DIGITAL TWIN CREATION FOR SLUMS IN BRAZIL BASED ON UAV DATA

S.S.Khawte [1]*, M.N.Koeva [1], C.M.Gevaert [1], S. Oude Elberink [1], A. Aguiar Pedro [2]

[1] Faculty of Geo-information science and Earth Observation, University of Twente, Enschede, The Netherlands
s.s.khawte@student.utwente.nl, (m.n.koeva, c.m.gevaert, s.j.oudeelberink)@utwente.nl
[2] Sao Paulo City Hall, Brazil- aapedro@prefeitura.sp.gov.br

Commission IV, WG IV/9

KEY WORDS: Informal settlements, 3D building reconstruction/modelling, Digital Twins, Unmanned Aerial Vehicles (UAV), Point clouds

ABSTRACT:

Favelas are the most common type of informal settlements found in Brazil. The Housing Secretariat, City Hall, Sao Paulo, has conducted surveys using Unmanned Aerial Vehicles (UAVs) for the favelas to facilitate the slum upgrading projects and has taken the initiative to create a digital twin of the slum areas. This study illustrates the feasibility of developing a methodological workflow to create a digital twin by automatic 3D building reconstruction in slums from the UAV point cloud and the 2D building footprints with a continuous link for updating the building semantic information. This study focuses on facilitating data integration and updating the semantic information into the 3D model to provide additional information about the individual buildings in the slums. The assessments concluded that the proposed workflow is suitable for creating digital twins for slums based on the UAV and 2D cadastral data. However, the 3D slum model had a few limitations, which are discussed in this paper.

1. INTRODUCTION

People migrate to cities in search of opportunities; however, due to the lack of available space or housing in the cities, some people tend the occupy the available land and settle with or without legal aid, and this gives rise to an unplanned form of urbanization/the informal settlements (Salazar Miranda et al., 2021).

In the 20th century, the government of Brazil attempted to eradicate the favelas to replace them with formal housing, but it had a lot of negative consequences (Duarte et al., 2021). Hence, in many cases, the slum upgrading projects were considered more appropriate than slum eradication as they focused more on improving the existing infrastructure than a physical intervention that might lead to relocation and cause the slum dwellers to lose their homes (Alliance, 2012; UN Habitat, 2018).

To proceed with the activities related to slum upgrading, the slums need to be mapped to access information related to the buildings, road infrastructure and other urban utilities. However, favelas often remain neglected on the cadastral map (Temba, 2014) due to their complex built environment, lack of accessibility, unsafe living conditions and an unhealthy environment to undertake the conventional methods of cadastral survey (Duarte et al., 2021). Remote sensing data such as aerial imagery can tackle most of the challenges, as it can be used to obtain precise information about the current situation in the slums (Kuffer et al., 2016).

The Housing Secretariat in City Hall in São Paulo, Brazil, has conducted surveys using Unmanned Aerial Vehicles (UAVs) for the favelas to facilitate the slum upgrading projects and has taken the initiative to create a 3D model of the slum areas, which will be very beneficial for slum upgrading projects. Visualization of the favelas in 3D started as a game within a miniature urban world called “Morrinho” (or “Little Hill”) by the local teenagers a few years back. The 3D miniature model of Rio was made using bricks, wood, Lego and other recyclable materials (Projeto Morrinho, 2012). This model motivated the municipal urban development agencies to implement it in the formal property market and use the 3D models to develop the slum area (Angelini, 2013).

Prior to the development of this research, semi-structured interviews were conducted with the stakeholders to understand the requirements of the stakeholders and the challenges the experts are currently facing while working with the data for the slums. According to the experts, the 3D slum model is needed to improve project planning and development activities related to slum upgrading. A 3D slum model will reduce the time and effort of going to the location and conducting field surveys. The workflow was expected to be open source or cost-effective where the input data would be the point cloud, and the building footprint and the output would be the 3D model with semantic information related to the individual houses in the slums.

This research develops a methodological workflow using the UAV photogrammetric point clouds and the cadastral data to help reconstruct the 3D buildings in the slums in Jardim Colombo, São Paulo, Brazil. In addition, this research also focuses on data integration to provide additional information about the individual buildings in the slums with implementation to update semantic information in the future to help create a Digital Twin of the slum. The generated 3D building model will be of immense help to the stakeholders, especially the government officials and the urban planners, to visualize how the houses are perceived in real life and would be helpful for the activities concerning slum upgrading.

2. MATERIAL AND METHODS

2.1 Study area and data description

São Paulo, one of the wealthiest cities in Brazil, is also home to informal settlements, ‘Favelas’. The slum area selected for this study is Jardim Colombo, located in the municipality of São

Paulo, Bairro do Morumbi (District Villa Andrade), situated in the Paraisopolis Complex (Figure 1). Paraisopolis is the second largest favela community in São Paulo (Mion, 2018). This area was selected due to the availability of the data provided by the City Hall, São Paulo, Brazil. In one of the initial meetings with a representative from the City Hall, it was mentioned that the 3D slum models would play a significant role in various slum upgrading activities. Geographical coordinates of the area are Latitude (ϕ): 23°11'15.57 "S, Longitude (λ): 45°48'38.45 "W. The slum area is around 13.4 hectares, with 2156 houses. All the data needed for this research was provided by the City hall, São Paulo, Brazil (see Table 1).

Figure 1: Study area

Data	Data format
UAV point cloud	.E57 (converted to .las)
Orthophoto	.ecw (GSD =3.8cm)
Building polygons	.shp (polygon)
Contour lines	.shp (polyline)

Table 1: Information on data used

2.1.1 UAV data

The aerial images were captured by the experts from São Paulo (AmbGis, 2019) with the help of a drone, Phantom 4 pro (version 1) with a 20 MP camera with a maximum image size (frame) of 5472*3648. The image acquisition was carried out from 13/05/2019 to 09/07/2019. The images were captured at a flying height of 120m with 80% longitudinal and 70% lateral overlap. The images captured had a Ground Sampling Distance (GSD) of 3.8cm. The collected data were further processed to generate, a rectified orthomosaic and a Dense point cloud. The products were georeferenced to the SIRGAS 2000 coordinate system using the UTM projection for Zone 23 South.

2.1.2 Vector data

The Building footprints were delineated manually by the experts (AmbGis, 2019) from São Paulo on a scale of 1:500 to 1:200 in order to maintain the details using the generated orthomosaic with the help of GIS software. The generated shapefiles were validated by the field surveyors in São Paulo. During the survey, information regarding the construction material used for the buildings in slums, the number of floors and the identification of alleys was collected.

Contour lines were extracted by the experts (AmbGis, 2019) from São Paulo from the Digital terrain model (DTM). After removing the non-terrain elements, the voids were filled in by creating a 3D model from the interpolation between the altimetric dimensions. The contour lines were generated with 1m spacing on a 1:500 scale.

2.2 Methodology

The methodology of this study consists of four main stages; data acquisition, data pre-processing, 3D building reconstruction and implementation of semantic information and data visualisation. The methodology workflow using in this study is summarised in Figure 2 (Khawte, 2022).

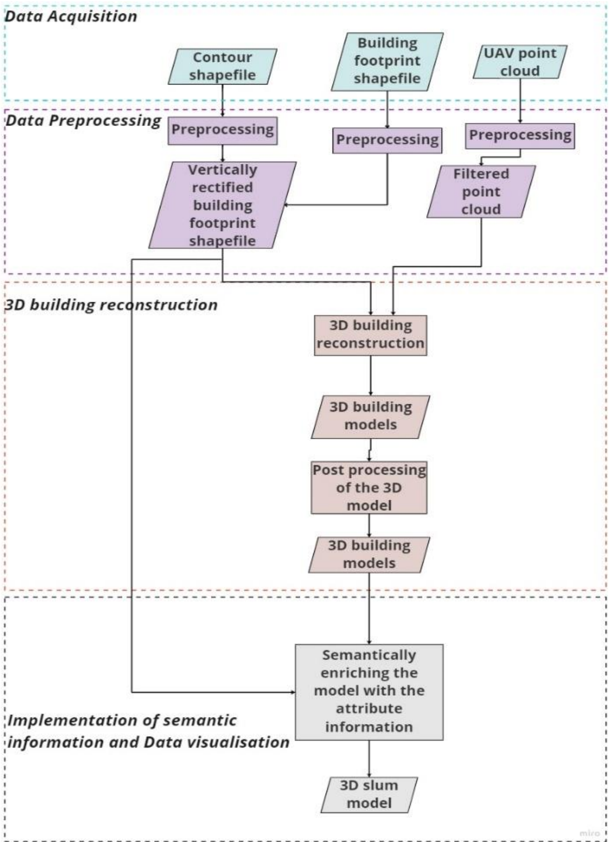

Figure 2: Methodology flowchart

2.2.1 Pre-processing point cloud and 2D datasets

Since this research focuses on 3D building reconstruction, only building points in the point cloud are needed. The building points in the point cloud were obtained by clipping the whole point cloud with the building footprint shapefile using an ETL (Extract, Transform and Load) platform, FME (Feature Manipulation Engine). Traces of vegetation in the filtered point cloud were segmented manually. Dense Image Matching (DIM) point cloud is subjected to a lot of noise or outliers, which could take place due to ambiguities during the image matching. Due to this, the filtered point cloud was further cleaned using the noise filter. The point cloud was filtered by defining a radius for the nearest neighbours, and a plane fitted. The algorithm removes the points if it is too far from the fitted plan (CloudCompare version 2.6.1. user manual, 2015) e. This process was used to eliminate most of the irregularities on the roof of the buildings, such as vegetation, water tanks etc., which could increase the errors in the surface construction of roofs.

The building footprint shapefile did not have the vertical coordinate/ Z coordinate. Hence, the building footprint shapefile was vertically rectified to the ground elevation to facilitate the 3D building reconstruction process. The shapefile with contours was used to create a DEM raster using a local interpolation method using a GIS platform. The mean values of the pixels in the DEM lying inside the building the footprint shapefile were used as an attribute to define the Z value to rectify the shapefile vertically.

2.2.2 3D building reconstruction

The 3D building reconstruction with the point clouds is the most crucial step in this research. The 3D model was generated following the algorithm of (Xiong et al., 2014; Xiong et al., 2016), which used the 3D point cloud and the building footprints (2D cadastral data) to reconstruct the buildings as 3D polygons. The entire area was divided into three zones; zone 1, zone 2 and zone 3, each having 10, 5 and 11 sub-zones, respectively. The algorithm was applied to one sub-zone at a time to assist the process of 3D reconstruction.

Point cloud segmentation is one of the important steps in defining the roof structure of the buildings by clustering the points that lie in the same planar face into one segment. The roof was segmented using the surface growing method, which uses a 3D Hough Transform to detect the planar seed surfaces in a 3D point cloud (Elberink and Vosselman, 2009; Vosselman et al., 2004). The surface growing method of segmentation has two stages; the determination of seed surfaces and the growing of the detected surfaces which lie in the same plane. A small set of nearby points that forms a planar surface is selected as a seed surface. The Hough Transform determines whether the points within the defined radius fit in the same plane. Then, the surface growing stage begins. The segmentation parameters; seed neighbourhood radius, a growing search radius, maximum distance from the point to the surface, and a minimum number of points in a segment were then defined to help segment the roofs.

2.2.3 Creation of the digital twin of the slums

The 3D reconstruction techniques from point clouds often lead to the loss of semantic information in the resulting 3D model. The semantic information of the model helps the users to use the 3D model for various applications apart from just visualisation (Yao et al., 2020). An implementation that allows the dynamic update of the semantic information in the model is beneficial in real-time monitoring, obtaining remote access, and planning activities (Singh et al., 2021). To aid the creation of a digital twin, a direct link should be created between the 3D geometry and its metadata to exchange the information, which can be done using an ETL platform (Heaton and Parlikad, 2020). The national and regional government have started using the digital twin of the cities for urban planning. Hence a semantically-enriched 3D model enables the users to use the model for various purposes other than just 3D visualisation (Singh et al., 2021; Yao et al., 2020). A semantically enriched 3D slum model would facilitate the creation of a Digital Twin of the slums, which would help the planners with the slum upgrading.

Every building of the generated 3D slum model was linked to the semantic attribute information using the ETL. This provides the users for continuous update of the digital twin model. The information related to the individual buildings in the slum environment was extracted from the attributes of the building footprint shapefile. Additional development was performed to achieve continuous updating of the semantic information. The individual 3D slum buildings were linked to the information related to the construction material used, the area in m^2, number of floors, house number, building height values, and terrain elevation values. A workflow was created to add new information about individual houses that could be updated if the house number was known. The model was exported as a KML (Keyhole Markup language) file and was visualised in Google Earth Pro along with the semantic information of the individual house. Visualising the results in Google Earth Pro was preferred as it is free, can be easily shared with the stakeholders, and provides a perception for any project which is location-based (Google Earth ProTM - Atlas Networking, 2022).

3. RESULTS AND DISCUSSIONS

3.1 Pre-processing of point cloud data

The point cloud of the entire study area was clipped using the building footprint shapefile to obtain only the building points (non-ground) points, as seen in Figure 3. Since this research required only the building points, the effects of shadows and vegetation in the 3D reconstruction were minimised. The noise filter was applied to the entire point cloud by defining a spherical neighbourhood radius, considering the point density in that area (CloudCompare version 2.6.1. user manual, 2015) and fitting a plane (around each point of the cloud). The noise filter aided in decreasing the noise in the point cloud and this facilitated the segmentation and roof mapping process. The filtering also removed the unwanted roof furniture, such as water tanks and vegetation on the roof (Figure 4). However, filtering of vegetation in between the dense buildings caused occlusions within the building points, which was unavoidable, but its effect on the 3D building reconstruction was minimal.

The point clouds were analysed before and after filtering based on the number of points, point spacing, point density and internal accuracy. It showed that the number of points and the point density decreased after applying the noise filter and the point spacing increased, as seen in Table 2. The Root Mean Square Error (RMSE)/the standard deviation also decreased in the filtered point cloud compared to the original point cloud, suggesting that filtering helped increase the internal accuracy of the point cloud. There was an increase in the internal accuracy of the filtered point cloud as the unwanted noise over the roof structures was minimised, giving rise to a smoother surface, causing it easier to fit a plane.

Figure 3: Left: Point cloud covering entire area, Right: Filtered point cloud only with building footprints

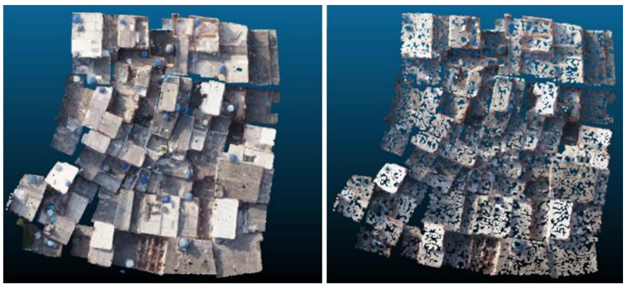

Figure 4: Left: Original point cloud with water tanks and roof furniture, Right: Filtered point cloud eliminated the waters tanks and outliers from the roof

Points		Point spacing (m)		Point density (m2)		Internal accuracy (RMSE)	
Original Point cloud	Filtered Point cloud	Original Point cloud	Filtered Point cloud	Original Point cloud	Filtered Point cloud	Original Point cloud	Filtered Point cloud
4,652,938	1,695,544	0.16 m	0.26 m	38.49 m2	14.31 m2	0.0108	0.0083
						0.0293	0.021
						0.0541	0.037
						0.0338	0.0245
						0.0270	0.0228
Average Internal accuracy (RMS)						0.0310	0.0227

Table 2: Comparison of the original and filtered point cloud

3.2 3D building reconstruction

3.2.1 Segmentation

Segmentation is one of the first and most important steps in roof surface modelling. To facilitate the process of segmentation, several parameters have to be set, and these parameters depend on the spatial appearance of the objects in the laser data, such as the minimum size of the object to be detected, the point density of the point cloud etc. The seed neighbourhood radius was set to 2m. The growing search radius was set to 1m since the average point spacing of the resulting filtered point cloud was around 0.2-1m. The maximum distance of a point to the surface was set to a default of 0.3m. The minimum segment size was set to 30 as the minimum segment size was dependent on the point density, which had an average value of (15-20 points/m2) (Xiong et al., 2015). The segmentation results are shown in Figure 5.

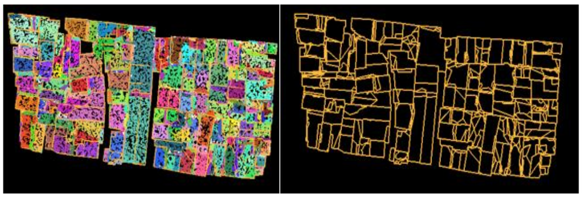

Figure 5:Left: Optimal segmentation, Right: segmentation map

3.2.2 3D model

The final 3D model obtained is shown in Figure 6. Out of the total of 2156 buildings, 2146 buildings were correctly modelled. Around ten houses were not modelled perfectly. This was due to noise filtering errors or the occlusions of vegetation covering the roofs of the houses. The model was generated directly in a vector format of a 3D polygon shapefile.

Figure 6: The generated 3D slum model

3.3 Digital twin of slums

To go toward the regular updating of the digital twin, a workflow for semantic information updating was further developed using an ETL platform. To implement the semantic information in the 3D model, all the buildings from each sub-zone were combined and aggregated into a single zone. A counter was used to create a unique ID for the 3D buildings. The 3D geometries of the buildings were transformed into 2D geometry polygons. The 2D building footprints were converted into points. A transformer was used to pass the attributes from points (obtained from the 2D shapefile) to polygons (obtained from the 3D shapefile).The resulting attributes were then merged into the original 3D geometries using the unique ID which was set for the 3D buildings. The three zones were processed separately and merged as an entire area. A conditional clause was applied to facilitate the future update of new semantic information.

The information related to construction materials, area of the house (m^2), house number, and the number of floors was used from the building footprint shapefile and was updated in the model. The model was visualised in Google Earth. Implementation was made to update any semantic information related to any individual house in the future based on the details of the house number. Figure 7 shows the final results of the model.

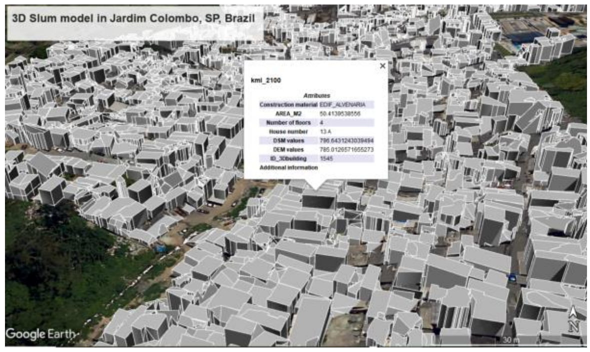

Figure 7: The final 3D model of the buildings in the slums updated with the semantic information

3.4 Limitations

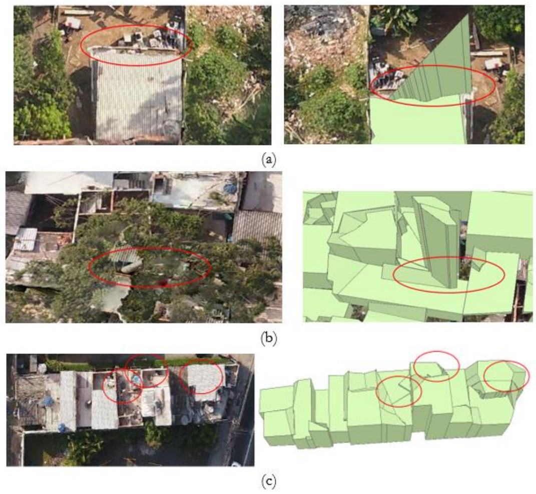

Figure 8: Errors in the 3D reconstruction of buildings in the slums : a) Erroneous spikes on the edges of the building, b) Error in the 3D building generation due to presence of vegetation c) Irregular roof structures

Due to the noise in the UAV point cloud, some erroneous spikes were observed, as seen in Figure 8. Few areas displayed more errors than others and needed to be filtered again by increasing the neighbourhood radius of the filtering algorithm to approximately 1m. In this case, the process of 3D reconstruction was repeated. The generated model still required post-processing using GIS software which needed manual editing. The errors in the 3D models were seen around the edges of the model. This could be due to the errors in the image matching. The presence of vegetation between the dense houses also affected the 3D model creation. In such a condition, the buildings were wrongly modelled, or some buildings (a total of ten buildings) were not modelled. The irregular roof structures in most buildings in the slums gave rise to non-smooth surfaces during the creation of the models, which is due to the errors in segmentation (over-segmentation).

3.5 Evaluation of the model

A qualitative approach, including semi-structured interviews with the stakeholders, was used to evaluate the proposed workflow. Five interviewees were questioned on the feasibility of the methodology, usability and fitness of the model, and satisfaction with the method used for visualisation. The interview was then followed by a few questions related to the strengths and limitations of the model.

Four out of five participants remained neutral regarding the algorithm's feasibility for practical applications, and three out of five participants agreed that the software was open source and cost-effective. Four out of five participants strongly agreed that the presented level of details of the 3D model is sufficient for the buildings in the slum. The comment on the geometry of the building model was debatable as two participants disagreed, two remained neutral, and one agreed that it was satisfactory. All four agreed on the possibility of inputting the semantic information into the model and were satisfied with the method used for visualising the model.

All the participants were asked whether "The presented 3D slum model can be used for applications related to slum upgrading activities (Yes/No)". Three participants responded affirmatively as, *"The 3D slum model could be used to visualise the existing buildings and gather information, which would be helpful for the urban planners for slum upgrading and would help to share the data easily with the slum dwellers*". Two participants responded negatively as "*The cartographic accuracy of the model was not guaranteed and hence could not be used for land regularisation*".

4. CONCLUSIONS

The main goal of the current study was to develop a methodological workflow to automatically reconstruct a 3D slum model using the data from the UAV and the 2D footprint in São Paulo, Brazil. The study also aimed at developing a method to input and update the attribute information in the generated 3D model to facilitate the creation of a digital twin of the slum. The results of this study indicated that the suggested semi-automatic method could be used to create a semantically-enriched 3D slum model efficiently.

Some limitations caused by the algorithm Xiong et al. (2014, 2016) could be further explored. Over-segmentation of the roofs was observed due to irregular roof structures, which gave rise to erroneous spikes in some regions near the edges of the buildings due to the noise in the point cloud. It was seen that some areas in the point cloud had more noise and needed to be filtered more, possibly due to the errors in image matching. Most areas needed manual post-processing to eliminate the spikes and get a clean model. It was also observed that the algorithm could not handle processing a large area at once, so the area had to be clipped into smaller areas for better results of 3D reconstruction. Around ten houses were not modelled due to vegetation between the houses or canopy over the roofs.

This research used a qualitative evaluation method for the generated 3D slum. The semi-structured interviews were carried out with the stakeholders to evaluate the model. The interviews helped to gain insight into how the generated 3D model is useful to the stakeholders for practical use. From the interviews, it can be concluded that the resulting 3D model of the favela could be used in meetings with the slum dwellers to aid in exchanging information between the planners and the residents, as the model can be easily visualised and shared using Google Earth Pro.

5. RECOMMENDATIONS

For future work, in-depth research should be conducted to find a reasonable approach to tackle unwanted spikes automatically. The automatic detection and removal of the unwanted spikes in the model will save much time in obtaining a spike-free model. Furthermore, future researchers can also work on developing methods for automatic extraction of the rooflines from the orthophotos. Future researchers working on developing a 3D slum model can conduct fieldwork and use the field data to validate the results. Therefore, the methodology used in this study is recommended to be tested with other study areas and other datasets (such as point clouds obtained from ALS) to understand its interoperability.

ACKNOWLEDGEMENTS

This paper has been adapted from the master's thesis titled '3D modelling of slums based on UAV data' authored by Sharvi Khawte at Faculty ITC, University of Twente, The Netherlands. The authors are grateful to the City Hall, Sao Paulo, Brazil for the provision of data and for participating in the interviews for this research.

REFERENCES

Alliance, C., 2012. Cities without Slums. Action Plan for Moving Slum Upgrading to Scale 1–32.

AmbGis, 2019. Relatório Técnico – Jardim Colombo Levantamento Planialtimétrico Cadastral por Aerofotogrametria e Geração de Nuvem de Pontos Utilizando Drone.

Angelini, A.M., 2013. Model Favela: Youth and second nature in Rio de Janeiro. City University of New York.

CloudCompare version 2.6.1. User manual, cloudcompare.org (20 May 2021).

Duarte, F., Fajardo, W., Ratti, C., 2021. Embracing the Informal, MIT Technology Review.

Elberink, S.O., Vosselman, G., 2009. Building reconstruction by target based graph matching on incomplete laser data: Analysis and limitations. *Sensors* 9, 6101–6118. https://doi.org/10.3390/s90806101

Google Earth Pro™ - Atlas Networking., 2022. https://www.atlasnet.eu/solutions/google-maps-for-work/google-earth-pro/ (16 June 2022).

Heaton, J., Parlikad, A.K., 2020. Asset Information Model to support the adoption of a digital twin: West Cambridge case study. *IFAC-PapersOnLine* 53, 366–371. https://doi.org/10.1016/j.ifacol.2020.11.059

Khawte, S.S., 2022. 3D modelling of slums based on UAV data. University of Twente (Master's thesis). https://purl.utwente.nl/essays/90898

Kuffer, M., Pfeffer, K., Sliuzas, R., 2016. Slums from space-15 years of slum mapping using remote sensing. *Remote Sensing* 8. https://doi.org/10.3390/rs8060455

Mion, V., 2018. Undergrowth Urbanism: The Role of User-Generated Practices in the Informal City. A Methodology for Analysis and Intervention Based on the Case Study of Paraisópolis in São Paulo, in: Sustainable Urban Development and Globalisation. *Springer International Publishing*, pp. 99–116. https://doi.org/10.1007/978-3-319-61988-0_8

Projeto Morrinho, 2012. Història | Projeto Morrinho | Rio de Janeiro, Brazil. https://www.projetomorrinho.org/pt-historia (31 October 2021).

Salazar Miranda, A., Du, G., Gorman, C., Duarte, F., Ratti, C., Fajardo, W., 2021. Favelas 4D : Scalable methods for morphology analysis of informal settlements using terrestrial laser scanning data. *MIT Technology Review*.

Singh, M., Fuenmayor, E., Hinchy, E.P., Qiao, Y., Murray, N., Devine, D., 2021. Digital twin: Origin to future. *Applied System Innovation* 4, 1–19. https://doi.org/10.3390/asi4020036

Temba, P., 2014. 3D Cadaster of Irregular Settlements in Brazil—Case Study of Belo Horizonte City. *Journal of Geodesy and Geomatics Engineering* 1, 29–37. https://doi.org/10.17265/2332-8223/2014.12.004

UN Habitat, 2018. Slum Almanac 2015/2016. Notes and Queries s4-XII, 413–413.

Vosselman, G., Gorte, B.G.H., Sithole, G., Rabbani, T., 2004. Recognising strucutre in laser scanner point clouds. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 32, 33–38.

Xiong, B., Elberink, S.O., Vosselman, G., 2016. Footprint map partitioning using airborne laser scanning data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* III–3, 241–247. https://doi.org/10.5194/isprsannals-III-3-241-2016

Xiong, B., Oude Elberink, S., Vosselman, G., 2015. Reconstruction of 3D objects-3D4EM https://3d4em.netlify.app/rl1/ (19 June 2022).

Xiong, B., Oude Elberink, S., Vosselman, G., 2014. Building modelling from noisy photogrammetric point clouds. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* II–3, 197–204. https://doi.org/10.5194/isprsannals-ii-3-197-2014

Yao, S., Ling, X., Nueesch, F., Schrotter, G., Schubiger, S., Fang, Z., Ma, L., Tian, Z., 2020. Maintaining semantic information across generic 3D model editing operations. *Remote Sensing* 12, 1–20. https://doi.org/10.3390/rs12020335