

# Chapter 7

## Remote Sensing Techniques for Village Identification: Improved Electrification Planning for Zambia



Catherina Cader, Alin Radu, Paul Bertheau and Philipp Blechinger

**Abstract** Access to energy remains a challenge in many regions of Africa. In Zambia, only approximately 28% of the total population of 17 million has access to electricity, with even lower access rates of 5% in rural areas. One of the first challenges in providing these regions with reliable electricity is identifying the location of small settlements that still lack access to electricity. Systematic electrification planning requires in detail information about the current extent of electrification and the spatial location and distribution of villages and households without access. If this is available, transparent planning mechanisms can assess different electrification options such as stand-alone systems, mini-grids or grid extension. This paper aims at detecting a sample of Zambian villages without electricity through remote sensing techniques. These techniques involve applying various machine learning algorithms to classify medium resolution Sentinel 2 multispectral imagery. As results show, it is possible to identify the location and spatial extension of rural settlements in the research area. However, for an accurate assessment of the population in the respective areas, more information, such as population distribution is needed. These results will support official bodies such as the Rural Electrification Authority (REA) as well as private project developers with an entrepreneurial interest in the region. Thereby, this knowledge enables improved legal and regulatory decisions as well as increased private sector participation.

**Keywords** Remote sensing · Village detection · Spatial planning  
Energy access · Zambia

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M. Mpholo et al. (eds.), *Africa-EU Renewable Energy Research and Innovation Symposium 2018 (RERIS 2018)*, Springer Proceedings in Energy,  
[https://doi.org/10.1007/978-3-319-93438-9\\_7](https://doi.org/10.1007/978-3-319-93438-9_7)

## 7.1 Introduction

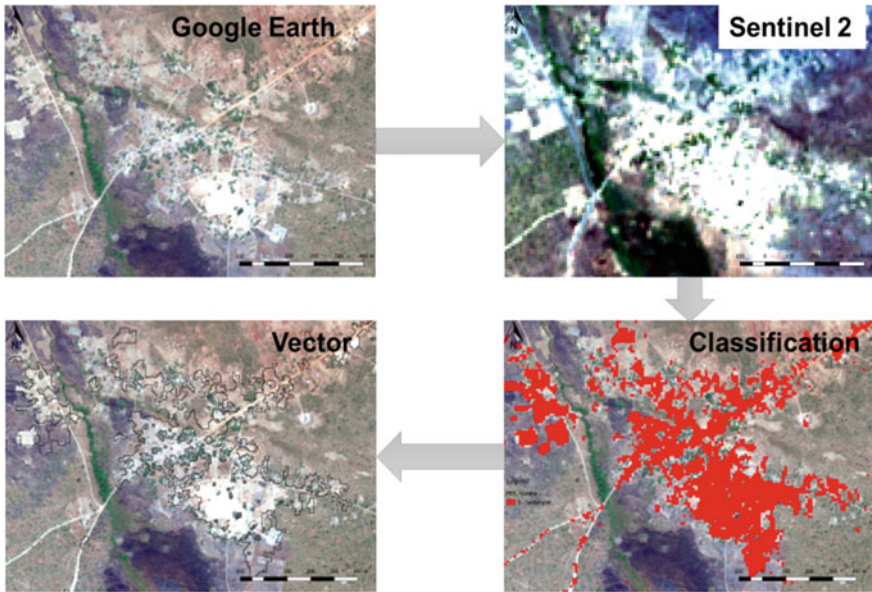
Although the situation in Sub Saharan Africa has strongly improved in recent years, lack of access to electricity is still a problem. In 2016, only 43% of the population in the region had access to electricity. In Zambia, the situation is no exception, with two thirds of the 17 million people lacking electricity [1]. Systematic electrification planning requires in detail information about the current extent of electrification and the spatial location and distribution of villages and households without access to reliable electricity. If this is available, transparent planning mechanisms can assess different electrification options such as stand-alone systems, mini-grids or grid extension [2, 3].

Remote sensing involves applying machine learning algorithms to classify medium resolution Sentinel 2 multispectral imagery [4]. This method provides quick and accurate results on large areas with minimum costs, since many satellite imagery providers offer their products for free, as well as a significant amount of open source satellite image processing software exists. As a final product we aim to identify the location and spatial extent of rural settlements in the research area. Combining this with traceable night light emissions on satellite imagery and infrastructure data will reveal the level of energy access of each settlement. These results may support official bodies such as the Rural Electrification Authority (REA) as well as private project developers with an entrepreneurial interest in the region. Thereby, this knowledge could enable improved legal and regulatory decisions as well as increased private sector participation.

## 7.2 Remote Sensing as a Solution

For this analysis, a combination of remote sensing and GIS tools is used (Fig. 7.1) to identify and then quantify the spatial extent of inhabited areas in wards in the Northern Province of Zambia. For this purpose we used Level 2A [5] multispectral images of the Sentinel-2 mission. Due to their higher resolution of 10 m, only four of the 12 bands provided were considered: Blue (with a wavelength of 490 nm), Green (560 nm), Red (665 nm) and Near Infrared (835 nm). The other geographic and demographic data (ward shapefiles, population count and density per ward) were collected from secondary sources [6].

The data was analyzed using the Semi-Automatic Classification Plugin (SCP) for QGIS [7] and various other QGIS tools (clip raster, raster to vector). The processing was carried out using the Minimum Distance Classification (MDC) algorithm.



**Fig. 7.1** Example of satellite image analysis (based on Copernicus Sentinel data 2017) overlaid on Google Satellite (© 2018 TerraMetrics)

### 7.3 Methods

The cloud free images were downloaded from the European Space Agency SciHub, for the months of July, September and October 2017.

In order to improve accuracy of classification results, some preprocessing steps need to be taken [8]. The pixel information was converted to Top of Atmosphere Reflectance and Dark Object Subtraction was applied to each Sentinel-2 scene, using SCP. As a second preprocessing step, scenes were clipped at ward level, in order to minimize areas of interest for faster processing.

Processing of each clipped ward consists of two steps: training area input and the application of a classification algorithm. The training areas are manually defined by the user, based on the visual inspection of the land cover. Classes are then defined accordingly: water, swamp, bare land, built-up, beach, vegetation and the Minimum Distance Classifier is applied. It calculates the Euclidean distance between the spectral signatures of the training input areas and the image pixels, assigning the class of the closest spectral signature [7].

After the classification of all wards, post-processing steps are required. The classification raster files obtained should be transformed to vectors, in order to easily eliminate irrelevant classes and small polygons.

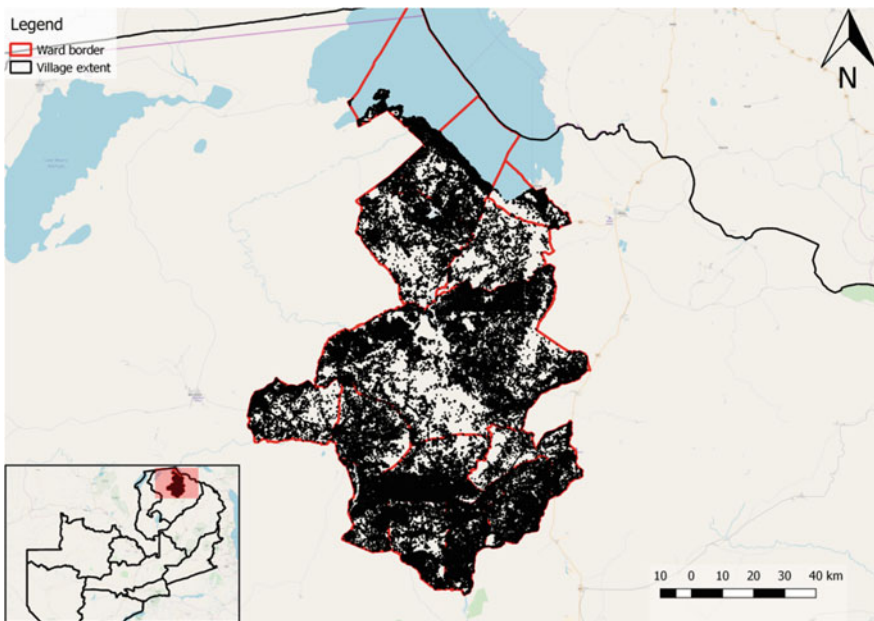
## 7.4 Results

All the resulted vector files (each for every ward) were then merged, in order to get an overview of the whole area (Fig. 7.2).

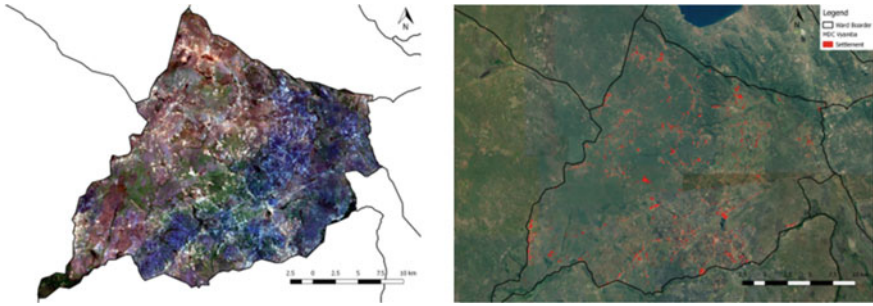
The filtering process eliminated all polygons that had a surface area of less than 1000 m<sup>2</sup>, which is the equivalent of 10 pixels and thereby eliminates small irrelevant regions.

In areas covered mainly by vegetation, the overall accuracy was calculated at over 90% (Fig. 7.3). However, it has been observed that in areas which contain swamp or sandy beaches, the built-up class is overestimated due to the similarity of spectral signatures, resulting in a drop in accuracy to a minimum of approximately 50% (Fig. 7.4). Accuracy can be improved by the use of high (5 m) resolution satellite imagery, such as RapidEye [9], which provides their data at no cost for academic or non-profit purposes.

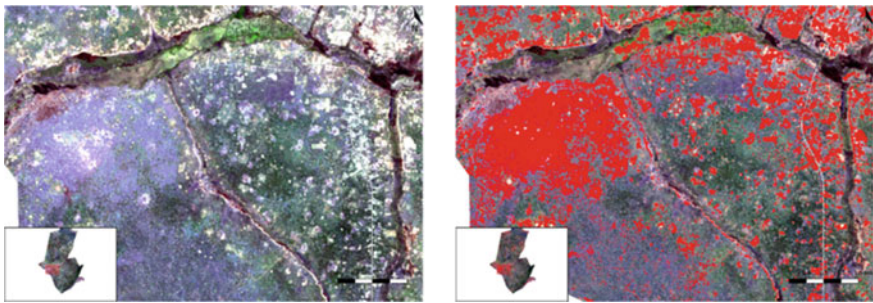
A number of 14 wards were classified, with a total surface area of approximately 10,000 km<sup>2</sup> and, according to citypopulation.de, a total population of almost 90,000 inhabitants [6]. From the total surface area, 0.05% was attributed to the “built-up” class. The resulting file which indicates the location and spatial extent of villages could be overlaid on grid data, in order to get a better idea of the village distance to the grid.



**Fig. 7.2** Overview of the classified wards [overlaid on Open Street Maps © OpenStreetMap contributors under Open Data Commons Open Database License (ODbL)]



**Fig. 7.3** Vyamba ward, an example of high accuracy village detection analysis (based on Copernicus Sentinel data 2017), overlaid on Google Satellite (© 2018 TerraMetrics)



**Fig. 7.4** Malalo ward, overestimation of built-up areas in a swamp environment (based on Copernicus Sentinel data 2017)

## 7.5 Conclusion

Remote sensing can be used as a tool for the detection of built-up areas, specifically villages, regarding their position and extent. This information could then be used for the electrification prioritization of villages, through combining it with, for example, grid data. This data can then be used in decisions such as grid extension (if the village is close to the grid) versus mini-grid (if the village is too far from the grid). In combination with other open source data such as Worldpop [10] or Global Human Settlement Layer [11], it could also provide rough population estimates for the detected villages. This would then enable decision makers to use algorithms that weigh parameters such as population, surface area and distance to the grid in order to prioritize villages according to these parameters.

## References

1. IEA, *World Energy Outlook 2017* (OECD Publishing, Paris/IEA, Paris, 2017), p. 115
2. P. Bertheau, A. Oyewo, C. Cader, C. Breyer, P. Blechinger, Visualizing national electrification scenarios for Sub-Saharan African countries. *Energies* **10**(11), 1899 (2017)
3. D. Kaundinya, P. Balachandra, N. Ravindranath, Grid-connected versus stand-alone energy systems for decentralized power—a review of literature. *Renew. Sustain. Energy Rev.* **13**(8), 2041–2050 (2009)
4. Sentinel-2 Images. [http://www.esa.int/Our\\_Activities/Observing\\_the\\_Earth/Copernicus/Sentinel-2/Data\\_products](http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2/Data_products). Accessed 21 Mar 2018
5. Level 2A Products. <https://earth.esa.int/web/sentinel/user-guides/sentinel-2-msi/product-types/level-2a>. Accessed 21 Mar 2018
6. T. Brinkhoff, City population—population statistics in maps and charts for cities, agglomerations and administrative divisions of all countries of the world [online]. (2018), <http://citypopulation.de>. Accessed 10 Oct 2017
7. L. Congedo, Semi-automatic classification plugin documentation. Release 5(3.6.1) (2016)
8. C. Song, C. Woodcock, K. Seto, M. Lenney, S. Macomber, Classification and change detection using Landsat TM data. *Remote Sens. Environ.* **75**(2), 230–244 (2001)
9. RapidEye Satellite Imagery. <https://www.planet.com/products/satellite-imagery/files/160625-RapidEye%20Image-Product-Specifications.pdf>. Accessed 21 Mar 2018
10. WorldPop Population Layer. [http://www.worldpop.org.uk/data/get\\_data/](http://www.worldpop.org.uk/data/get_data/). Accessed 21 Mar 2018
11. Global Human Settlement Layer. <http://ghsl.jrc.ec.europa.eu/data.php>. Accessed 21 Mar 2018

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