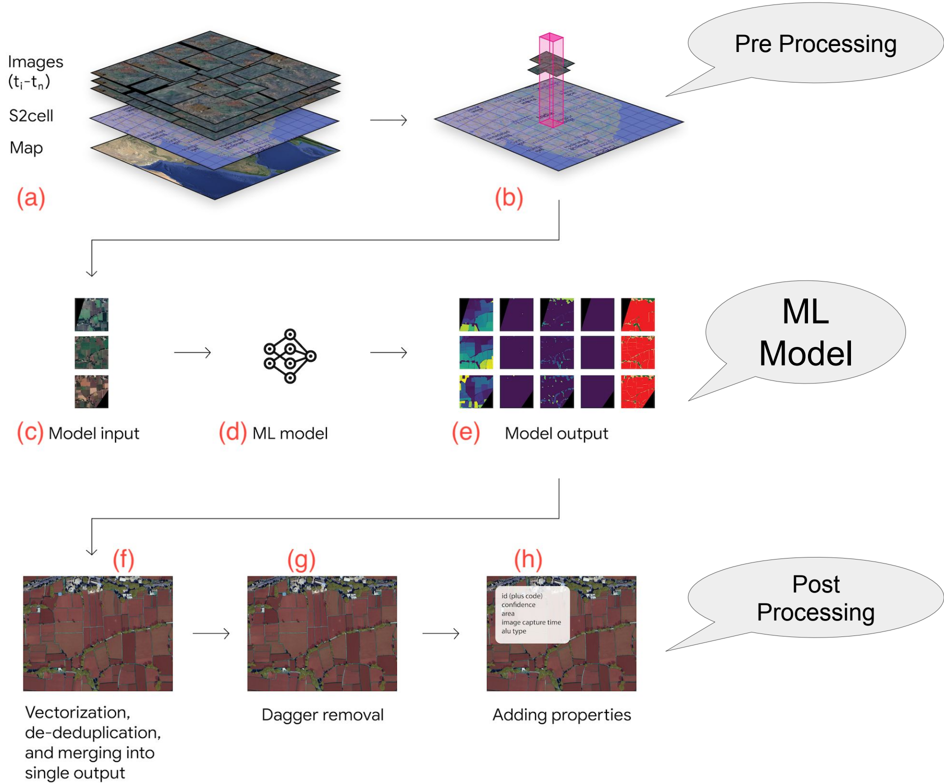
Agricultural Landscape Understanding (ALU)

High Quality Dataset Creation



Features	No. of Samples
Fields	105955
Ponds	456
Other water	1083
Trees	101825
Wells	332

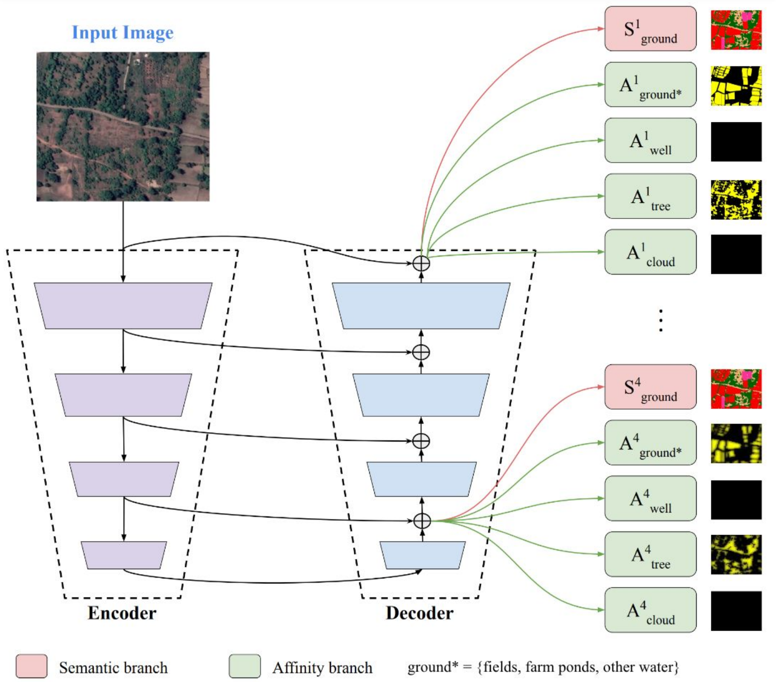
Complete ML System



Agricultural Landscape Understanding (ALU)

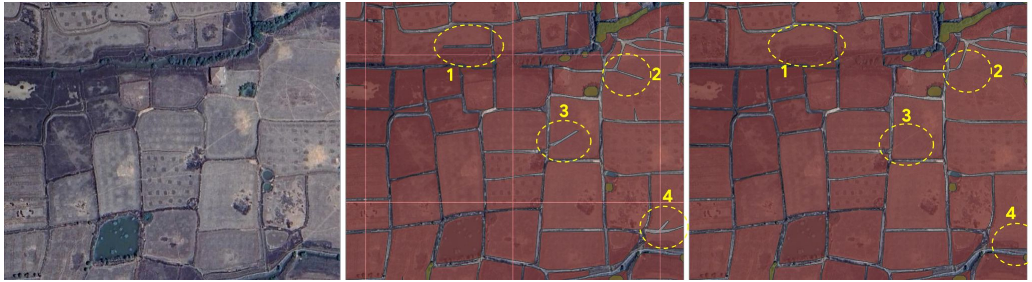
- U-Net based convolutional network which generates per-pixel semantic class and pixel-pair affinities in a single pass at multiple resolutions for all 4 instance layers
- Cascaded graph partitioning algorithm which uses these predictions to obtain instance segmentation

Our definition of layers models height-based distinction of agricultural features and models physical constraints and overlap



References: [SSAP]

Agricultural Landscape Understanding (ALU)

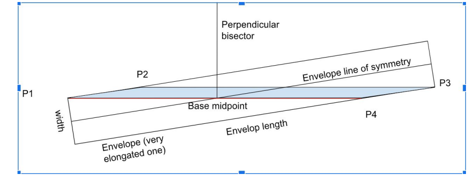


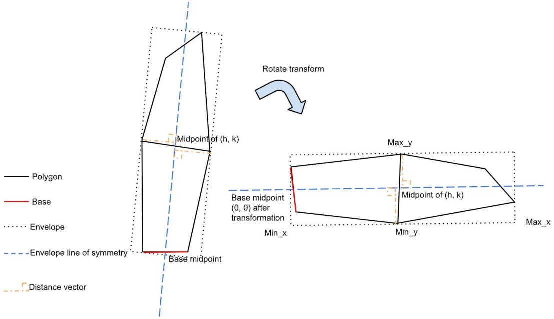
Multiple postprocessing steps to generate land-use maps from ML predicted masks

- Vectorization
- De-duplication
- Boundary refinement (e.g., dagger removal)
- Feature identification
- Spatial Indexing and Data Partitioning
- Identification and Exclusion of Non-Agricultural Areas

Dagger removal

- find a rectangular envelope of the dagger points
- use the length and width of the envelope to identify the elongated dagger-like shape

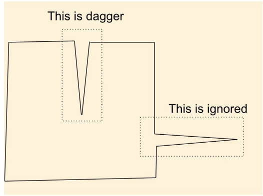


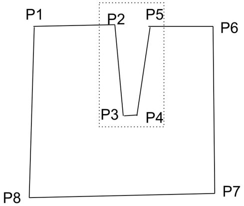


Agricultural Landscape Understanding (ALU)

Input: A Polygon with vertex sequence $P = \{p_1, p_2, ..., p_n\}$
Output: Polygon without daggers with vertices $P' \in P$
$\mathcal{H}$: Convex Hull of P
$Q = \mathcal{H} \cup P$; `// Points in P which are on the hull`
for *each pair* $(q_i, q_j) \in Q \times Q$ **do**
  if $(q_i, q_j \in P)$ *and* $isDagger(q_i, q_j, P)$ **then**
    $P \leftarrow \text{removeDagger}(q_i, q_j, P)$;
  end
end
return P

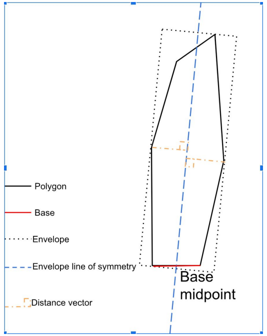
Algorithm 3: Dagger Removal

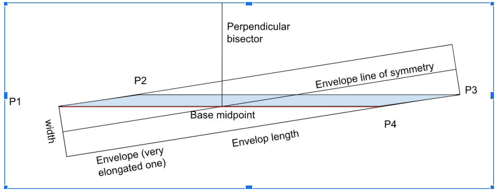


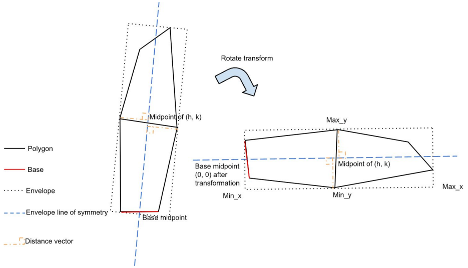


Input: Polygon P, Points $q_i, q_j \in P$, Dagger Threshold d_t,
Angle Threshold a_t
Output: True, if (q_i, q_j) is base of a dagger; False, otherwise.
Find the midpoints m_b of the base edge (q_i, q_j)
for *all pairs* $(q_h, q_k) | h \neq i \neq j \neq k$ **do**
  Find midpoint m_t of line segment (q_h, q_k)
  Calculate vector $V = m_t - m_b$
  `// Consider vectors with angles which are not too steep`
  if *angle between* V *and base edge* $(q_i, q_j) < a_t$ **then**
    `// Rotate` Q_l `around` M_b `using vector` V
    $T_l \leftarrow \text{Rotate}(Q_l, V, M_b)$
    `// Calculate minimum rectangle envelope`
    $R \leftarrow \text{MinimumRectangleEnvelope}([T_i..T_j])$
    Cond1: $abs(\min_y R) \approx abs(\max_y R)$
    Elength = $max_x R - min_x R$
    Ewidth = $max_y R - min_y R$
    Criterion: Elength / (max(Ewidth, Base length)
    if *Cond1 and Criterion* $> d_t$ **then**
      return True
    end
  end
end
return False

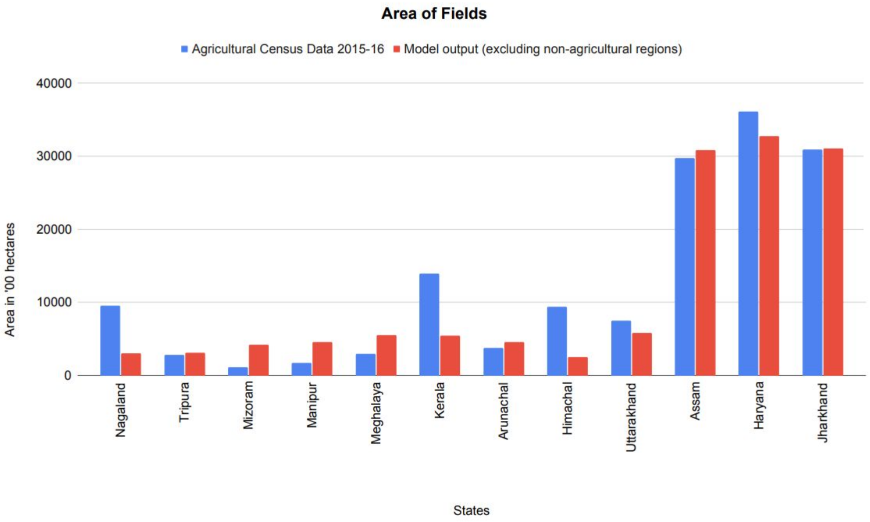
Algorithm 4: Algorithm isDagger: checks if the the set of points considered, with q_i, q_j as base points, forms a dagger

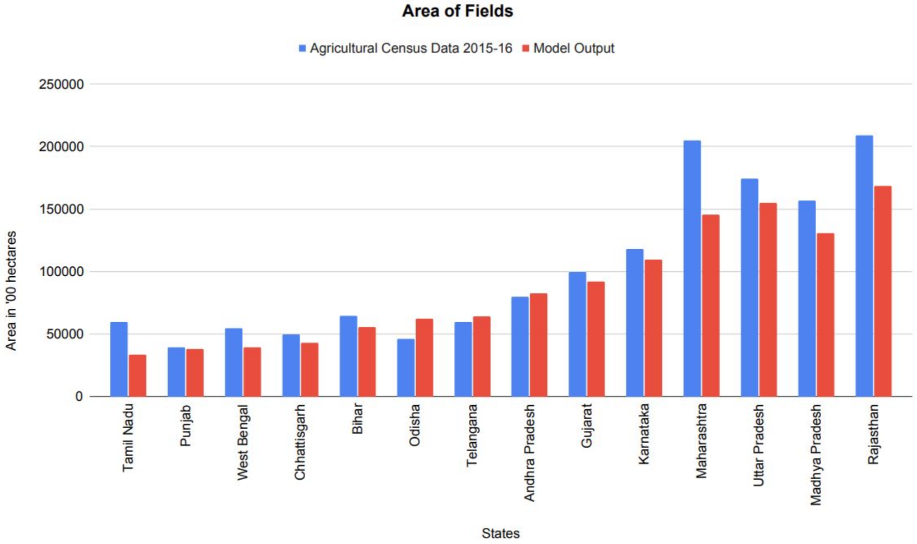






ALU: Large-Scale Evaluation Against Census





Google DeepMind

ALU API Launched 2024 Q4

agri.withgoogle.com

- **Option 1: Specify by a S2Cell ID (level 13) directly.**

Request S2cell ID

Response: Landscape feature (red)

- **Option 2: Specify by a coordinate point (latitude and longitude)**

Request Altitude and longitude

S2Cell ID of the request coordinate

Response: Landscape feature (red)

Feature Property	Type	Description
id	string	A feature ID, represented by the plus code of the centroid of the feature. https://plus.codes
properties.alu_type	enum	Represents the type of feature. List of enum values • field • farm_pond • other_water • dug_well • trees
properties.area_sq_m	float64	Represents the area of feature in square meters.
properties.class_confidence	float64	Represents the confidence in the accuracy of the classification.
properties.capture_timestamp_usec	unit64	Represents the capture timestamp in microseconds for the observation's source image.

Policy & ALU

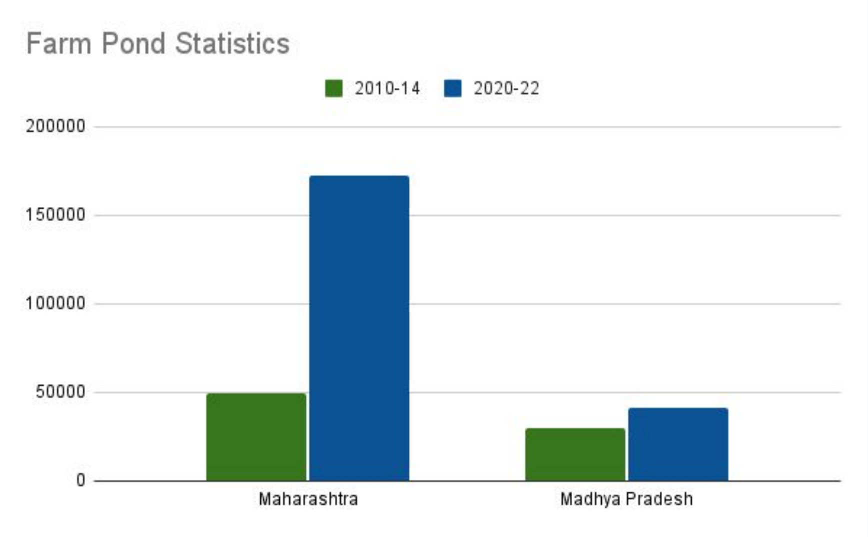
ALU: a tool to study spatio-temporal trends at high resolution across India

Spatio-temporal trends in ALU features can potentially help in quantifying the effects of policy changes (work in progress)

Policy Driven Growth In Water Infrastructure By SmallHolder Farmers

Right: Increase in farm ponds seen across 2 comparable states, before and after a policy reform incentivizing farm ponds in one of them.

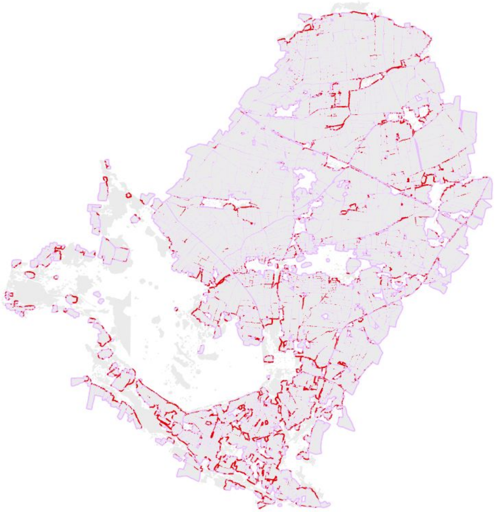
Farm Ponds



Trees Along Farms (TAF)

Initial pan-India Metrics (per our model):

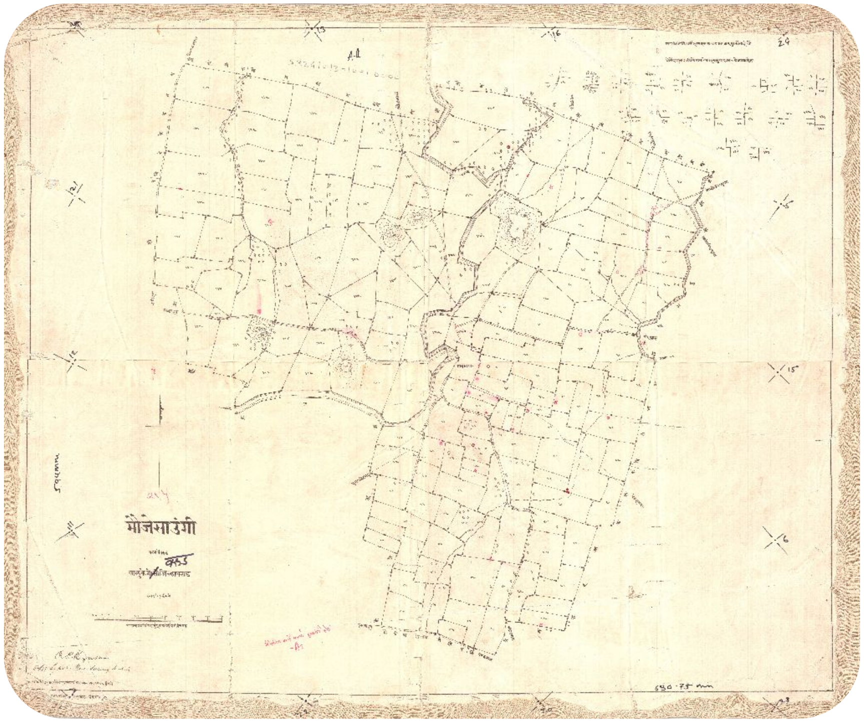
- Current Trees Cover: 57K sq km (~ Croatia)
- Potential Afforestation: 402K sq km (~ Germany)



Cadastral Mapping - Modernizing Land Records

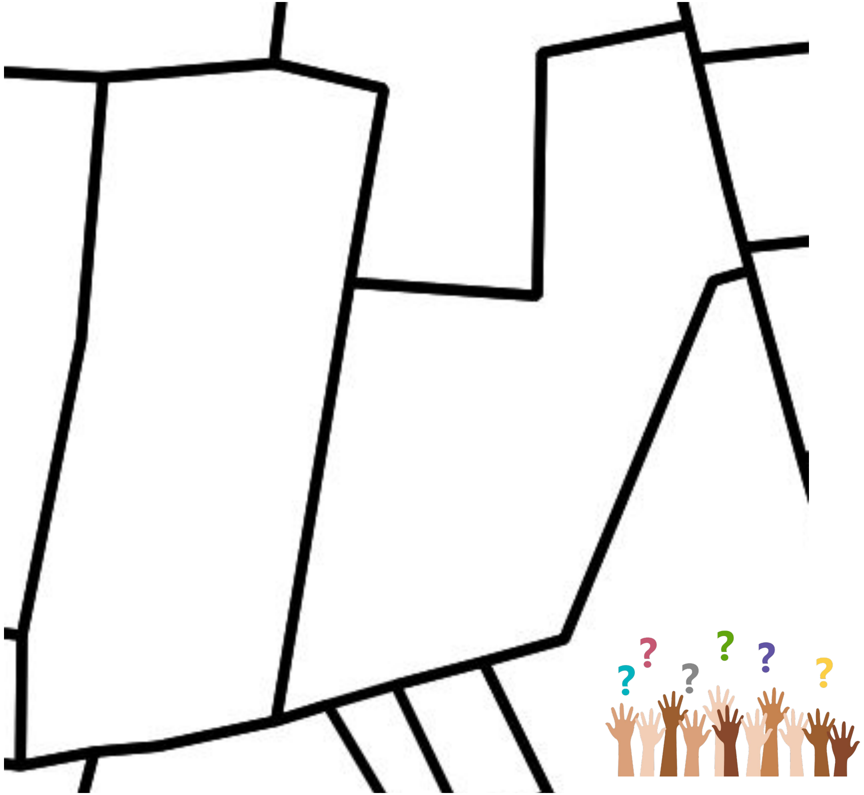
A long time ago, in a galaxy far away... there were paper maps

They were scanned and vectorized into GIS geometries (using ALU boundaries)



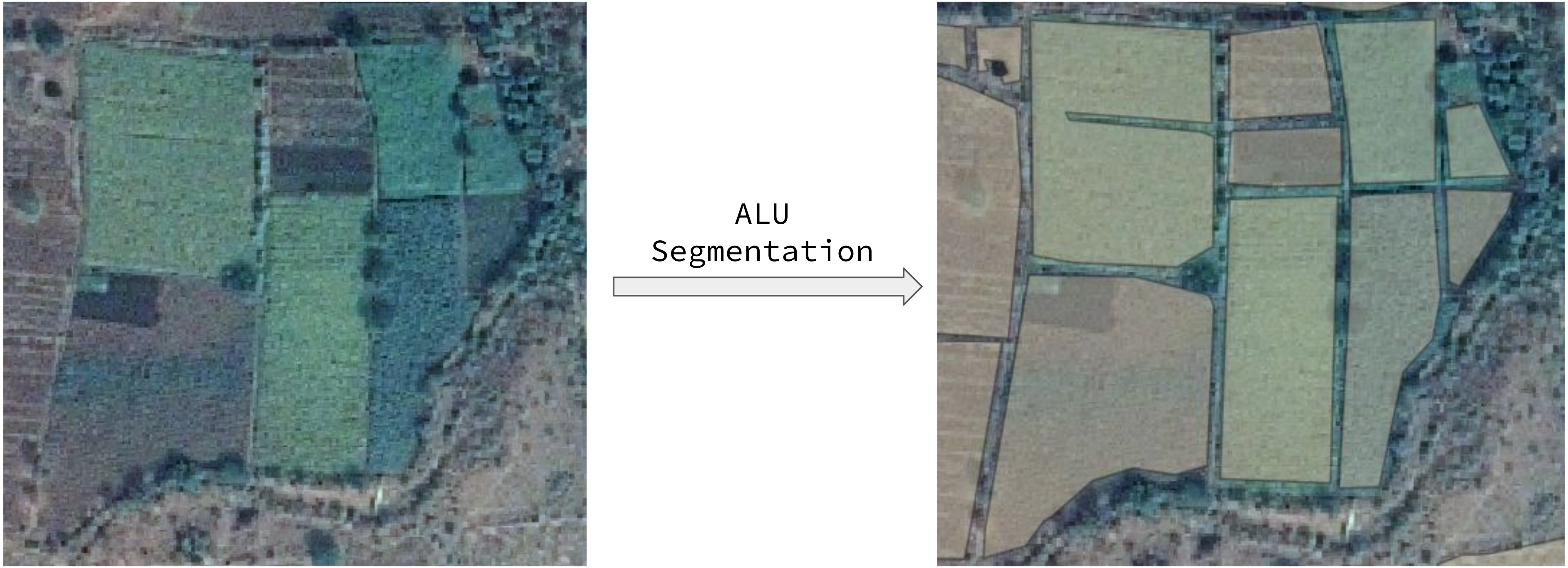
In collaboration with IIT Bombay

Overlaying the digitized maps on modern satellite images found a persistent mismatch of over 50m: across **40k+** villages, over **300,000 sq. km** in MH alone!



A scanned village map

Overlaid on satellite post geo-referencing



Satellite images cannot be processed simply, but **segmented farm plots** are substantially easier! An image processing problem becomes geometric and discrete.

A Mathematical Formulation

Inputs

Space partition S (original map)

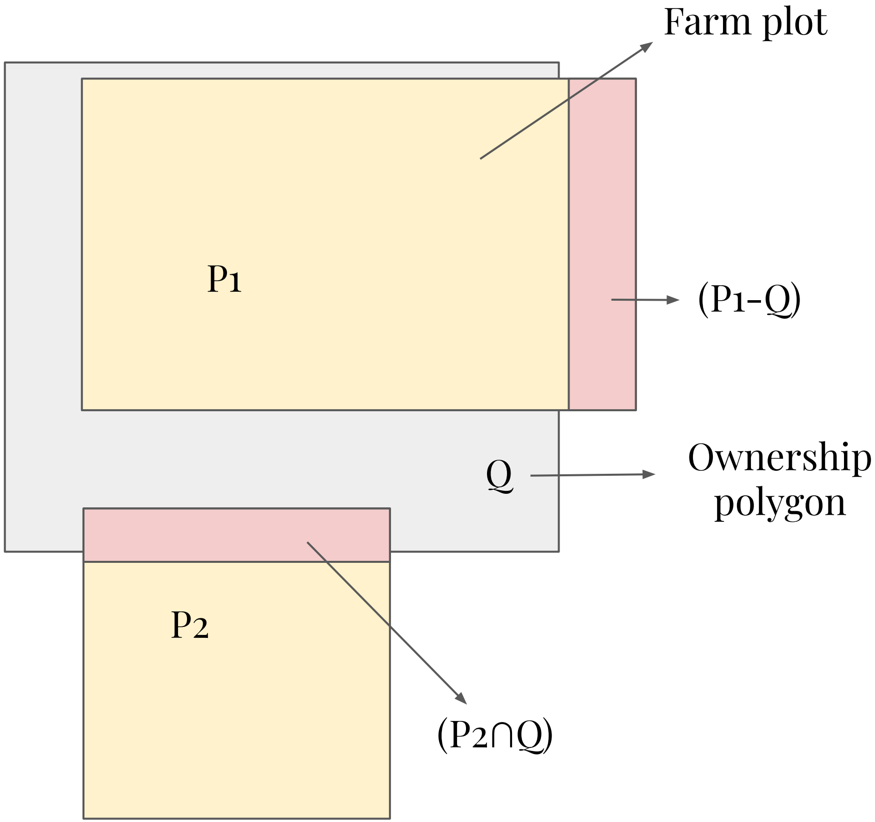
Ground reality layer of farm polygons G

Minimize **excess area** of S relative to G

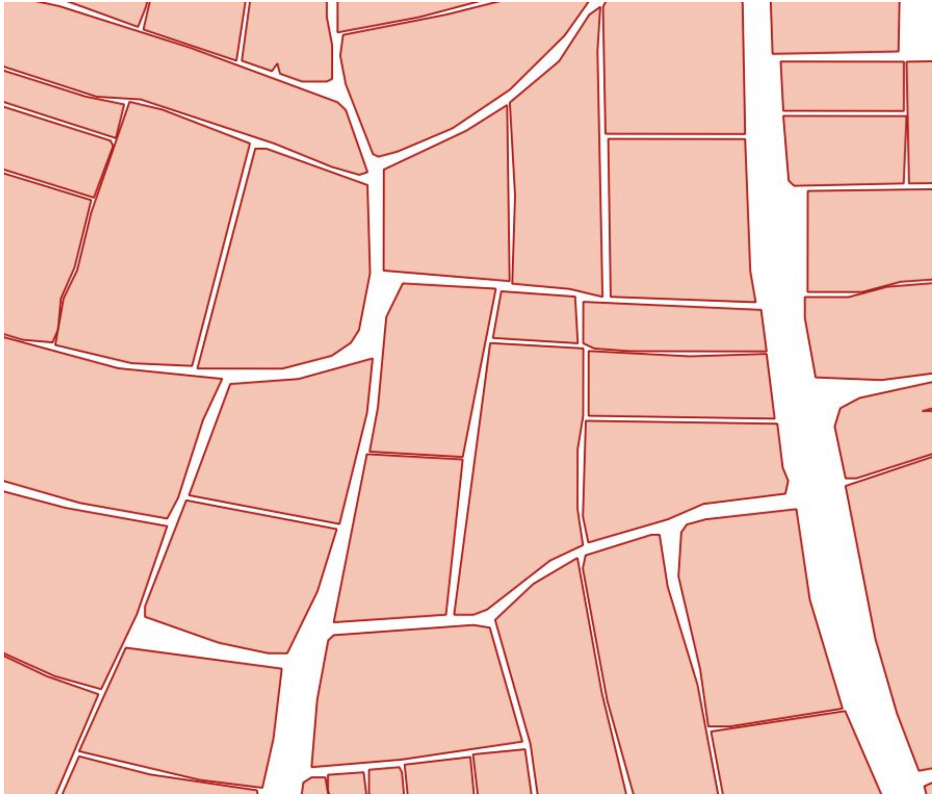
Ensure area and shape deviation is below a certain threshold

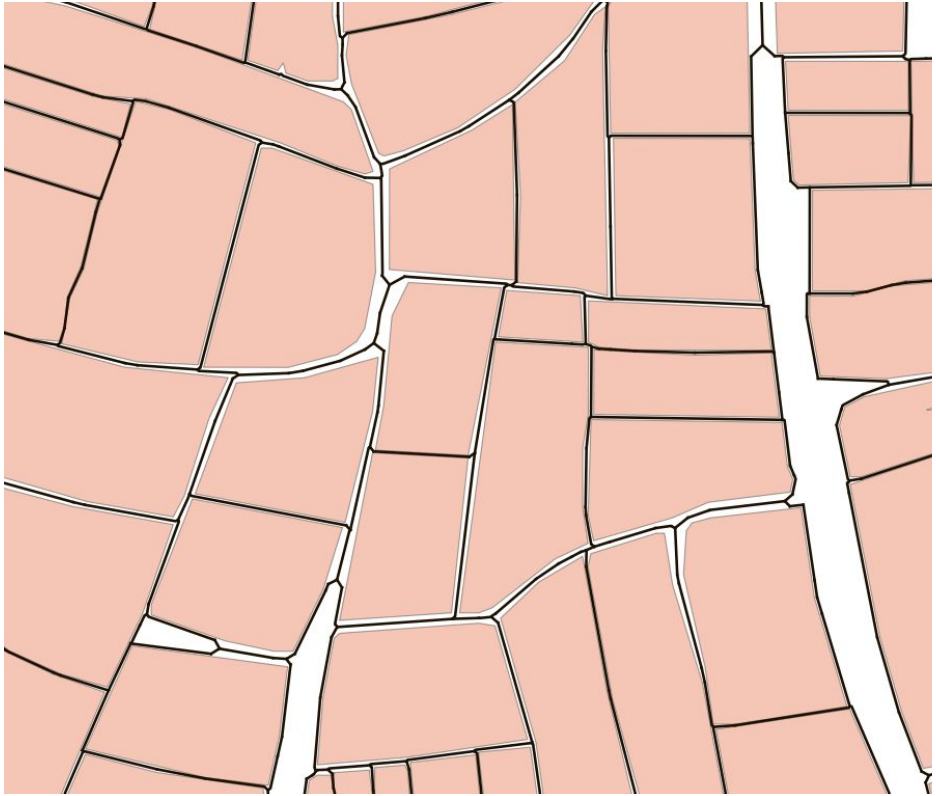
Output

A space partition S' (modified map) with transformed sets of nodes and edges

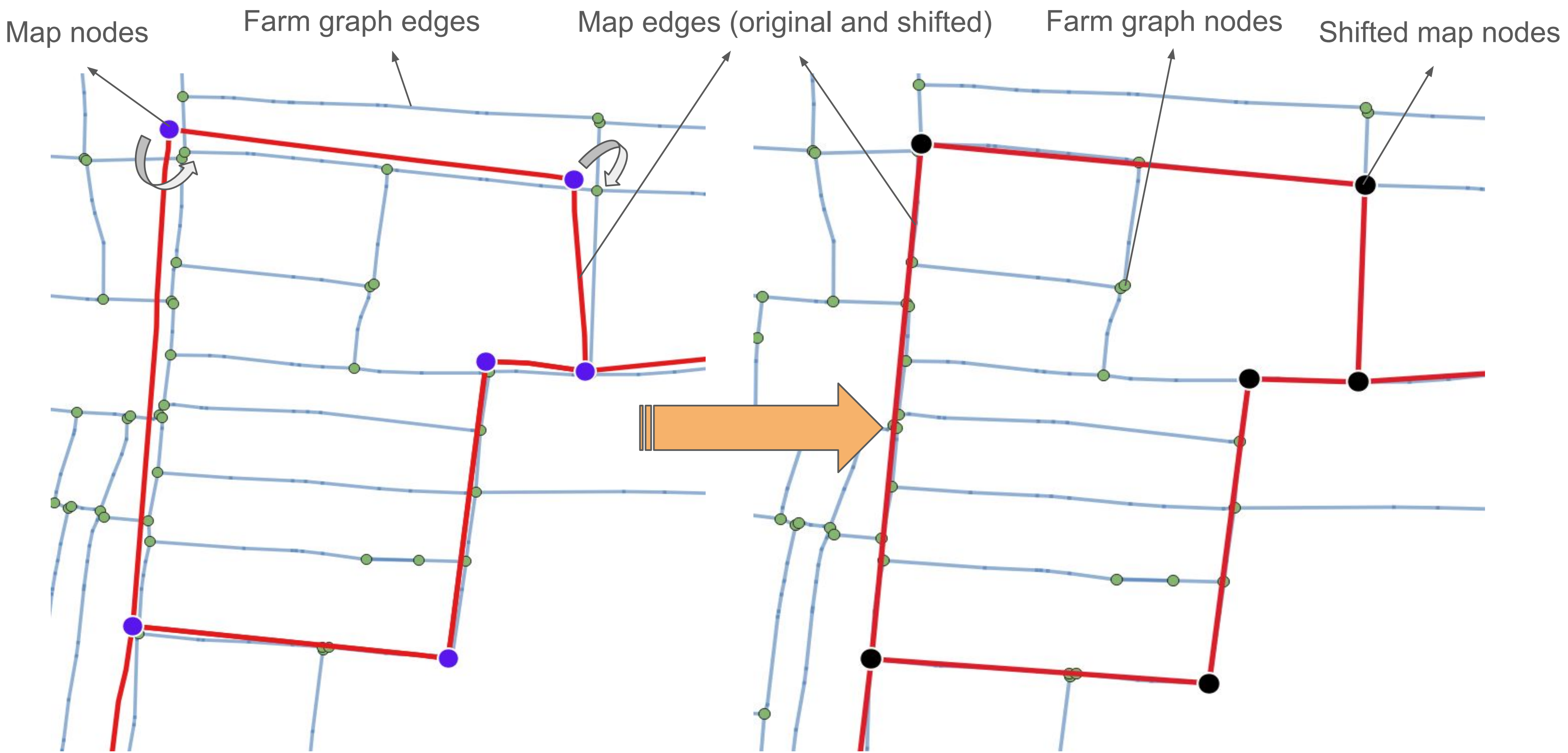


$$\text{Excess Area}(Q) = \sum_{P} \min\{P-Q,\ P\cap Q\}$$

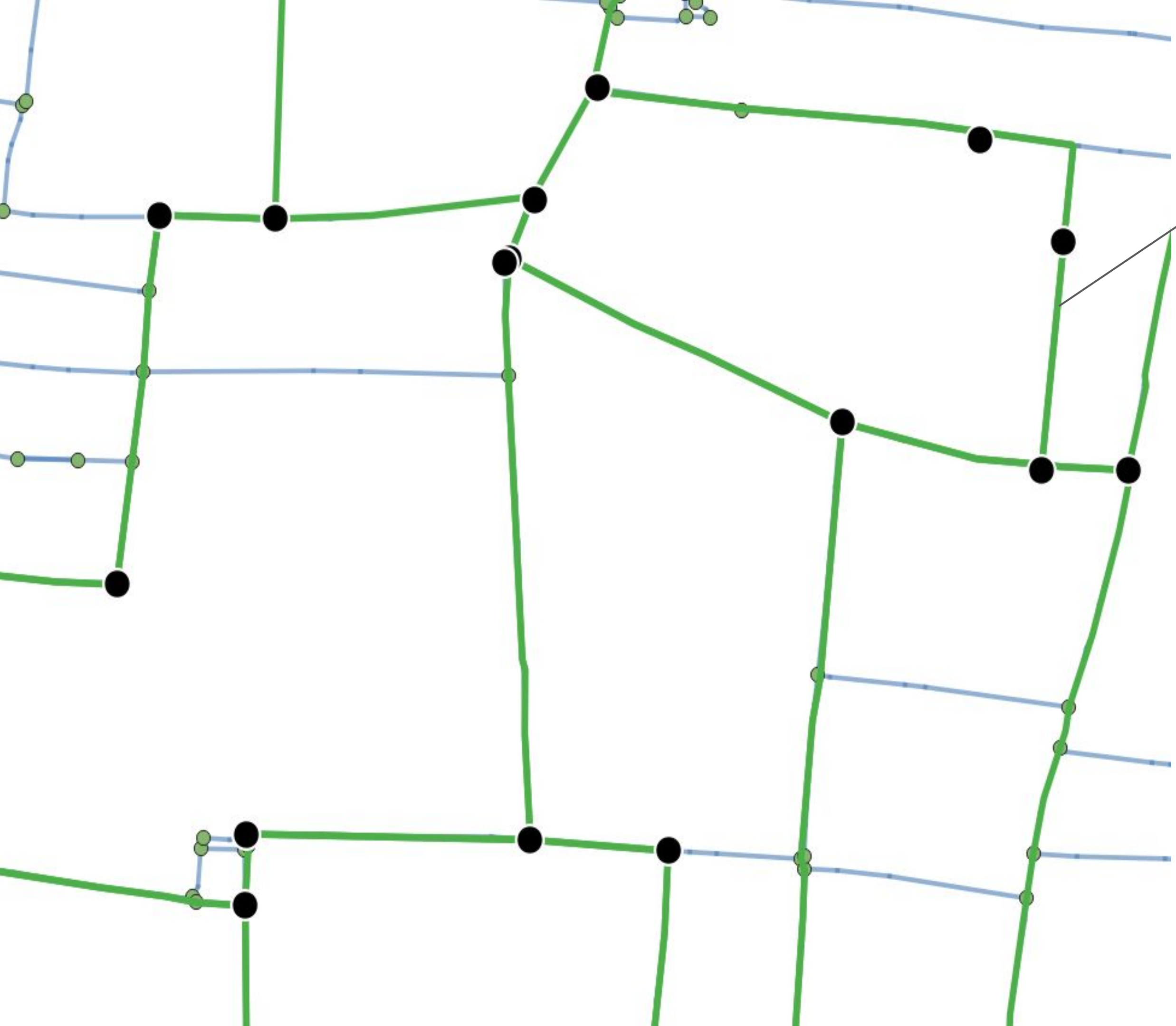




To precisely align our modified map with farm boundaries: to do this, we must first create a **Voronoi partition** on the segmented satellite image to create a planar farm graph.



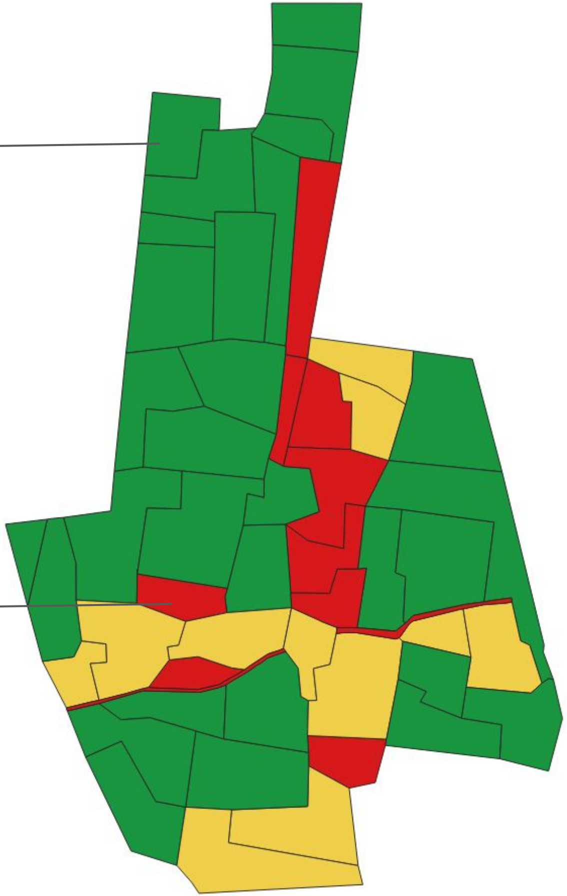
The ownership map is processed polygon-by-polygon, with each polygon's available nodes being **latched** onto the farm graph.



Map edges that “hug” the farm boundary

Finally, the **possession boundary** is created by tracing farm edges: the intended effect is to assign each farm an owner!

Green:
under 4%
deviation



Red:
above 6%
deviation

A pilot village: coloured by quality

Black: points
measured on
the field

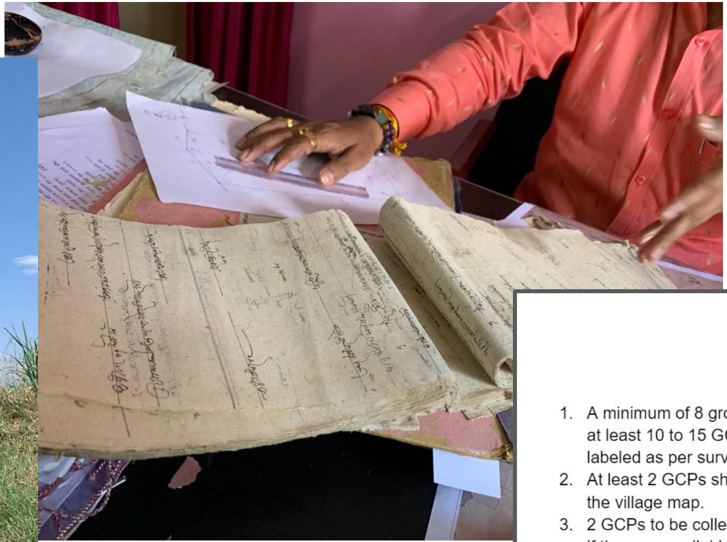
Red:
proposed
map

Avg. error: 2.2m

Village	Number of survey plots	% of survey numbers with over 95% farm rating	% of survey numbers within 5% of geo-referenced area, perimeter and deviation
matargaon	41	58.33	61.11
deolanakh	41	50.00	47.22
dagdagad	52	83.67	63.27
kharburdi	59	50.00	47.50
gopa	78	76.00	45.33

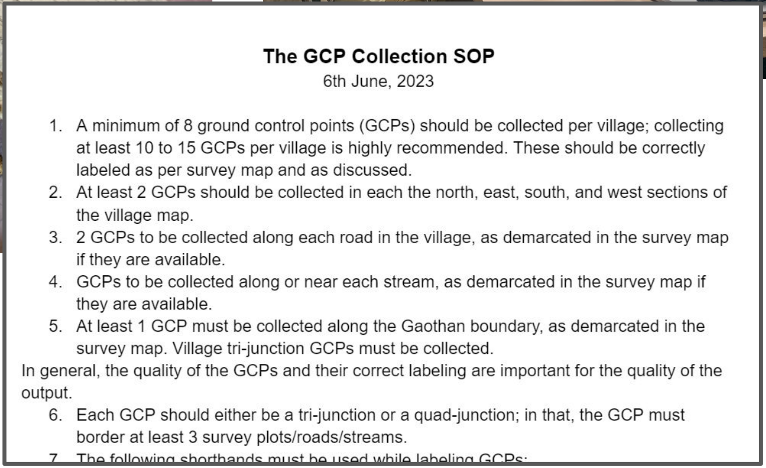
Results on pilot villages: over **45%** of plots consistently match all constraints!

Validating Outputs: Field Validation



Field visits

Drafting field SOPs



The GCP Collection SOP

6th June, 2023

1. A minimum of 8 ground control points (GCPs) should be collected per village; collecting at least 10 to 15 GCPs per village is highly recommended. These should be correctly labeled as per survey map and as discussed.
2. At least 2 GCPs should be collected in each the north, east, south, and west sections of the village map.
3. 2 GCPs to be collected along each road in the village, as demarcated in the survey map if they are available.
4. GCPs to be collected along or near each stream, as demarcated in the survey map if they are available.
5. At least 1 GCP must be collected along the Gaothan boundary, as demarcated in the survey map. Village tri-junction GCPs must be collected.

In general, the quality of the GCPs and their correct labeling are important for the quality of the output.

6. Each GCP should either be a tri-junction or a quad-junction; in that, the GCP must border at least 3 survey plots/roads/streams.
7. The following shorthands must be used while labeling GCPs:

Our Solutions

Agricultural Landscape Understanding [ALU]

1. Panoptic Segmentation *High Res Sat Images → Fields, wells, ponds, trees...* API Launched	2. Superresolution for Segmentation *Low Res Sat + High Res Sat Reference → Field boundaries* New latent diffusion based model

Agricultural Monitoring and Event Detection [AMED]

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Data challenges …………….. Algorithmic challenges

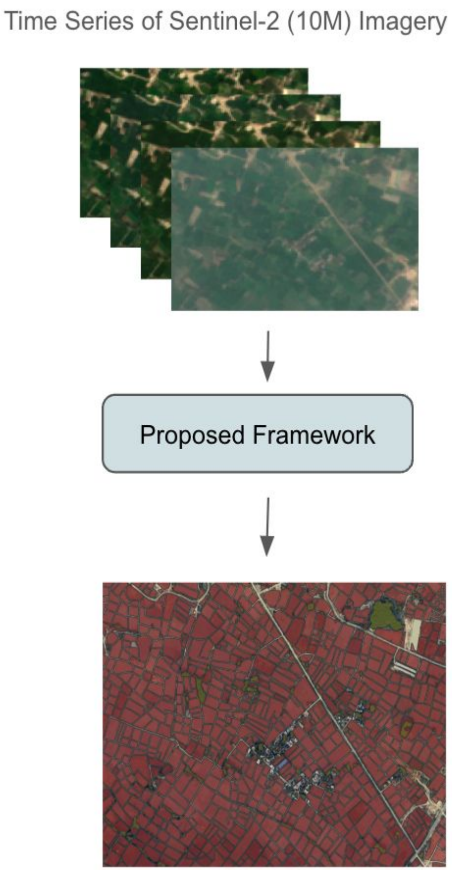
Global expansion & In-season freshness

HighRes imagery refresh rate does not match rate required to provide in-season model outputs.

Public high temporal resolution **(weekly) Sentinel-2 data** to get **near real time field boundaries** at with **submeter level accuracy**.

In India's smallholder farming systems, field boundaries are highly dynamic, changing seasonally.

SUPER RESOLUTION



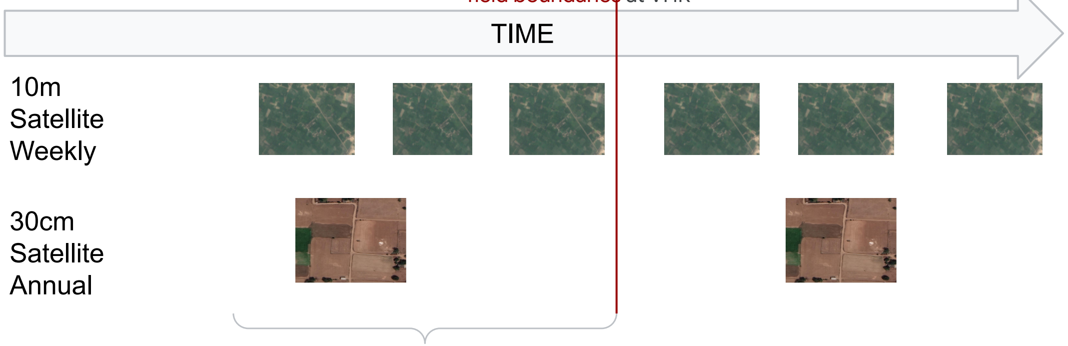
Super Resolution for Segmentation

Problem

Inputs:
(1) a sequence of multi-temporal, multi-spectral, multi-source LR images
(2) an older VHR Reference Image

Desired Output:
Segmentation mask delineating field boundaries at VHR

Desired Output:
Segmentation mask
delineating
field boundaries at VHR



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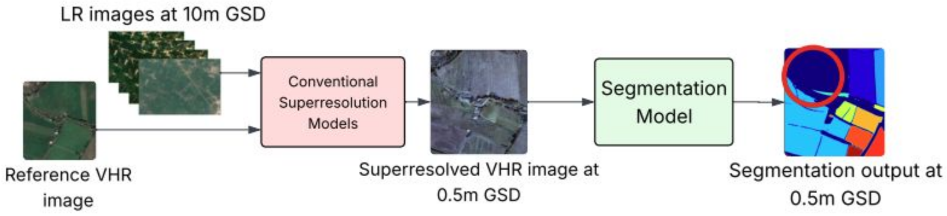
Why do current methods fail?

Previous approaches mainly follow the paradigm of
- Super-resolution in the pixel space, followed by
- Segmentation on the super-resolved image

Limitations:
- Low scale factor (< 16x) super-resolution
- Inadequate to reveal crucial features for field boundaries



Google DeepMind

SEED-SR: Segmentation Embedding Enhancement via Diffusion - for Super Resolution

Problem

Inputs:
(1) a sequence of multi-temporal, multi-spectral, multi-source LR images
(2) an older VHR Reference Image

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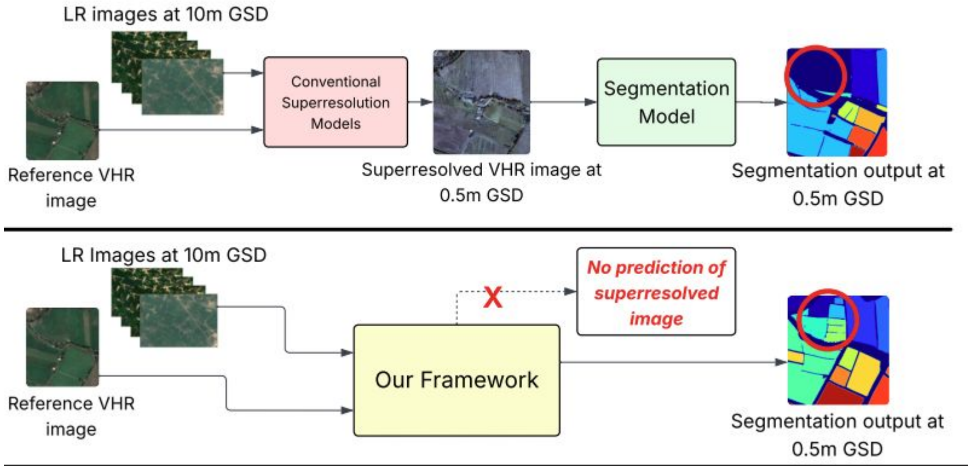


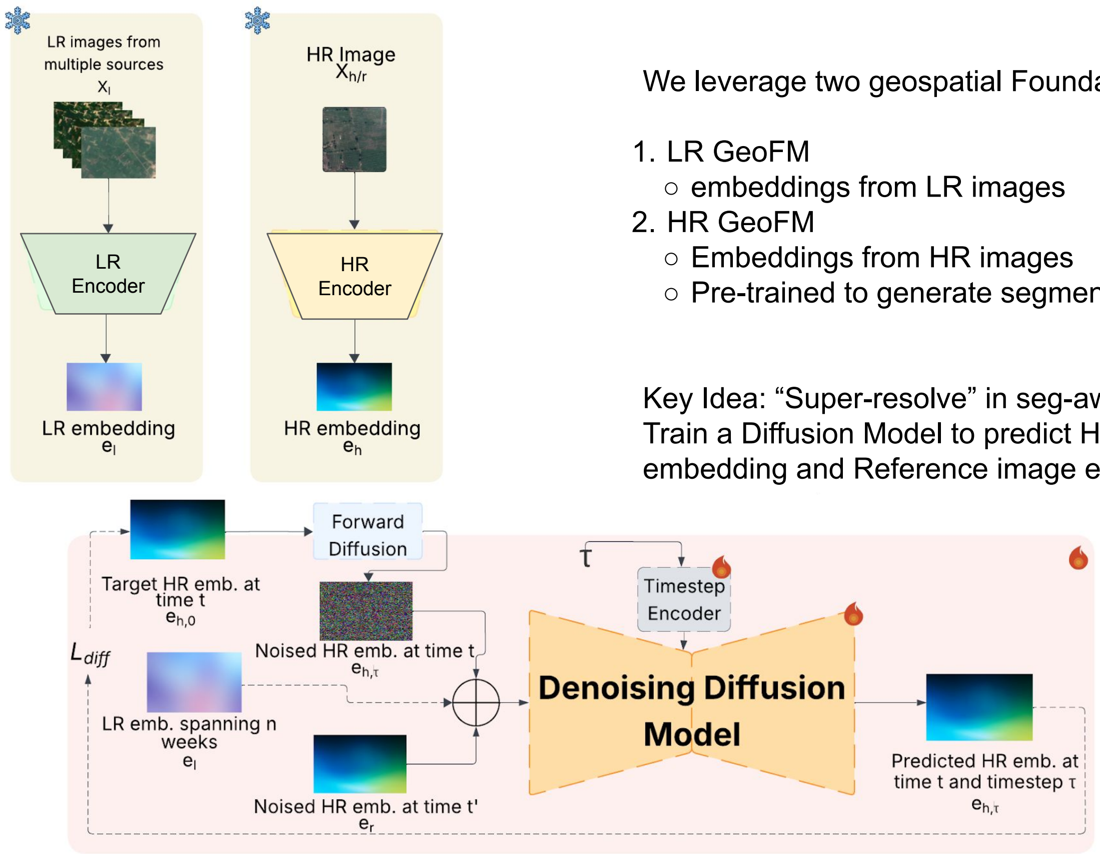
Our Contributions

- We develop a task-specific, super-resolution method to generate VHR segmentation maps (at 50cm GSD), at **20x** super-resolution.
- SEED-SR showcases a unique way to leverage multiple pre-trained large-scale geo-spatial foundation models with latent diffusion models.

Google DeepMind

Submitted to NeurIPS 2025

SEED-SR: Segmentation Embedding Enhancement via Diffusion - for Super Resolution



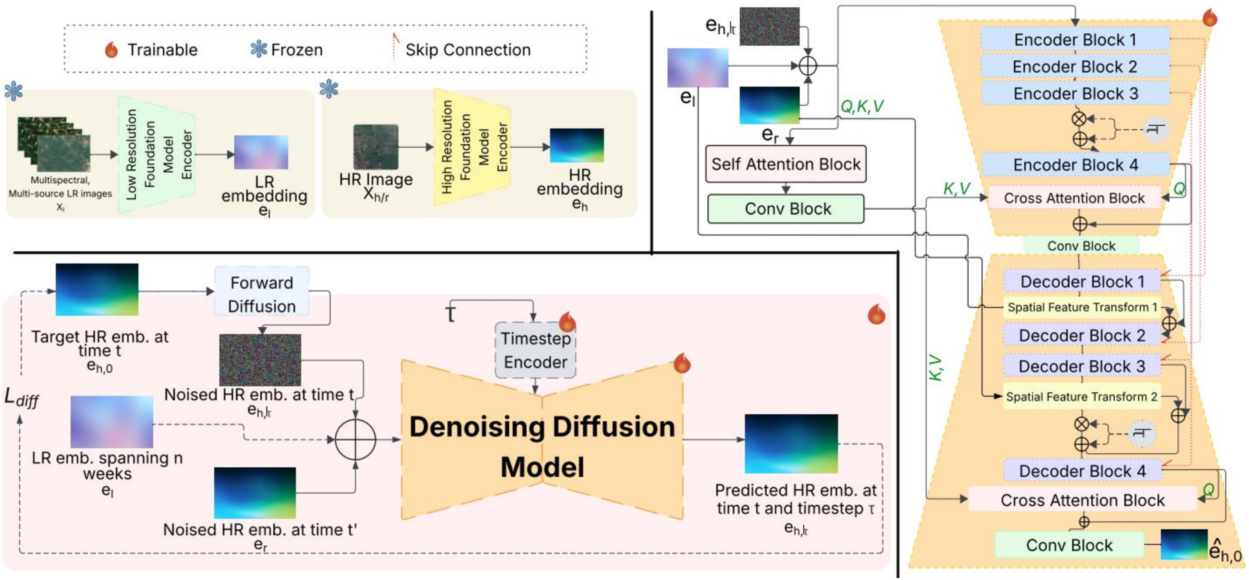
We leverage two geospatial Foundation Models:

1. LR GeoFM
   - embeddings from LR images
2. HR GeoFM
   - Embeddings from HR images
   - Pre-trained to generate segmentation maps

Key Idea: “Super-resolve” in seg-aware latent space
Train a Diffusion Model to predict HR embedding from LR embedding and Reference image embedding

Google DeepMind

SEED-SR: Segmentation Embedding Enhancement via Diffusion - for Super Resolution

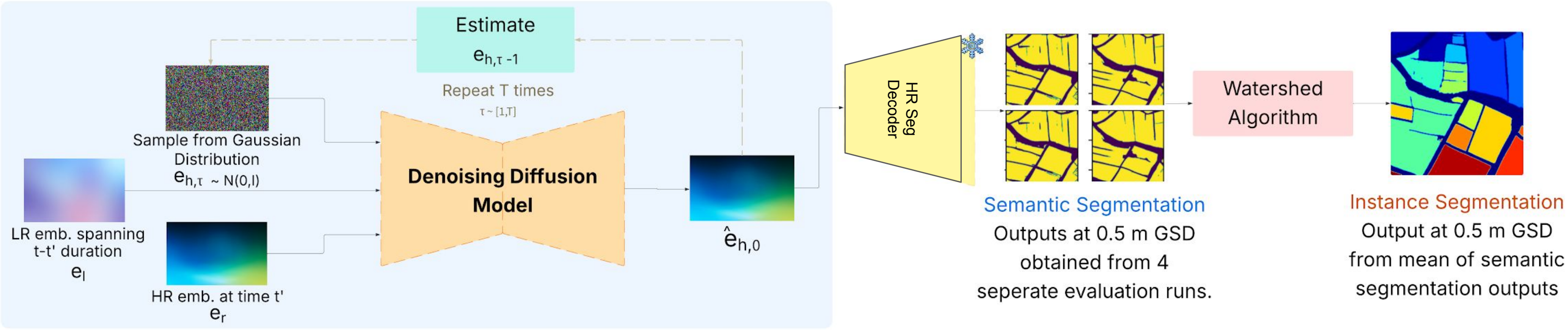


Training

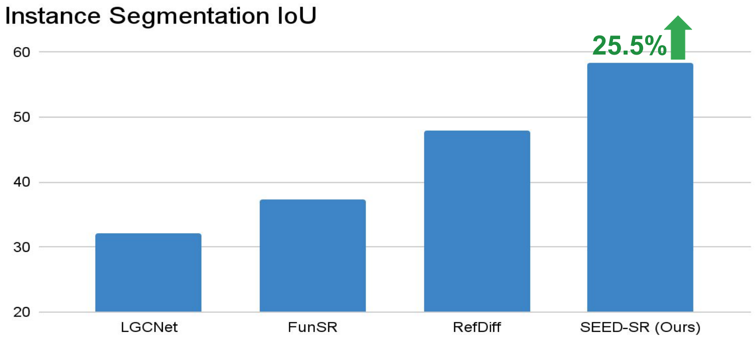
HR FM embeddings are very high-dimensional (120,120,3840) which makes diffusion challenging

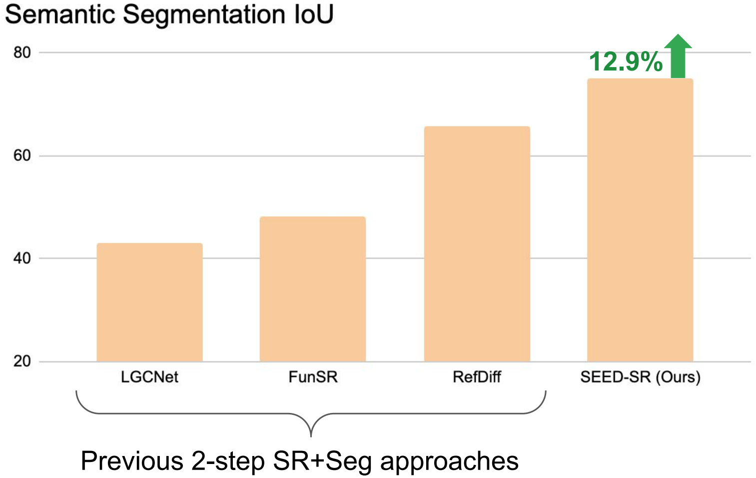
Our architectural innovations in the UNet within DDPM allow the dIffusion process to yield information-rich embeddings

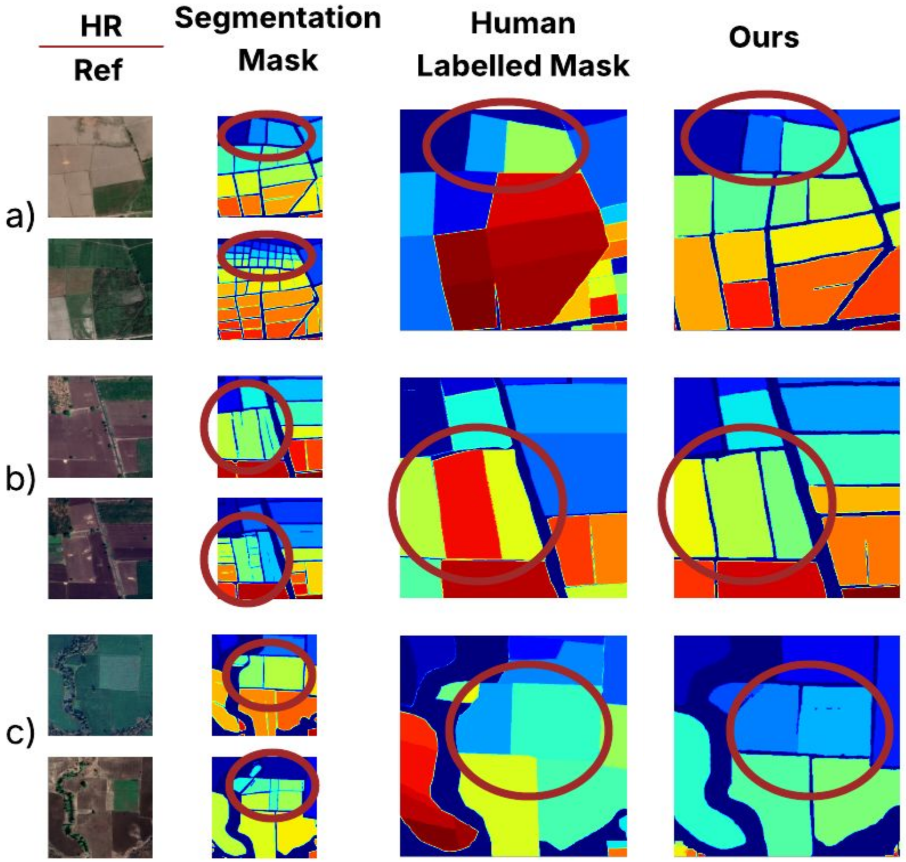
SEED-SR: Segmentation Embedding Enhancement via Diffusion - for Super Resolution



Inference







References: LGCNet FunSR ,RefDiff

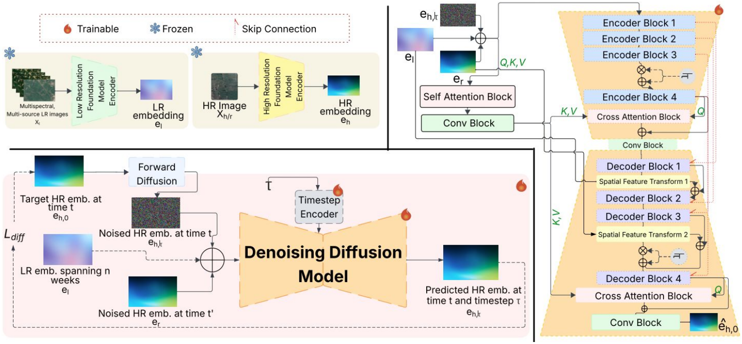
SEED-SR: Segmentation Embedding Enhancement via Diffusion - for Super Resolution

Going forward….

- Improve running time of computationally intensive inference
  - Around 40s for 1 km^2

- Integrate with ALU to utilize high-revisit-frequency satellite images

- Lays the foundation for a combined ALU + AMED model



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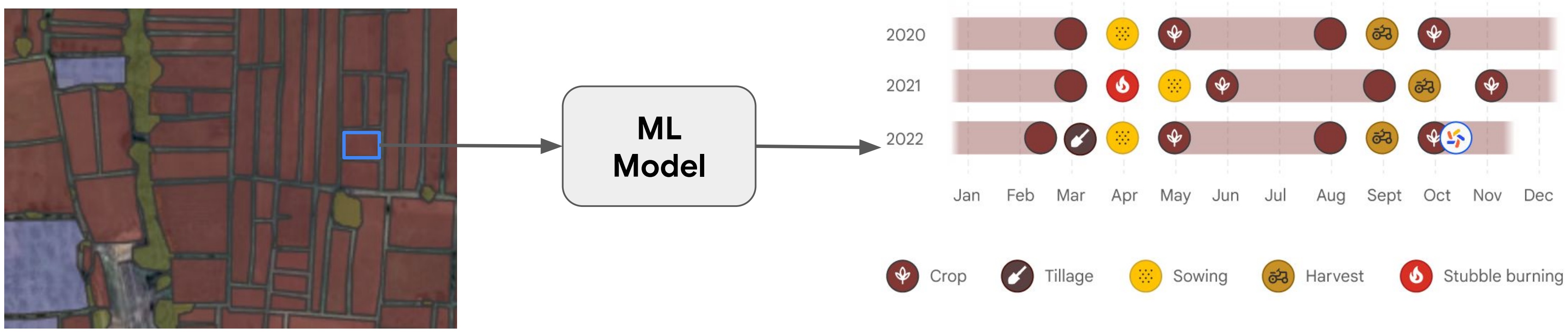
Data challenges .... Algorithmic challenges

Agricultural Monitoring & Event Detection (AMED)

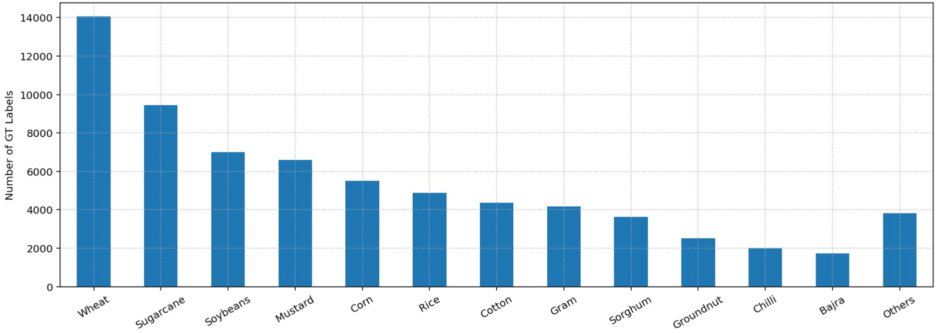


AMED: In-Season Crop Classification

Problem

Identify the crop type <u>within a field</u> for an active crop season

In-season: as it is growing



Challenges

- Insufficient labelled datasets
  - Limited set of crops
  - Not suitable for smallholder farms
- Large number of crop types with long tailed distribution
  - 12 crops - 95% of the data
  - Remaining 63 crops - 5%

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Crop Classification

Key contributions:

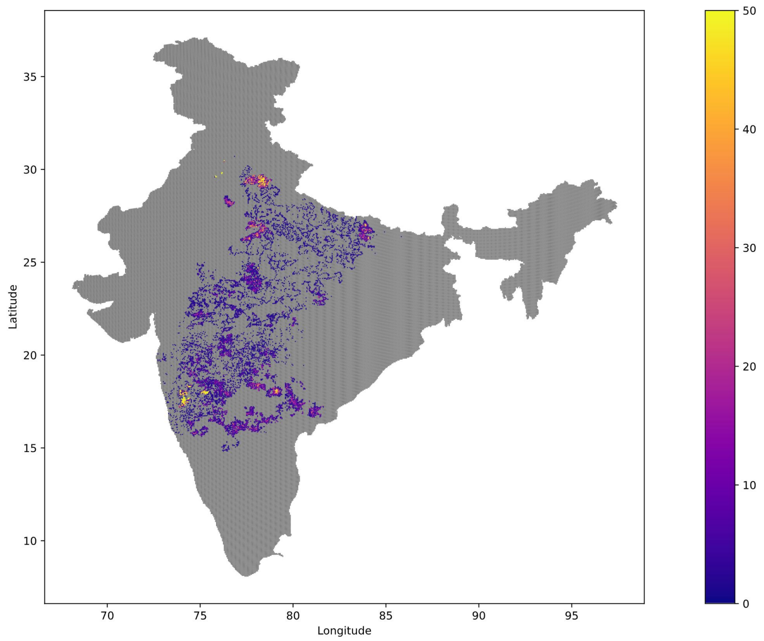
- Geographic generalization:
    - Models work off-the-shelf on unseen regions
- In-season crop identification:
    - Crop identification 2 months into season (vs post-season)
- Large scale verification:
    - Predictions evaluated using average at state-level scale

AMED: In-Season Crop Classification

Training Data Generation

- Labelled data from Annotators
- Combined with
  - Satellite images (Sentinel 1, 2)
  - ALU outputs

~70K samples → 32K after filtering



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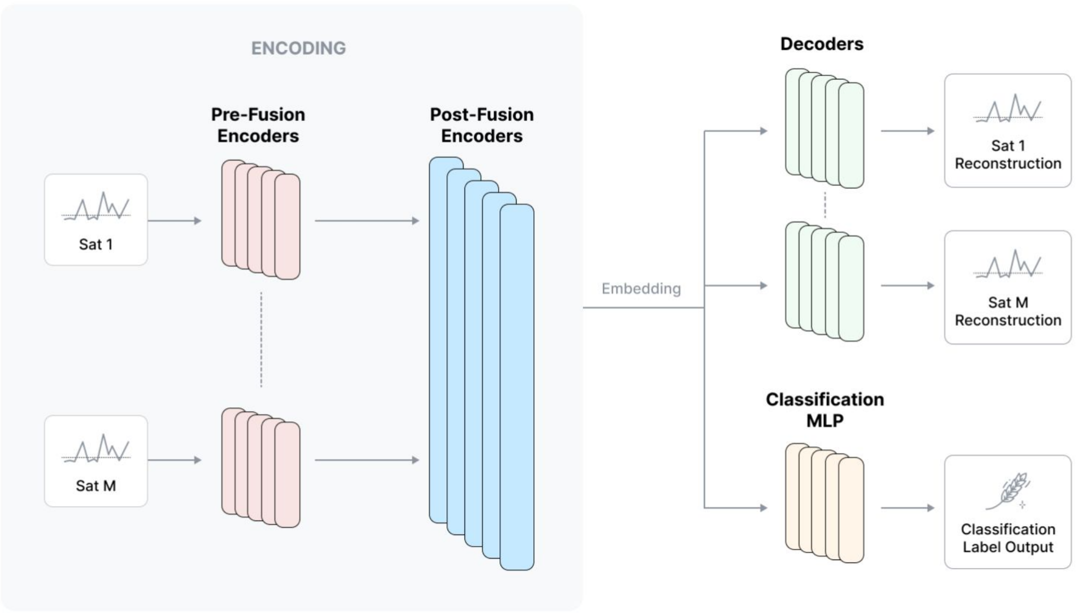
AMED: In-Season Crop Classification



Multi-class Classification Task

Transformer based encoder-decoder architecture

Pretraining-Fine tuning approach

Masked autoencoder pretraining

Fine tuned for classification

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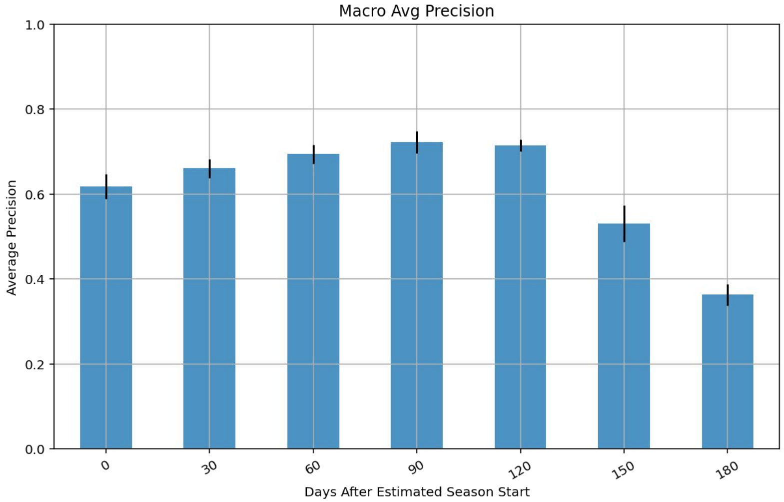
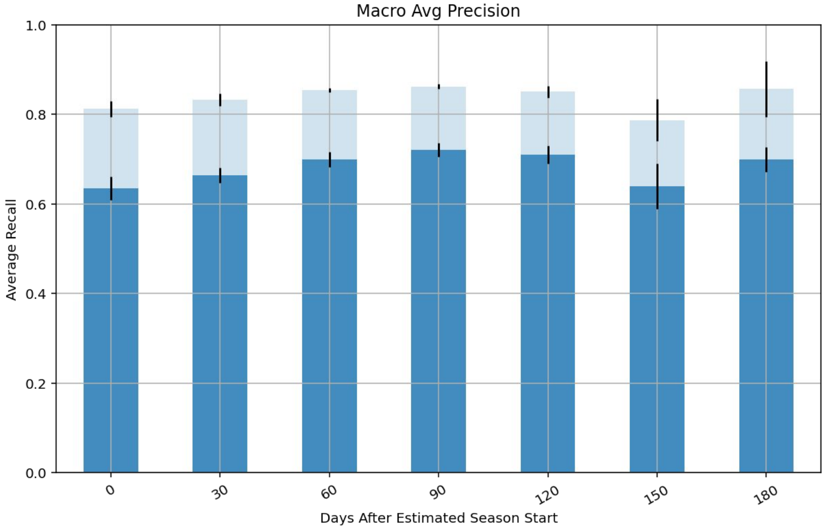
AMED: In-Season Crop Classification

Results





- Performance improves rapidly for first 2-3 months into the season.

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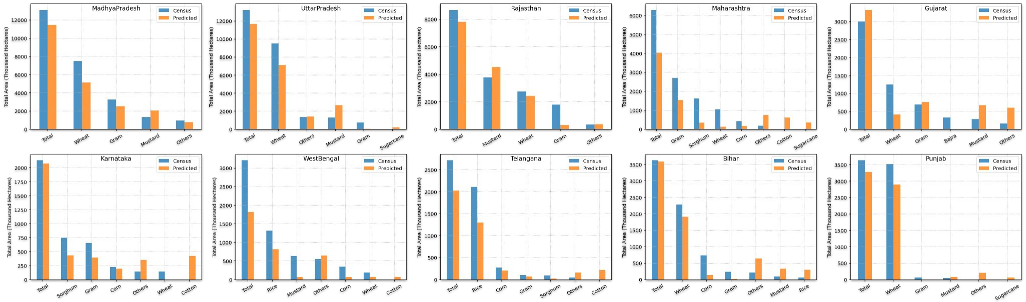
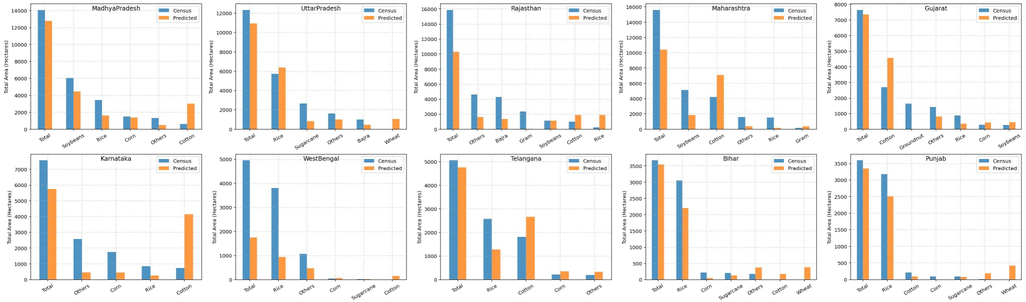
AMED: Large-Scale Evaluation Against Census 2023-24

Winter



Monsoon



Overall similarity across India

	Monsoon	**Winter**
Cosine Sim	0.75	0.94

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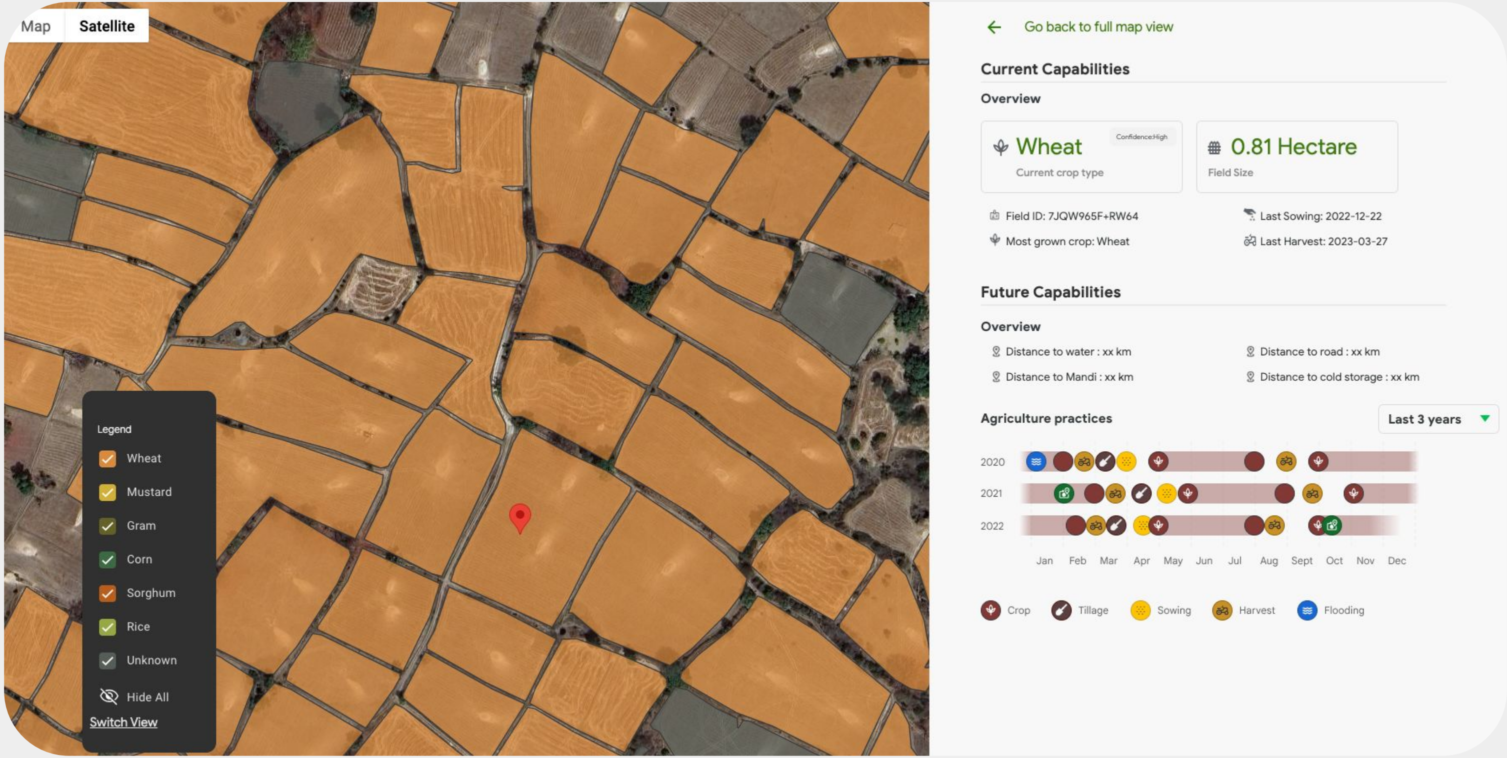
Ag Landscape Monitoring & Event Detection

Launched



ALU and AMED

Financial assistance → Conditional financial assistance

Condition = Cropping / crop type

Timely information for data driven evidence based decision making for effective allocation of resources

Applications:

- Ag Input (Fertilizer allocation)
- Financial (Loans, insurance, aid)
- Farm Equipment allocation
- Advisory

Our Solutions

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Data challenges …………….. Algorithmic challenges

Street View

Crop Type

Crop Stage

Crop Health

Crop Height

Crop Yield

Ag. Practices

Problem: Collecting labeled data at scale is hard
Goal : Use information rich street view images

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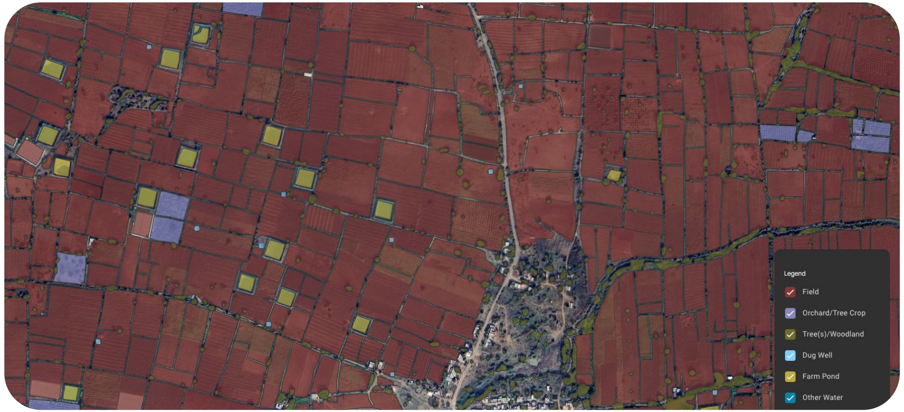
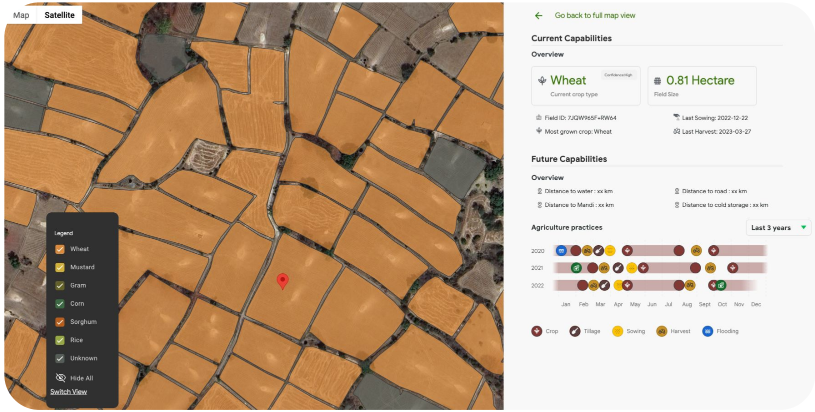
Q&A



Legend
Field
Orchard/Tree Crop
Tree(s)/Woodland
Dug Well
Farm Pond
Other Water



Map
Satellite
Legend
Wheat
Mustard
Gram
Corn
Sorghum
Rice
Unknown
Hide All
Switch View
Go back to full map view
Current Capabilities
Overview
Wheat
Confidence:High
Current crop type
0.81 Hectare
Field Size
Field ID: 7JQW965F+RW64
Last Sowing: 2022-12-22
Most grown crop: Wheat
Last Harvest: 2023-03-27
Future Capabilities
Overview
Distance to water : xx km
Distance to road : xx km
Distance to Mandi : xx km
Distance to cold storage : xx km
Agriculture practices
Last 3 years
2020
2021
2022
Jan Feb Mar Apr May Jun Jul Aug Sept Oct Nov Dec
Crop
Tillage
Sowing
Harvest
Flooding