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# Chapter 9

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



Henri Debray, Monika Kuffer , Christien Klaufus, Claudio Persello, Michael Wurm, Hannes Taubenböck, and Karin Pfeffer

**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

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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 downhill, 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).

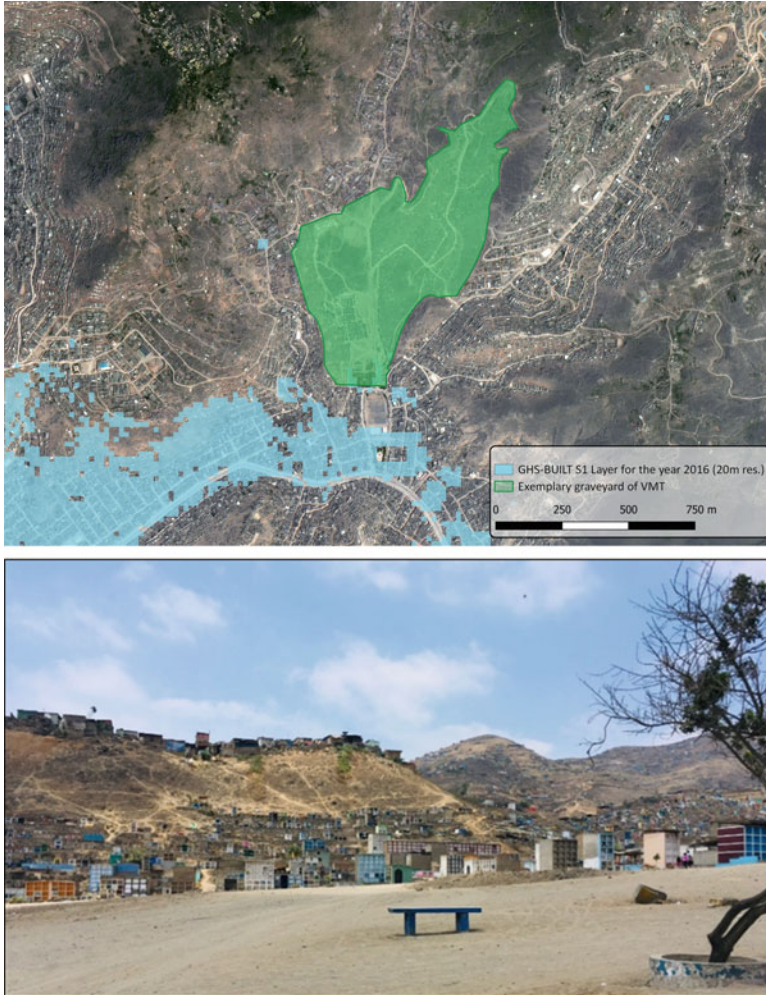
In remote sensing literature, spatial investigations regarding graveyards have been motivated mainly by two purposes, i.e. detection of archaeological sites and crime detection. In the field of archaeology, remote sensing is an efficient, non-destructive technique to detect ancient cemeteries (Balz et 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.

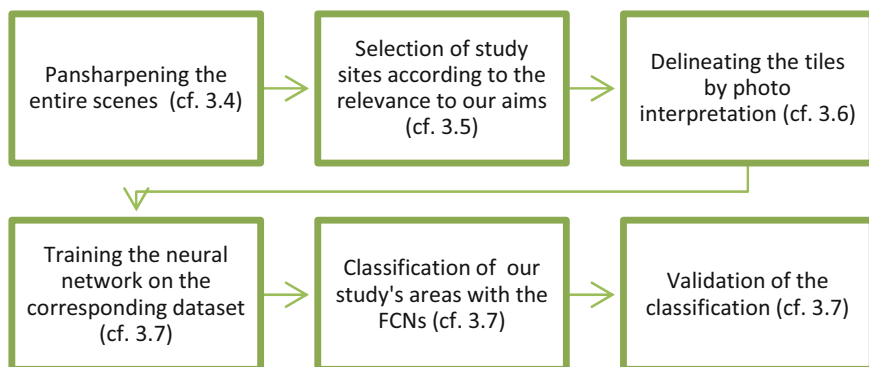
The *informal housing areas* constituting the *barriadas* are built outside of the legal frame of formal planning as well as spatially outside of planned areas. These areas are built rapidly on the flanks of hills; they show an organic pattern forming around clearly defined roads, which run roughly parallel 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<sup>2</sup>, 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

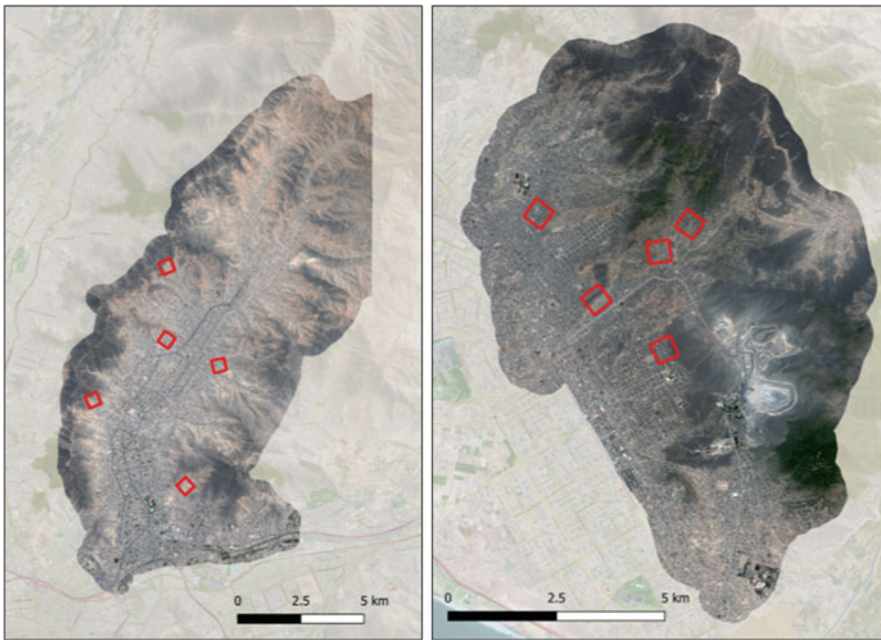
In this study, we developed a streamlined workflow (methodology) to map the dynamics of informal graveyards and informal housing areas in their direct vicinity. The methodology relied on the use of VHR satellite images and consisted of six steps (Fig. 9.3): (1) overall *pre-processing* of raw data; (2) 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<sup>2</sup>, 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<sup>2</sup>, 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 Triunfo (right) and the ten AOIs (red squares)



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<sup>2</sup>. 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<sup>2</sup>. 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<sup>2</sup>.
- *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<sup>2</sup> 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  $13 \times 500$  (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  $13 \times 500$  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 to  $10^{-5}$  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:

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

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

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

and:

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

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

## 9.4 Result and Discussion

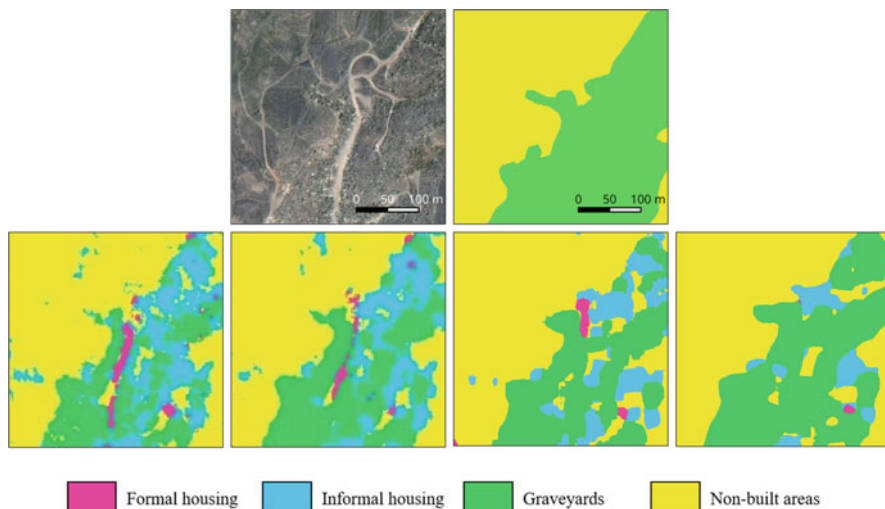
### 9.4.1 The Classification Results Using FCNs

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		
	<i>F1 score</i>	<i>UA</i>	<i>PA</i>	<i>F1 score</i>	<i>UA</i>	<i>PA</i>
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		
	<i>F1 score</i>	<i>UA</i>	<i>PA</i>	<i>F1 score</i>	<i>UA</i>	<i>PA</i>
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		

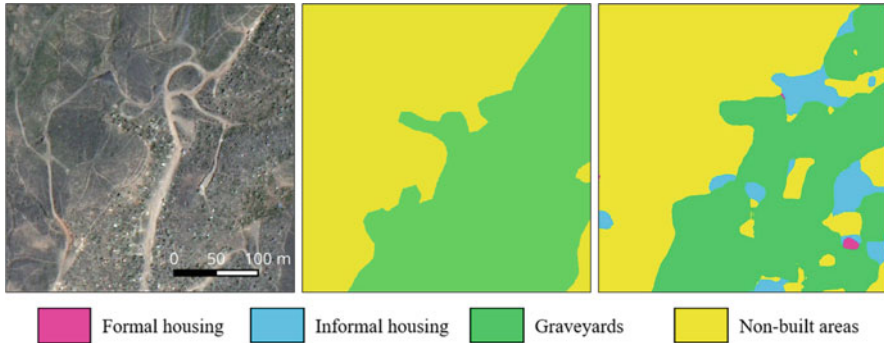


**Fig. 9.5** Top: Input Pleiade image of the graveyard of Virgen de Lourdes (left) and ground-truth delineation (right) Bottom: Exemplified outputs on the same Pleiade image of the graveyard of Virgen de Lourdes with FCN-DK3 (left) to FCN-DK6 (right)

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  $\overline{F1}$  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-expanding 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
<b>F1 Score</b>	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.

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