BRICK KILN DETECTION IN NORTH INDIA WITH SENTINEL IMAGERY USING DEEP LEARNING OF SMALL DATASETS

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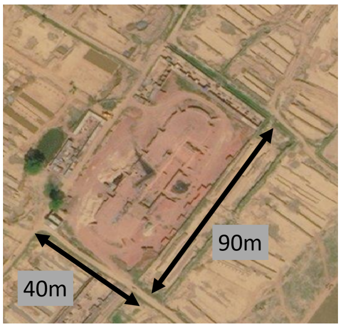
ABSTRACT: Urban air pollution has been rising across several developing countries in Asia. In cities lying in Indo-Gangetic plains of South Asia, air pollution is a result of urbanization growth e.g. construction and industrialization. Brick kilns, factories that make construction bricks, are significant pollutant emitters due to excessive coal usage. Being an unregulated industry, brick kilns are often overlooked in emission inventories due to non-availability of brick kiln locations. We propose a remote sensing-based approach to prepare brick-kiln location map over large-area that can be used in emission inventories in North India. In this paper we used unique features of brick kilns of the bull trench kiln (BK) type to identify them in open remote sensing dataset - Sentinel 2. This is an 'automatic target recognition' problem in which deep learning-based approaches have been very promising. To overcome requirement of huge training dataset for deep learning-based target recognition, we used transfer learning and fine-tuning approach to achieve recognition with a small dataset of 200 samples per class. Apart from the brick-kiln, urban, vegetation and fallow land samples were also prepared for training. Publicly available data: 10 meter resolution Sentinel-2 optical imagery was used for deep learning followed by use of PALSAR for post-processing. Over the region lying of east of New Delhi a hotspot of brick kilns exist that serve to the construction activities in surrounding regions. The brick kiln's producer accuracy with the use of publicly available satellite data was 72.3% and user accuracy was 99.1%. We find the brick kilns are located in those where horizontal or vertical urban growth is taking place. By analyzing the NDVI over the brick kiln locations, their age of operation and impact on operations due to governmental policies could also be estimated. These brick kiln locations can be further used for land-use emission inventories to assess PM2.5 and black carbon emissions as well as their concentration by chemical transport modeling.

1 Introduction

1.1 Background

History of brick making in India is almost 4000 years old. Several brick structures have been excavated in the Indus Valley civilization archaeological sites where bricks were used for granaries, sewer system and other historic infrastructure. Even today in most South Asia bricks are 'building blocks' in construction. Although much of the developed world reinforced concrete constructed buildings, in South Asia masonry buildings are common that mostly use bricks. A rudimentary style of brick manufacturing is employed in South Asia where heat by fuel combustion is passed through clay brick cakes. The facility such brick are manufactured are called brick kilns and are usually found around urban boundaries of many cities in South Asia. There is no official estimate of number of brick kilns but it is assumed to be more than 100,000 brick kilns (Maithel et al., 2012). The common type of brick kilns used in India are of Bull Trench Kiln type, where usually coal, biomass, agricultural residue and industrial byproducts are used as fuel (Rajarathnam et al., 2014). They are known to emit high amounts of black carbon $PM_{2.5}$ and SO_2. A detailed discussion of emission associated with different brick kiln types is provided elsewhere (Maithel et al., 2012).
Although several studies have researched on the environmental and health impacts of brick kiln in Dhaka, Kathmandu and Indian cities (Raut, 2006; Haack and Khatiwada, 2007; Le and Oanh, 2010; Guttikunda, Begum, and Wadud, 2013; Darain et al., 2013; Rajarathnam et al., 2014; Bhat et al., 2014), the research related mapping brick locations itself is limited and recent (Bian and Xie, 2016). The central pollution controlling body in India recently stated that more than 70% brick kilns are not registered (CPCB, 2017), hence unlicensed. In a high resolution remote sensing image (< 3 meter) brick kilns can be identified by through three features: brick kiln chimney, bricks pile, slabs pile (Haack and Khatiwada, 2007; Bian and Xie, 2016). Further in nadir orthometric view, these features are laid out in a ellipsoidal or a circular manner depending on the type of brick kiln. Further, shadow of brick kiln chimney (if imagery acquired low elevation of the sun) can be a useful indicator for visual indicator for optical imagery. These features are shown in Figure 1. With optical imagery care needs to be taken about the acquisition month. In dry seasons lack of surrounding green vegetation results in similar spectral response of dry soil and brick kiln. Another reason that may have prevented identification of brick kiln through remote sensing is the high cost of high resolution imagery



(a) Brick kiln

(b) Smoke from brick kiln

Figure 1: Brick kiln examples as seen in the (a) high resolution imagery (Digital Globe, Google Earth), appears ellipsoidal with a chimney shadow and (b) chimney emit black smoke

specially when brick kilns are sparsely spread. However remote sensing may not be able to distinguish between active and inactive brick kilns. So far, only Foody et al. (2019) have a developed a map to identify brick kilns from space by using high resolution images drawn from Google Earth. However Google Earth imagery is not updated on a regular basis, even so in rural areas. This is a limitation as brick kiln often cease and start their operation by responding to market forces. Thus a key challenge remains how can brick kiln be monitored regularly or more specifically can public dataset with repeat pass be used for mapping brick kilns in South Asia.

1.2 Objective

The objective of this study is detect brick-kilns over a region in Northern India Sentinel 2 imagery. The originality of this paper is to demonstrate the use of open imagery for mapping brick kilns .

2 Methodology

The flowchart for mapping brick kiln locations is shown in Figure 2.

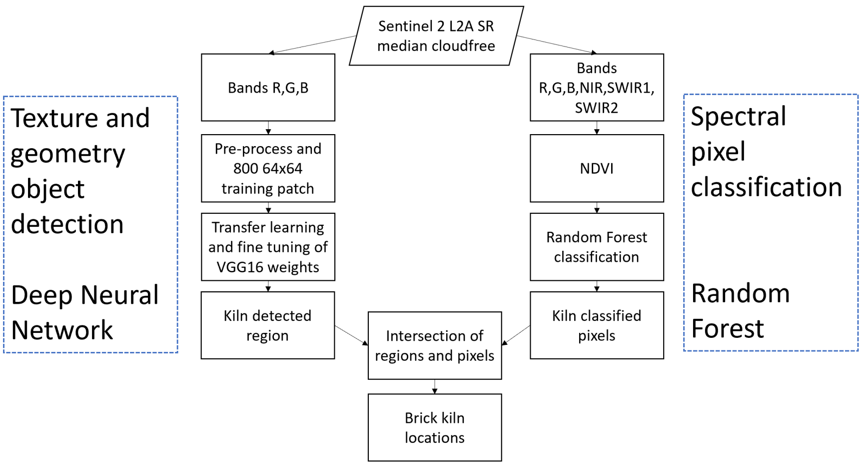


Figure 2: Processing flowchart for identification of brick kiln.

2.1 Data

Sentinel-2A: Sentinel 2 L2A optical dataset was downloaded from Google Earth Engine (GEE) (Gorelick et al., 2017). GEE has the advantage of providing atmospheric and geometrically corrected mosaiced Sentinel 2 dataset.

AW3D30:ALOS World 3D DSM at 30 m resolution open dataset was used to extract digital building height dataset over the study location. The details of this approach are mentioned in Misra, Avtar, and Takeuchi (2018).

(a) Brick kiln A (high res.) (b) Brick kiln A (med. res.) (c) Brick kiln B (high res.) (d) Brick kiln B (med res.)

Figure 3: Brick kiln examples as seen in the reference high resolution imagery (Digital Globe, Google Earth) (a) and (c), and the medium resolution Sentinel 2A imagery (b) and (d).

PALSAR2: Phased Array type L-band Synthetic Aperture Radar (PALSAR2) is a L-band microwave synthetic aperture radar sensor aboard the ALOS2 (Advanced Land Observing Satellite) satellite, launched in 2014 by Japan Aerospace Exploration Agency (2016). Level1.1 'Fine Mode (Full (Quad.) Polarization)' in 'Strip Map' observation mode at 3m resolution was obtained from JAXA as part of another project. PALSAR dataset was used for exploring chimney detection from polarimetric SAR dataset.

GHSL:Global Human Settlement Layers, Built-Up Grid provides rasterized built-up area globally for 1975, 1990, 2000 and 2015 at 30 m resolution (JRC European Commission and CIESIN Columbia University, 2015). The data corresponding to built-up regions for 2015 was used to mask out built-up areas. *GIS thematic layers*: Road network and river network GIS vector dataset was obtained from Hijmans (2011) to explore drivers for the location of brick kilns.

2.2 Location

The location for this research was the region surrounding the Delhi state in India. This region lies in the floodplains of the river Yamuna. This area is crossed by the Hindon river, a tributary of Yamuna. The floodplains are covered with rice alluvial top soil. In terms of built-up natures, it is mostly a peri-urban area, with sub-urban to rural agricultural land-use types. In the last two decades has seen increasing construction activity in the region bordering New Delhi and Ghaziabad city. This makes it an attractive region for setting brick kilns due to abundance of raw material in the form of top soil and close proximity to its market (construction spots, in this case).

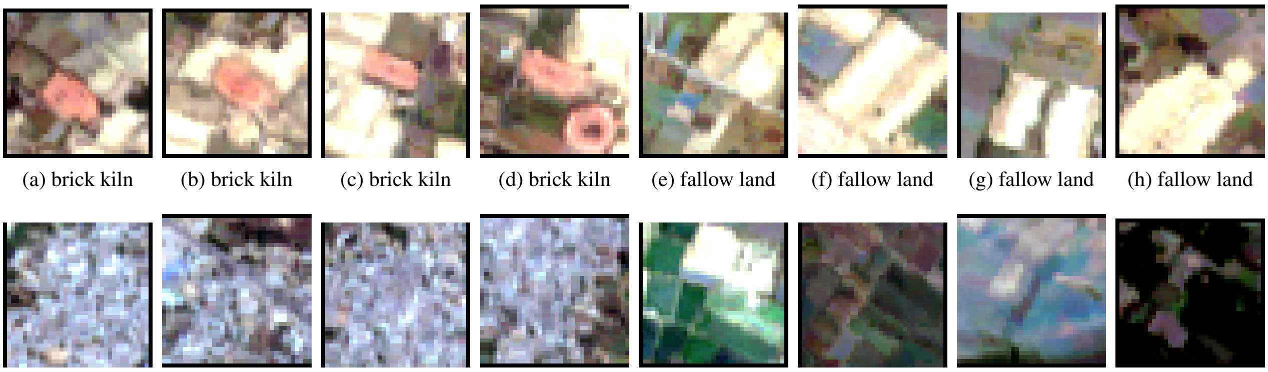
2.3 Preparation of training patches

First the brick kilns were identified visually to prepare an inventory fo the location of brick kilns. Identification of brick kilns in the Sentinel imagery is difficult due to its relatively coarse nature. High resolution imagery from Google Earth was used for this task. Some examples of the effect of resolution is shown in Figure 3. After determining the locations of the brick kilns, 200 training patches from Sentinel-2 of band red, green and blue, sized 64×64 pixel were prepared for each of the 4 classes - brick kilns fallow land, built-up and vegetation. About 80 patches were prepared for validation and testing. The patches were all scaled from their radiance values to 0 to 256 using a 'min-max' scaler. The minimum and maximum of each of the patch was as follows red: 0.227 to 0.074, green: 0.187 to 0.083 and blue: 0.148 to 0.059. These patches are shown Figure 4. Data augmentation using translation, rotation by 50^o and vertical and horizontal flipping was used to enhance the training sample size.
These patches were fed to a deep learning algorithm: transfer learning with fine tuning. To train the weights of the network, VGG-16 network weights pre-trained on 'imagenet' dataset was used. This network was trained for 500 epochs with a batch size of 64 and using the 'Adam' optimizer for the 'categorical cross entropy' loss function. In the fine tuning step, first 13 layers were frozen and the weights of the rest of the layers were fine-tuned using stochastic gradient descent using small learning rate (0.0001) and momentum (0.9)

3 Result and discussions

3.1 Brick kiln identification

Originally transfer learning was able to achieve a training and validation accuracy as 65.42% and 66.33%, and the loss as 0.84 and 0.86. After fine tuning, there was further improvement to training and validation accuracy as 85.12%



(a) brick kiln (b) brick kiln (c) brick kiln (d) brick kiln (e) fallow land (f) fallow land (g) fallow land (h) fallow land

(i) built-up (j) built-up (k) built-up (l) built-up (m) vegetation (n) vegetation (o) vegetation (p) vegetation

Figure 4: Examples of 64×64 pixel training patches prepared for brick kiln (a-d), fallow land (e-h), built-up (i-l) and vegetation (m-p).

Table 1: Confusion matrix for identification of brick kilns.

	Predicted yes	Predicted no	Producer accuracy
Actual yes	221	61	72.3%
Actual no	2	-	
User accuracy	99.1%		

and 86.67%, and the loss as 0.36 and 0.52. The fine tuning learning is shown in Figure 5. This was further enhanced by taking intersections of the identified regions with the spectrally classified pixels. The final confusion matrix is shown in Table 1. The accuracy of the detection is low when the soil is spectrally similar to the brick kilns. This occurs in the arid soil where the soil appears red and similar to brick kilns.
The precision was 12/33 (36%) and recall was 12/17 (70%). The reason for low precision was over-classification is likely presence of high urban backscatter. It is expected that using other information like normalized difference built-up index (NBDI) (Zha, Gao, and Ni, 2003) may help in overcoming this limitation.

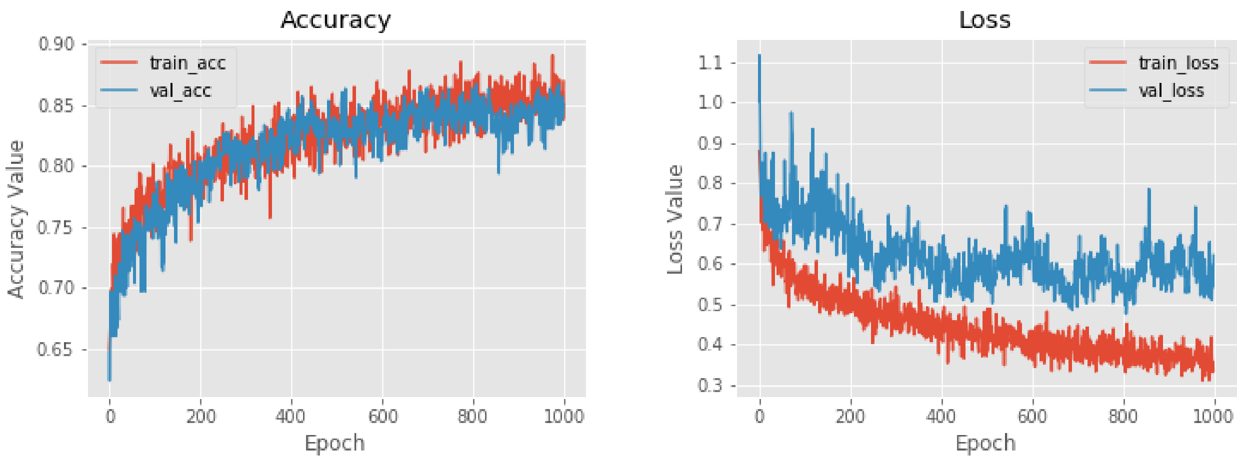
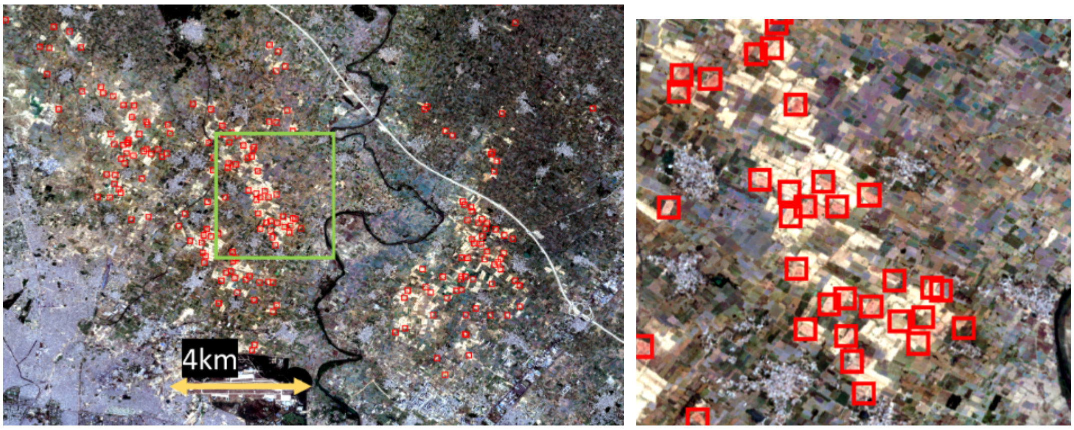


Figure 5: Training and validation accuracy and loss result.

3.2 Drivers of brick kiln locations

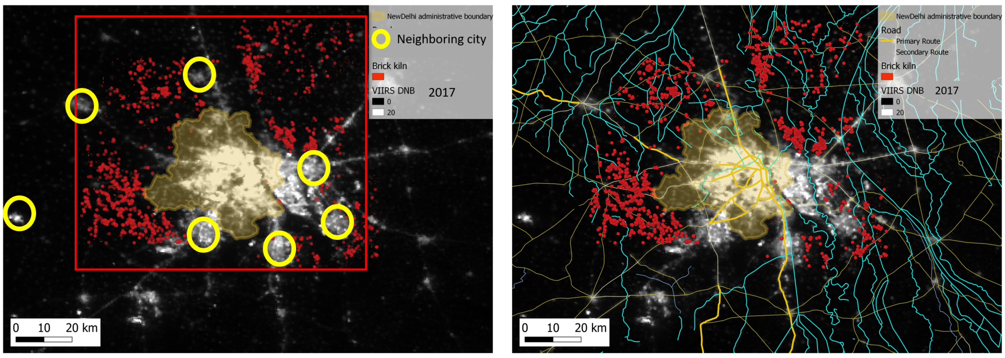
1564 brick kilns were detected around New Delhi. This almost 1.5 times the number discussed by Guttikunda and Calori (2013) over the same area. Brick kilns are located in clusters situated between urban agglomeration of satellite towns (Figure 7(a)). These land are surrounded by fields and have low prices compared to the prices in cities. The brick kilns are located long the flood-plains (river Yamuna) and along secondary roads (Figure 7(b)). Flood-plains provide with fine alluvial clayey soils and water which is required for making bricks. However this implies depletion



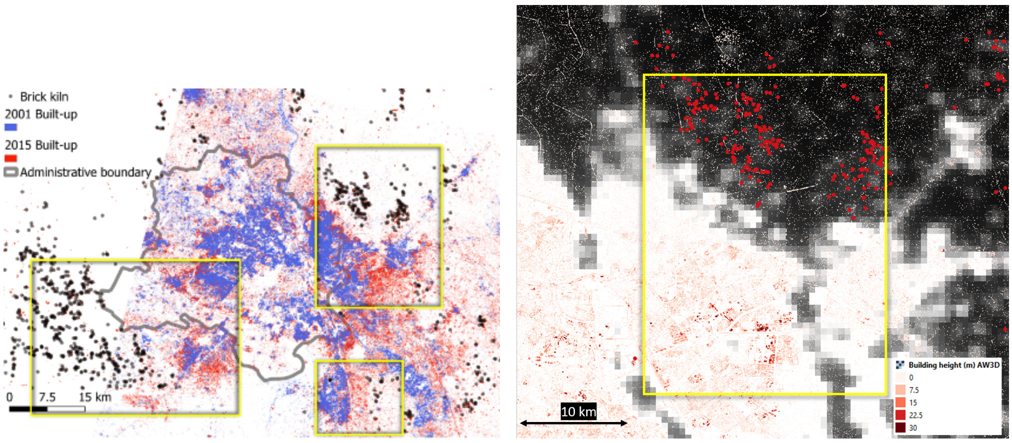
(a) North-eastern New Delhi (b) Zoomed-in inset

Figure 6: Brick kilns around New Delhi identified by the current methodology. Brick kilns detected in the north-eastern portion of New Delhi (a) and a zoomed-in view (b) of the detection.

of fertile top soil for making bricks over a long period of time. Brick kilns are located along secondary roads to transport bricks instead of highways. This is because other more sophisticated finished goods factories are usually located along the highways. Another feature is that brick kilns exist at the built-up edge of city or in the rural-urban zone where urban growth is taking place. New construction requires bricks, and wherever dense horizontal expansion has taken place, brick kilns are present(Figure 7(c)). Similarly, brick kilns are also located near (< 10 km) multi-storey residential buildings.

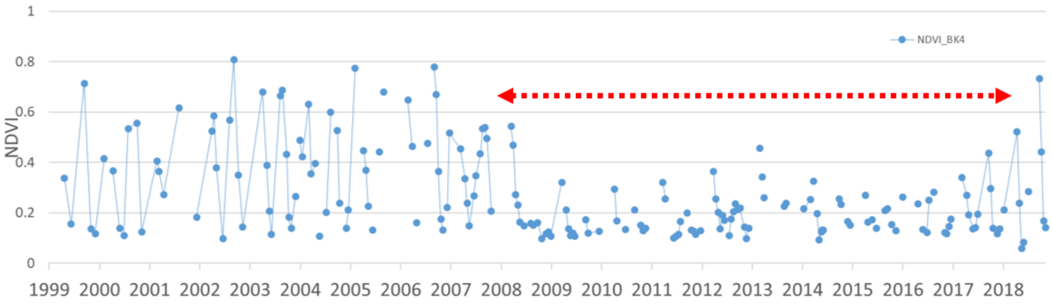


(a) New Delhi and satellite town (b) Road and river network

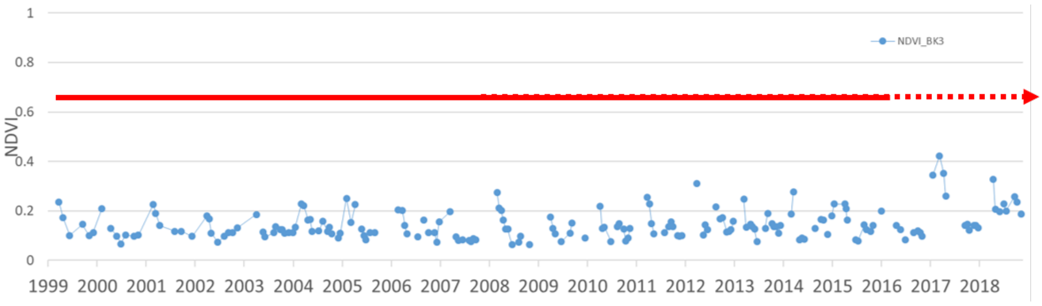


(c) Horizontal growth (d) Vertical growth

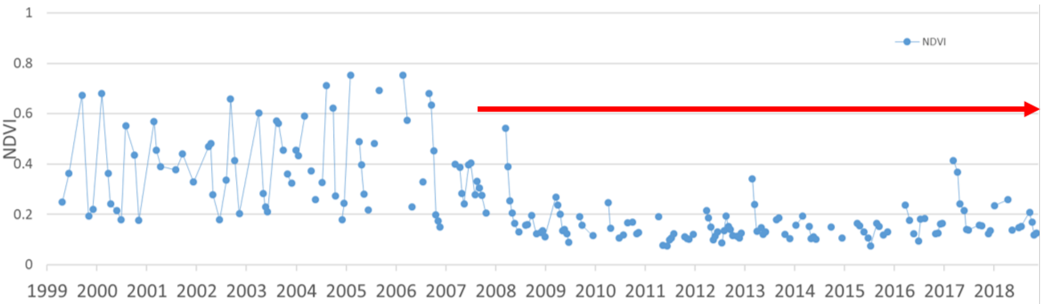
Figure 7: Location of brick kilns correspond to availability of low priced land away from major urban agglomeration (a) but with proximity to river and road (b). Construction based on region of horizontal expansion (c) and vertical expansion (d) is another driver of brick kilns. In (d), the basemap is nighttime light from VIIRS and building heights derived form AW3D30.



(a) Active from 2008 to 2018



(b) Active from before 1999



(c) Active from 2008 - present

Figure 8: NDVI calculated over the brick kiln locations reflect brick kiln's age of operation as shown in (a) 2008-2018, (b) always active and (c) active since 2008. Solid line denote active period, dotted line denotes currently inactive brick kiln.

3.3 Age of brick kiln operations

Based on field surveys, we noticed that active brick kiln sites are covered with soil and dust whereas abandoned brick kilns are covered under vegetation of grass and shrubs. Based on this observation, NDVI was calculated over some brick kiln locations using cloud-free Landsat7 imagery. Some examples are shown in Figure 8. A sharp decrease or increase in NDVI compared to its previous values points to start or cease of operations at a particular site. In Figure 8 (a), operations started in 2008 and ceased in 2017, as can be inferred by large NDVI amplitudes prior and post brick kiln operating period. After this, the site was converted to a vegetation farmland again. In Figure 8 (b), the brick kiln operations have always taken place since the years before 1999 and continued till date. In Figure 8 (c), a field was converted to brick kiln in 2008. Another interesting aspect of note is the slight increase in NDVI during 2017 at all the brick kiln locations. This could be a result of Indian government's policy of demonetization that barred the use of cash for large scale transactions. The policy was reported to adversely effect businesses relying mostly on cash transactions. Since most of the brick kiln monetary transactions are also based on cash, the slight increase in NDVI implies the effect of demonetization policy on brick kiln operations.

4 Conclusion

Brick kilns are known to be major emitters of black carbon, sulfur dioxide and other fine particulate matter, yet their spatial distribution remains largely unknown. We successfully demonstrated the use of publicly available dataset, Sentinel 2, with deep learning methodology to detect brick kiln locations on a large spatial scale with an accuracy of about 86.1%. We found 1564 brick kilns around New Delhi and they are located where clay and water is available, along non-highway roads. They are also located near regions of horizontal or vertical construction. They lie at urban-rural interface and are usually less than 20 km away from urban boundaries. Also brick kilns are non permanent structures whose duration of operation can be estimated by their historic NDVI values. Finally, current emission inventories do not consider brick kiln, and this dataset could help reduce the missing contribution to urban concentrations. As for the future steps, other cities will also explored through our methodology.. However visual identification showed that in other cities as well most brick kilns were located near a lake or a river. Areas in and around New Delhi have much higher number of brick kilns than other cities. This could be because New Delhi is the largest urbanized agglomeration in India. The number of brick kilns in each city could depend on both built-up area and its expansion rate. Previous approaches have statistically determined the number of brick kilns in each city using the population as the independent variable (Paliwal, Sharma, and Burkhart, 2016). Our technique provides a method for assessing such assumptions. Further we need to estimate the age of operations for all the brick kilns to find the historical emissions. This is important because brick kilns do not operate all year round. Instead they operate only during the dry season in northern India and surrounding countries. Availability of high spatio-temporal resolution imagery, for example Planet imagery, can help us identify the exact operation duration each year by tracking the plume from the chimney stack. In addition brick kiln operations lead to top-soil loss and usually the operations cease when economic viable availability of top soil is depleted. This may be monitored by using InSAR techniques. This could be beneficial in estimating historic brick production from a region and therefore the coal consumed and consequently net historic emission of black carbon and CO_2.

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