From Space to Regulation
Detecting Kilns Across South Asia, Enforcing Compliance in India

Presenter Name: **Nipun Batra**

Team: Zeel B Patel, Rishabh Mondal, Shataxi Dubey, Suraj Jaiswal, Jeet Parab, Heer Kubadia, Shardul Junagade, Sarath Guttikunda

10-06-2025

Outline

- What are brick kilns?
- Social good challenges of brick kilns
- Traditional solutions
- Our solution
- Experiments & Results

Space to Policy:

Scalable Brick Kiln Detection and Automatic Compliance Monitoring with Geospatial Data

Authors: Zeel B Patel[1], Rishabh Mondal[1], Shataxi Dubey[1], Suraj Jaiswal[1], Sarath Guttikunda[2], **Nipun Batra**[1]

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Published in ACM Journal on Computing and Sustainable Societies in May 2025

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Motivation: Air Pollution

- Air pollution kills 7 million people every year.

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- 22% fatalities occur in India alone.

Motivation: Air Pollution

- Brick kilns contribute to 8%-14% of air pollution in India.

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- Growing urbanisation demands increase in brick production.

Motivation: Air Pollution

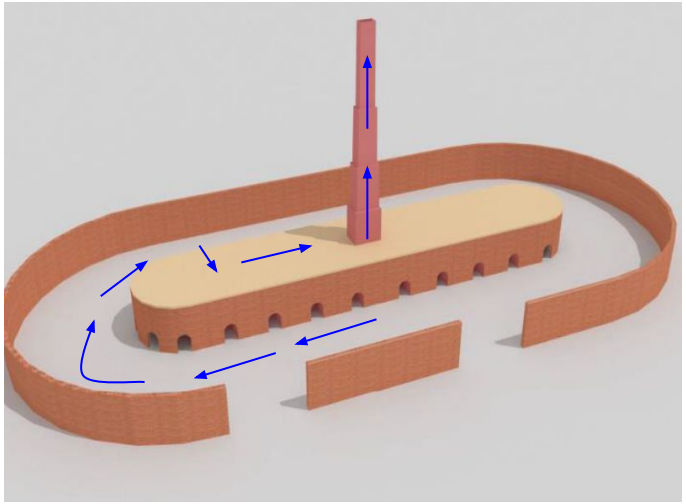
- Brick kilns contribute to 8%-14% of air pollution in India.
- Growing urbanisation increases brick production.
- In India, the demand for bricks is projected to rise from around 250 billion standard brick units (SBUs) per year in 2012-17 to 750-1000 billion SBUs annually by 2032-37*.

* https://www.greentechknowledgehub.de/sites/default/files/2023-07/Guidance%20docuemnt%20_Brick%20Kilns%20India.pdf

Background: Brick Kiln Types

Circular Fixed Chimney Bull's Trench Kiln (CFCBTK)

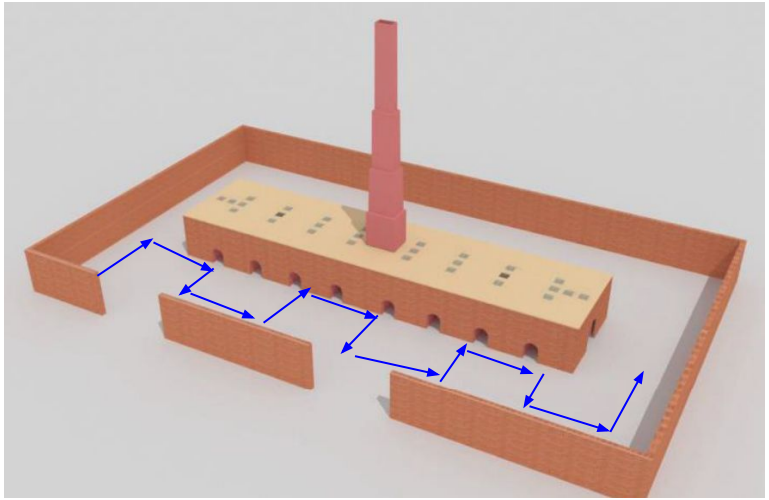
Fixed Chimney Bull's Trench Kiln (FCBTK)



Fire follows straight path

Background: Brick Kiln Types

Zig-Zag Kiln



Fire follows zigzag path

Background: Brick Kiln Types

Fixed Chimney Bull's Trench Kiln (FCBTK)

Zigzag kiln is 40% more efficient compared to FCBTK

Zig-Zag Kiln

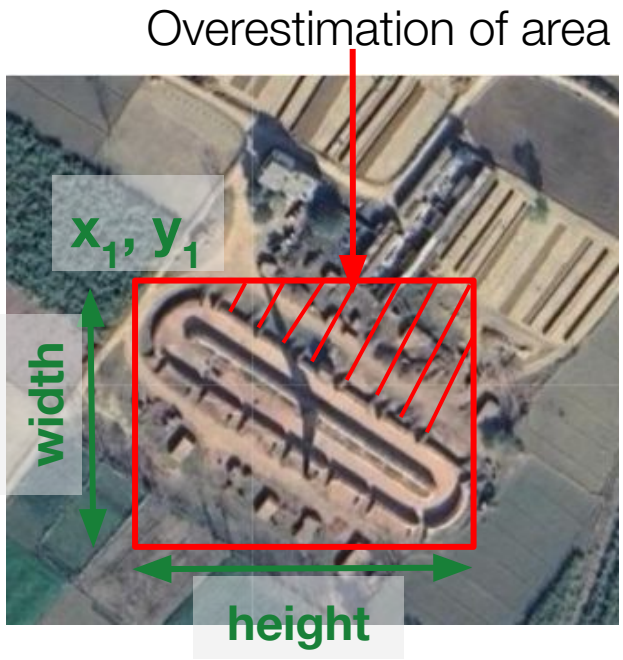
Objectives

Aim	Application	Stakeholders/End-users
Geo-locating brick kilns	Efficient survey management	Policymakers
	Improved emission inventory for air quality modeling	Researchers
Compliance monitoring	Identifying non-compliant brick kilns	Policymakers
Classification into technologies (Zigzag v/s FCBK)	Analyze trend of technology adaptation over time	Policymakers/Researchers

Problem: Geo-locating brick kilns

- According to an air quality expert, manual annotation of an area spanning approximately 10,000 km^2 typically takes around 12 hours.
- Scaling this process for India requires more than 7000 hours.
- Can not keep pace with dynamic growth of kilns.

Solution: Scalable Object Detection



Axis-aligned Bounding Box
x_1, y_1, w, h

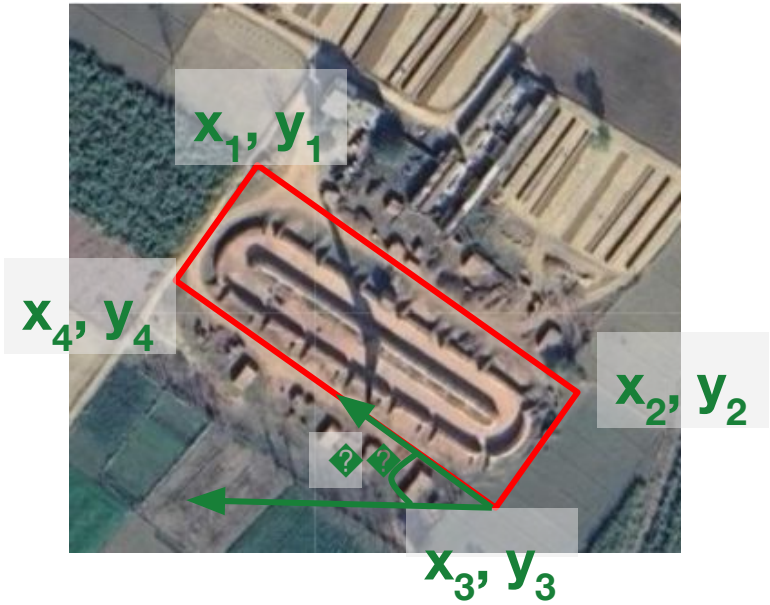
Oriented Bounding Box

Solution: Scalable Object Detection

Overestimation of area

Axis-aligned Bounding Box

x_1, y_1, w, h



Oriented Bounding Box

$x_1, y_1, x_2, y_2, x_3, y_3, x_4, y_4, \theta$

Solution: Scalable Object Detection

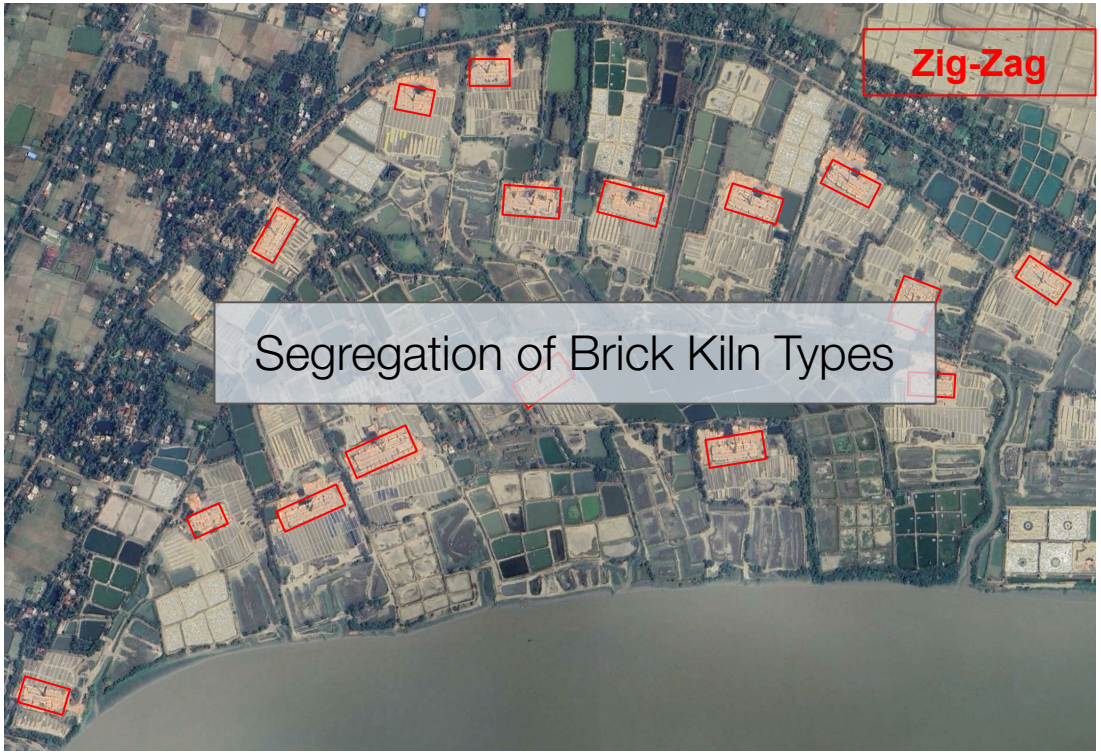
Satellite Imagery: Input to the object detection model

Solution: Scalable Object Detection

Output:
Detection of Brick kilns

Solution: Scalable Object Detection

Output:
Classification of Brick kiln types



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Solution: Scalable Object Detection

Output:
Compliance monitoring of kilns

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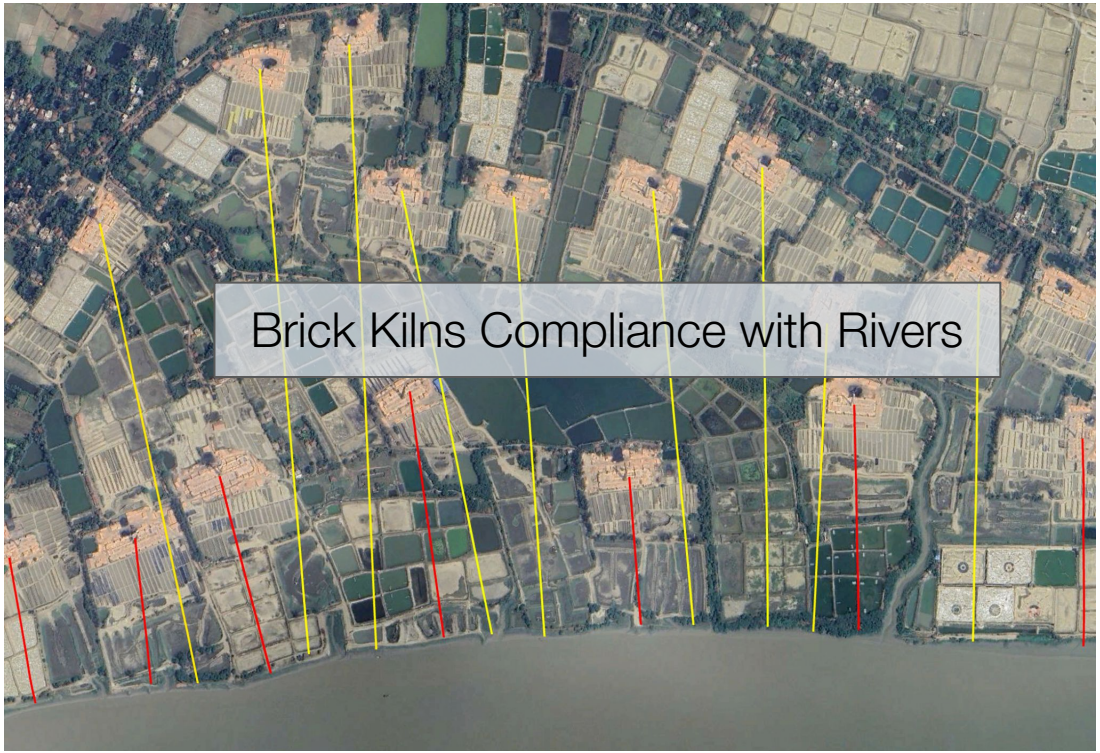
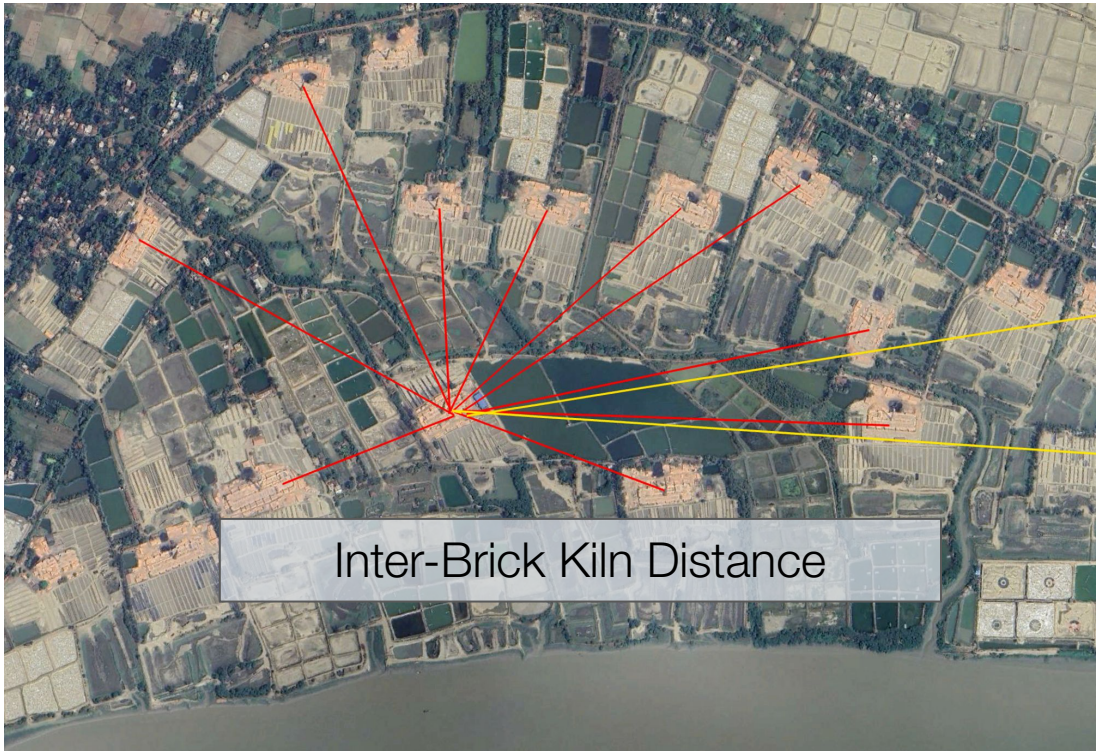
Solution: Scalable Object Detection

Output:
Compliance monitoring of kilns



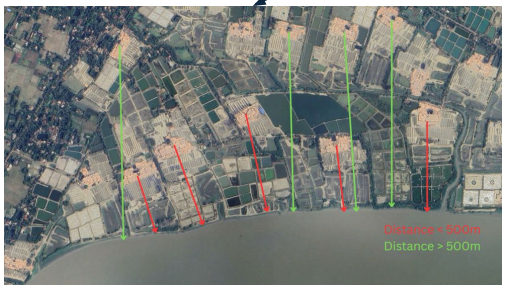
Solution: Scalable Object Detection

Output:
Compliance monitoring of kilns

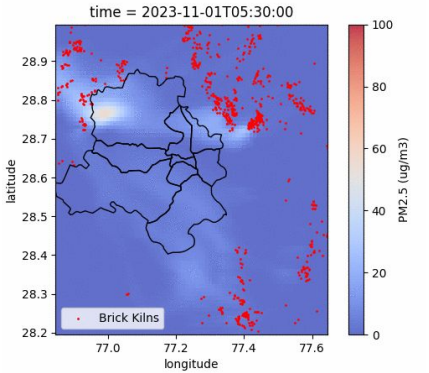


Solution: End to End ML Pipeline

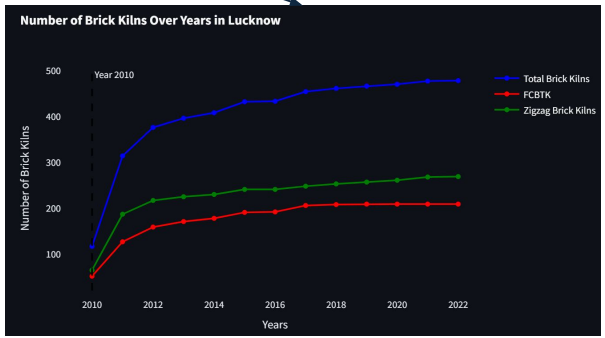
Class-aware Brick Kilns detection



Automatic Compliance Monitoring



Air Pollution simulations for What-if scenarios



Evolution of technology over time

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Total Kilns detected

1524 CFCBKs

13057 FCBTKs

16057 Zig-zag Kilns

30638 Kilns

Satellite Imagery Used

Images: ESRI	Resolution: 0.3-1.22m/px	Purpose: Annotation

CFCBTK

FCBTK

Zig-Zag

Satellite Imagery Used

Images: ESRI	Resolution: 0.3-1.22m/px	Purpose: Annotation

CFCBTK

FCBTK

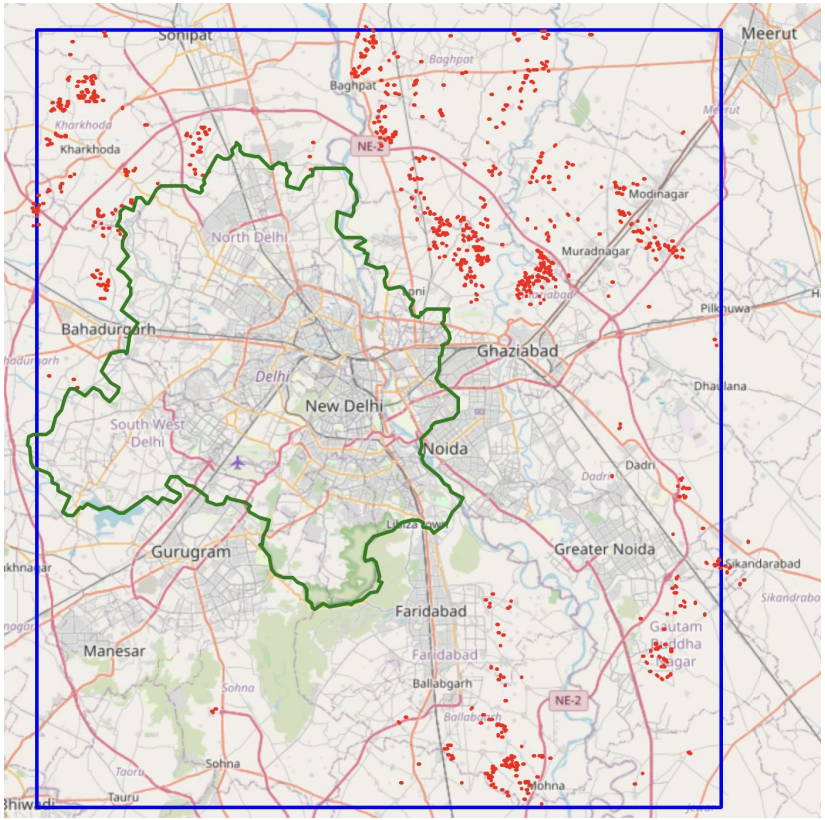
Zig-Zag

Images: Planet	Resolution: 4.77 m/px	Purpose: Training

Selection of Initial Region

- Initial data chosen on four criteria :

  Delhi Airshed, India (Highly polluted)



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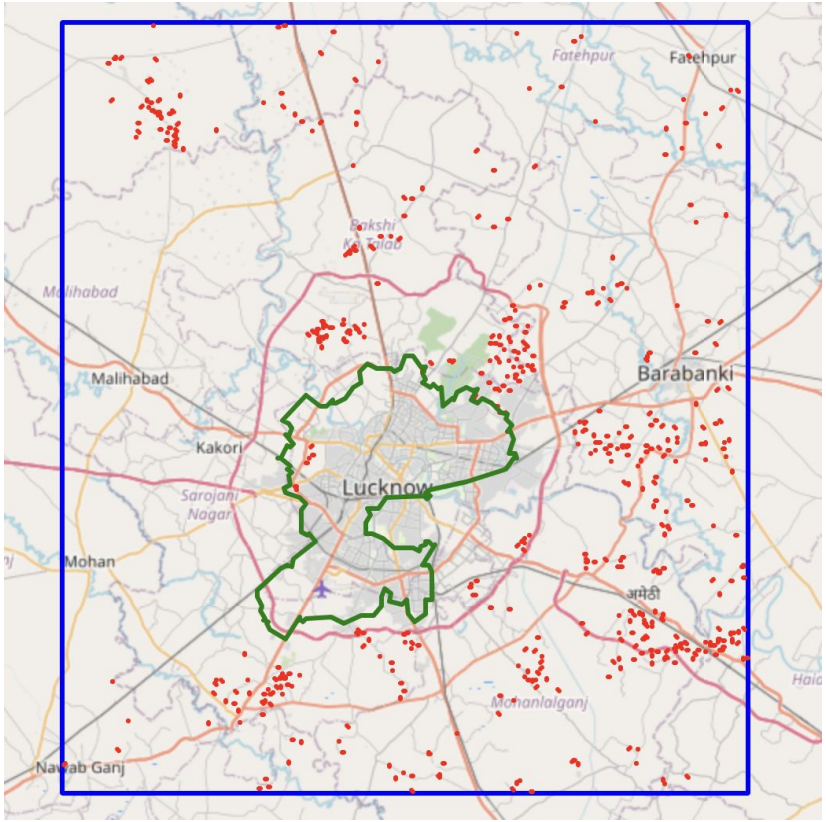
Selection of Initial Region

- Initial data chosen on four criteria :

  Lucknow Airshed (Highly populated)



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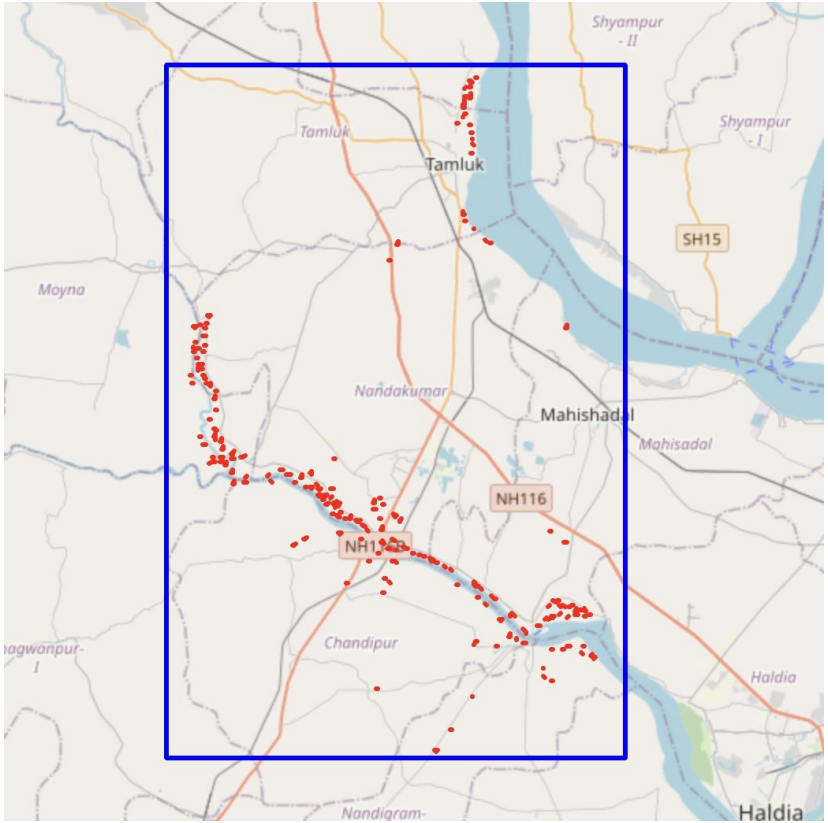
Selection of Initial Region

- Initial data chosen on four criteria :

  West Bengal Airshed

  (High likelihood of kilns)



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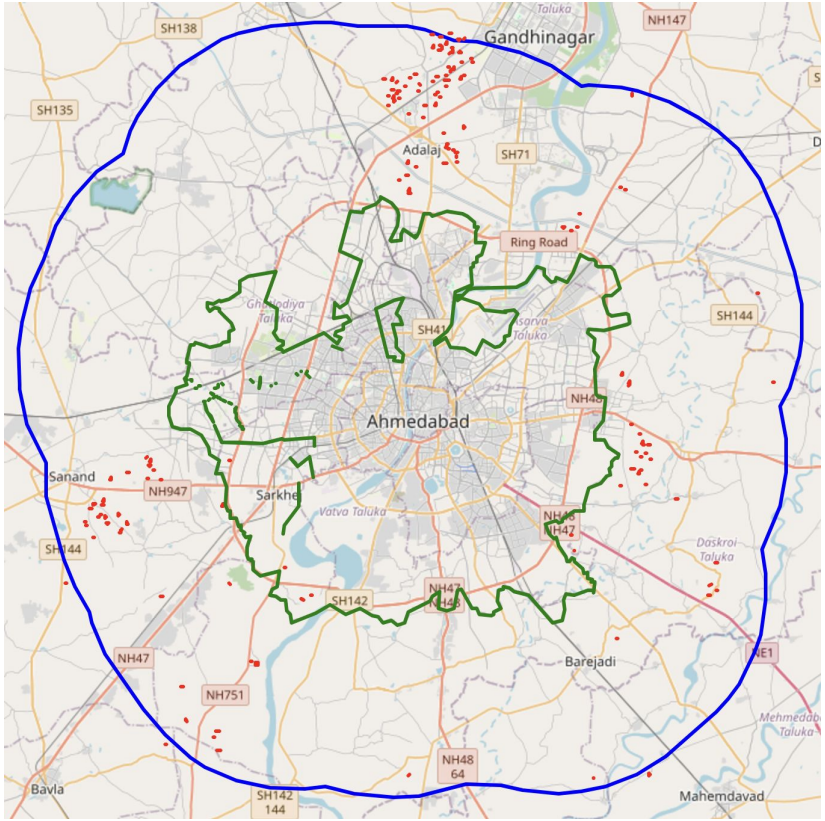
Selection of Initial Region

- Initial data chosen on four criteria :

  Ahmedabad (Non-attainment city)



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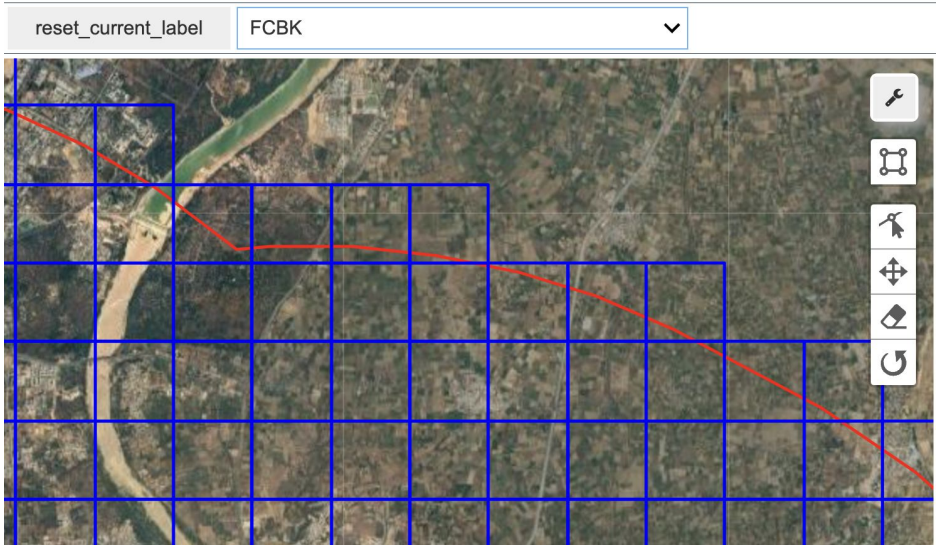
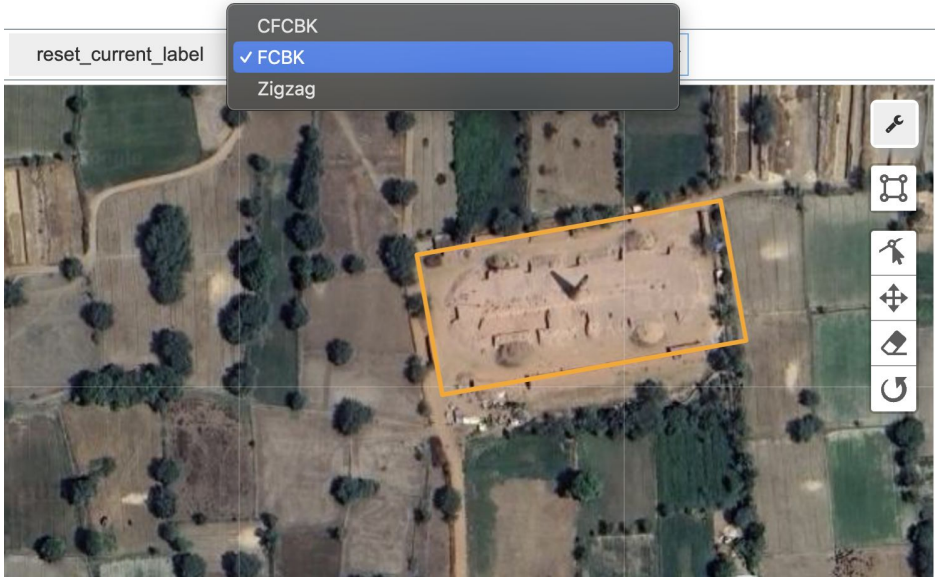
Dataset coverage

Annotation Interfaces & Process



Division of region in grids of 1 Km^2



Annotation Tool interface

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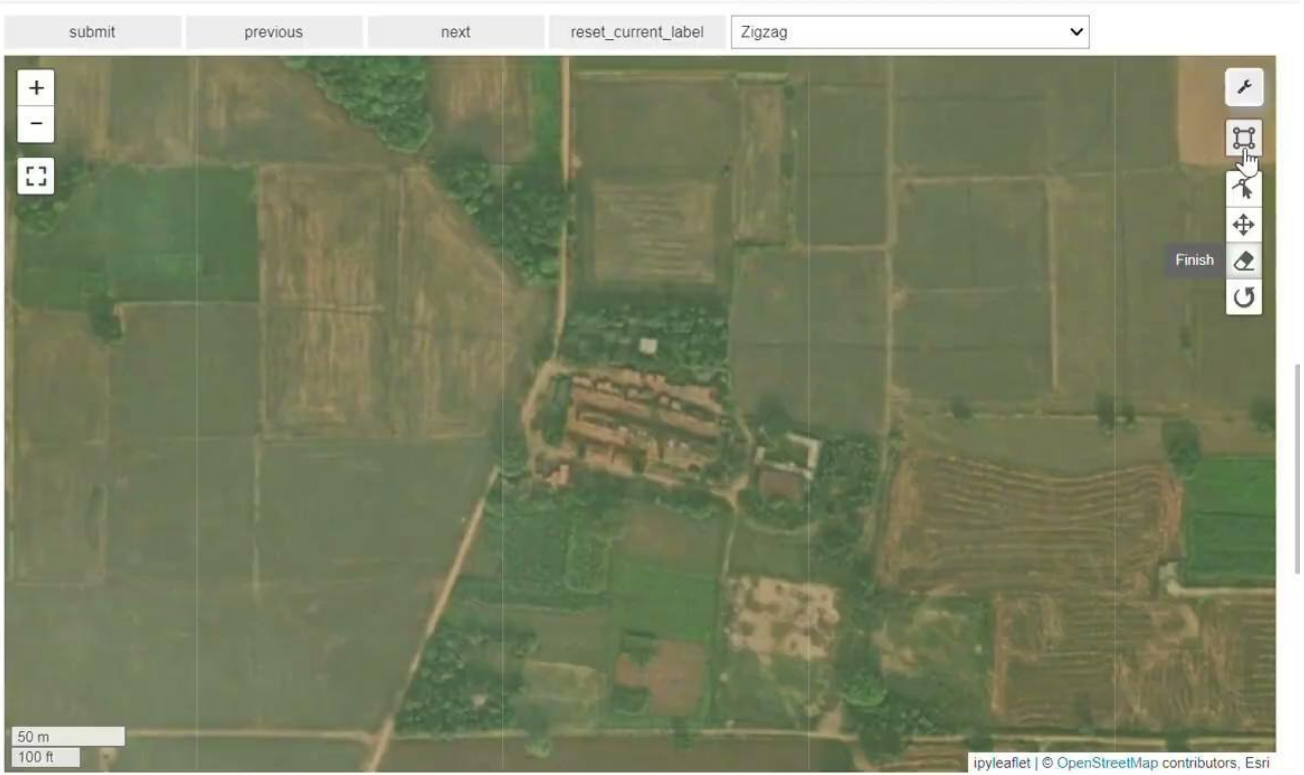
Annotation Interfaces & Process



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Initial Dataset

Airshed	Area (Km^2)	Total Kilns	Annotation Time (hours)
Delhi Airshed	6937	783	58
Lucknow Airshed	3962	492	33
West Bengal Airshed	639	199	5
Ahmedabad 10 Km Airshed	3480	147	29
Total	**15018**	**1621**	**125**

Model Choice

- Yolo an object detection model which is fast and perform detections in single pass
- Two oriented bounding box variants of Yolo: **Yolov8** and **Yolov11**
- Evaluated model on weighted mAP

Model Performance

Model	CFCBK	FCBK	Zig-zag	Weighted mAP
yolov8l-obb	0.61	0.58	0.83	0.62
yolov8x-obb	0.63	0.55	0.82	0.63
yolov11x-obb	0.66	0.57	0.80	0.66
yolov11l-obb	0.68	0.51	0.76	0.66
yolov8m-obb	0.68	0.54	0.79	0.66
yolov11m-obb	**0.73**	**0.61**	**0.83**	**0.71**

Generalization Challenge

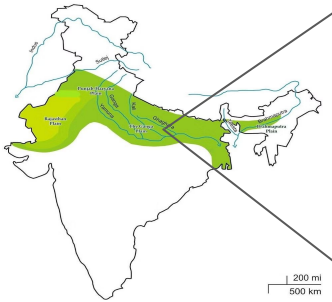
Leave One Region Out: Test Region excluded from training						
Test Region	mAP	TP	FP	FN	P	R
Delhi Airshed	0.04	317	421	632	0.43	0.33
Lucknow Airshed	0.32	221	206	275	0.52	0.45
West Bengal Airshed	0.16	64	83	142	0.44	0.31
Ahmedabad 10 Km Airshed	0.18	18	47	131	0.28	0.12

TP: True Positive FP: False Positive
P: Precision R: Recall

Higher exclusion error than inclusion error

Iterative Expansion Strategy

Indo-Gangetic Region



Satellite Image (Uttar Pradesh)

Trained Model

YOLOv11

Prediction

Detected Kilns 26978

Initial Training Set

15627 new kilns updated

Hand Validation

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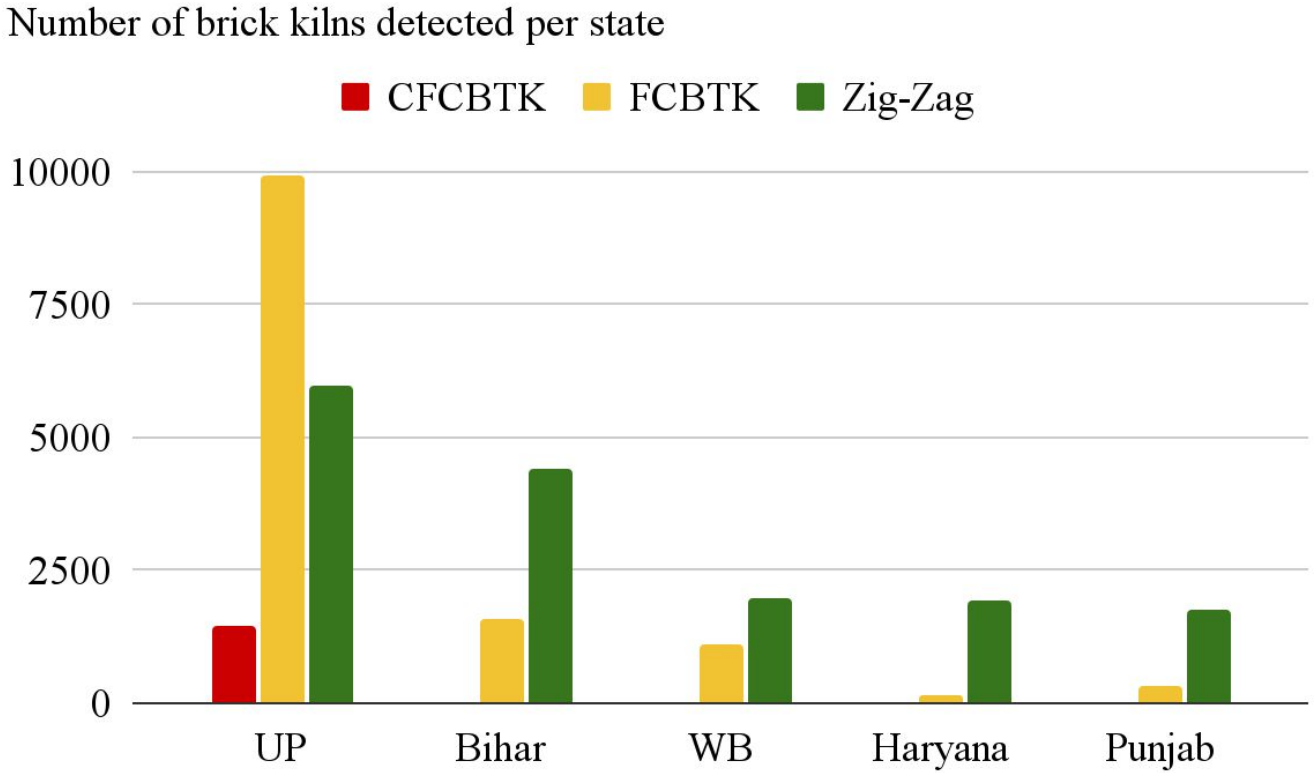
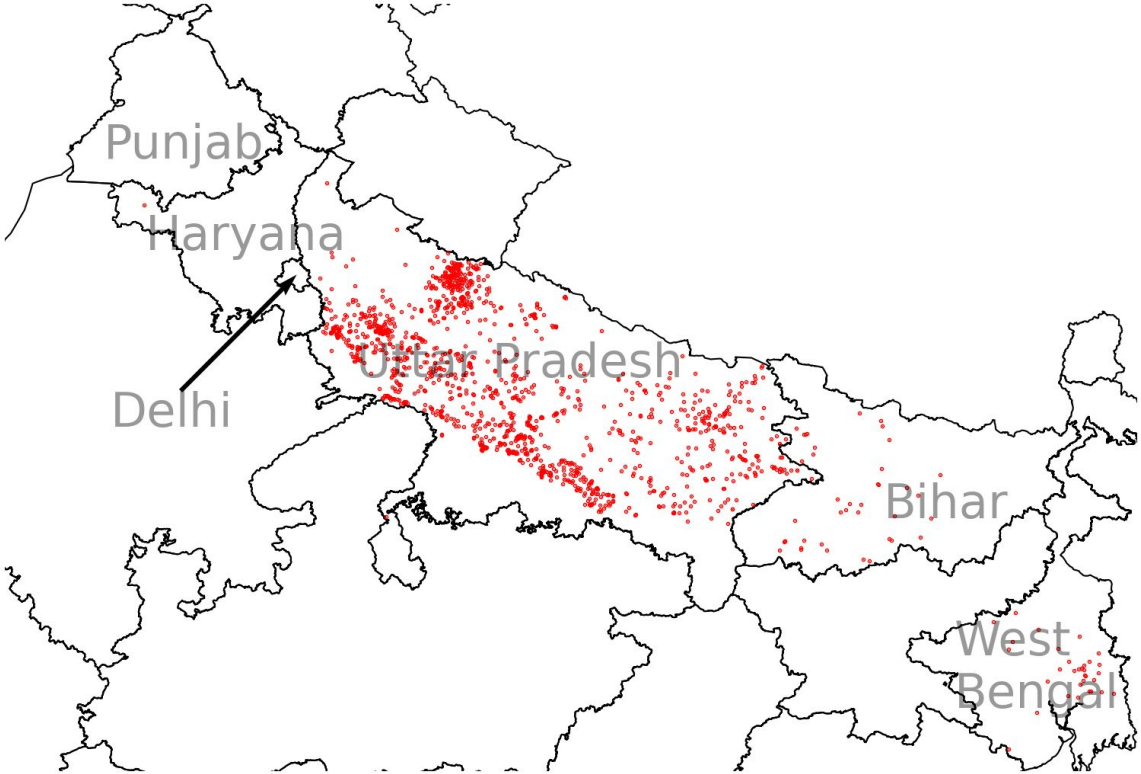
Detected Kilns

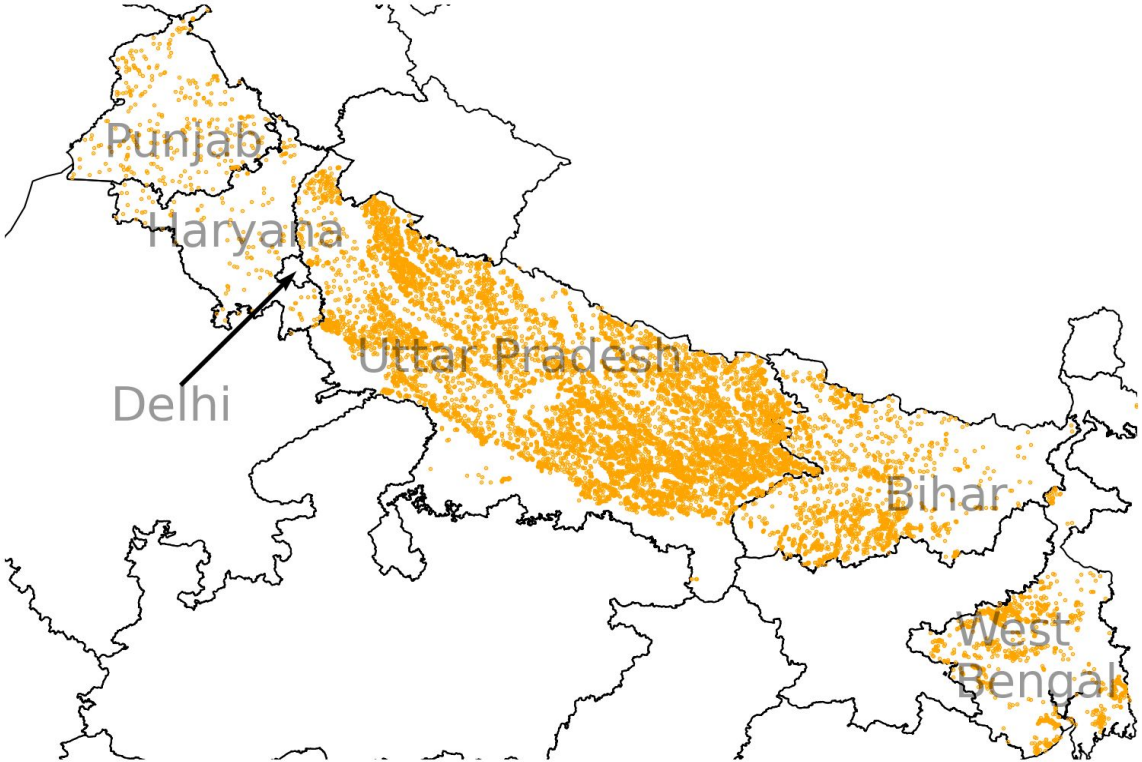


Detected and hand-verified 30638 brick kilns from 5 states.

Detected Kilns: CFCBTK



Detected Kilns: FCBTK



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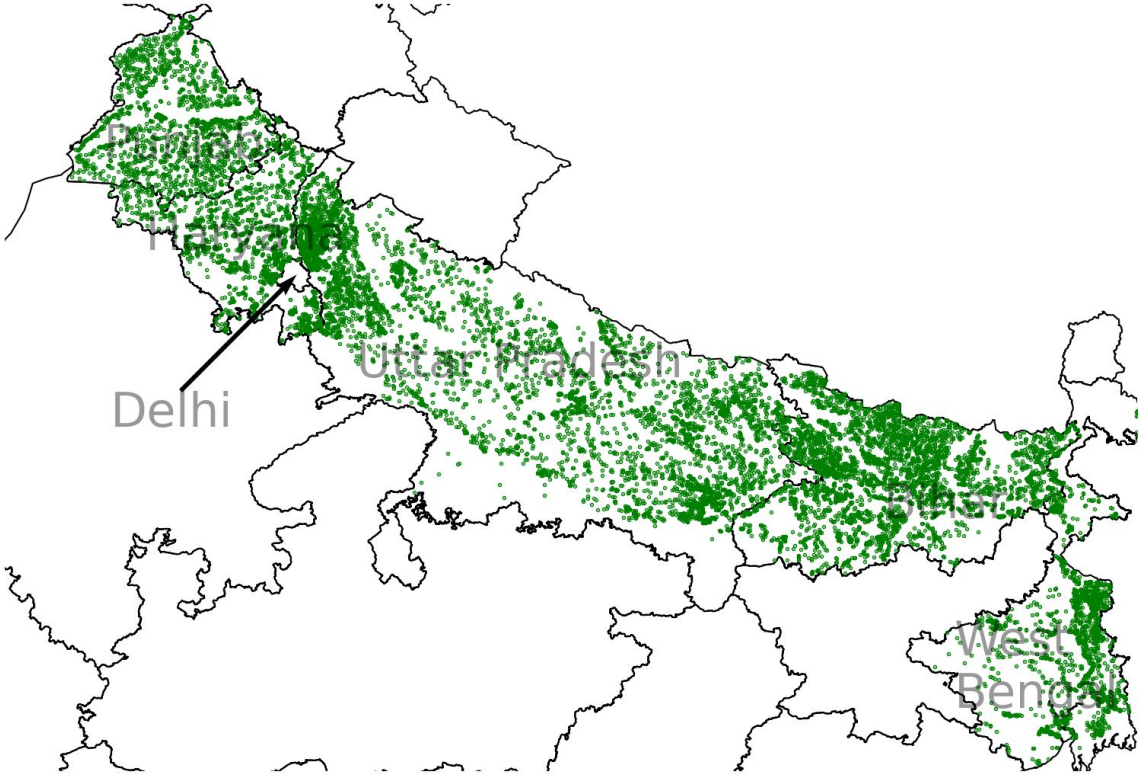
Detected Kilns: Zig-zag



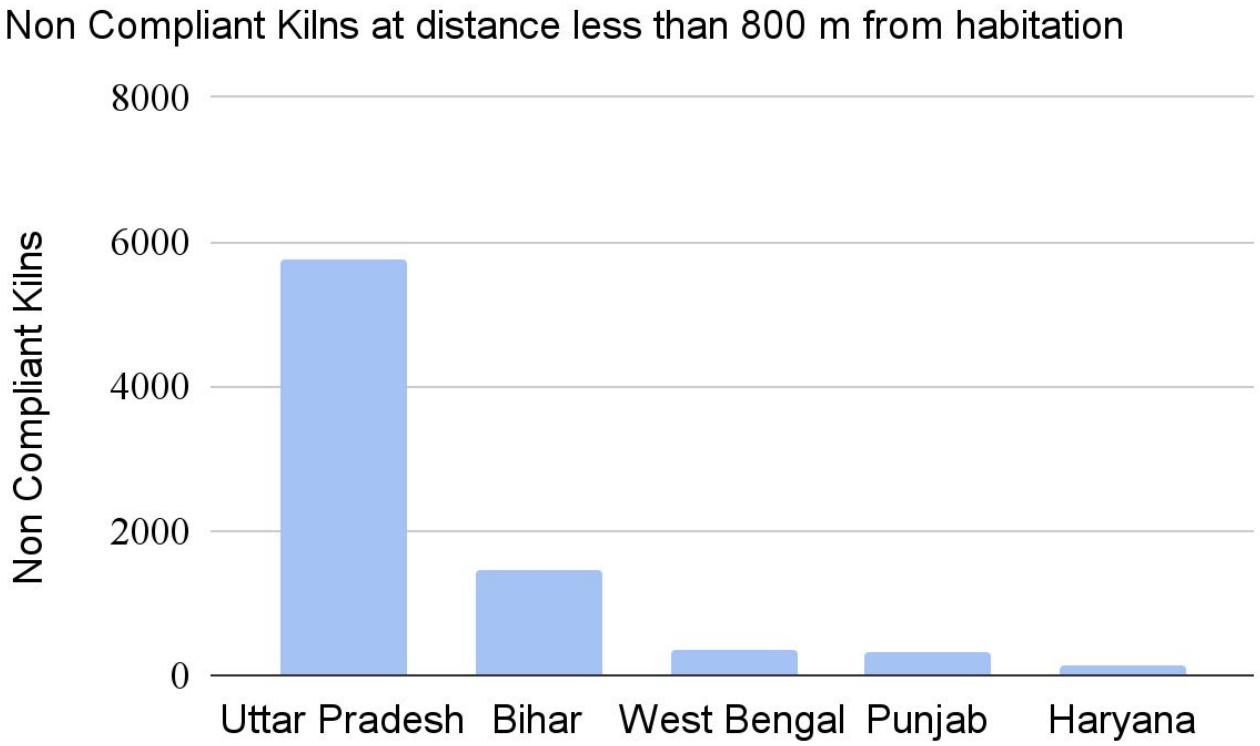
Big Data Resources

- **OpenStreetMap** offers a vast array of geographic datasets.
- Dataset includes detailed geometry information for **railway tracks, highways, rivers, schools and habitation**.
- **Indian Government's Data Portal** provides geolocation data of **hospitals and nursing homes**.
- **LandScan global population dataset** provides **population distribution**, helps in analyzing population exposure to brick kilns air pollution

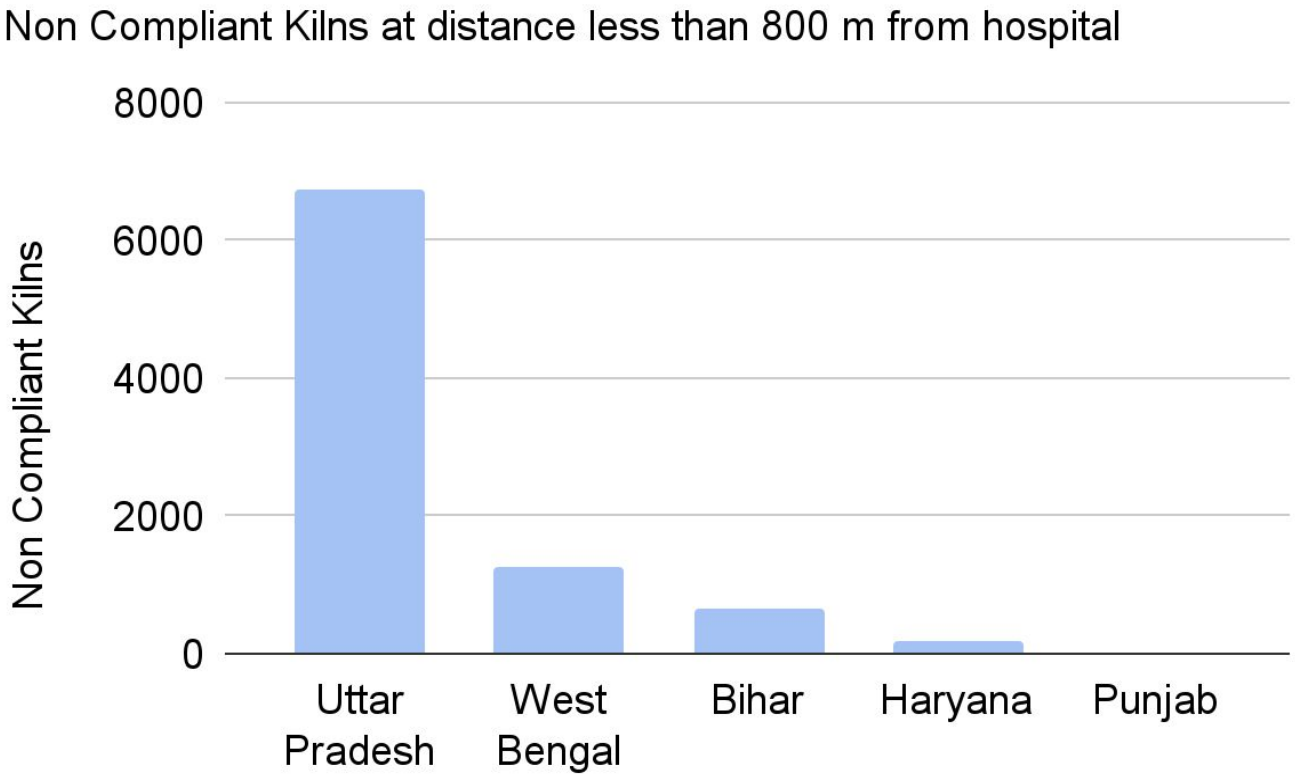
Distance based Compliance Monitoring

- Distance from human habitats should be > 800 m
- Inter-brick kiln distance should be > 1 Km

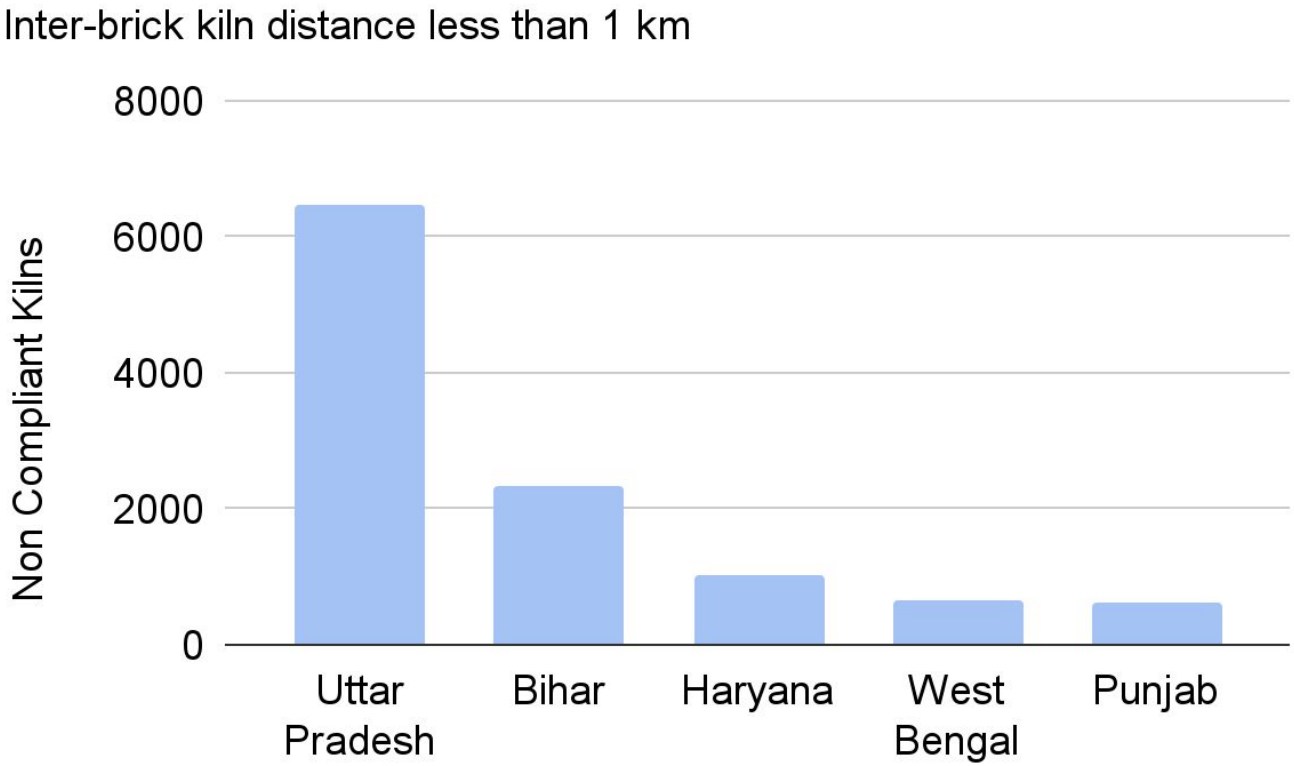
Distance based Compliance Monitoring



Distance based Compliance Monitoring

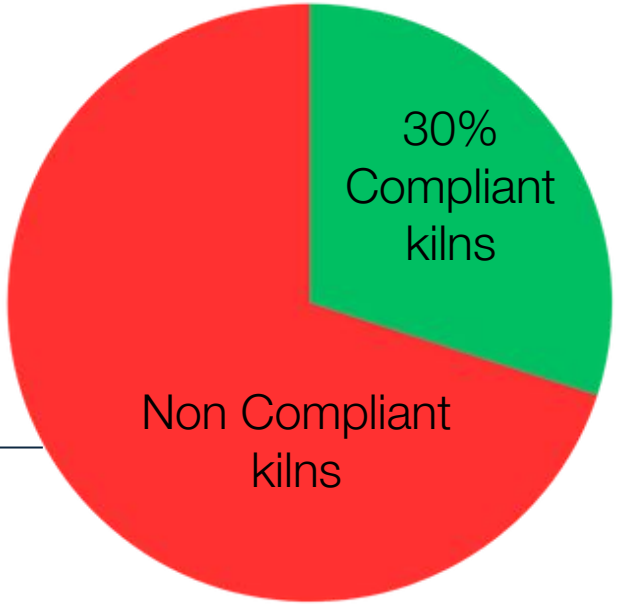


Distance based Compliance Monitoring

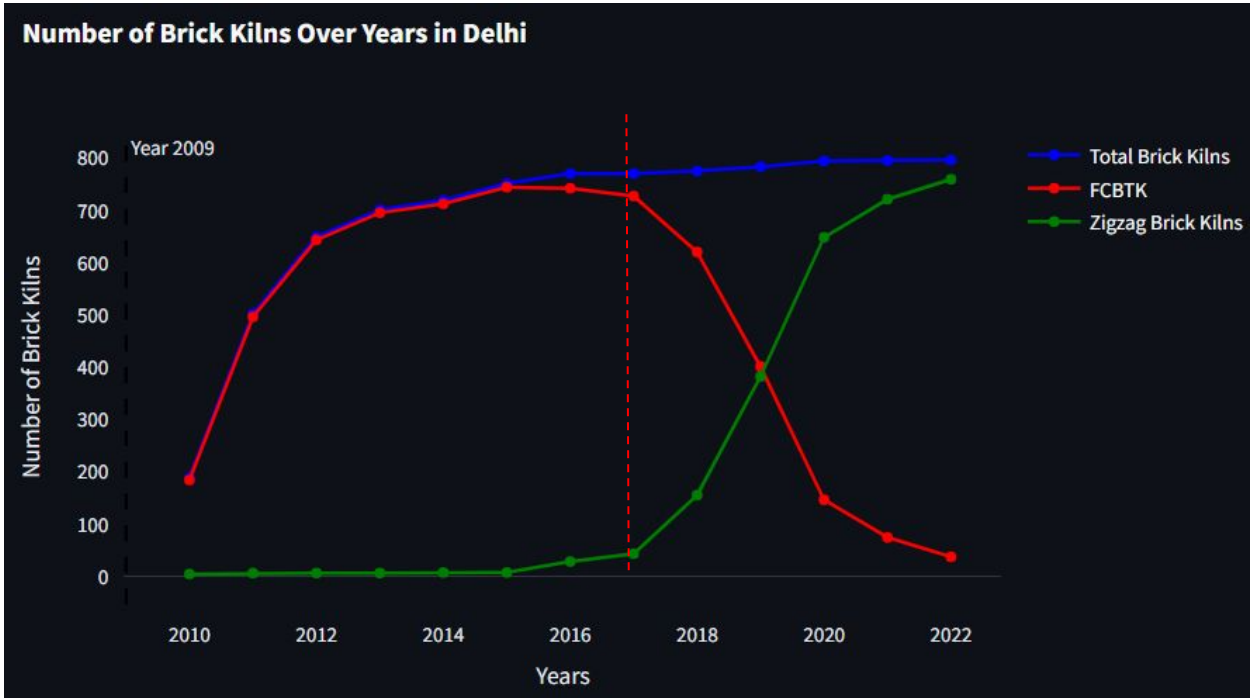


Distance based Compliance Monitoring

70% Kilns violate at least one compliance rule

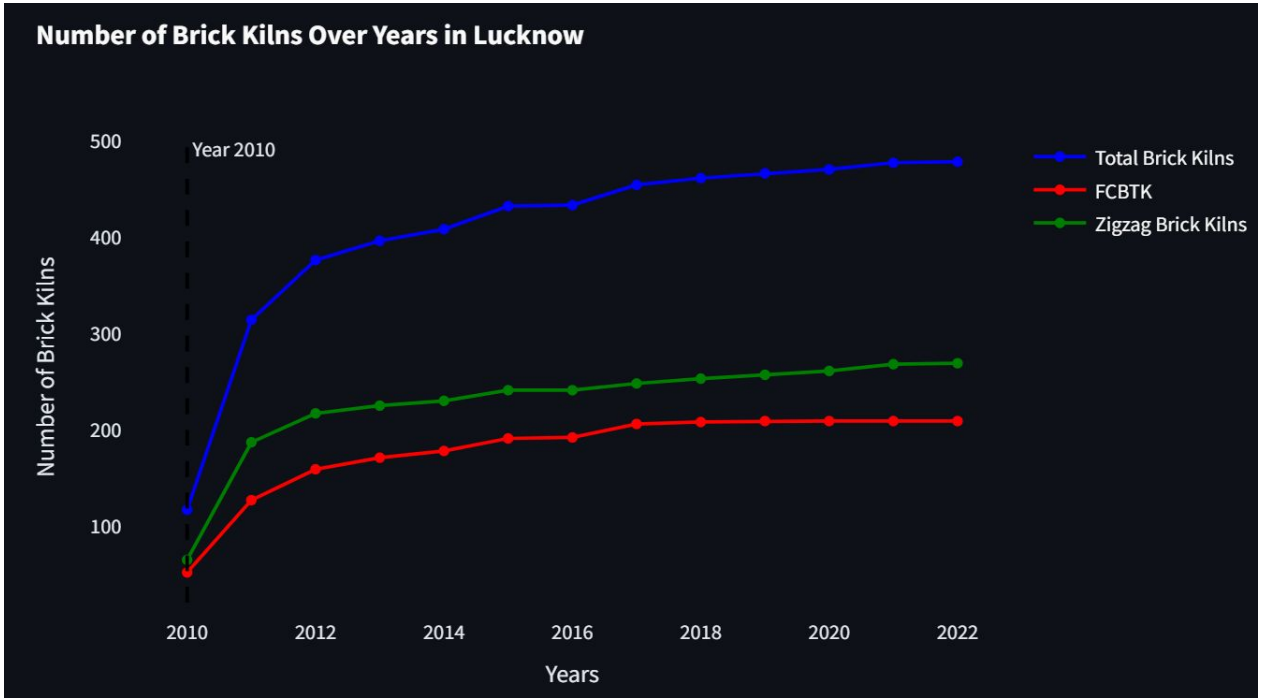


Technology based Compliance



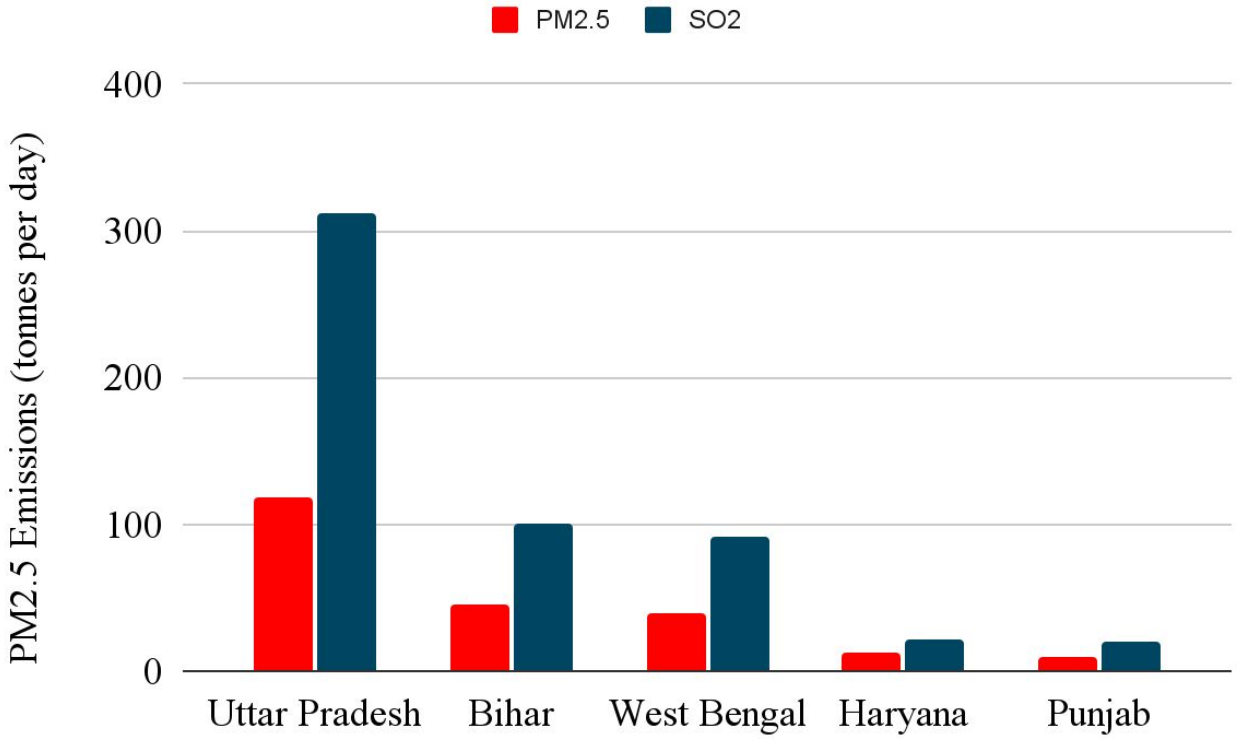
In Delhi, there is a shift to Zig-zag kiln technology post 2017

Technology based Compliance



In Lucknow, growth of FCBTK and Zig-zag kiln is similar

Air Quality Impact Estimation



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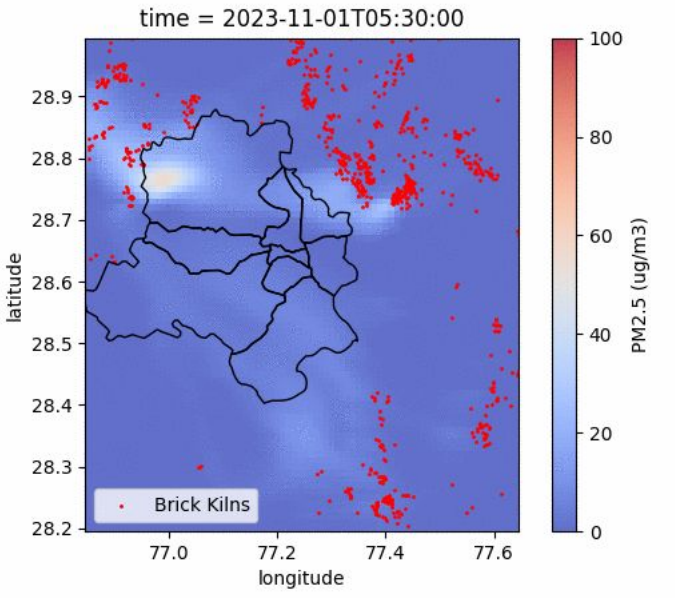
Air Quality Impact Estimation

- Using the inputs from Weather Research and Forecast Model, we ran Chemical Transport Model CAMx.
- CAMx reveals that brick kilns contribute 8% to total $PM_{2.5}$ in Delhi.



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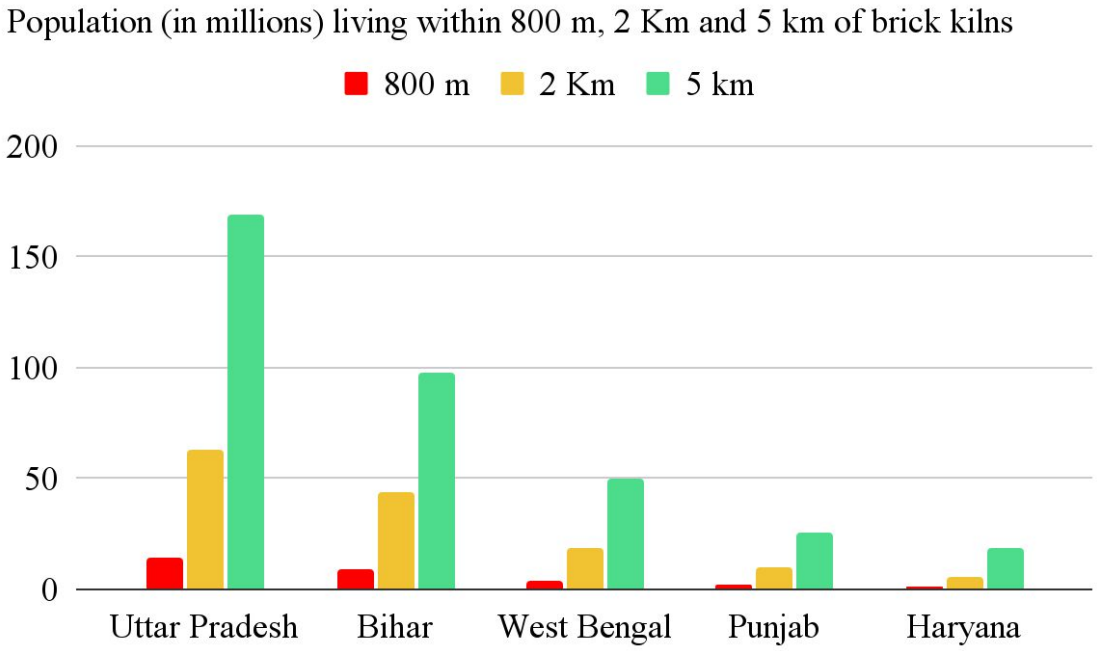
Population Exposure

- Estimation of population living near brick kilns using LandScan data.
- 30.66 Million people live within 800m of kilns



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Limitations

- Limited generalization capabilities in current architecture.
- Planet data is not shareable.
- Need for open and reproducible datasets, paving the way for SentinelKilnDB.

SentinelKilnDB:

A Large-Scale Dataset and Benchmark for OBB Brick Kiln Detection in South Asia Using Satellite Imagery

Under Review

Authors: Rishabh Mondal[1], Jeet Parab[2], Heer Kubadia[1] Shataxi Dubey[1], Shardul Junagade[1], Zeel B Patel[1], **Nipun Batra**[1]

[1]Indian Institute of Technology Gandhinagar [2]IIIT Surat

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Why SentinelKilnDB ?

- **Restricted Sharing**: Planet imagery is licensed strictly for non-commercial academic use.

Dataset Sharing Guidelines for the Education and Research Basic Program

Follow

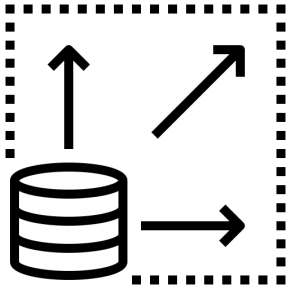
Jean Bryant
October 25, 2024 at 5:29 PM

Planet's **Education and Research Basic** program provides access to satellite imagery for non-commercial, academic, and research purposes. This program is designed to support educational and research projects while safeguarding Planet's proprietary imagery. **Please note that datasets containing raw or original Planet imagery data cannot be made publicly accessible** under this program.

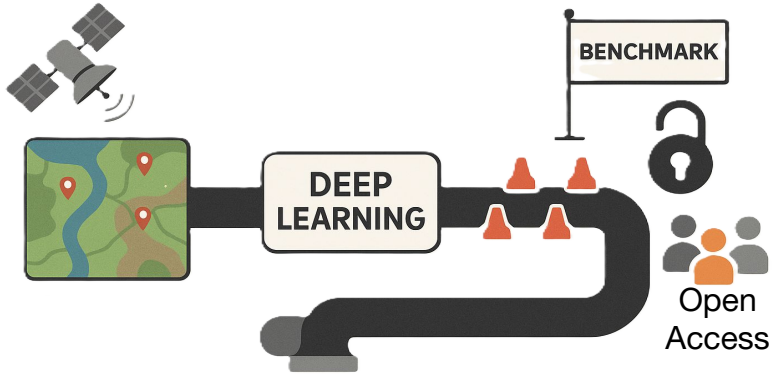
Why SentinelKilnDB ?

- **Restricted Sharing**: Planet imagery is licensed strictly for non-commercial academic use.[1]
- **Expensive & Hard to Scale:** Planet imagery requires costly institutional subscriptions.
    - Increases financial barriers, making large-scale or long-term studies difficult to conduct.

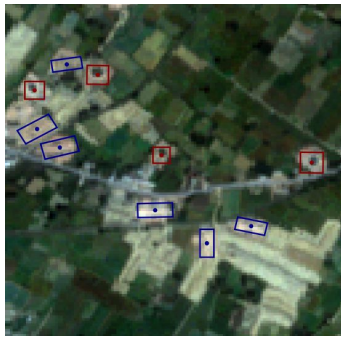
Goals of SentinelKilnDB



Large Scale Open Source
Brick Kiln Dataset



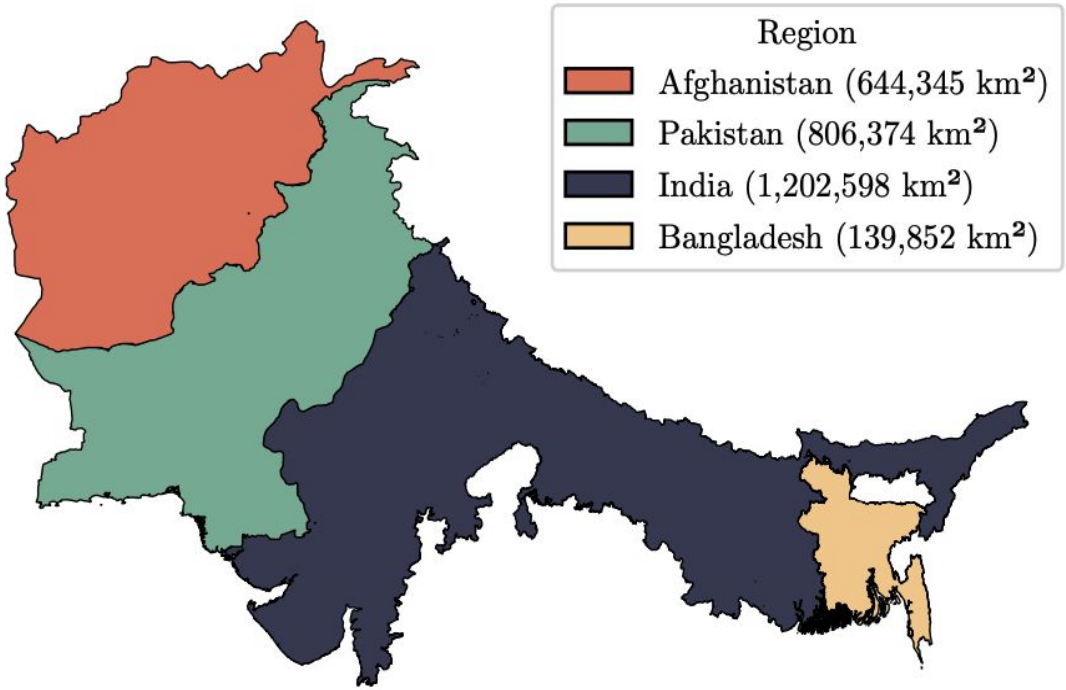
Reproducible and Open benchmark
using Satellite Imagery



First low-resolution oriented
bounding box (OBB) dataset.

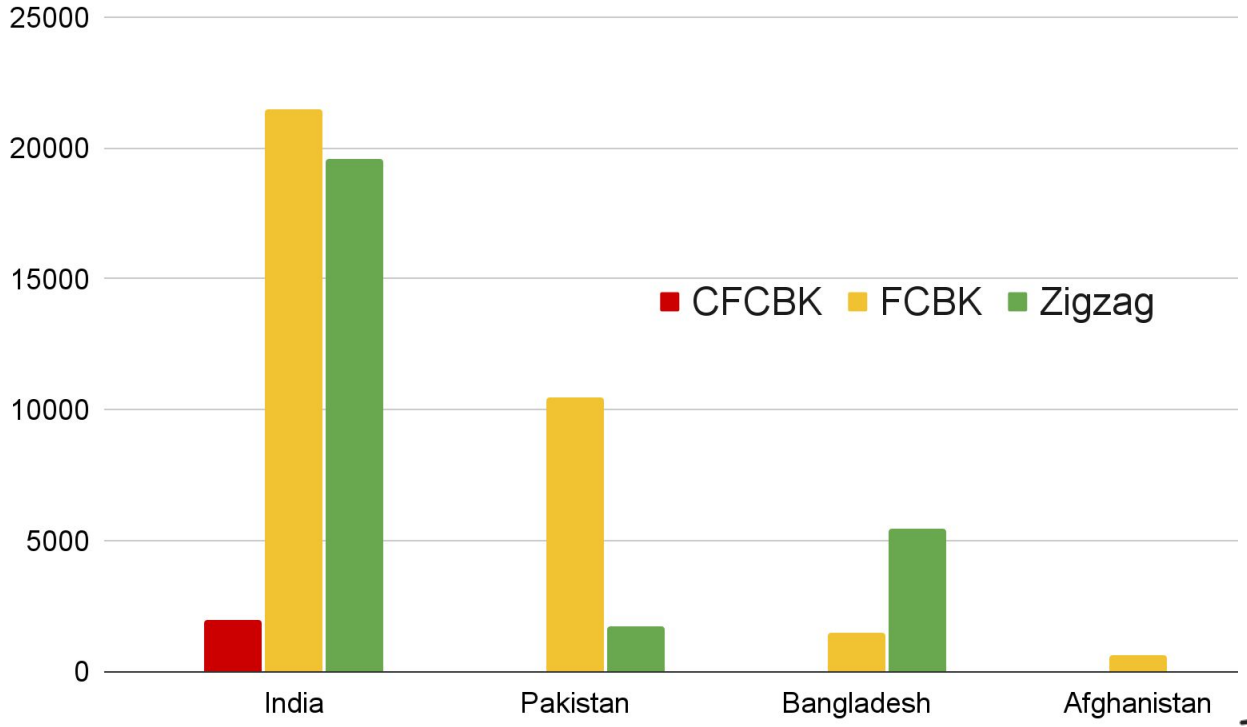
Dataset Overview

Area Coverage: 2.8 M km^2 across India, Bangladesh, Pakistan, and Afghanistan.



Dataset Overview

Brick kiln counts: Class-wise brick kiln counts for each country.



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Dataset Overview

Brick kiln counts: Class-wise brick kiln counts for each country.

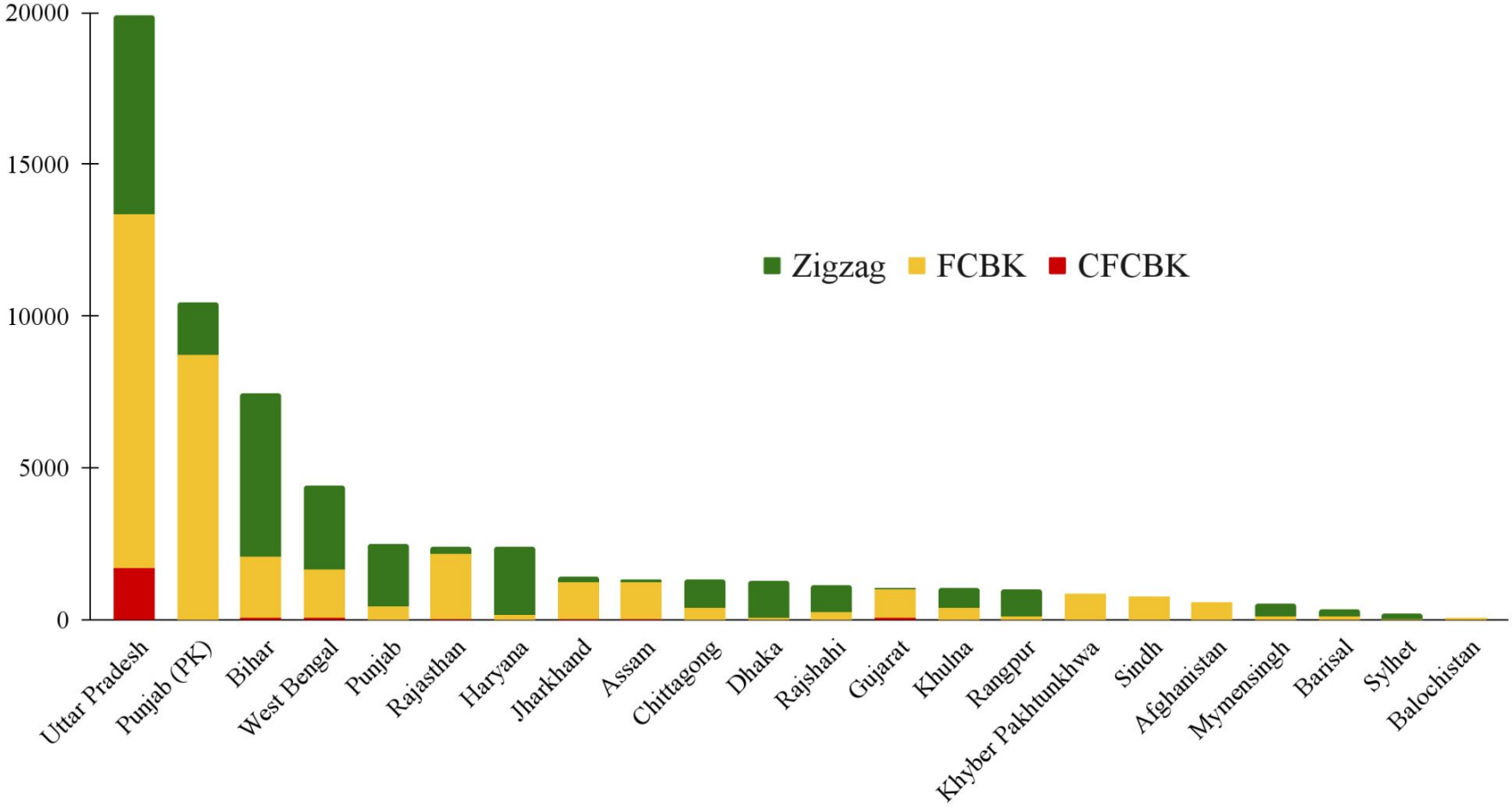
Country	State/Region	CFCBK	FCBK	Zigzag	Total	Images
India	9 states	1939	21451	19592	42982	54479
Bangladesh	8 divisions	2	1461	5440	6903	8598
Pakistan	4 provinces	3	10443	1731	12177	14886
Afghanistan	34 provinces	0	608	1	609	744
Total	-	1944	33963	26764	62671	78707

Dataset Overview

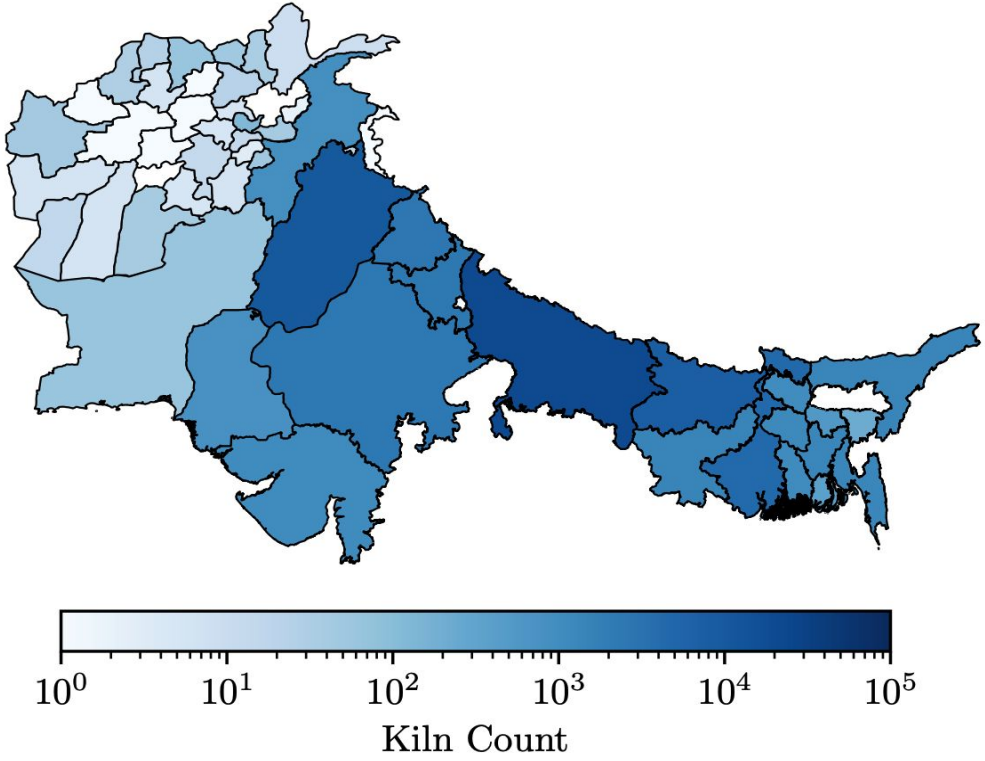
- Public Release: Sentinel-2 Imagery with OBB + AABB Labels
- Includes both Oriented Bounding Box (OBB) and Axis-Aligned Bounding Box (AA) annotations

Sample images from the dataset with corresponding OBB annotations.

Statewise Brick Kilns Count

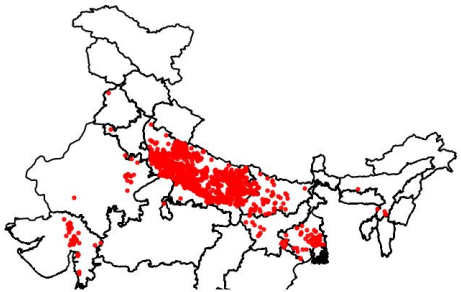


Brick Kilns distributions by Region

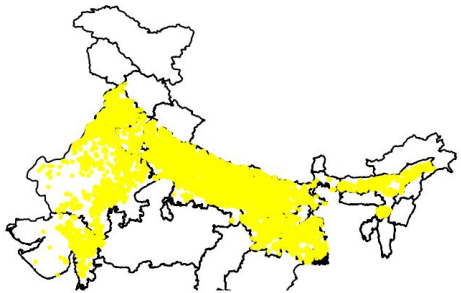


Brick Kilns distributions in India

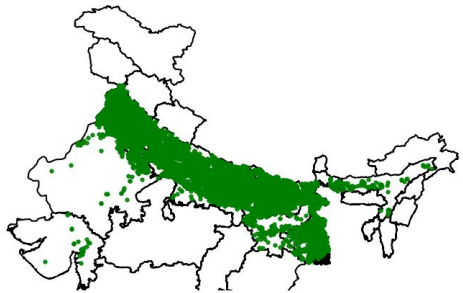
- India contributes over 42,000 kilns, primarily from Uttar Pradesh, Bihar, and West Bengal.
- India has a balanced mix of FCBK and Zigzag kilns, with sparse but the highest number of CFCBK kilns as compared to other regions.



CFCBK



FCBK

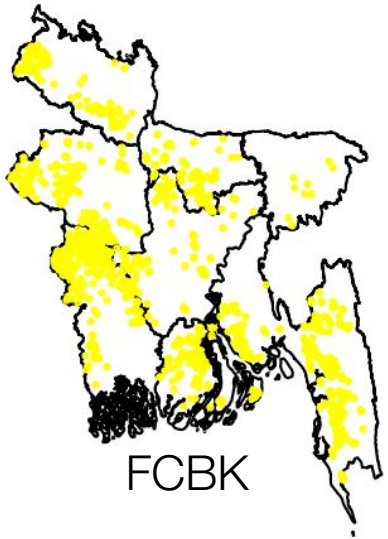


Zigzag

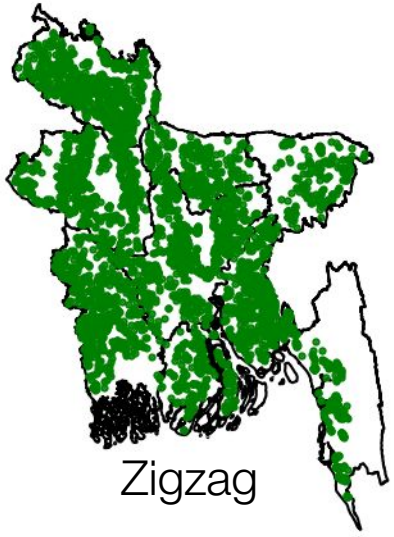
Brick Kilns distributions in Bangladesh

- Bangladesh contributes over 6,900 kilns to our dataset.
- It shows a strong dominance of Zigzag kilns, reflecting regulatory efforts toward cleaner technology.

CFCBK



FCBK

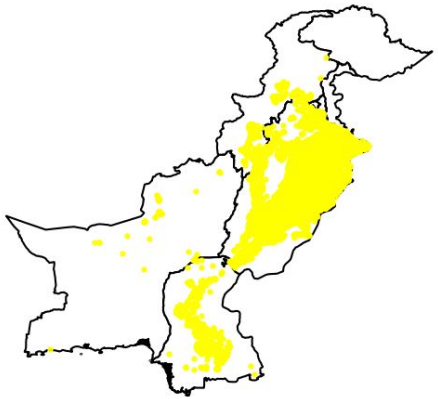


Zigzag

Brick Kilns distributions in Pakistan

- Pakistan contributes over 12,000 kilns to our dataset.
- It has a high concentration of FCBKs, particularly in the Punjab region.

CFCBK



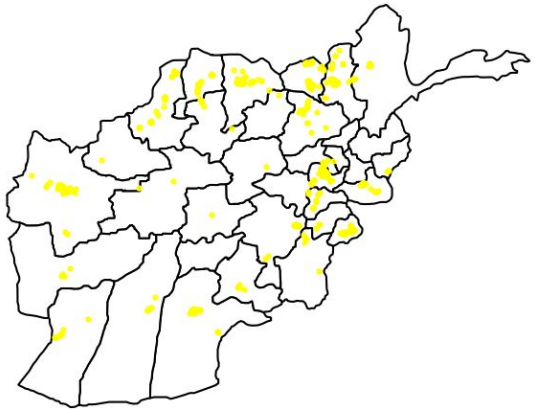
FCBK

Zigzag

Brick Kilns distributions in Afghanistan

- Afghanistan contributes with 600 kilns across 34 provinces.
- These entries are mostly discrete and primarily consist of FCBKs.

CFCBK



FCBK

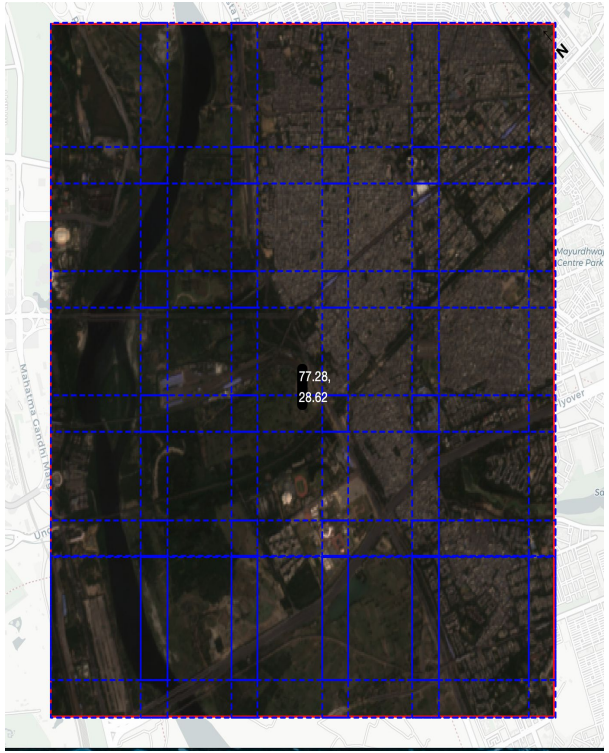
Zigzag

Image Creation Pipeline

SENTINELKILNDB	Space To Policy
Source: Google Earth Engine	Source: Mosaics API
Tile Size: 11000 x 11000 pixels	Tile Size: 4096 x 4096 pixels
Sentinel Imagery (10 m/pixel)	Planet Imagery (4.77 m/pixel)
Image Size: 128x128	Image Size: 640x640
Overlap between Images: 30 px	Overlap between Images: 64 px
Time Frame: Nov 2023 - Feb 2024	Time Frame: Nov 2023 - Feb 2024

Image Creation Pipeline

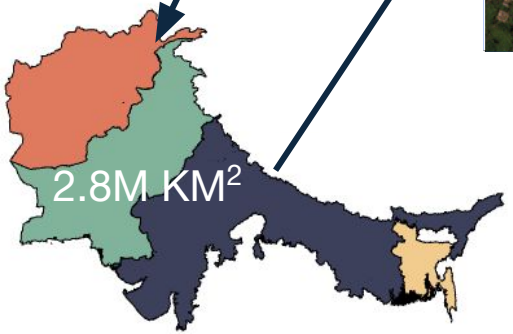
- Imagery Sources and Preprocessing : Sentinel Imagery.
- Sentinel-2 Surface Reflectance (RGB) via Google Earth Engine with Filtered for minimal cloud cover.
- Time Frame: Nov 2023 - Feb 2024; Peak brick kiln activity season.
- Patch Extraction: Sentinel tiles splitted into 128 × 128 pixel patches with 30-pixel overlap in latitude and longitude.



Label Creation Pipeline

YOLO11m-OBB
30K -Data (ACM JCSS)

Predict



Planet Imagery

Hand Validation

ESRI Imagery

Iterative Expansion Strategy:
4 Times

Expand Dataset : 63K Data

Label
Transfer

Sentinel-2 Imagery

SENTINELKILNDB

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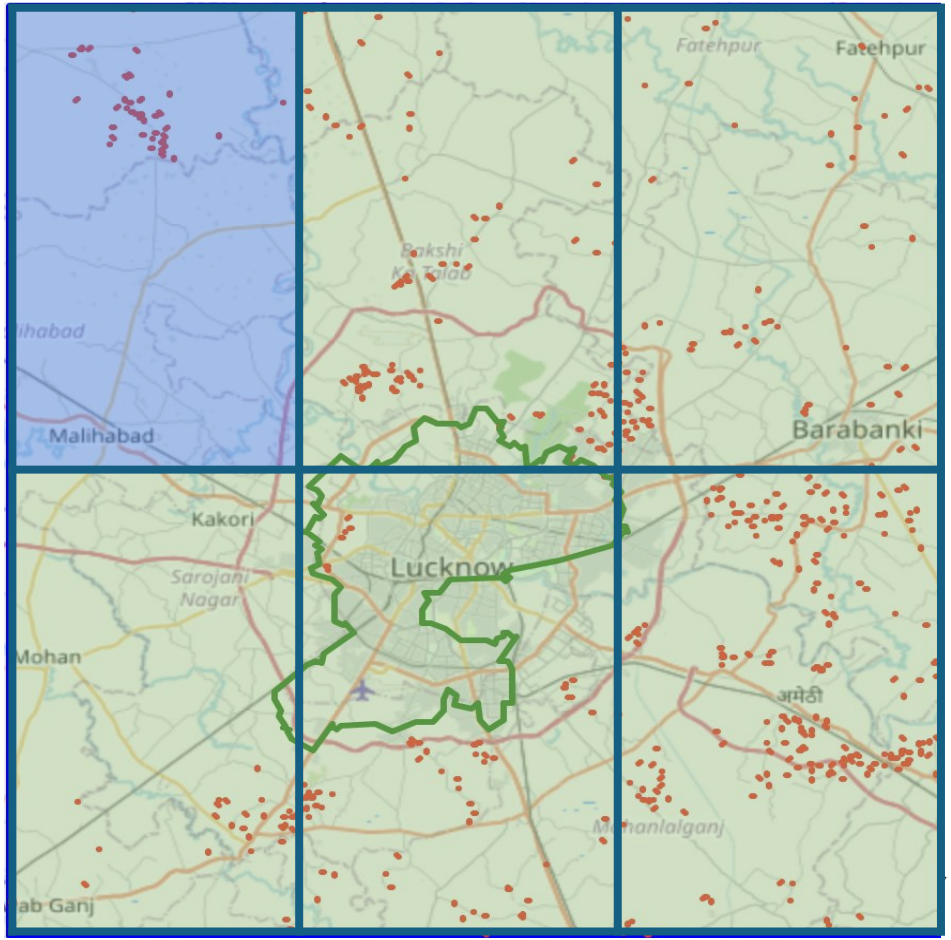
SentinelKilnDB Dataset Format and Release:

- **Data Available On:** Kaggle under CC BY-NC 4.0 License (Creative Commons Attribution–NonCommercial 4.0)
- **Dataset Composition:** 62,671 Sentinel-2 patches; Size: 128 × 128 pixels.
- **Native Resolution:** 10 meters/pixel
- **File Naming**:
  - **Image:** lat,lon.png
  - **Label:** lat,lon.txt
- **Label Format:** OBB format (DOTA, YOLO-OBB); AA format (YOLO).

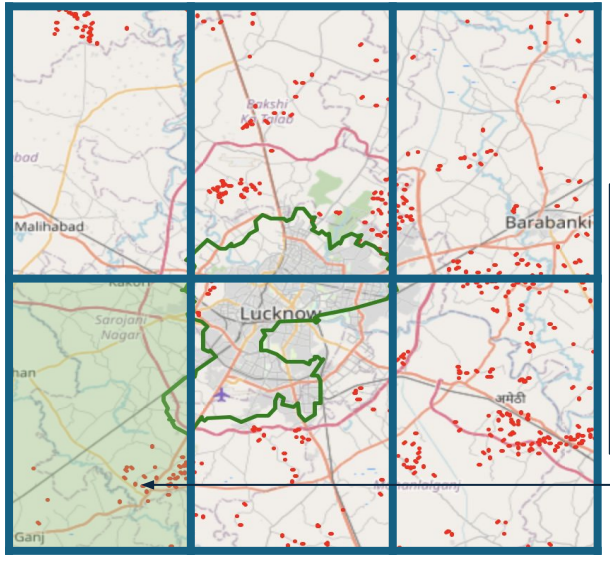
SentinelKilnDB Benchmark:

- **Task 1:** In-Region Detection
- **Goal:** Evaluate how well object detection models identify brick kilns within the same region they were trained on.
  - Brick Kilns



SentinelKilnDB Benchmark:

- **Task 2:** Out-Region Detection
- **Goal:** Assess how well models trained in one region can detect brick kilns in different, unseen regions.

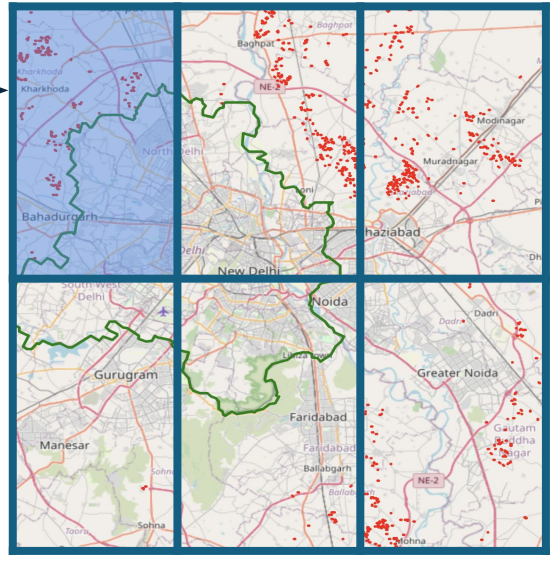


Lucknow Region

Train Region

Delhi Region

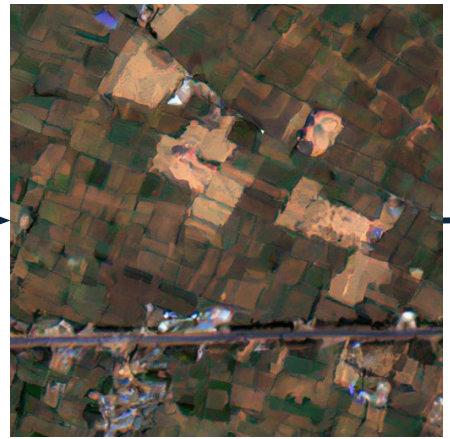
Test Region



SentinelKilnDB Benchmark:

- **Task 3:** Super-Resolution
- **Goal:** Apply super-resolution techniques to overcome Sentinel-2's resolution limits and enhance image quality and evaluate model performance.

Sentinel Imagery



Super-resolved Imagery

Model Performance

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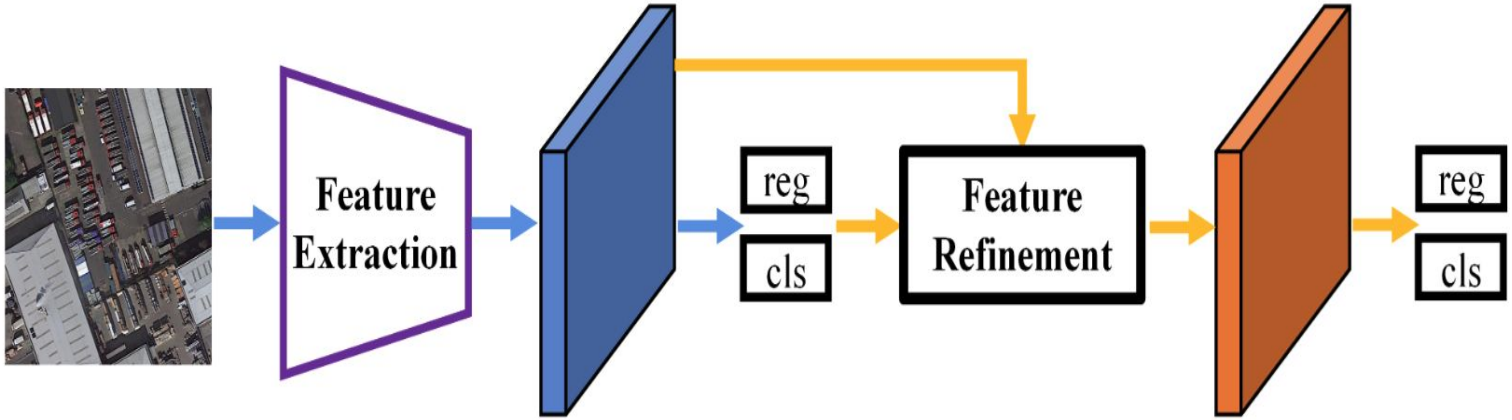
Result: Task 1 - In-Region Detection

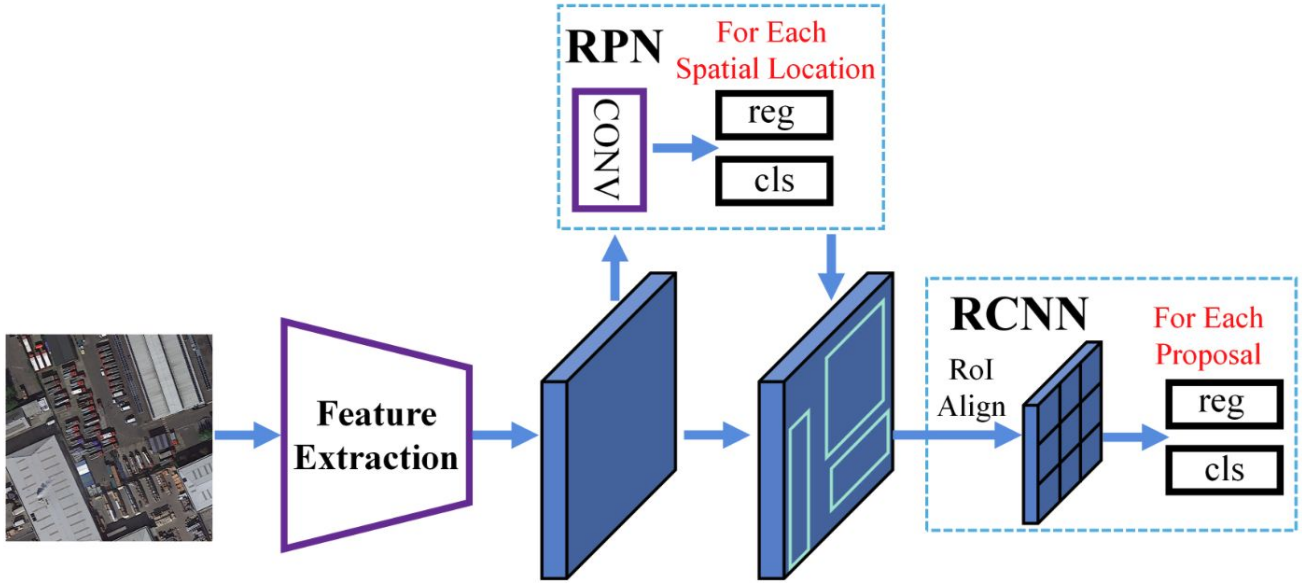
- **Data Setup:** Class-wise stratified split of dataset into training (60%), validation (20%), and test (20%) sets.
- **Results:** Transformer-based models and YOLO-OBB outperform other detection approaches.
- The object detection model struggles to distinguish between different kiln types.

One Stage Detectors



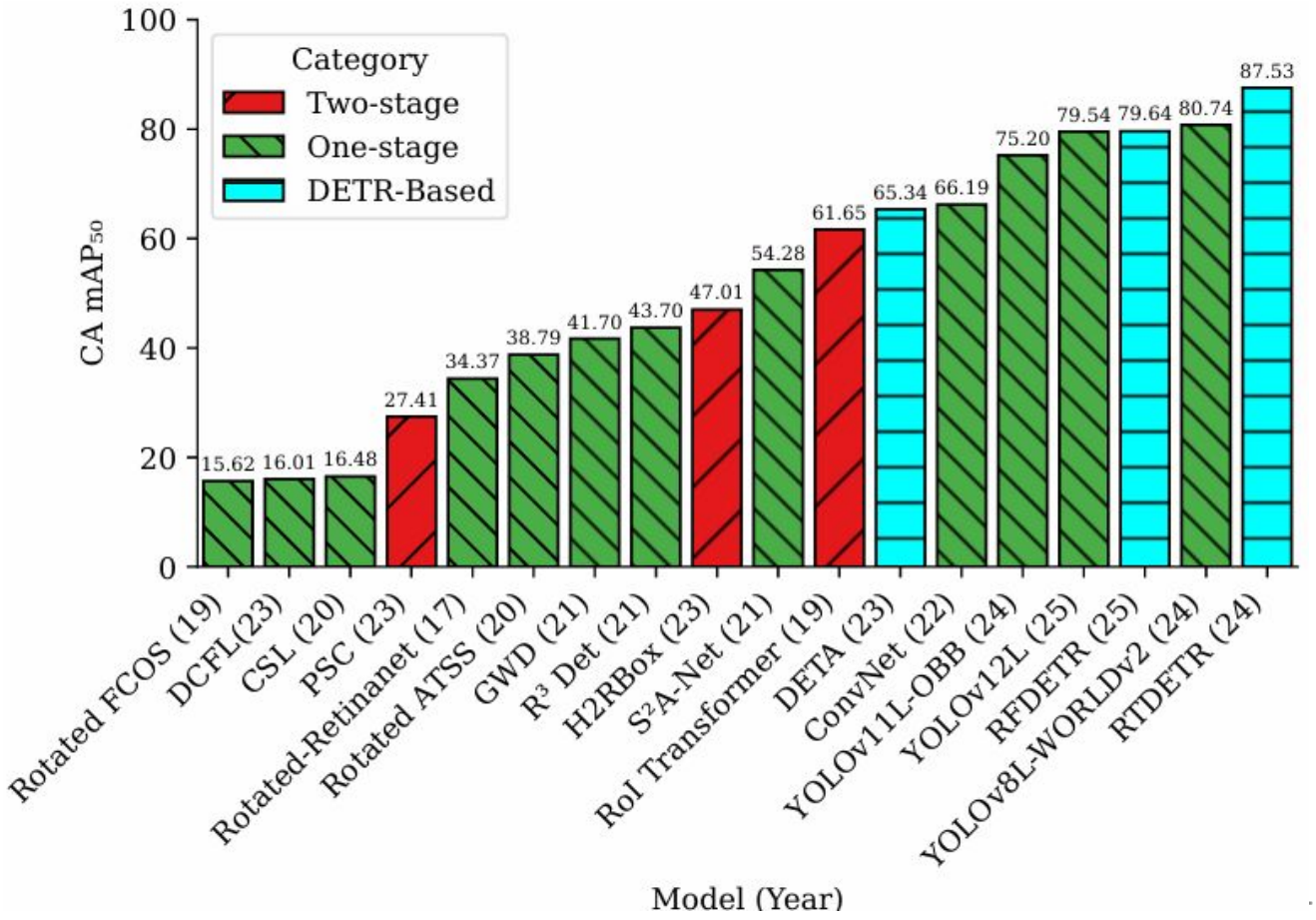
One Stage Detectors: Rotated FCOS, DCFL, CSL, Rotated-Retinanet, Rotated ATSS, GWD, R^3Det, S^2A-Net, ConvNet, Yolov8, Yolo11, Yolo12

Two Stage Detectors

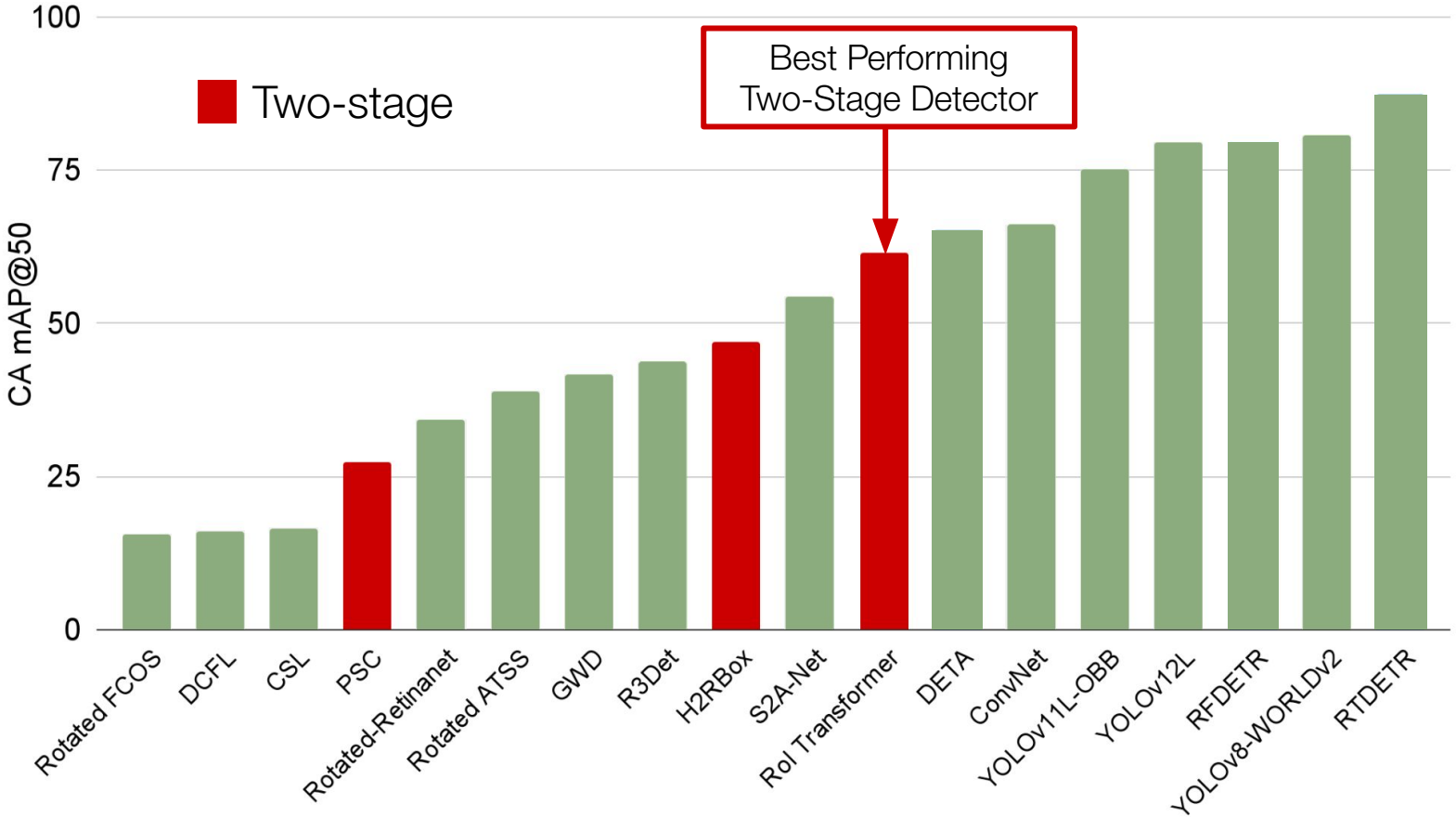


Two Stage Detectors: PSC, H2RBox, RoI Transformer

Findings: Task 1 - In-Region Detection

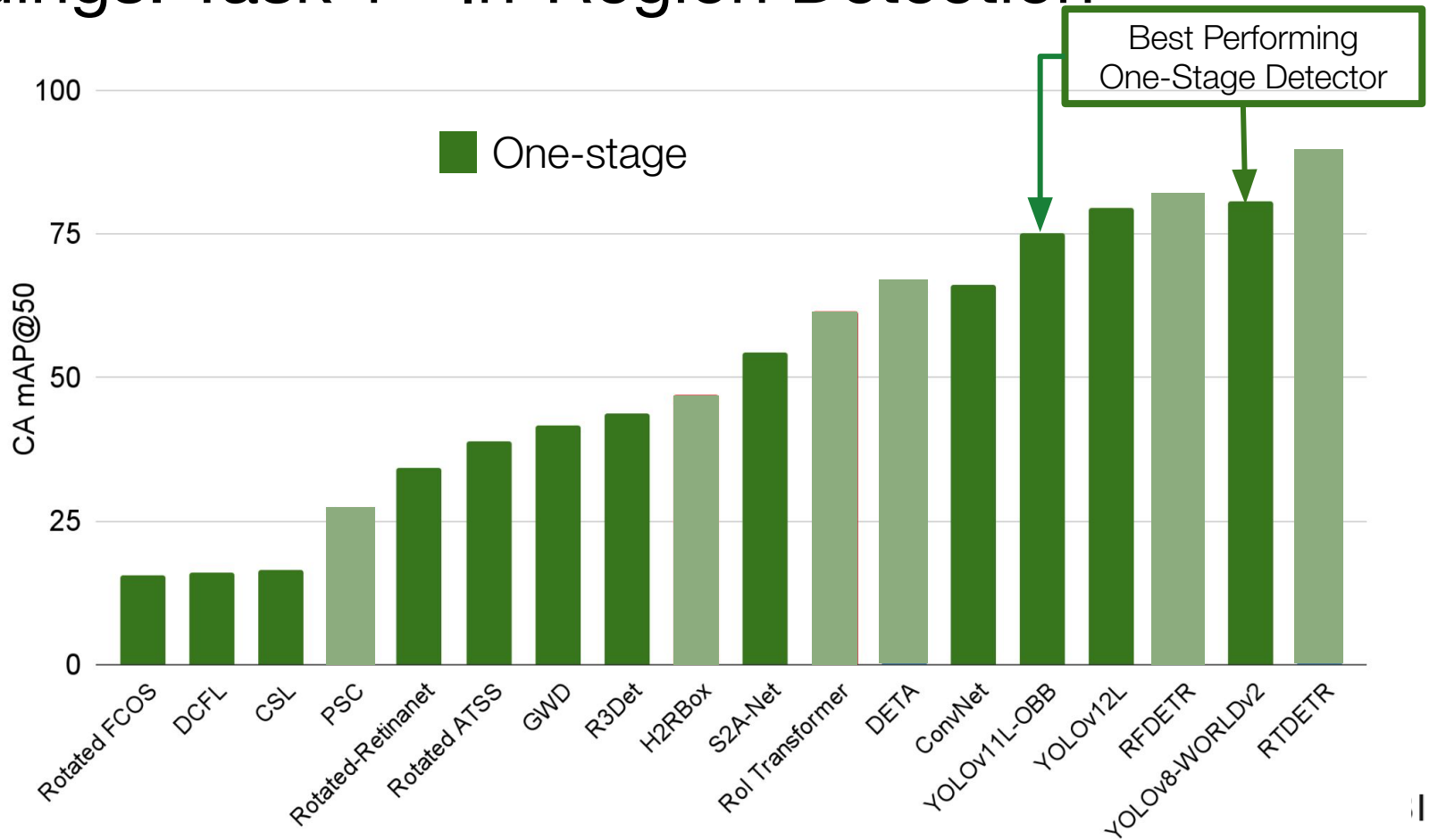


Findings: Task 1 - In-Region Detection

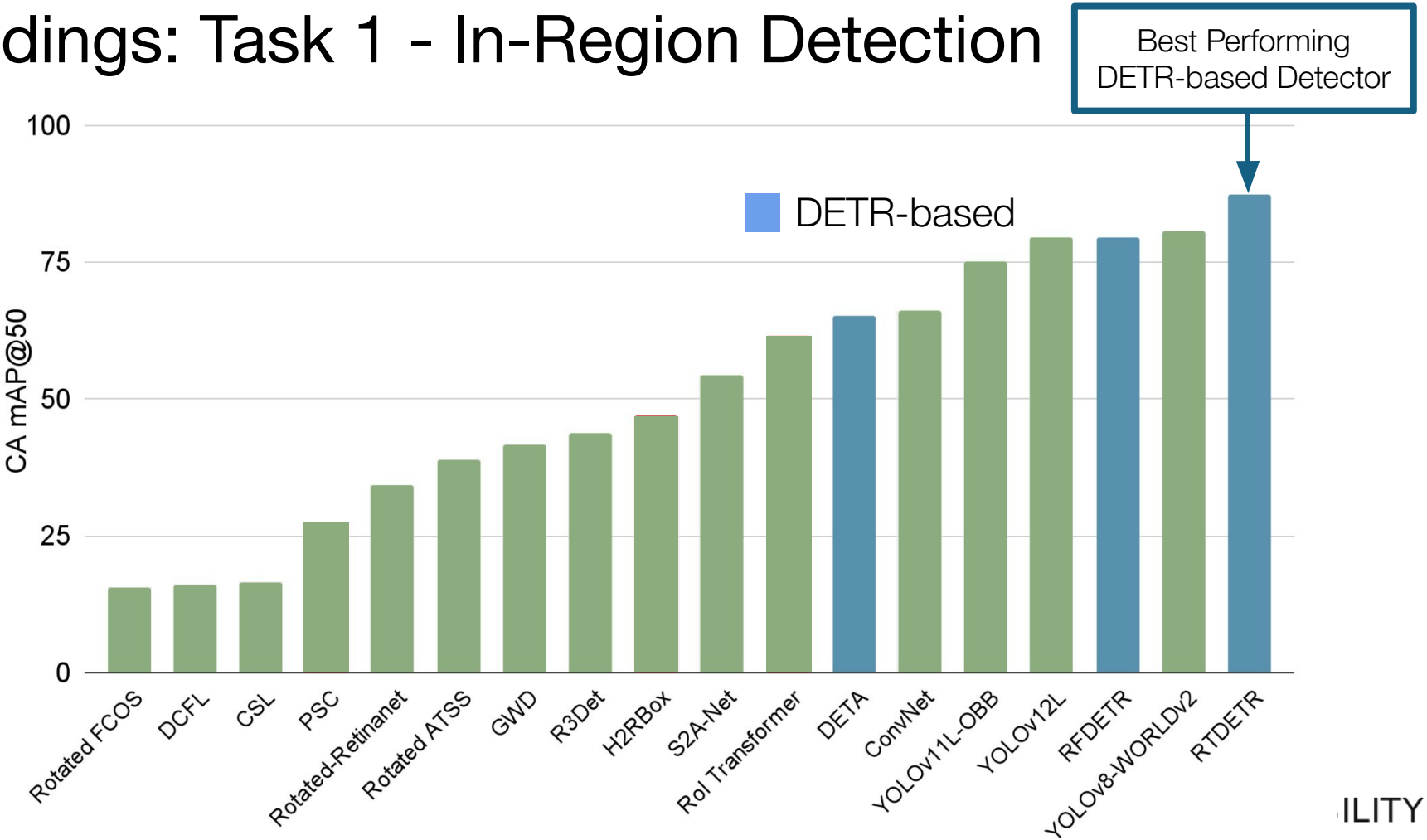


ILITY

Findings: Task 1 - In-Region Detection



Findings: Task 1 - In-Region Detection



ILITY

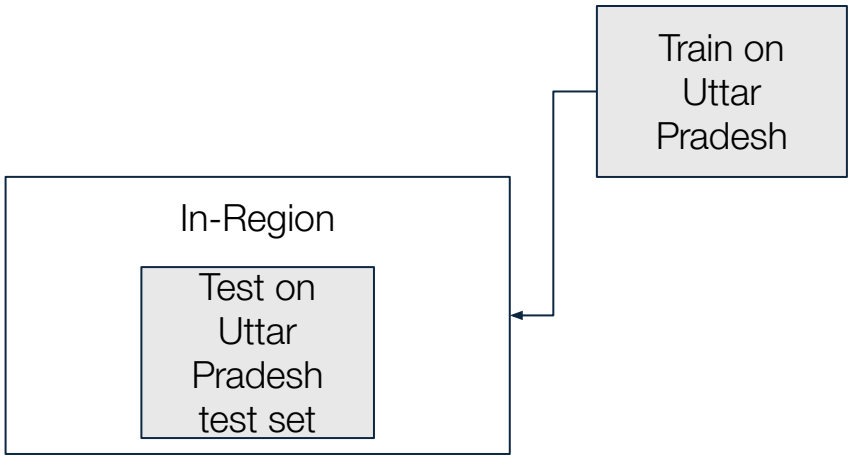
Findings: Task 1 - In-Region Detection

- **Results:** Transformer-based models and YOLO-OBB outperform other detection approaches.
- The object detection model struggles to distinguish between different kiln types.

Model Category	Model with highest CA mAP50
One Stage	YOLOv8L-WORLDv2, YOLO11L-OBB
Two Stage	RoI Transformer
DETR based	RT-DETR

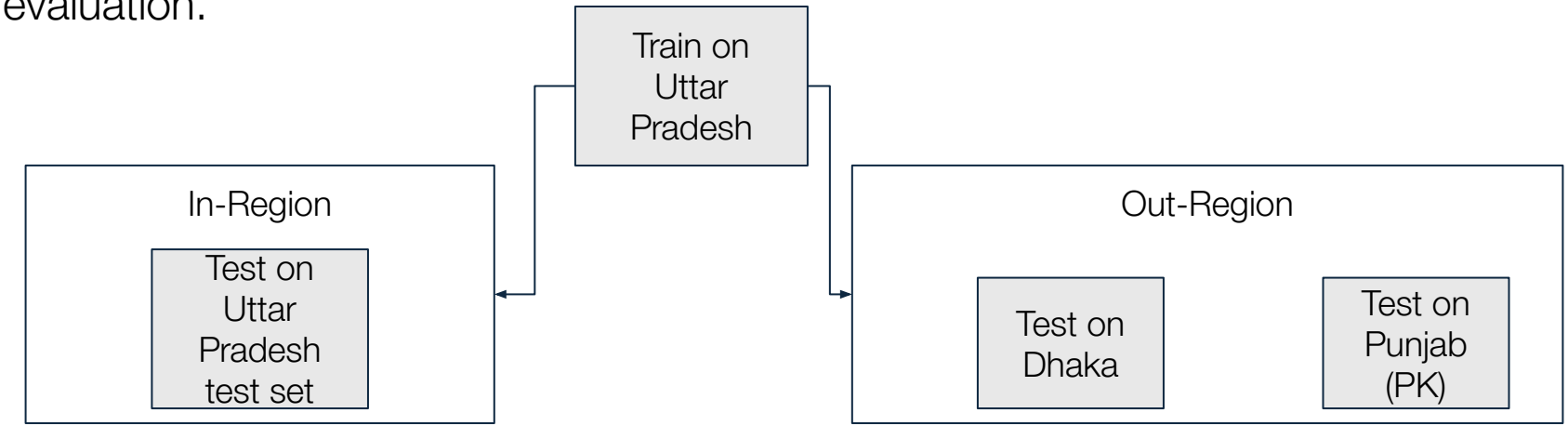
Result: Task 2 - Out-Region Detection

- **Data Setup:** Uttar Pradesh region is stratified split (60:20:20) for consistency.
- **Training Set:** Uttar Pradesh region (60%) .

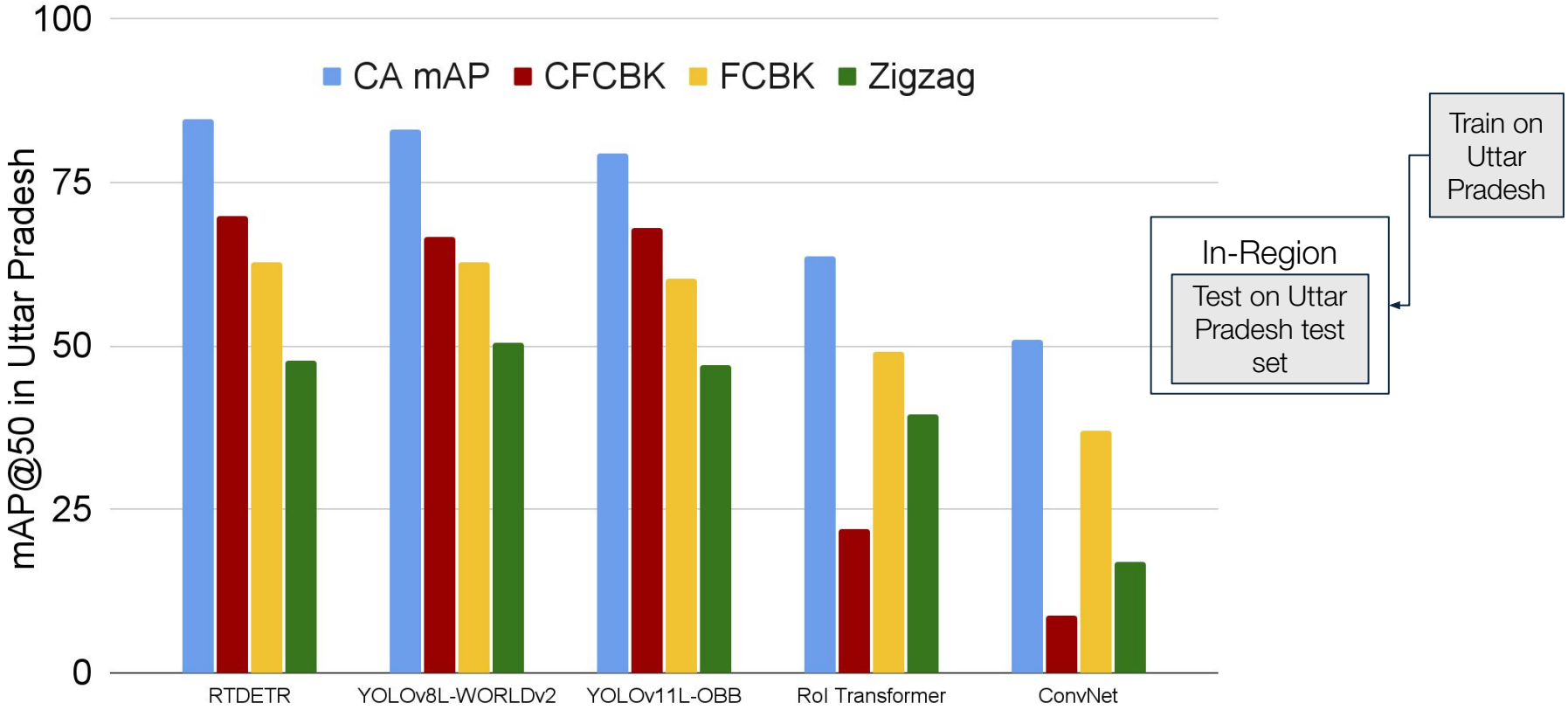


Result: Task 2 - Out-Region Detection

- **Data Setup:** Uttar Pradesh region is stratified split (60:20:20) for consistency.
- **Training Set:** Uttar Pradesh region (60%) .
- **Test sets:** Complete Punjab (PK) and Dhaka regions data for out-of-region evaluation.



Result: Task 2 - Out-Region Detection



mAP@50 is high in In-Region

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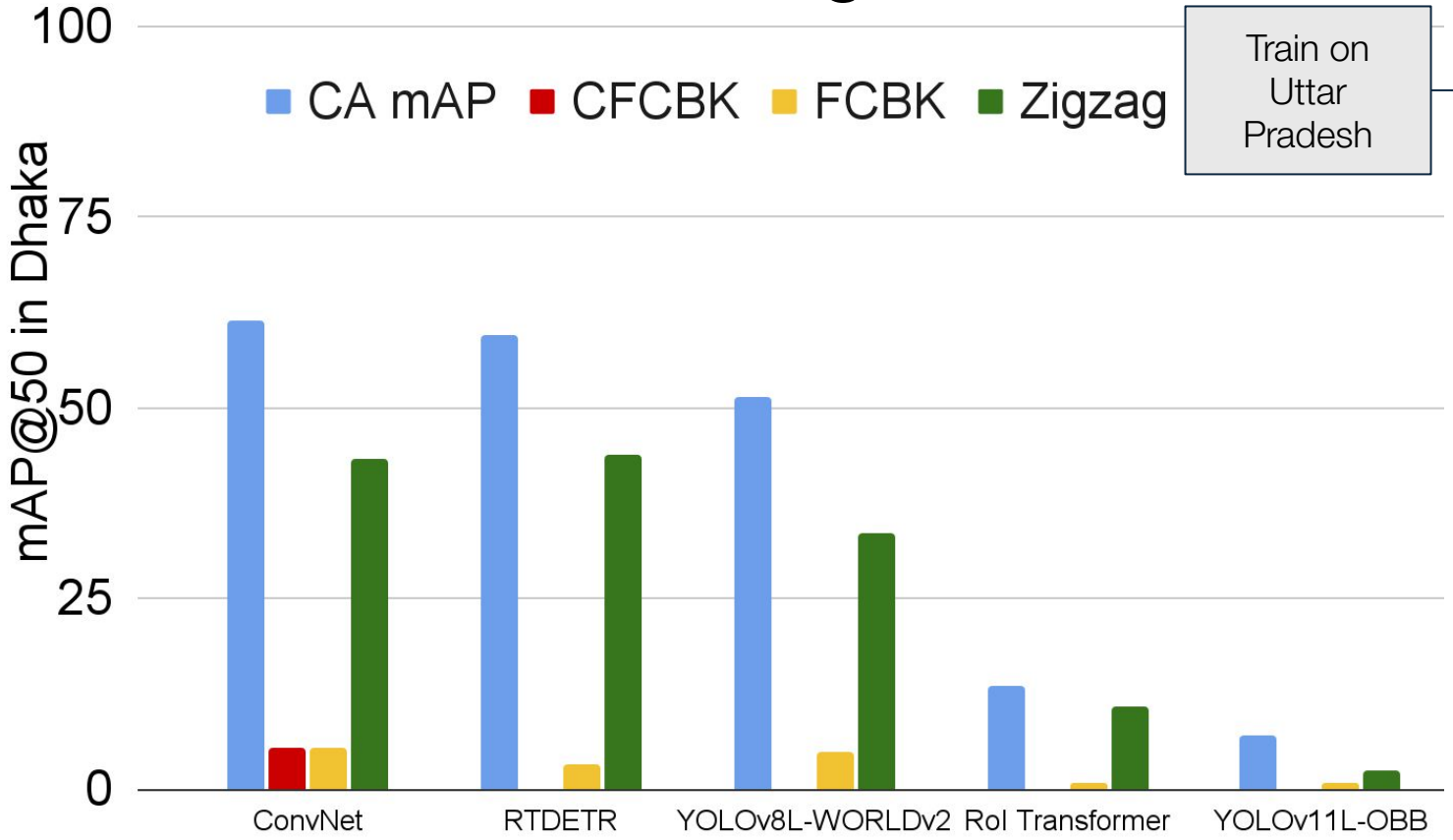
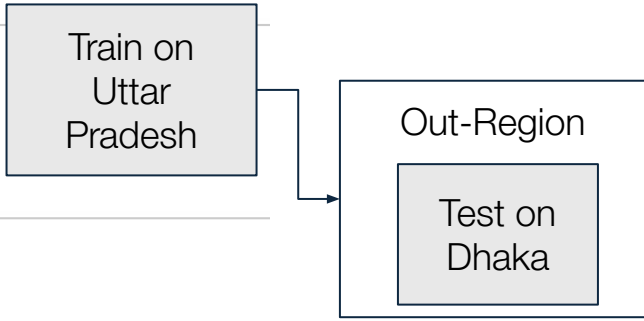
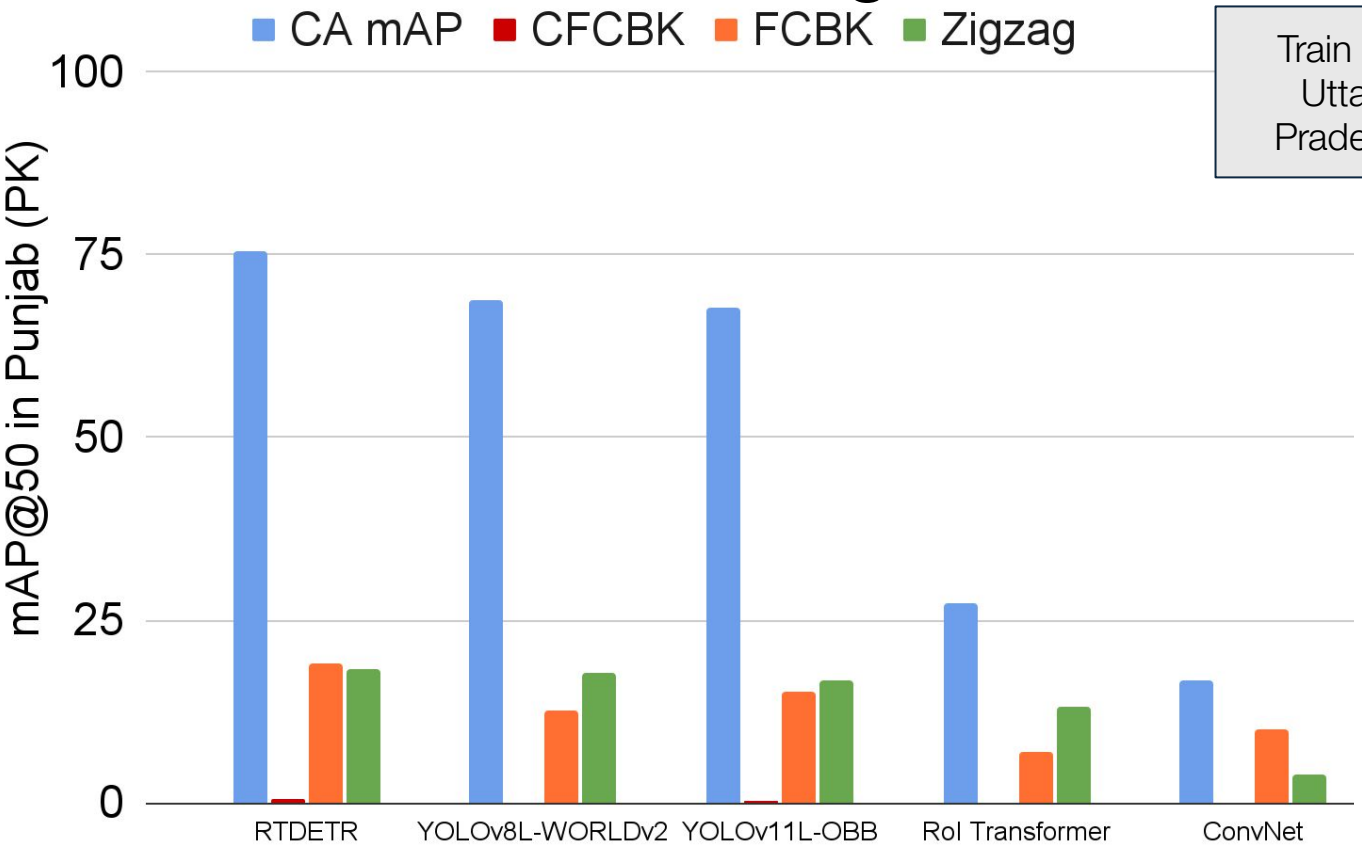
Result: Task 2 - Out-Region Detection





Performance Drop in Out of domain region

Result: Task 2 - Out-Region Detection



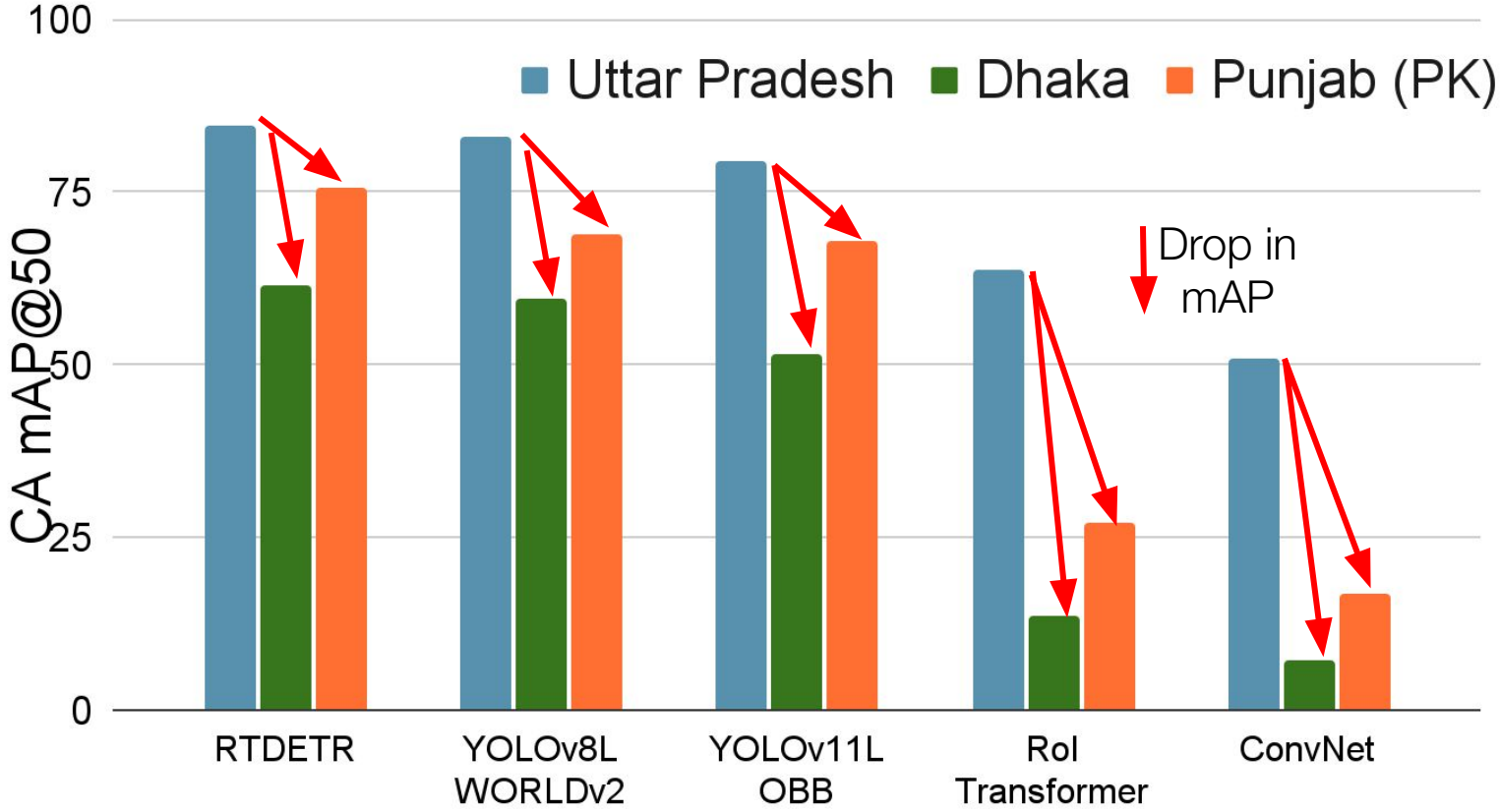
Train on Uttar Pradesh

Out-Region

Test on Punjab (PK)

Performance Drop in Out of domain region

Result: Task 2 - Out-Region Detection



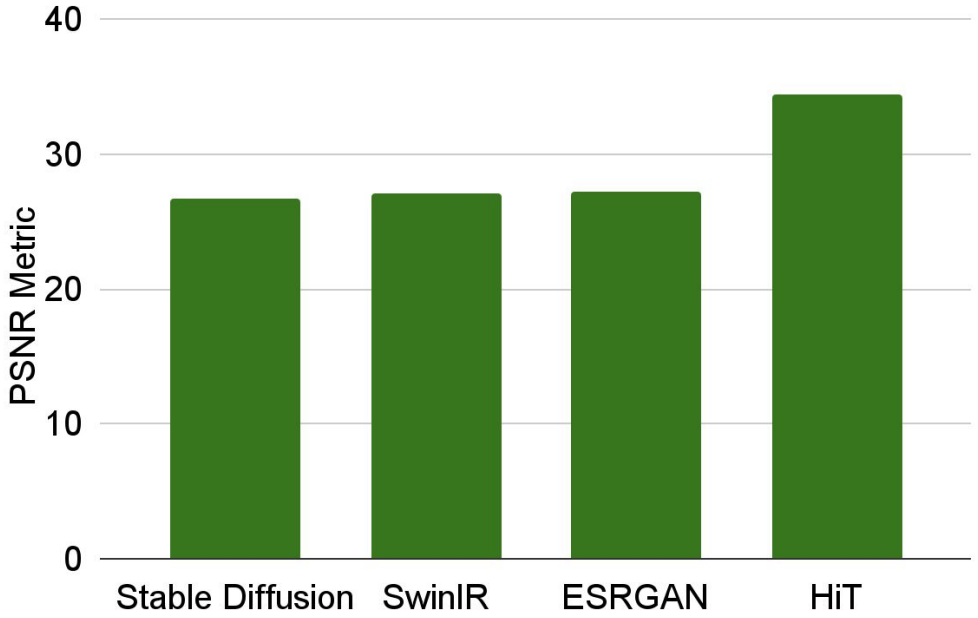
Challenge in domain generalization in low-resolution satellite imagery

Findings: Task 2 - Out-Region Detection

- In-Region Performance: All models performed well when evaluated within the region they were trained on.
- Cross-Region Challenge: Significant drop in unseen regions highlights domain shift and need for robust models.

Result: Task 3 - Super-resolution

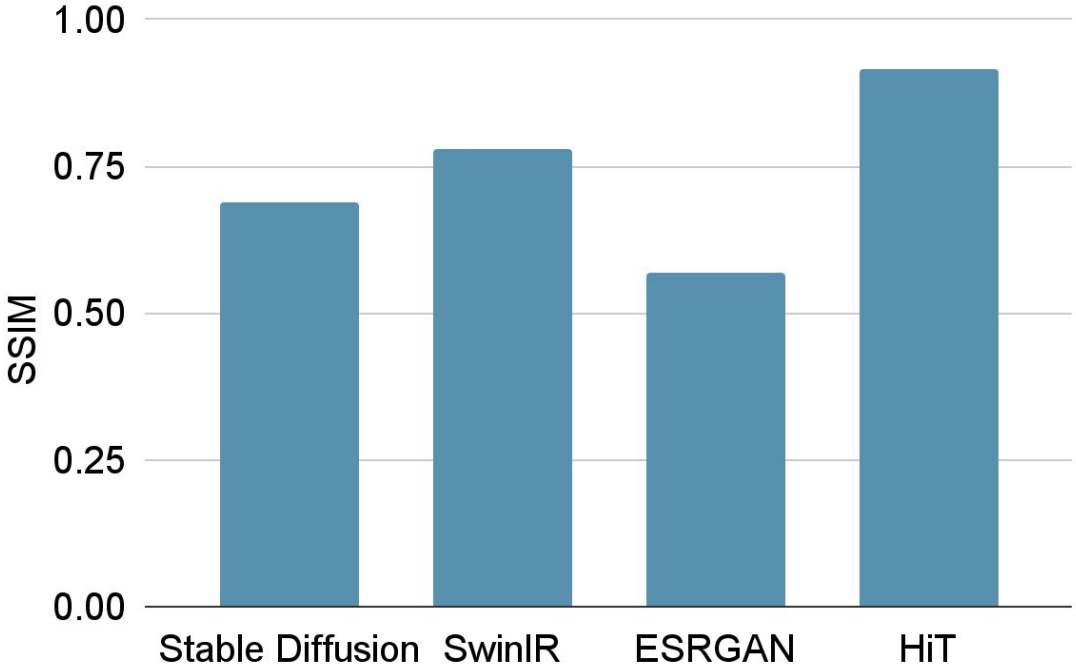
- **Data Setup:**
  Super-resolution techniques were applied to Sentinel-2 imagery (Delhi-NCR) with a 60:20:20 stratified split, and the enhanced images were used to test the best detection model.



PSNR Metric Comparison across Super-resolution Methods

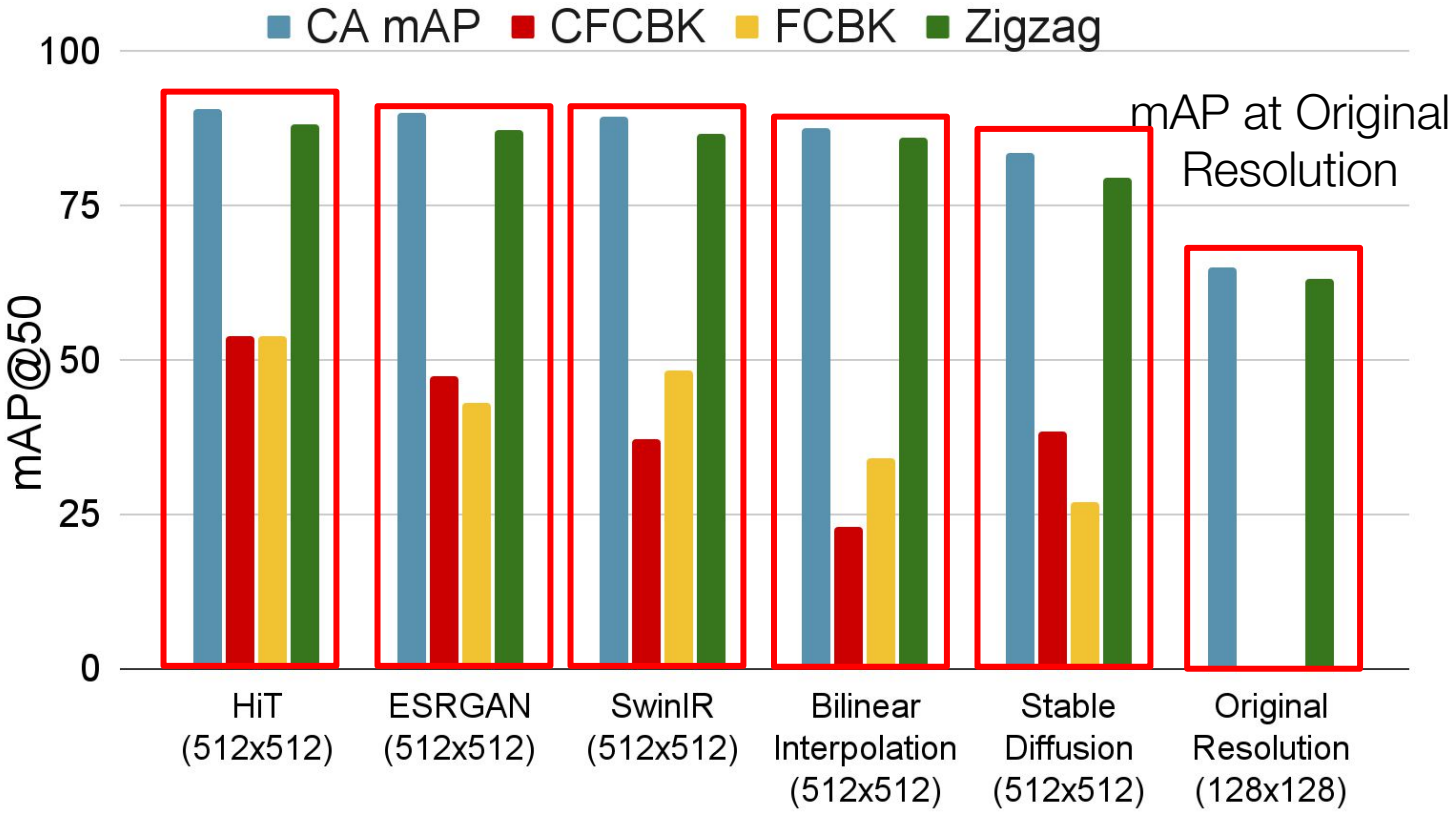
Result: Task 3 - Super-resolution

- **Data Setup:**
  Super-resolution techniques were applied to Sentinel-2 imagery (Delhi-NCR) with a 60:20:20 stratified split, and the enhanced images were used to test the best detection model.



SSIM Metric Comparison across Super-resolution Methods

Result: Task 3 - Super-resolution



mAP improves with Super-resolution Methods

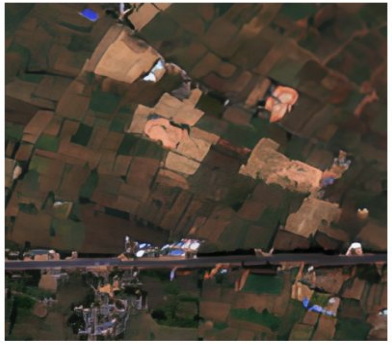
Result: Task 3 - Super-resolution

(a) Original Sentinel Imagery

(b) ESRI Wayback Imagery

(c) Planet Labs Imagery

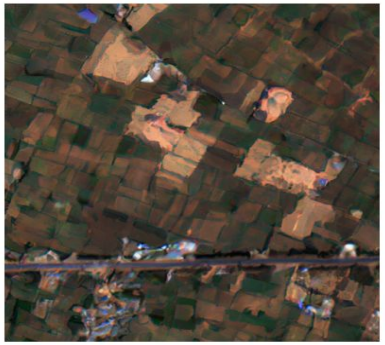
(e) Bilinear Interpolation



(f) SwinIR

(g) ESRGAN

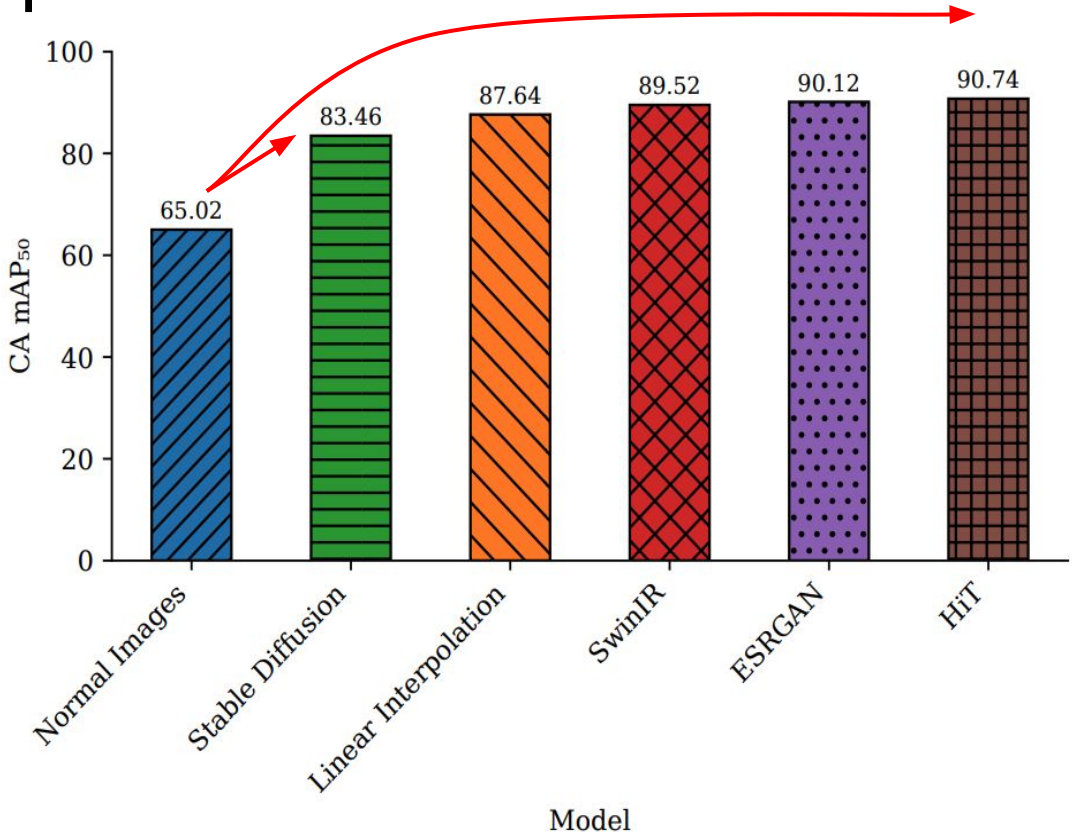
(h) HIT



(i) Stable Diffusion

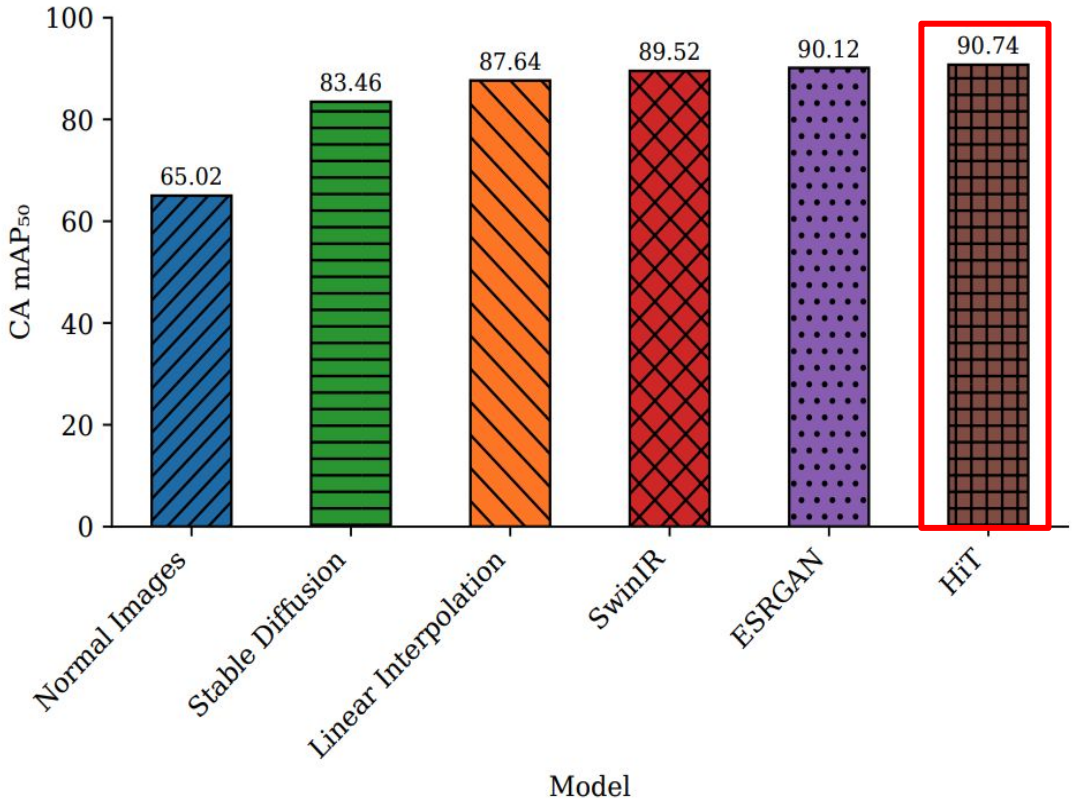
Findings: Task 3 - Super-resolution

- Both interpolation-based and learned super-resolution techniques significantly improve detection accuracy on low-resolution satellite imagery.



Findings: Task 3 - Super-resolution

- Both interpolation-based and learned super-resolution techniques significantly improve detection accuracy on low-resolution satellite imagery.
- Advanced methods like HiT achieve notable accuracy gains across all brick kiln categories



Applications

- We propose our dataset as a benchmark for oriented object detection (OBB) in low-resolution satellite imagery.
- It is comparable in scale to popular benchmarks like HRSC2016 and DOTA.
- To our knowledge, it is the first public dataset tailored for OBB model evaluation in low-res satellite data.

Applications

Largest Brick Kiln dataset on low resolution imagery

Dataset	Imagery	Classes	Quantity	Instances	GSD
VEDAI [38]	Aerial Imagery	9	1,210	3,640	0.125 m
HRSC2016 [29]	Google Earth	25	1,070	2,976	0.4 ∼ 2 m
DOTA-V1.0 [60]	Google Earth	15	2,806	188,282	0.1 ∼ 4.5 m
FGSD [7]	Google Earth	43	5,634	2,612	0.12 ∼ 1.93 m
DIOR-R [8]	Google Earth	20	23,463	192,518	0.5 ∼ 1 m
KILNDB (Our)	**Sentinel-2**	**3**	**78,694**	**105,933**	**10m**

Applications

Geographical Domain Adaptation & Active Learning:

- Our dataset enables evaluation of model robustness to geographic distribution shifts.
- Supports development of geography-aware SSL techniques for improved generalization.
- Due to high annotation cost and class imbalance, it’s ideal for benchmarking active learning in object detection.
- Helps reduce labeling effort while maintaining accuracy across diverse regions.

Conclusion

- Brick kilns are a major contributor of air pollution.
- Manually Locating kilns is labor-intensive.
- Satellite-based object detection speeds up mapping, but fails to generalize across regions reliably.
- High resolution Planet Imagery used previously has restricted sharing.
- Built a public dataset using Sentinel 2 imagery, which supports global scalability and fair benchmarking despite limited detail.
- Can use it with high-resolution data for a hybrid, multi-scale model to improve accuracy .

Limitations & Future Work

Resolution Constraints: The SentinelKilnDB dataset uses freely available Sentinel-2 imagery (10 m resolution), which limits fine-grained detail but supports scalable, real-world environmental monitoring.

Potential Improvements: Future research could combine Sentinel-2 with high-resolution data for hybrid detection or multi-scale fusion.