Chapter 9
Detection of Unmonitored Graveyards in VHR Satellite Data Using Fully Convolutional Networks

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Abstract Lima, Peru, is a highly dynamic urban region home to perpetually evolving informal areas. Earth observation (EO) studies on these areas focused almost solely on their inhabited parts, the informal housing. In this study, we propose to extend the focus to another component of the informal settlements: informal graveyards. Their emerging morphologies in Lima are similar to informal housing, making this particular distinction challenging. Furthermore, both graveyards and

This work was supported in part by the eScience project Dynaslum and by the Seed funding of the Center for Urban Studies, Amsterdam. We, further, acknowledge the European Space Agency (ESA) for providing the image data through its third-party missions as part of the project id35978.

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M. Kuffer, S. Georganos (eds.), *Urban Inequalities from Space*, Remote Sensing and Digital Image Processing 26, https://doi.org/10.1007/978-3-031-49183-2_9

housing typically experience joint, intertwined spatial development. The adjacency of graveyards and informal housing causes social and public health risks. Therefore, detection of boundaries between graveyards and adjacent (in)formal housing is essential, e.g. as an information basis for preventing the spread of diseases and supporting public health and safety in general. However, housing invasions on burial grounds have not yet been systematically monitored. Therefore, this study aims to develop a method for the distinction of graveyards from (in)formal housing. We combined anthropological field observations with fully convolutional networks (FCNs) with dilated convolution of increasing spatial kernels to acquire features of deep level of abstraction on Pleiades optical satellite images. The trained neural network developed reaches good accuracies in mapping informal graveyards, (in)formal housing, and non-built areas with an average F1 score of 0.878.

Keywords Lima · Barriadas · Informal graveyards · Supervised semantic segmentation · Fully convolutional networks · Urban remote sensing

9.1 Introduction

LIMA, the capital of Peru, with a metropolitan population of more than 10 million, is rapidly growing, including the expansion of informal settlements (Inostroza 2017). The growth of informal settlements, so-called *barriadas*, is a major driver of urban expansion (Riofrío 2003; Peters and Skop 2007) that happens predominantly in three peripheral cones (Fernández-Maldonado 2008). Besides new expansions, transformations in barriadas happen, e.g. places that were barriadas a decade ago have transformed into relatively well-developed and formalized areas (Fernández-Maldonado 2008; Payne 2001; Calderón 2004). After the rural exodus of the last century, triggered by guerrilla conflicts in the countryside in the 80s and 90s, new barriadas emerged due to migration to the city. They appeared on pockets of empty land – often steep hills – close to consolidated areas. Local urban planning authorities were unable to control these land invasions.

Within this uncontrolled urban development, *informal graveyards* appeared adjacent to informal settlements. Originally, the apparition of these informal graveyards stemmed from a lack of formal cemeteries for low-income groups. In the past decade, several clandestine graveyards were formalized, but due to a lack of affordable land both for housing and for graveyards, new informalities emerged (Klaufus 2020). The customs and processes related to burials and grave management tend to be informal. For instance, in the largest spontaneous graveyard in Lima, the cemetery of Virgen de Lourdes in the district of Villa María del Triunfo (VMT), the whole mortuary process is often organized by the dwellers of the informal settlements themselves. The mortuary process encompasses the selection of the plot, the building of the grave, the transportation of the body, the funeral service, and the burial act. This process is conducted in accordance with the traditions and available finances of the inhabitants, regardless of any formal regulations (Klaufus 2019). Additionally, those ‘deathscapes’ are cultural hotspots for the low-income groups, hosting dense pilgrimages and ritual celebrations such as offering food and drinks to the deceased (Klaufus 2019).

Those cultural habits combined with the intertwined development dynamics of informal settlements and graveyards can challenge public health. Health threats relate, for instance, to vector-borne diseases such as the Zika virus spread or communicable diseases such as the Covid-19 outbreak. For example, the stagnant water within small water reservoirs for flowers is believed to enhance the development of noxious mosquitos (Klaufus 2020; Snyder et al. 2017). These are responsible for the spread of diseases such as the Zika virus (as an example of an infectious mosquito-borne disease). In addition, the Covid-19 outbreak (as an example of a communicable disease) increases these challenges. In particular, informal settlements are vulnerable to the spread of infectious diseases due to their high densities and lack of access to sufficient clean water and health services (Corburn et al. 2020; Iacobucci 2020). This situation can also lead to groundwater contamination flowing to neighbouring areas, specifically downhills, and spreading further public health risks (Neckel et al. 2017; Zychowski and Bryndal 2015; Abia et al. 2018, 2019). Thus, the dynamics of spontaneous graveyards in the direct vicinity of informal settlements must be monitored.

In 2015, the municipality of the district of Villa María del Triunfo in Lima engaged in regularizing the physical arrangement of graves, the incompleteness of graves’ records, and the unsanitary mortuary practices. So far, few results have been achieved (Klaufus 2019). The Peruvian law states that cemeteries need to be physically separated by a high wall and a 2-m fringe from the surroundings to avoid infringements (Congreso de la Republica 1994). For that reason, the Peruvian Ministry of Health made an inventory of all graveyards in Metropolitan Lima (DIGESA 2017), but this list is incomplete, and land invasions occur faster than state institutions are able to cope with them. In the present Covid-19 outbreak, increasing infection rates and mortalities trigger an increasing demand for burial grounds close to informal settlements (Corburn et al. 2020). Therefore, it is crucial to prevent their close proximity to buildings, to not further increase the risks for communities. Some studies have documented land grabbing by cemeteries (Klaufus 2020; Soliman 2015; Niță et al. 2014). However, although of high societal importance and the associated risks, land invasions on burial grounds have never been systematically monitored. This study addresses this issue by developing a remote sensing–based deep learning approach for detecting unmonitored graveyards.

Among the present remote sensing–based studies to detect informal settlements, fully convolutional networks (FCNs) (Persello and Stein 2017; Sherrah 2016; Wurm et al. 2019) demonstrated their superiority to traditional machine learning algorithms in streamlining the classification workflow by combining the spatial feature extraction and the supervised classification into a single framework. FCNs (Long et al. 2015) are neural networks designed to perform pixel-wise image classification. These approaches generally result in higher classification accuracies than conventional machine learning approaches. Recent FCN architectures use an encoder–

decoder structure, introducing various strategies for up-sampling the feature maps learned by the encoder to the resolution of the input image (Badrinarayanan et al. 2017; Ronneberger et al. 2015). An alternative approach is to employ dilated (or atrous) convolutions (instead of down-sampling) to increase the filter's field of view (Yu and Koltun 2016; Chen et al. 2018). Even between classes with close semantic features, the FCNs showed their ability to distinguish informal from formal (Wurm et al. 2019; Stark et al. 2019) with higher accuracy than other methods (Persello and Stein 2017). Yet, most FCNs or other machine learning methods make only a binary classification (Stark et al. 2019; Duque et al. 2017; Leonita et al. 2018), ignoring differences within informal areas. Informal areas, although morphologically similar, are very diverse, even within the same city (Taubenböck et al. 2018; Ajami et al. 2019; Sliuzas et al. 2017). Nevertheless, the capability of FCNs to distinguish informal areas and informal graveyards, or housing areas and graveyards at large, which are thematic classes of similar physical appearance, has not been explored. Many tombs have the physical features and material qualities of small houses: brick walls, corrugated iron roofs, a tiny garden, and small fences that demarcate the plot. Besides, some tombs are stacked together in higher and larger structures, typically like adjacent brick houses. This makes them difficult to distinguish from a bird's eye view (Fig. 9.1).

In remote sensing literature, spatial investigations regarding graveyards have been motivated mainly by two purposes, i.e. detection of archaeological sites and crime detection. In the field of archaeology, remote sensing is an efficient, non-destructive technique to detect ancient cemeteries (Balz et al. 2017; Křivánek 2017). It is suited to support the preservation of archaeological patrimony (Menozzi et al. 2017; Al Raeid et al. 2016). For crime detection, remote sensing allows to find clandestine burials of victims of crime (Evers and Masters 2018; Silván-Cárdenas et al. 2017), especially using infrared (IR) or near-infrared (NIR) spectral bands. Yet, the developed techniques are meant to be used shortly after the burial. Remote sensing could be an effective tool for detecting (informal) graveyards, but to the best of our knowledge, it has not yet been systematically used for this purpose. Therefore, our study aims to test whether these two similar types of informal settlements can be distinguished with good accuracy by employing deep learning methods. We opt for deep learning methods due to the encouraging results of earlier very-high-resolution (VHR) image classification studies (Persello and Stein 2017; Bergado et al. 2016, 2018; Paisitkriangkrai et al. 2016) and informal settlement mapping studies (Persello and Stein 2017; Mboga et al. 2017). We do not intend to improve the network architecture of FCNs, but to explore the capabilities of existing approaches to our specific target domains. The study uses Lima as a case; however, the developed methodology has application potential for similar urban development processes, e.g. Manila (Philippines) (Taubenböck et al. 2018; Schultz 1989) or Cairo (Egypt) (Sambati 2012; El Barmelgy et al. 2016). This chapter was built on an earlier published conference paper (Debray et al. 2019).

Fig. 9.1 Ground picture of tombs (left) and informal houses (right) credit to Roel Roscam Abbing (above) and bird's eye view (Pleiades image) of the graveyard of El Sauce (delineated in green) and the surrounding formal and informal settlements (below)

9.2 Information Gaps in Global Datasets

Unmonitored graveyards, in Lima, can cover large areas and are continuously expanding (Fig. 9.2). Graveyards are gradually intertwined with surrounding informal developments. Both developments show very complex spatial patterns and are often spatially interlocked. And, due to morphologic similarities, they are difficult to map cartographically. They are also not differentiated in standard data products of

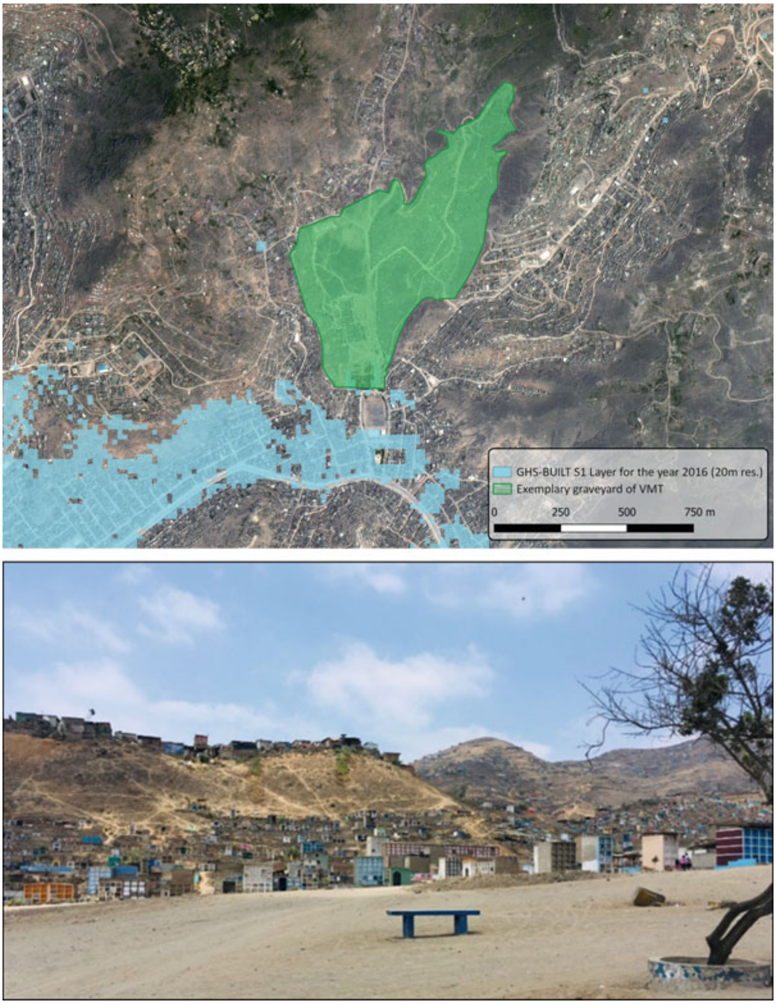

Fig. 9.2 Example of the graveyard Virgen de Lourdes (above) credits to Karin Pfeffer and surrounding built-up areas not captured by the Global Human Settlement built-up S1 2016 layer (below). (Source: Joint Research Centre of the European Commission)

built-up areas. To illustrate these shortcomings, three very popular standard data products were used, namely the Global Human Settlement Layers, the Global Urban Footprint (GUF), and the WorldPop population data. The Global Human Settlement Layers (GHS-BUILT S1) and the Global Urban Footprint (GUF) describe built-up surfaces and, therefore, could be expected to cover the barriadas and the cemeteries.

Illustrated in Fig. 9.2, the first problem is the total omission of the area in the GHS-BUILT S1 (Corbane et al. 2018); the same is the case in the GUF (Esch et al. 2012). Typically, synthetic-aperture radar (SAR)-based built-up mapping systems show better performance in arid urban environments as compared to optical systems (Esch et al. 2012). However, neither the informal settlements nor the graveyards were captured in our example. This gap was also present in the last official (and today outdated) local zoning plan (2007) (Instituto Metropolitano de Planificaciòn 2017). In this plan, only formal settlements and settlements recently formalized were mapped by the official institution in charge of the regularization of property deeds, i.e. COFOPRI (2020).

Another issue, but a very different data problem in such morphologically complex areas, was observed in the WorldPop population layer (Sorichetta et al. 2020). Overlaying the population data (100 m grids) with the boundary of the graveyard Villa María del Triunfo (Fig. 9.2), around 2150 people were assumed to live in the graveyard. The erroneous allocation of population to graveyards contributes to the underestimation of population statistics in the surrounding densely built-up informal settlements.

Due to the identified shortcomings of existing global datasets, such as the Global Human Settlement Layers, the Global Urban Footprint, and the Worldpop population data, these datasets could not be used in this study to derive information on the location of informal settlements. This reveals the information gaps related to informal developments and shows the relevance of proposing a streamlined workflow to overcome this impediment.

9.3 Methodology

9.3.1 Morphological Characterization of Informal Settlements and Graveyards

As mentioned above, the morphology of both the informal settlements and graveyards in Lima is highly complex. We depict the morphological characteristics of the two types below.

The *informal housing areas* constituting the *barriadas* are built outside of the legal frame of formal planning as well as spatially outside of planned areas. These areas are built rapidly on the flanks of hills; they show an organic pattern forming around clearly defined roads, which run roughly parallel to the height lines (Fig. 9.1). These patterns stand in contrast to the grid road network typical of Southern American cities (Kostof 1991). The buildings are clustered at varying densities, essentially varying between almost isolated buildings (in 'younger' parts of the *barriadas*), buildings in rows with enough room in-between to walk by, buildings in dense clusters with little to no space in-between but often managing small inner courtyards. The buildings are mostly rectangular or square one-family houses; they tend to be smaller the further they are from planned areas. The buildings have a rough but persisting alignment, locally parallel to the road.

The *graveyards* studied here stem from a mix of formalization and unplanned, informal processes. They are spontaneously grown as an unformal extension of formal graveyards or as standalone and share some features with the informal housing areas. These shared features include some structures built on top of tombs can be mistaken for small housing shacks, blurring the borders between those two types of informal built-up areas, especially from a top view. However, the graveyards differ as they feature few maintained streets within their sites or surrounding areas. Still, they show a dense lattice of paths between tombs emerging from uncoordinated walking practices within the graveyards. Graveyards are densely occupied by graves, with gaps between individual graves, in a seemingly homogeneous manner (exception made of the steep slopes where the organization of tombs is more determined by the terrain). The graves can vary in size with respect to their adjunct structures but are relatively small, ranging between around 3 and 20 m^2, the largest hardly oversizing an informal house. This contrasts with the more institutionally structured parts of the graveyards, which host sizeable rectangular structures of stacked funeral niches. In satellite images, those parts of graveyards present a noisier aspect due to the small size of the built-up structures and their configuration. The tombs, in general, face the line of the local slope, giving an overall organic aspect to the ensemble.

9.3.2 *Overall Methodology*

In this study, we developed a streamlined workflow (methodology) to map the dynamics of informal graveyards and informal housing areas in their direct vicinity. The methodology relied on the use of VHR satellite images and consisted of six steps (Fig. 9.3): (1) overall *pre-processing* of raw data; (2) selection of relevant *study sites*; (3) photo-interpretation and *manual delineation* of relevant classes of urban structures; (4) *training of the neural network*; (5) *classification* of the study sites by the trained neural network; and (6) *validation* of the classification accuracy. The following paragraphs further detail the dataset, information gaps, and different steps taken.

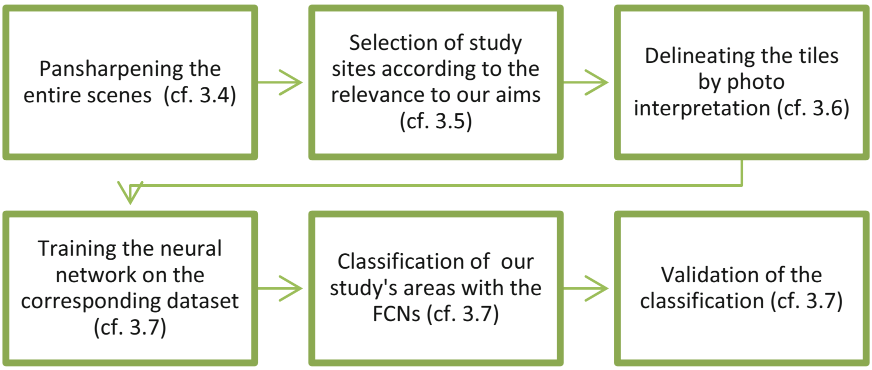

Fig. 9.3 Workflow of the overall methodology

9.3.3 Dataset

The spatial dataset contained a set of panchromatic and multispectral Pleiades images. The scenes were acquired for two different areas (see Fig. 9.4): Villa Maria del Triunfo (VMT) with an area of approximately 80 km^2, located Southeast of the historical centre of Lima bordered by a mountain with the graveyards mentioned above of Virgen de Lourdes on its slope and San Juan de Lurigancho (SJL) covering approximately 170 km^2, a more recently developed district in the North of Lima. We acquired cloud-free images from two different years (2013 and 2016) for both areas. The scenes were taken on 21st of February 2013 and 27th of March 2016 for SJL and on the 13th of April 2013 and on the 2nd of January 2016 for VMT. These two peripheral districts have many barriadas, mostly situated on steep slopes (Calderón 2004; COFOPRI 2020) as well as a large share of the spontaneously grown graveyards, showing the relevance of studying these complex areas in this chapter. Furthermore, between 2013 and 2016, changes concerning barriadas and graveyards were visually noticed in the acquired satellite images.

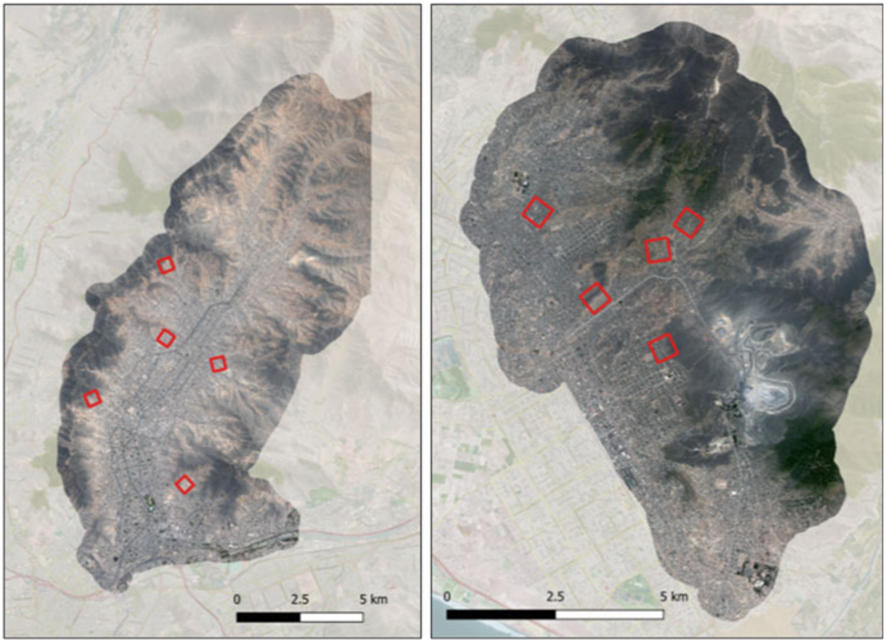

Fig. 9.4 Pan-sharpened Pleiades scenes of San Juan de Lurigancho (left) and Villa Maria del Triumfo (right) and the ten AOIs (red squares)

9.3.4 Pre-processing of Satellite Data

To prepare the Pleiades satellite data for our analysis, we applied the *Esri* pan-sharpening method of the *ArcGIS* software to the panchromatic and multispectral Pleiades images (ESRI). The pan-sharpening approach usually combines high-resolution panchromatic images (grayscale) with lower resolution multiband images (coloured) of the same scene and produces a high-resolution coloured image. This was done to benefit from both, the spatial and the spectral resolution of this sensor. With it, the neural network could be consistently trained for classification at the same resolution of 50 cm.

9.3.5 Selection of the Areas of Interest

From the two study areas, we chose ten large areas of interest (AOIs) that suited our training purposes (Fig. 9.4) for the experiments. These AOI are squares of 1000 by 1000 pixels. The guiding principle of the selection was to provide as much as possible the variations of the physical layouts of areas used for housing and of areas used for burial while complying with the following two criteria: (1) An AOI contained at least two different types of designated urban structures being the same between 2013 and 2016; (2) AOIs have a variated panel of spectral responses for relevant urban structures; hence, as often as possible, AOIs were chosen from overlapping regions of multiple images. Five AOIs were chosen in SJL and five in VMT (Table 9.1). This amount of selected data provided enough material to train our FCN in a robust enough manner.

9.3.6 Visual Classification of Informal Housing Areas Versus Informal Graveyards

For training our classifier, we need to have consistent labels on the target classes. In the case of this study, these are the two urban structure types of interest: 'graveyards' and 'informal housing areas'. However, within the AOIs, we also find other land use

Table 9.1 Division of ground truth's classes with regard to the areas

	Area number									
Classes	1	2	3	4	5	6	7	8	9	10
Formal housing	X	X	X	X	X	X		X	X	X
Informal housing	X	X	X	X	X	X	X	X	X	
Graveyards			X		X		X	X		
Non-built areas	X	X	X	X	X	X	X	X	X	X

types in the vicinity of these two structures. These other land use types also had to be integrated into the learning process of the neural network. Therefore, we also added two other classes (i.e. 'formal housing areas' and 'non-built areas'). Thus, the neural network was trained to detect four thematic land cover classes. As discussed above, no comprehensive dataset or labels exist that provide actual reference data of land use characteristics of informal urban areas. Therefore, by visual image interpretation, we manually digitized the reference data based on the morphologic characteristics presented below. In addition, we used the latest plans of zoning (2007) (Instituto Metropolitano de Planificaciòn 2017), anthropological field observation conducted by the third author, and photo-interpretation.

We used the following criteria to map the reference data by photo-interpretation or field observations:

- *Formal housing:* The area should have at least the size of a building block, i.e. roughly 500 m^2. A characteristic is the grid system of its layout, typical for South American cities inherited from the planning tradition originating in the 'Laws of the Indies' (1573) (Kostof 1991). The roads are made of asphalt. They are at least partially on the latest land use maps of Lima (note: the map is from 2007, and land use may have changed since).
- *Informal housing*: The area should at least cover a small cluster of self-built houses, i.e. roughly 200 m^2. Those buildings must show an organic pattern, clearly distinguishable from the grid pattern of planned areas. The area should be served by a section of a mud road or no obvious road at all.
- *Graveyards*: They may or may not appear on formal maps (the current mapping of the graveyards is incomplete). Thus, the areas had to be indicated based on field observations. We focused on significant patches, i.e. a minimum of 2500 m^2.
- *Non-built areas*: The area should neither have any building on available maps nor have any distinguishable building on the Pleiades' images. They are not digitized as 'non-built area' in direct surrounding of built-up areas if that area is not significantly large. We opted for a threshold of an area larger than roughly 15,000 m^2 which refers to an approximate buffer area above which we assume that two built-up clusters are not related.

From the ten AOIs, we extracted 22 tiles of 1000 by 1000 pixels each (as many by AOI as the number of multi-temporal scenes covering the AOI – that is to say three at the maximum, one at the minimum). The types of land-use classes present in each AOI are summarized in Table 9.1.

Based on the spatial and semantic definitions, we labelled the four classes (i.e. the four types of thematic image objects) across the 22 tiles in vector format. This was done with the control of one person with local experience to ensure consistency as far as possible. For the training of the FCN, we produced the corresponding pixel-wise labelled tiles in raster format at a resolution of 50 cm.

9.3.7 Training of the Fully Convolutional Network, Classification, and Validation

For training the FCN, we split the 22 pairs of Pleiades tiles and labelled ground-truth tiles into test, training, and validation sets. Two aims guided the split: First, the FCN had to be trained as little as possible on the same AOI to prevent overfitting during training; second, training had to be performed on images from both 2013 and 2016 to enhance the diversity of spectral responses for the four thematic target classes. There were 13 training and testing tiles and 9 validation tiles. Thus, we tested the predictions of our neural network on a dataset which was spatially independent of the training dataset. In this study, we adopted a lightweight FCN architecture exploiting dilated convolutions using the structure presented in (Persello and Stein 2017) as it showcased good results on the differentiation of urban morphological structures. For the classification, we experimented with different structures of those neural networks, with a depth of 3–6 layers as in (Persello and Stein 2017).

The training was processed using backpropagation of a stochastic gradient. We had the FCN trained on 13 × 500 (being the number of training and testing tiles and the number of samples within a tile, respectively) random samples of patch size of 125 pixels. We validated on 13 × 500 other random patches. Two different learning rates were used, following (Persello and Stein 2017). The first learning rate of 10^{-4} was used for 280 epochs and then was reduced to10^{-5} for 20 more epochs to optimize the learning on the plateau.

The networks considered here were implemented using the MatConvNet library version 1.0-beta-23 compiled with CUDA-8 toolkit and cuDNN support.1. All experiments were performed on a desktop workstation with an Intel Xeon CPU E5-2643 at 3.4 GHz, 128 GB of RAM, and a Dual Nvidia Quadro K2200 GPU.

The final step is the classification of the study area into our four thematic classes, with the trained networks producing labelled images.

We, then, evaluated the class-wise accuracy of the trained network on the validation set using the class-wise F1 score as:

$$\mathrm{F1} = \frac{2 \times \mathrm{UA} \times \mathrm{PA}}{\mathrm{UA} + \mathrm{PA}}$$

where UA is the user accuracy and PA is the producer accuracy, given respectively as:

$$\mathrm{UA} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

and:

$$\mathrm{PA} = \frac{\text{True positives}}{\text{True positives} + \text{True negatives}}$$

We also report the global accuracy of the network, denoted $\overline{\text{F1}}$ as the mean of the F1 score over all the classes.

9.4 Result and Discussion

9.4.1 *The Classification Results Using FCNs*

Accuracy assessment for the testing sets of the four classes 'graveyards', 'informal housing', 'formal housing', and 'non-built areas' are shown in Table 9.2. As expected, the more we added layers in depth to the neural network, the higher the accuracy. However, the additional neural network layers were computationally costlier for the training having an almost geometric progression (1 h, 6 h, 24 h, and 72 h), pointing toward a training time superior to five days if we were to add a further layer. Thus, we limited the training to a 6 layer-deep network, resulting in the choice to use the FCN-DK6.

Qualitatively, we also witnessed an improvement of the classification (1) thematically and (2) morphologically. First, the addition of extra layers managed to reduce misclassification. In Fig. 9.5, we can observe the improvement made between the FCN-DK3 and FCN-DK6 in differentiating 'informal housing' from 'graveyards'. Also, the specific elements existing across multiple land use types such as roads became more and more accurately associated with the specific contextual class. An example of this amelioration through deeper FCN is shown in Fig. 9.5. The line of 'formal housing' is a road running across the cemetery, being misclassified by the

Table 9.2 Accuracy of the testing set and training time according to the depth of the neural network applied

Network	**FCN-DK3**			**FCN-DK4**		
	F1 score	*UA*	*PA*	*F1 score*	*UA*	*PA*
Formal housing	0.798	0.774	0.824	0.821	0.793	0.851
Informal housing	0.542	0.555	0.530	0.596	0.615	0.578
Graveyards	0.652	0.687	0.620	0.779	0.810	0.750
Non-built areas	0.863	0.869	0.857	0.886	0.895	0.877
$\overline{F1}$	0.714			0.770		
Training time	1 h			6 h		
Network	**FCN-DK5**			**FCN-DK6**		
	F1 score	*UA*	*PA*	*F1 score*	*UA*	*PA*
Formal housing	0.827	0.784	0.875	0.859	0.847	0.871
Informal housing	0.594	0.693	0.520	0.688	0.718	0.660
Graveyards	0.825	0.885	0.773	0.840	0.802	0.882
Non-built areas	0.884	0.862	0.907	0.888	0.896	0.880
$\overline{F1}$	0.782			0.819		
Training time	24 h			72 h		

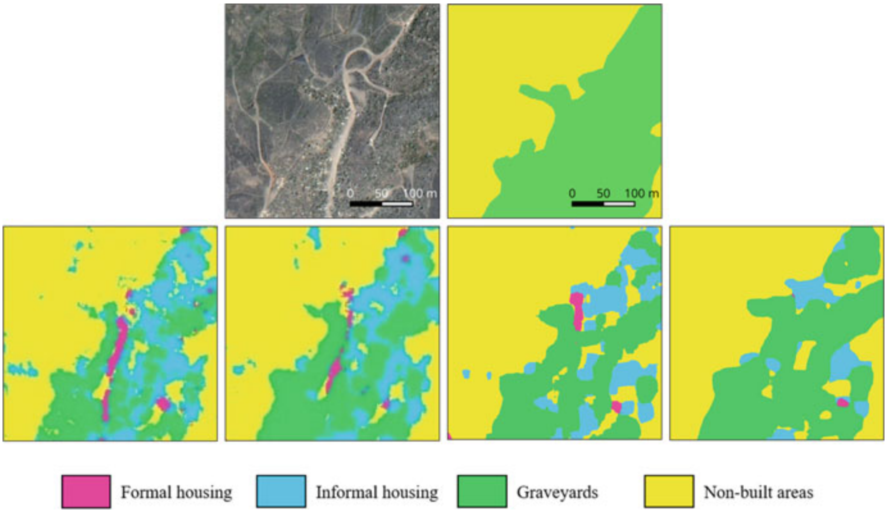

Fig. 9.5 Top: Input Pleiade image of the graveyard of Virgen de Lourdes (left) and ground-truth delineation (right) Bottom: Exemplified outputs on the same Pleiade image of the graveyard of Virgen de Lourdes with FCN-DK3 (left) to FCN-DK6 (right)

FCN-DK3 and being progressively correctly classified as belonging to the graveyard entity. Then, as noticeable in Fig. 9.5, added layers contributed to giving an overall morphological consistency, fitting better and better the grain size of the labelled data (see also Fig. 9.5). The increase in the softening of the classification provides edges to the morphologic units, seemingly almost soft enough to consider it to be a baseline for an object-based segmentation.

Quantitatively, the $\overline{\mathrm{F1}}$ reaches 0.819 with the DK6 (Table 9.2). Although being satisfying on an average consideration, we must take a closer look at the FCN accuracy for the two main urban structures at stake here. The F1 scores reached for those classes are 0.840 (graveyards) and 0.688 (informal housing). The F1 score of the informal housing is lower compared to the others, because the delineation of informal settlements in training had uncertainties (Kohli et al. 2016). In the case of Lima, those uncertainties appear especially on the fringes of the hills. Between the planned grid pattern of the formal housing areas and the organic shape of spontaneously grown informal housing areas often lays a planned grid pattern adapted to the local constraints of the topography. Hence, a non-trivial, often blurred interpretation of the progressive changes of morphology between formal and informal areas is existent. Therefore, such a layout is prone to inaccuracies even in visual image interpretation based on a clear morphologic guideline. Thus, the training data used for the 'informal housing' class is an uncertain aspect as the addition of certain formal housing areas to it makes the training data fuzzier.

The classification outputs we obtained from the semantic segmentation are exemplified in Fig. 9.6. For comparison, the original Pleiades image and the manually labelled reference data are shown side by side.

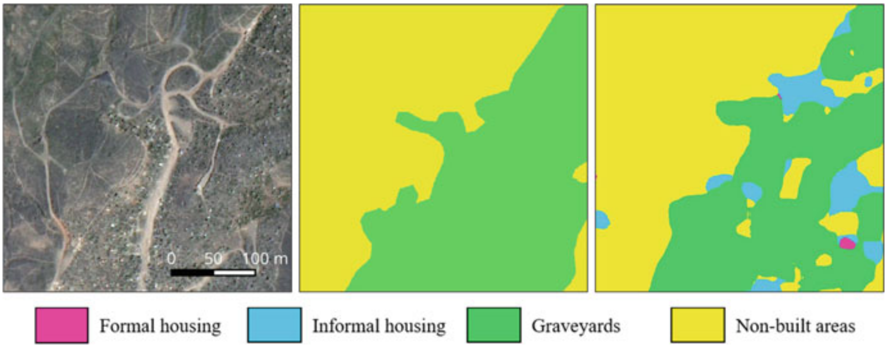

Fig. 9.6 Exemplified results for the location of the graveyard of Virgen de Lourdes and its surrounding. Pleiades image (left) and manual delineation (middle) FCN prediction (right)

Visually, the results show that the FCN is both accurate and capable of fine-grained predictions. The trained FCN can discriminate the intertwined classes of living and deathscapes on Pleiades images where the digitized reference data was aggregated at a coarser scale, in compliance with the minimum area set in our criteria for each class (Sect. 9.3.6) (Fig. 9.6).

9.4.2 Classification of 'Living Scapes' and 'Deathscapes' by FCNs

The aim of our study was to evaluate the use of FCNs to distinguish informal graveyards of Lima and informal housing. We trained the FCN on graveyards, informal housing areas, as well as other types of land use such as formal buildings and non-built area. However, by doing so, we added uncertainties in the training due to the often-difficult delineations between areas. The fuzzy boundaries between informal and formal settlements are a common problem (Kohli et al. 2016). It can lead to misclassifying formal and informal housing areas. Nonetheless, the main motivation of the study was to propose a way to highlight the coalescing fringes of ever-expending informal housing area and unmonitored informal burial grounds. Against this background, we aggregated the two thematic classes of housing area (formal and informal housing) posteriori of the classification. The classification results reveal beneficial increase of the accuracy by reducing the thematic content to these two defining classes, i.e. the spatial relations between housing area (or living scapes) and graveyards (or deathscapes). This aggregation results in the average $\overline{F1}$ 0.878 and significantly improves the ability of the method to distinguish between living and deathscapes (Table 9.3).

Table 9.3 Accuracy by merging the classes 'formal housing' and 'informal housing' into 'Housing area'

Class	Housing area	Graveyards	Non-built areas
F1 Score	0.907	0.840	0.888

9.4.3 Discussion

This study developed a partially automatized solution to map complex and intertwined urban land use classes (living and deathscapes) that show only small morphological differences in satellite images and are mostly unmonitored. Our study case was Lima, and, more precisely, its peculiar (unmonitored) informal graveyards and their surrounding housing areas. Their visual similarities and the structural diversity within graveyards and housing areas make classification a challenging task.

In general, informal urban developments are often omitted or not well captured in mapping products (Aguilar and Kuffer 2020) and population estimates, and such areas come along with very high uncertainties (Thomson et al. 2020). In the case of Lima, the low performance of such standard mapping products can also be attributed to the complex landscape, the high dynamics, the rugged terrain, and the low contrast between built-up and surrounding areas (Almaaroufi et al. 2019).

Nonetheless, human interpreters manually delineate these land use classes by visual image interpretation. This was done based on a clear morphologic concept for a small sample, with prior ground knowledge of Lima. Based on these labels, we tested whether a specifically trained neural network is capable of mapping these complex land use classes. Furthermore, the importance of the spatial context in the manual delineation oriented our choice of a neural network that can use contextual information. The neural network design choice was additionally dependent on a trade-off between the baseline accuracy it could reach and how light our neural network should be in terms of computational weight (Learning 2016). Unsurprisingly, deeper networks yielded better accuracies and were more computationally exigent. In this regard, we chose the FCN-DK6 structure for our neural network because of the substantial increase in accuracy compared to the FCN-DK5. However, this went along with an increase in computation time from 24 to 72 h. The increase in computation time also indicated that an even deeper network might not meet tolerable computation time by local users. However, this could be solved by cloud computation solutions (Aguilar and Kuffer 2020).

The results obtained by the selected neural network structure, once trained on our dataset, showed comparable accuracies as reported by previous studies on informal settlements. The class-wise accuracy was around 85% for the different classes. The exception was the class of 'informal housing' that had an accuracy below 70% due to mixed up with 'formal housing'. We assume this is a consequence of not having sufficiently good and extensive training data to differentiate the two residential land use classes. This reveals a constant challenge: The more specific target objects get in image classification, the more unlikely it is to have sufficient training data. Although this study shows that high accuracies can be achieved by FCNs even on target classes of morphologic similarities, the cost of concept and time for producing such consistent reference data remain high.

Furthermore, challenges arise by the tenuous visual difference between the target objects: First, the ‘non-built areas’ and the ‘graveyards’ (both having a lot of bare ground) and second, on the ‘graveyards’ and ‘informal housing’ (both having small and irregular built-up structures with varying densities), this neural network performed very well. However, the limitations in terms of training data and the complexity of classes caused a weaker capability to distinguish between ‘informal housing’ and ‘formal housing’. Moreover, this specific neural network structure has already been proven to fit very well in this specific classification task (Persello and Stein 2017; Ajami et al. 2019; Mboga et al. 2017). Nonetheless, by aggregating those two classes in a post-classification fashion, the two main target classes were proven to be distinguishable very well. This is proof of the potential of this methodology to monitor the relationship between deathscapes and living scapes in general, particularly in Lima.

In general, urban remote sensing literature hardly accounts for the differences in living scapes and deathscapes and, therefore, typically disregards their mutual dynamics (Debray et al. 2019). However, capturing these differences is highly relevant in many applications, in general, and for the specific case of Lima. Many cities face land use competition between the need for urban residential expansions and the increasing land demand for deathscapes while remaining largely unmonitored (Niță et al. 2014; Taubenböck et al. 2018; Al Raeid et al. 2016; Sambati 2012; Abdulhameed 2017). Data that allow differentiating these two classes of built-up areas are also relevant for many spatial models. First, the location of deathscapes might come as non-negligible help in the scope of the improvement of models concerning population estimation in complex morphologies (Kuffer et al. 2019; Patel et al. 2020). Second, for urban planning and management, such cohabitation is important to know to allow for reasonable interventions in regard to land use conflicts (Soliman 2015; Niță et al. 2014). Third, in support of health campaigns, the location but also the interlinkages between informal housing and deathscapes need to be critically monitored and potential health threats well understood (Neckel et al. 2017; Zychowski and Bryndal 2015; Abia et al. 2018, 2019). Last, this data is crucial in the scope of developing a true understanding of the dynamic of living scapes and deathscapes through a temporal analysis of consecutive updates (Niță et al. 2014). For these purposes, existing deep learning methods show high potential proving high accuracies.

However, there is scope for further development: For decision-making, even the accuracy of above 80% reached may not be reliable enough (Leonita et al. 2018). For urban planning, the developed methods need to be scaled up to the city scale at least to produce policy-relevant mapping outputs; however, data availability and costs are a challenge in the VHR domain. Beyond our test case of Lima, the transfer is challenging because sufficient and more extensive training data are required to achieve better accuracies; moreover, we will have to account for the, most likely, inevitable loss of accuracy in the case of a transfer learning approach, especially when dealing with diverse types of structural morphology (Stark et al. 2020). It seems that a major axis of improving the reliability of such methods resides in focusing on informal housing detection. With the help of additional data on informal settlements (Guidance: citizen groups responding to COVID-19 in LMIC 'slums' and other deprived areas 2020; Wang et al. 2019), it would be possible to train the neural network to be more proficient at detecting informal housing, and in turn, differentiating living scape and deathscapes with better accuracy.

In general, the results present the potential of deep learning approaches to generate spatial information on two very complex urban thematic classes, i.e. informal living and deathscapes developments. Both are typically not covered in urban mapping products.

9.5 Conclusion

Land invasions due to high pressure on land are part of the growth of Lima. A large part of its population growth cannot be absorbed by the formal housing areas, e.g. due to a lack of housing provision for low-income groups. This pressure drives people to settle in unpopular and exposed locations. Thus, it comes that housing areas grow on the steep, unsuitable slopes informally. And, it even drives newcomers to settle close, around, or even inside graveyards located on these slopes. In Lima, those land invasions and the burial grounds share a similar morphologic appearance and can be found in the same vicinities, making any distinction from a bird's eye view challenging. Both types of informal developments are largely under-monitored. However, the FCNs we trained were capable of classifying these two types of structures separately with high accuracies. The distinction was facilitated by the fact that the high spatial awareness of our FCNs came at a lower computational cost compared to traditional Convolutional Neural Networks (CNN) thanks to the FCN dilated kernels. A series of four FCNs with increasing numbers of layers were trained. The deeper the FCN was, the higher the accuracy. However, this came ultimately at the cost of computational power and time, making the four-layer-deep FCN-DK6 our final candidate. This network performed with high accuracy in distinguishing deathscapes and informal living scapes. Still, limitations arise in the fine-grained semantic distinction between formal and informal living scapes. We identify this limitation as being the consequence of a severe lack of up-to-date reference data. We argue that this method shall prove useful in direct application to localize and monitor the dynamics of the borders between living scapes and deathscapes. Training the developed FCN algorithm to a wider and more diverse area is ultimately required to inform the planning and decision-making process.

References

Abdulhameed M (2017) Analytical comparison between informal-random-housing and graveyards housing – a case study-housing inside the Northern Gabana Area, in Cairo City. J Al-Azhar Univ Eng Sector 12(44):1242–1252. https://doi.org/10.21608/auej.2017.19191

Abia ALK, Ubomba-Jaswa E, Schmidt C, Dippenaar MA (2018) Where did they come from – multi-drug resistant pathogenic Escherichia coli in a cemetery environment? Antibiotics. https://doi.org/10.3390/antibiotics7030073

Abia ALK, Alisoltani A, Ubomba-Jaswa E, Dippenaar MA (2019) Microbial life beyond the grave: 16S rRNA gene-based metagenomic analysis of bacteria diversity and their functional profiles in cemetery environments. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2018.11.302

Aguilar R, Kuffer M (2020) Cloud computation using high-resolution images for improving the SDG indicator on open spaces. Remote Sens 12(7):1–17. https://doi.org/10.3390/rs12071144

Ajami A, Kuffer M, Persello C, Pfeffer K (2019) Identifying a slums' degree of deprivation from VHR images using convolutional neural networks. Remote Sens 11(11). https://doi.org/10.3390/rs11111282

Al Raeid F, Di Valerio E, Di Antonio MG, Menozzi O, Abdalgader El Mziene MAS, Tamburrino C (2016) The main issues of the Cyrene necropolis and the use of remote sensing for monitoring in the case of the eastern necropolis. Libyan Stud 47(2016):7–30. https://doi.org/10.1017/lis.2016.8

Almaaroufi S, Golda-Pongratz K, Jauregui-Fung F, Pereira S, Pulido-Castro N, Kenworthy J (2019) Place-making through the creation of common spaces in Lima's self-built settlements: El Ermitaño and Pampa de Cueva as case studies for a regional urbanization strategy. Urban Sci 3(4):112. https://doi.org/10.3390/urbansci3040112

Badrinarayanan V, Kendall A, Cipolla R (2017) SegNet: a deep convolutional encoder-decoder architecture for image segmentation. IEEE Trans Pattern Anal Mach Intell. https://doi.org/10.1109/TPAMI.2016.2644615

Balz T et al (2017) Detect, map, and preserve Bronze & Iron Age monuments along the pre-historic Silk Road. IOP Conf Ser Earth Environ Sci 57. https://doi.org/10.1088/1755-1315/57/1/012030

Bergado JR, Persello C, Gevaert C (2016) A deep learning approach to the classification of subdecimeter resolution aerial images. IEEE Int Geosci Remote Sens

Bergado JR, Persello C, Stein A (2018) Recurrent multiresolution convolutional networks for VHR image classification. IEEE Trans Geosci Remote Sens 56(11):6361–6374. https://doi.org/10.1109/TGRS.2018.2837357

Calderón J (2004) The formalisation of property in Peru 2001 – 2002: the case of Lima. Habitat Int 28:289–300. https://doi.org/10.1016/S0197-3975(03)00072-9

Chen LC, Papandreou G, Kokkinos I, Murphy K, Yuille AL (2018) DeepLab: semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Trans Pattern Anal Mach Intell. https://doi.org/10.1109/TPAMI.2017.2699184

COFOPRI, "COFOPRI," CAMPAÑA DE EMPADRONAMIENTO, Lima (2020)

Congreso de la Republica (1994) Ley de Cementerios y Servicios Funerarios, p 4

Corbane C, Politis P, Syrris V, Pesaresi M (2018) GHS built-up grid, derived from Sentinel-1 (2016). R2018A. European Commission, Joint Research Centre (JRC) [Dataset]

Corburn J, Vlahov D, Mberu B, Riley L, Caiaffa WT (2020) Slum health: arresting COVID-19 and improving well-being in urban informal settlements. J Urban Health

Debray H, Kuffer M, Persello C, Klaufus C, Pfeffer K (2019) Detection of informal graveyards in lima using fully convolutional network with VHR images. In: 2019 Joint Urban Remote Sensing Event, JURSE. https://doi.org/10.1109/JURSE.2019.8808983

DIGESA (2017). http://www.digesa.minsa.gob.pe/DEPA/inv_cementerio.asp

Duque JC, Patino JE, Betancourt A (2017) Exploring the potential of machine learning for automatic slum identification from VHR imagery. Remote Sens 9(9). https://doi.org/10.3390/rs9090895

El Barmelgy M, Hawas S, Ashour S, Attiaa G (2016) The Eastern Necropolis in Cairo and its buffer zone (Towards a sustainable conservation strategy). Procedia Environ Sci. https://doi.org/10.1016/j.proenv.2016.04.016

Esch T et al (2012) TanDEM-X mission – new perspectives for the inventory and monitoring of global settlement patterns. J Appl Remote Sens 6(1):061702–061711. https://doi.org/10.1117/1.jrs.6.061702

ESRI. Fundamentals of panchromatic sharpening

Evers R, Masters P (2018) The application of low-altitude near-infrared aerial photography for detecting clandestine burials using a UAV and low-cost unmodified digital camera. Forensic Sci Int 289:408–418. https://doi.org/10.1016/j.forsciint.2018.06.020

Fernández-Maldonado AM (2008) Expanding networks for the urban poor: water and telecommunications services in Lima, Peru. Geoforum 39(6):1884–1896. https://doi.org/10.1016/j.geoforum.2007.11.007

Guidance: citizen groups responding to COVID-19 in LMIC 'slums' and other deprived areas (2020) IdeaMapsNetwork

Iacobucci G (2020) Covid-19: deprived areas have the highest death rates in England and Wales. BMJ. https://doi.org/10.1136/bmj.m1810

Inostroza L (2017) Informal urban development in Latin American urban peripheries. Spatial assessment in Bogotá, Lima and Santiago de Chile. Landsc Urban Plan 165:267–279. https://doi.org/10.1016/j.landurbplan.2016.03.021

Instituto Metropolitano de Planificaciòn. Listado de Planos de Zonificacion (2017)

Klaufus C (2019) Superstar-Saints and Wandering Souls: the cemetery as a cultural hotspot in Latin American cities. In: Selin H, Rakoff RM (eds) Death across cultures: death and dying in non-Western. Springer, New York, pp 275–294

Klaufus C (2020) Safeguarding the house of the dead: configurations of risk and protection in the urban cemetery. Int J Urban Reg Res. https://doi.org/10.1111/1468-2427.12890

Kohli D, Stein A, Sliuzas R (2016) Uncertainty analysis for image interpretations of urban slums. Comput Environ Urban Syst 60:37–49. https://doi.org/10.1016/j.compenvurbsys.2016.07.010

Kostof S (1991) The city shaped: urban patterns and meanings through history. London

Křivánek R (2017) Comparison study to the use of geophysical methods at archaeological sites observed by various remote sensing techniques in the Czech Republic. Geosciences 7(3):81. https://doi.org/10.3390/geosciences7030081

Kuffer M, Persello C, Pfeffer Itc K, Sliuzas R, Rao V (2019) Do we underestimate the global slum population?. In: 2019 joint urban remote sensing event, JURSE. https://doi.org/10.1109/JURSE.2019.8809066

Learning D (2016) Deep learning – goodfellow. Nature

Leonita G, Kuffer M, Sliuzas R, Persello C (2018) Machine learning-based slum mapping in support of slum upgrading programs: the case of Bandung City, Indonesia. Remote Sens 10(10):1522. https://doi.org/10.3390/rs10101522

Long J, Shelhamer E, Darrell T (2015) Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE computer society conference on computer vision and pattern recognition, vol 07-12-June, pp 3431–3440. https://doi.org/10.1109/CVPR.2015.7298965

Mboga N, Persello C, Bergado JR, Stein A (2017) Detection of informal settlements from VHR images using convolutional neural networks. Remote Sens 9(11). https://doi.org/10.3390/rs9111106

Menozzi O, Di Valerio E, Tamburrino C, Shariff AS, d'Ercole V, Di Antonio MG (2017) A race against time: monitoring the necropolis and the territory of Cyrene and Giarabub through protocols of remote sensing and collaboration with Libyan colleagues. Libyan Stud 48(2017): 69–103. https://doi.org/10.1017/lis.2017.13

Neckel A, Costa C, Mario DN, Sabadin CES, Bodah ET (2017) Environmental damage and public health threat caused by cemeteries: a proposal of ideal cemeteries for the growing urban sprawl. Urbe. https://doi.org/10.1590/2175-3369.009.002.AO05

Niță MR, Iojă IC, Rozylowicz L, Onose DA, Tudor AC (2014) Land use consequences of the evolution of cemeteries in the Bucharest Metropolitan Area. J Environ Plan Manag. https://doi.org/10.1080/09640568.2013.815607

Paisitkriangkrai S, Sherrah J, Janney P, Van Den Hengel A (2016) Semantic labeling of aerial and satellite imagery. IEEE J Select Topics Appl Earth Observ Remote Sens 9(7):2868–2881. https://doi.org/10.1109/JSTARS.2016.2582921

Patel A, Shah P, Beauregard BE (2020) Measuring multiple housing deprivations in urban India using Slum Severity Index. Habitat Int 101(March):102190. https://doi.org/10.1016/j.habitatint.2020.102190

Payne G (2001) Urban land tenure policy options: titles or rights? Habitat Int 25:415–429

Persello C, Stein A (2017) Deep fully convolutional networks for the detection of informal settlements in VHR images. IEEE Geosci Remote Sens Lett 14(12):2325–2329. https://doi.org/10.1109/LGRS.2017.2763738

Peters PA, Skop EH (2007) Socio-spatial segregation in metropolitan Lima, Peru. J Lat Am Geogr 6(1):149–171. https://doi.org/10.1353/lag.2007.0009

Riofrío G (2003) Urban slums reports: the case of Lima, Peru. In: UN-Habitat global report on human settlements. London, pp 195–228

Ronneberger O, Fischer P, Brox T (2015) U-net: convolutional networks for biomedical image segmentation. In: Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics). https://doi.org/10.1007/978-3-319-24574-4_28

Sambati S (2012) City of the Dead, a disputed slum in the heart of Cairo. Territorio

Schultz GW (1989) Cemetery vase breeding of dengue vectors in Manila, Republic of the Philippines. J Am Mosq Control Assoc

Sherrah J (2016) Fully convolutional networks for dense semantic labelling of high-resolution aerial imagery, pp 1–22

Silván-Cárdenas JL, Corona-Romero N, Madrigal-Gómez JM, Saavedra-Guerrero A, Cortés-Villafranco T, Coronado-Juárez E (2017) On the detectability of buried remains with hyperspectral measurements. In: Springer JA, Carrasco-Ochoa JF, Martínez-Trinidad, Olvera-López JA (eds) Lecture notes in computer science, vol 10267. Springer, Cham, pp 201–212. https://doi.org/10.1007/978-3-319-59226-8_20

Sliuzas R, Maarseveen M, Pfeffer K, Kuffer M, Baud I (2017) Capturing the diversity of deprived areas with image-based features: the case of Mumbai. Remote Sens 9(4):384. https://doi.org/10.3390/rs9040384

Snyder RE, Boone CE, Cardoso CAA, Aguiar-Alves F, Neves FPG, Riley LW (2017) Zika: a scourge in urban slums. PLoS Negl Trop Dis. https://doi.org/10.1371/journal.pntd.0005287

Soliman AM (2015) impact of cemeteries on the development of urban settlements in Egypt: the case of Minia and Kharga. J Architect Plan Res

Sorichetta A, Hornby GM, Stevens FR, Gaughan AE, Linard C, Tatem AJ (2020) High-resolution gridded population datasets for Latin America and the Caribbean in 2010, 2015, and 2020. Sci Data:1–12. https://doi.org/10.1038/sdata.2015.45

Stark T, Wurm M, Taubenbock H, Zhu XX (2019) Slum mapping in imbalanced remote sensing datasets using transfer learned deep features. In: 2019 Joint Urban Remote Sensing Event, JURSE. https://doi.org/10.1109/JURSE.2019.8808965

Stark T, Wurm M, Zhu XX, Taubenbock H (2020) Satellite-based mapping of urban poverty with transfer-learned slum morphologies. IEEE J Select Topics Appl Earth Observ Remote Sens 13: 5251–5263. https://doi.org/10.1109/JSTARS.2020.3018862

Taubenböck H, Kraff NJ, Wurm M (2018) The morphology of the Arrival City – a global categorization based on literature surveys and remotely sensed data. Appl Geogr 92:150–167. https://doi.org/10.1016/j.apgeog.2018.02.002

Thomson DR et al (2020) Need for an integrated deprived area 'Slum' Mapping System (IDEAMAPS) in Low – and Middle – Income Countries (LMICs). Soc Sci 9(5):1–17. https://doi.org/10.3390/socsci9050080

Wang J, Kuffer M, Roy D, Pfeffer K (2019) Deprivation pockets through the lens of convolutional neural networks. Remote Sens Environ 234(January). https://doi.org/10.1016/j.rse.2019.111448

Wurm M, Stark T, Zhu XX, Weigand M, Taubenböck H (2019) Semantic segmentation of slums in satellite images using transfer learning on fully convolutional neural networks. ISPRS J Photogramm Remote Sens 150(February):59–69. https://doi.org/10.1016/j.isprsjprs.2019.02.006

Yu F, Koltun V (2016) Multi-scale context aggregation by dilated convolutions. In: 4th international conference on learning representations, ICLR 2016 – conference track proceedings

Zychowski J, Bryndal T (2015) Impact of cemeteries on groundwater contamination by bacteria and viruses – a review. J Water Health 13(2):285–301. https://doi.org/10.2166/wh.2014.119