Eye in the Sky: Detection and Compliance Monitoring of Brick Kilns using Satellite Imagery

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ABSTRACT

Air pollution kills 7 million people annually. The brick manufacturing industry accounts for 8%-14% of air pollution in the densely populated Indo-Gangetic plain. Due to the unorganized nature of brick kilns, policy violation detection, such as proximity to human habitats, remains challenging. While previous studies have utilized computer vision-based machine learning methods for brick kiln detection from satellite imagery, they utilize proprietary satellite data and rarely focus on compliance with government policies. In this research, we introduce a scalable framework for brick kiln detection and automatic compliance monitoring. We use Google Maps Static API to download the satellite imagery followed by the YOLOv8 model for detection. We identified and hand-verified **19579 new brick kilns across 9 states within the Indo-Gangetic plain**. Furthermore, we automate and test the compliance to the policies affecting human habitats, rivers and hospitals. Our results show that a substantial number of brick kilns do not meet the compliance requirements. Our framework offers a valuable tool for governments worldwide to automate and enforce policy regulations for brick kilns, addressing critical environmental and public health concerns.

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1 INTRODUCTION

Air pollution kills seven million lives globally, with 22% of these fatalities occurring in India alone [13]. In 2020, India recorded an annual average $PM_{2.5}$ (particulate matter of size $\leq$ 2.5 μm) level of 24 $\mu g/m^3$, significantly surpassing the WHO's annual limit of 5 $\mu g/m^3$[2]. Brick kilns, a significant pollution source, contribute to 8%-14% of air pollution in South Asia (World Bank, 2020). In this region, 144,000 brick kilns generate 0.94 million tonnes of PM, 3.9 million tonnes of CO, and 127 million tonnes of CO_2 annually, employing 15 million workers including children [11].

Monitoring these unregulated kilns using traditional survey methods is labor and resource-intensive. Uttar Pradesh Pollution Control Board (UPPCB) conducted a manual survey [1] of brick kilns violating government regulations in the state on the order of National Green Tribunal (NGT). They found that 35% of brick kilns did not have a valid Consent to Operate (CTO) from UPPCB under the Air (Prevention and Control of Pollution) Act, 1981 [1]. Automatic detection and compliance monitoring from satellite imagery can fully automate and complete such analysis end-to-end in a few hours.

Air quality researchers manually annotate the brick kilns using tools such as Google Earth Engine. 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 would take over 4000 hours of work. It'd take a person more than 2.5 years to completely annotate India if they spend on an average 4 hours daily for annotation. Brick kilns are frequently established in new locations or relocated, further complicating the scalability of manual annotation.

Recent studies (Lee et al., 2021) have explored convolutional neural network (CNN) classification models such as VGG16 [6], ResNet [5], and EfficientNet [12] for brick kiln identification using imagery from private satellites. While existing methodologies lack precision in pinpointing the geographic coordinates of brick kilns, a crucial requirement for distance-centric compliance monitoring, YOLO offers a viable solution. YOLO's capacity to generate bounding boxes around brick kilns facilitates the extraction of precise location data, overcoming the challenge posed by traditional classification models.

Our paper proposes a scalable framework for brick kiln detection using Google Maps' publicly available satellite imagery and YOLOv8 [7]. We collect over **7 million satellite images from Google Maps Static API** for this study. We focus on two types of brick kilns in Indo-Gangetic plain: Zigzag and Fixed Chimney Bull's Trench Kilns (FCBK). We used 762 brick kilns across Delhi-NCR provided by air quality experts to create our initial labeled dataset. Furthermore, we manually verify and annotated predicted positives to increase the dataset and retrain the model. We repeat this process several times to increase the labeled verified dataset.

After preparing the verified dataset, we investigate compliance with government policies regarding brick kilns, as outlined in the

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[1]http://www.indiaenvironmentportal.org.in/content/476577/order-of-the-national-green-tribunal-regarding-brick-kilns-operating-illegally-in-uttar-pradesh-12022024/

document by the Central Pollution Control Board [2]. These policies include:

- Ensuring that no two brick kilns are within 1 km of each other.
- Ensuring that brick kilns are situated at least 800 m away from human habitation.
- Ensuring that brick kilns are situated at least 500 m away from rivers.
- Ensuring that brick kilns are situated at least 800 m away from hospitals.

The **main findings** from our study are the following:

(1) We have identified **19,579** new brick kilns in the Indo-Gangetic plain spanning across **9** states, covering an area of **938,281** km^2. These kilns are analyzed to determine their different types, with Zigzag kilns being **40%** more efficient than FCBK in terms of emissions [3].
(2) We found that **9777** (about **50%**) of the brick kilns are within **1 km** of other kiln/kilns.
(3) As per our findings, **31.82** million people (**4.8%**) of the population in the region of study live within **800 m** of brick kilns.
(4) As per our findings, **1765** (**9%**) of the brick kilns are within **500 m** of rivers.
(5) As per our findings, **3057** (**16%**) of the brick kilns are within **800 m** of hospitals.
(6) **270** (**1.4%**) of brick kilns violate both the **800 m** rule from hospitals and the **500 m** rule from rivers.
(7) The number of brick kilns in Delhi-NCR has increased by **15%** in the previous twelve years.
(8) We estimate that PM2.5 emissions from brick kilns range from **1428** to **2856** tons per day. Converting all FCBK kilns to Zigzag would result in a **16%** reduction in emissions.
(9) The number of brick kilns in Delhi-NCR has increased by **15%** in the previous twelve years.

Finally, we have developed a web application[3] offering users an accessible and interactive interface for brick kiln detection in a given region of interest. Our work is **fully reproducible**, and all details/code required to reproduce our work can be found at this repo [4].

2 RELATED WORK

Machine learning techniques applied to satellite imagery have been utilized to identify brick kilns in South Asian regions. One study [10] employs a gated neural network that decouples classification and object detection tasks to identify brick kilns. The study utilizes a deep learning architecture inspired by Inception-ResNet and the You Only Look Once (YOLOv3) object detector to locate brick kilns and evaluate it over 3300 km^2 area. In contrast, we evaluate our models on more than 100000 km^2 region (40x more region compared to Nazri et al. [10])with a much advanced model YOLOv8.

The scarcity of labeled data for training deep learning-based models has posed a challenge for brick kiln detection. Consequently, various approaches have been proposed to address this issue. A study by Misra et al. [9] employs a transfer learning-based approach to estimate brick kilns in North India using a limited dataset comprising 200 images per class. Most recently, Lee et al. [8] employed state-of-the-art machine learning models to predict over 7000 brick kilns in entire Bangladesh. We manually verified their predictions as our training data from Bangaldesh region. A recent report from United Nations Development Programme [5] also employs YOLOv3 algorithm to detect brick kilns around India but but it focused on only one category (FCBK) of brick kilns. In contrast, we detect both FCBK and ZigZag kilns using YOLOv8 model.

3 DATASET

In this section, we describe the dataset collection process and statistics of our data. Among multiple alternatives such as Google Earth Engine, Sentinel imagery and Google Maps Static (GMS) API, we found GMS API most suitable for our application due to lower rate limits and high resolution imagery provided by Google with production-level quality.

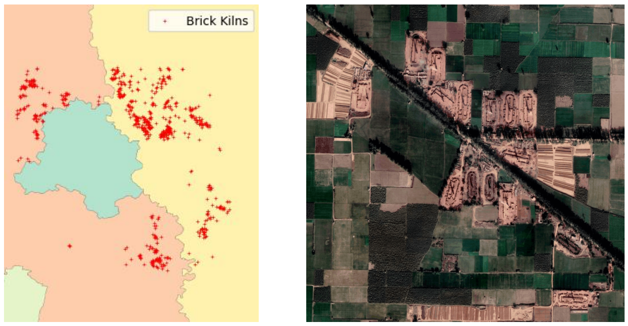
3.1 Google Maps Static (GMS) API

GMS API combines multiple satellite products to provide satellite imagery at multiple zoom levels. It uses center of the image (in latitude and longitude) and provides maximum of 1280×1280 sized snapshot. Following the previous work [8], we try to keep roughly 1 meter to pixel ratio for the images with zoom level 16 and scale=2 in the API. Note that by default the scale is 1 and thus zoom level 17 is needed to get 1 meter to pixel ratio images. With scale=2, **we reduced the number of images needed to be downloaded by 75%** while getting the same resolution imagery from the GMS API. With a single API query, we get a 1280×1280 sized tile. We experimentally found that, keeping 0.01 degree sliding window in both latitude and longitude allows us to have a reasonable overlap while ensuring full coverage of the entire region. We allow the overlap to ensure that if a brick kiln at the edge of the tile is not fully covered within the tile then it would be covered in the nearby tiles. With educational accounts in Google Cloud Platform, we could download 25,000 images per day per account. We estimate that **country like India can be downloaded in 84 days per account**. For example, if we have use APIs from two accounts, we can download the entire dataset in 42 days. However, we download only Indo-Gangetic plain since majority of the kilns are available in this region.

3.2 Indo-Gangetic Plain

3.2.1 Delhi-NCR. With guidance from an air quality domain expert [4], we curated a dataset of 762 brick kilns across Delhi-NCR. We then selected 400 coordinates up to two decimal places and downloaded data according to specified settings in the previous section. We download a total 400 images and manually label them resulting in 762 brick kiln images among all. We show the locations of labeled images in Figure 1 (a).

[2]https://cpcb.nic.in/uploads/Industry-Specific-Standards/Effluent/74-brick_kiln.pdf
[3]https://brick-kilns-detector.streamlit.app/
[4]https://github.com/rishabh-mondal/compass24
[5]https://www.undp.org/sites/g/files/zskgke326/files/2023-12/geoai_for_brick_kilns_v8_web_pages_002_0.pdf



(a) **(b)**

Figure 1: Our brick kiln (labeled) datasets from (a) Delhi-NCR (a) a sample images from Bihar.

3.2.2 Other regions. We download the entire landscape of states within Indo-Gangetic plain. In total, **we have downloaded the area of size approximately 938,281 square kilometer (**$\sim$ 30% **of India) from 9 states resulting in 1 million images**.

4 APPROACH

4.1 Problem Formulation:

Given an RGB image of size (1120,1120,3) the objective is to detect the brick kilns along with their respective types, Zigzag or FCBK, and determine the exact coordinates of the kilns along with the bounding box.

4.2 You Only Look Once (YOLO) Model:

The You Only Look Once (YOLO) model is a popular object detection algorithm known for its speed and accuracy. Unlike traditional object detection methods that involve multiple stages like region proposal, feature extraction, and classification, YOLO performs detection in a single pass through the network. of a convolutional neural network (CNN) backbone followed by several detection layers. These detection layers predict bounding boxes, confidence scores for those boxes, and class probabilities for the objects contained within the boxes. YOLO has undergone several iterations, with each version introducing improvements in terms of accuracy and speed. In this paper, we use YOLO version 8 [7] which is latest at the time of writing this paper.

5 EVALUATION

In this section, we present the evaluation of our models.

5.1 Experiments:

During the evaluation, we conducted the following experiments:

- **Initial Setup:** Initially, we partitioned our dataset (Delhi-NCR) into training and testing sets using an 80:20 ratio. Subsequently, we evaluated different versions of YOLOv8 to determine the best-performing model. As a result of this experiment, we fix YOLOv8-M model [7] for all further experiments.
- **Iterative Setup:** We utilized the initially trained model, which was trained on 80% of the Delhi-NCR dataset, to directly predict on various states within the Indo-Gangetic region. Afterward, we hand-validated the predicted positive instances and updated our initial training set with the new dataset. We followed this process multiple times to iteratively refine our model.

5.2 Results:

With the iterative fine-tuning process, we identified a total of **19,579 brick kilns** across 9 states, as illustrated in Table 1. In Figure 2, the detection of various types of brick kilns using YOLOv8 with bounding boxes is depicted.

Table 1: Number of brick kilns detected per state.

State	# of Zigzag	# of FCBK	Total
Uttar Pradesh	4174	3336	7510
Bihar	3455	683	4138
Haryana	2214	137	2351
Punjab	2045	282	2327
West Bengal	1626	665	2291
Jharkhand	57	309	366
Uttarakhand	164	69	233
Madhya Pradesh	73	139	212
Himachal Pradesh	133	18	151
Total	13941	5638	19579

6 DEPLOYMENT

We have expanded our investigation into compliance, a critical focus emphasized by numerous stakeholders due to its direct association with specific interventions. As per the pollution control board's Revised Compliance Standards as of February 22, 2022, the compliance rules and our finding are discussed in the following subsections.

6.1 Compliance with rivers

Brick kilns are required to maintain a minimum distance of 500 meters from rivers. Our research reveals that 1,765 (9%) of the brick kilns surveyed fail to meet this criterion in the Indo-Gangatic region. Table 1 illustrates the percentage of brick kilns that do not comply with regulations across various states in the Indo-Gangetic region. In Figure 1, we show compliance with river regulations in Haryana. Red dots indicate instances of non-compliance.

6.2 Compliance with hospitals

Brick kilns are mandated to maintain a minimum distance of 800 meters from hospitals. However, our findings reveal that 3057 (16%) of the brick kilns fail to meet this requirement. Table 2 presents the percentage of brick kilns that fail to comply with hospital distance regulations across different states in the Indo-Gangetic region.

Figure 2: Detection of FCBK and Zigzag brick kilns using YOLOv8 with bounding boxes. The numbers mentioned at the top of bounding boxes are confidence scores.

Table 2: Brick kilns violating compliance (< 0.5 km) with rivers across various states.

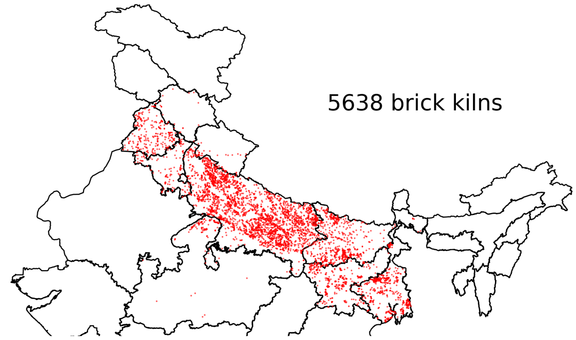
States	Percentage (Brick Kilns)
Punjab	8.47%
Haryana	17.71%
Uttar Pradesh	3.99%
Bihar	7.23%
West Bengal	16.72%
Jharkhand	28.44%
Madhya Pradesh	15.56%
Himachal Pradesh	16.56%
Uttarakhand	10.29%

6.3 Compliance with intra brick kilns distance

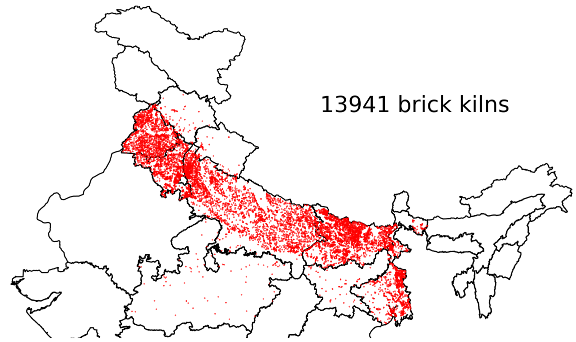
According to regulations, brick kilns should be at least 1 km apart from each other. Our study revealed that approximately 50% of the brick kilns, totaling 9777, are located within 1 km of another kiln or kilns. We calculate the pair-wise distances from our Delhi-NCR dataset and found that 684 out of 762(90%) brick kilns violate the first policy. Figure 6 shows the kilns violating the minimum distance policy.

6.4 Compliance with population

According to pollution control board, brick kilns should maintain a minimum distance of 800 meters from human habitation. Our study reveals that 31.82 million individuals, constituting 4.8% of the population in the surveyed region, reside within this 800-meter radius of brick kilns. Table 3 outlines the population distribution within different proximity ranges of brick kilns. It provides data on populations within 0.8 km, 2 km, and 5 km distances from brick kilns, along with total population figures for each state. Overall, the table highlights the significant number of people living near brick kilns across the surveyed states.



(a)



(b)

Figure 3: Our detected brick kilns (a) Fixed Chimney Bull's Trench Kilns (FCBTK) (b) Zigzag Kilns.

Table 3: Brick Kilns Breaking Compliance (< 0.8 km) with Hospitals Across Various Regions

States	Percentage (Brick Kilns)
Punjab	14.55%
Haryana	3.96%
Uttar Pradesh	21.43%
Bihar	9.91%
West Bengal	25.46%
Jharkhand	9.58%
Madhya Pradesh	7.75%
Himachal Pradesh	24.46%
Uttarakhand	9.44%

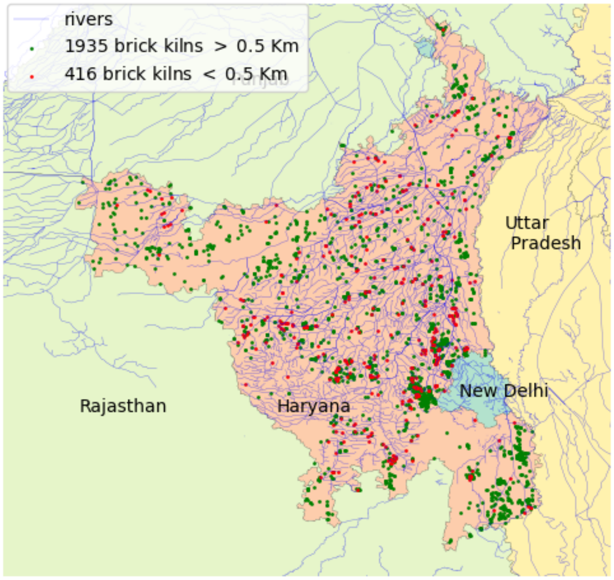


Figure 4: Compliance with rivers in Haryana. We did the same study for all states and the results are presented in Table 2.

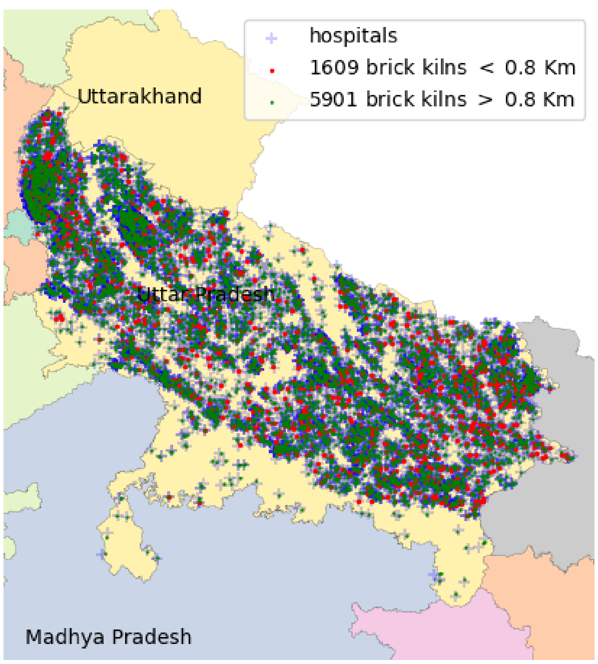


Figure 5: Compliance with hospitals in Uttar Pradesh. We did the same study for all states and the results are presented in Table 3.

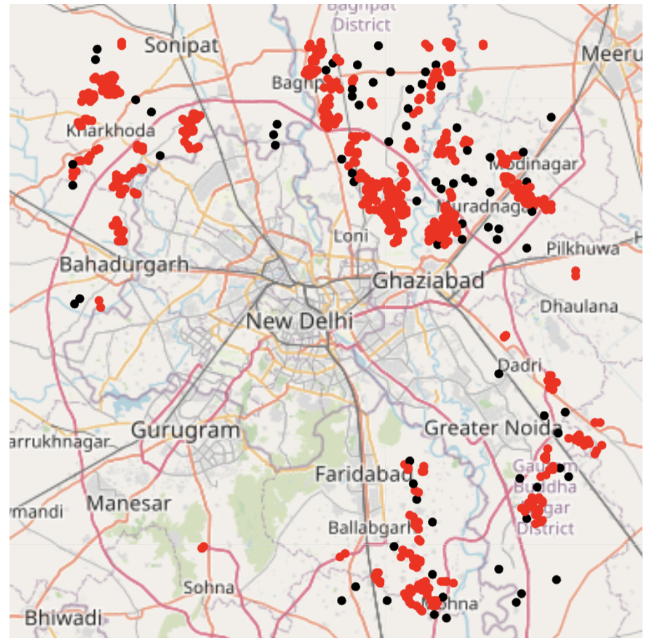


Figure 6: Brick kilns are failing to adhere to the government policy requiring a minimum distance of 1 km between them. Of the 762 surveyed kilns, 684 (90%) were identified as non-compliant. Non-compliant kilns are marked with Red dots, while compliant ones are denoted by black dots.

Table 4: Population within K km of Brick Kilns.

State	Population within K km			Total
	< 0.8 km	< 2 km	< 5 km	
Uttar Pradesh	13.81 M	63.32 M	168.83 M	233.00 M
Bihar	9.43 M	44.22 M	98.41 M	124.90 M
West Bengal	4.35 M	18.54 M	50.47 M	102.10 M
Madhya Pradesh	258.06 K	1.40 M	5.84 M	84.69 M
Jharkhand	406.06 K	2.04 M	8.32 M	38.94 M
Punjab	1.95 M	10.03 M	25.64 M	31.04 M
Haryana	1.12 M	6.34 M	19.36 M	29.63 M
Uttarakhand	319.41 K	1.31 M	3.91 M	11.64 M
Himachal Pradesh	175.10 K	680.47 K	2.11 M	7.61 M
Total	31.82 M	147.88 M	382.88 M	663.55 M

6.5 Estimation of Emissions

In this section, we provide the estimation of emissions from brick kilns. The emission factors (g/brick) obtained from Guttikunda et al. [3] are as follows: "PM2.5": 6.8, "PM10": 9.7, "SO2": 4.6, "NOx": 4.7, "CO": 90.0, "CO2": 520, "BC": 2.8

According to Guttikunda et al. [3], small-scale kilns produce less than 15,000 bricks per day, while large-scale kilns produce more than 30,000 bricks per day. Hence, we computed emissions for both 15,000 and 30,000 bricks per day per kiln to obtain a range of emissions in table 5. We have further segregated the brick kilns based on the two most common brick kiln types in India: Zigzag

Table 5: Emissions in tons per day while assuming 15000 and 30000 bricks per day per kiln. This analysis can be used to estimate the reduction in emissions if a more efficient kilns (such as Hoffman kilns) are installed replacing FCBK or Zigzag kilns.

State	(15,000 bricks/day/kiln)		(30,000 bricks/day/kiln)	
	PM2.5	PM10	PM2.5	PM10
Bihar	281.11	401	562.22	802
Haryana	149.47	213.22	298.94	426.43
Himachal Pradesh	9.98	14.23	19.95	28.46
Jharkhand	35.01	49.94	70.01	99.87
Madhya Pradesh	18.65	26.6	37.29	53.19
Punjab	153.92	219.56	307.84	439.12
Uttar Pradesh	595.72	849.78	1191.44	1699.56
Uttarakhand	17.07	24.36	34.15	48.71
West Bengal	167.34	238.71	334.68	477.41
Total	1428.27	2037.38	2856.53	4074.76

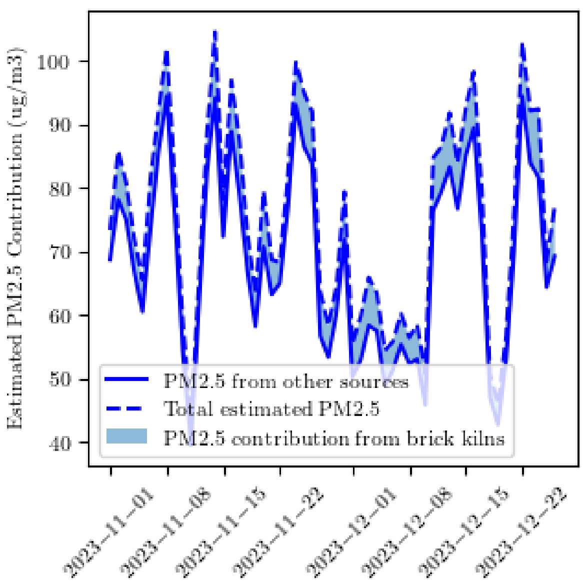


Figure 7: Contribution of brick kilns to PM2.5 pollution in Delhi-NCR estimated by WRF-CAMx. We found that brick kilns contribute 8% to the PM2.5 pollution during Nov-Dec of 2023.

and FCBK (Fixed Chimney Bull's Trench Kiln). We found that 71% of the brick kilns are Zigzag kilns and the rest are FCBK. Zigzag is 40% more efficient than FCBK in terms of emissions [3].

With our updated emission inventory including the identified brick kilns, we ran a Chemical Transport Model (CTM), WRF-CAMx over the Delhi-NCR region for Nov-Dec 2023 with the help of an air quality expert and found that brick kilns contribute 8% of PM2.5 pollution in the region.

We estimate PM2.5 emissions from brick kilns to be 1428 to 2856 tons per day. If all FCBK kilns are converted to Zigzag, this range will reduce to 1198 to 2396 tons per day, i.e., a reduction of 16%. If all the kilns are converted to Hoffman kilns [3], the range will reduce to 200 to 400 tons per day, i.e., a reduction of 86%.

6.6 Evolution of Kilns Over Time

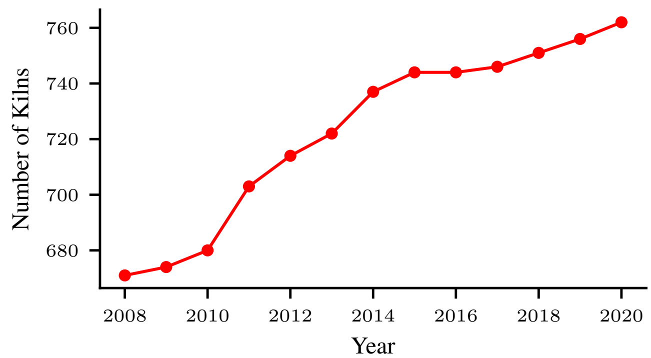


Figure 8: The number of brick kilns in Delhi-NCR has increased by 15% in the previous twelve years.

Finding the evolution of kilns over time can be helpful to understand the growth and subsequent effects (such as air pollution). Such studies can also help study effects of mitigation strategies or interventions. However, currently, GMS API does not provide a way to download the past images. We manually looked through historical imagery for the brick kiln sites that we verified in our study for the Delhi-NCR region in the Google Earth Engine Interface. We show the increase in brick kiln sites in the Delhi-NCR region in Figure 8. We found that out of the 760 brick kilns present today, less than 650 existed in 2008, and the numbers have increased by 15% in the past 15 years. We emphasize that if satellite imagery is available, we can use our models (instead of manual inspection) to scale this detection over a large geographical space. In the future, we plan to train on models on lower-resolution satellite products that are available across a longer time period.

7 LIMITATIONS AND FUTURE WORK

We now address some limitations and propose future work.

- In the current work, we have only looked at the image input. However, brick kilns often co-occur or are often clustered together owing to the presence of favourable soil conditions. Thus, leveraging location information within the model can help model localize better for that area.
- Current literature is limited to using RGB imagery for brick kiln detection. We plan to use multi-spectral imagery to potentially improve the accuracy of predictions.
- In the current work, we have assumed each training example to be equally important. In the future, in an attempt to further scale our models, we plan to leverage active learning methods to query strategically. This may greatly reduce the labelling cost.

- In the future, we plan to use satellite imagery of lower resolutions such as Sentinel and Landsat products to further scale our proposed techniques. An additional advantage of these lower resolution imagery is the availability of historical data.

8 CONCLUSIONS

In this paper, we presented a deployment of our methods for detecting brick kilns and their regulatory violations using satellite data and computer vision. We found that the proposed models can scale efficiently for a large geographical region such as Indo-Gangetic plain and thus can be used to aid for regulatory purposes and inventory management. Such scalable approaches can also maintain the inventory over time and thus be used to study effect of mitigation strategies.

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