Final report

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

IGC International Growth Centre

Remote sensing for measuring housing supply in Kigali

Felix Bachofer
Sally Murray

January 2018

When citing this paper, please use the title and the following reference number:
C-38418-RWA-1

DIRECTED BY LSE UNIVERSITY OF OXFORD

FUNDED BY UKaid from the British people

Remote Sensing for Measuring Housing Supply in Kigali

Final Report

Felix Bachofer, with Sally Murray

Funding reference: 1-VCU-VRWA-VXXXX-38418

Version: 01/2018

<u>Contact Information:</u>

Dr. Felix Bachofer
Email: Felix.Bachofer@uni-tuebingen.de

Phone: +49 7071 29-77528
Department of Geography
Ruemelinstr. 19-21
72070 Tuebingen
Germany

CONTENT

Figures

Tables

SUMMARY

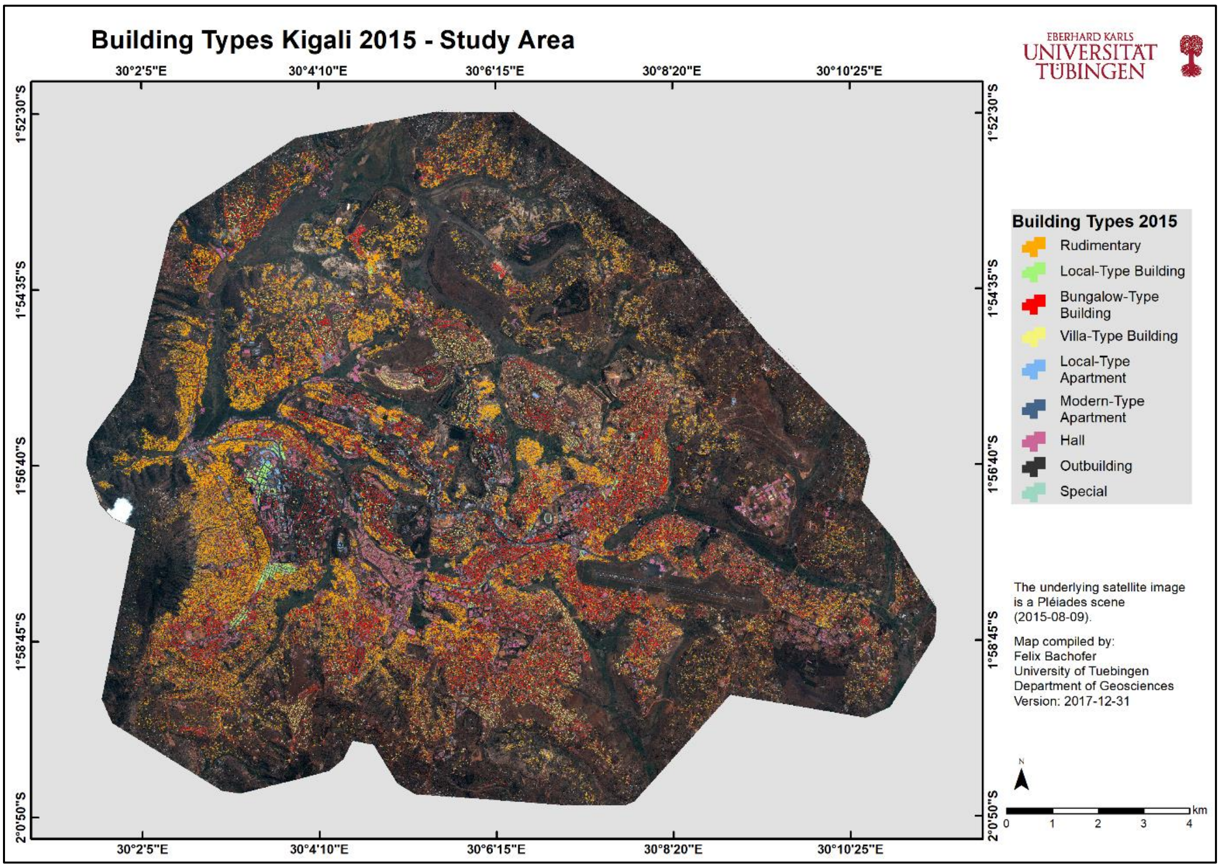
The objective of this project was twofold:

1. To provide the first reasonably comprehensive dataset to the City of Kigali (and collaborating researchers) on the stock of buildings in the city, and changes in the building stock, over time (particularly, comparing 2008/9 with 2015 building supply).

2. To test the potential of remote sensing to cost-effectively monitor building and housing supply in data-poor cities, for uses such as city planning, housing supply management, and property valuation.

The main outcome of the project is a spatial dataset, which shows the change of the building stock in Kigali from 2008/2009 to 2015 on the building level. It contains each building footprint and typology in 2009, the building footprint and typologies in 2015, and the type of change observed for each building (e.g. no change, renovated, greenfield building…).

To produce these data, images of Kigali were obtained from the Pléiades stereoscopic satellite (for 2015) and aerial images (for 2008/9). The data covers only the main urban area of Kigali province, not the more rural periphery (Fig. 1.). For the 2015 image data, a semi-automated process of remote sensing, followed by manual correction, were then applied, to identify building footprints and classify these into building typologies. The data and analysis for 2015 was made available by the 'Rapid Planning' project for the University of Tuebingen. Image quality for 2009 made an automated process impossible, so a change detection was conducted manually.



Findings Regarding the Building Supply

189,871 built-up structures were identified for 2015 in the study area. For 2008/9. We estimate a total of 148,823 buildings.

This is approximately a 27% increase in the number of buildings. Over the same period, the city population grew substantially, from approximately one million, to approximately 1.4 million. This suggests a shortfall in supply, with one new building for only every eighth new resident of the city. The *ground cover,* in m2, of the city, expanded by 25%, equivalent to approximately 10.4m2 for each new resident.

Rudimentary buildings constituted the largest share of the building stock, at around 80%. However, as expected, they consumer far less land than higher-quality typologies, so accounted for just 55% of building *ground cover* (in m2).

The data shows an increase in the *quality* of Kigali's buildings, as well as rapid *expansion* on the urban periphery, which contrasts strongly with effective stagnation in most central areas. Between 2008/9 and 2015, in the study area, approximately:

- **46,400 buildings were newly built.** Most (37,000) were of the 'rudimentary' category, but this represented only a 20% increase in the number of rudimentary buildings versus 2008/9. The largest *proportional* increases were seen in the higher-quality 'villa' and 'modern apartment' categories, increasing three-fold and 2.3-fold respectively. The number of 'local'-type commercial buildings did not increase at all. Overall, there is a clear pattern of increased construction of more modern, higher-value, buildings as compared to lower-quality buildings. Areas on the North-East periphery of the central city saw by far the most new construction, whereas little new construction was seen in central areas (Fig. 13).

- **4,300 buildings were demolished and newly built – or improved substantially enough to appear as new buildings and change their category**. Almost a third of 2015 modern apartments were on land that held a different building typology in 2008/9, suggesting these are particularly likely to be built in higher-demand areas, replacing older building types. Just over 10% of bungalows, villas, and 'local' apartments were on sites with differently classified buildings in 2008/9. No rudimentary or local buildings were in this category, showing these are being built on new land, or land previously used in the same low-value way. Major renovations or rebuilding was most common in suburban areas of Kigali (Fig. 15).

- **11,900 buildings were improved in detectable ways not substantial enough to change their classification.** Around 10% of buildings in each main typology were improved in this way from 2008/9 to 2015, with a slightly higher proportion (13%) for apartment buildings, and slightly lower proportion (6%) for bungalows and villas. 8% of rudimentary and 10% of 'local'-type buildings were improved without reclassification.

- **5,300 buildings were demolished without rebuilding.** The highest concentration of demolished buildings were in the 'rudimentary' category; 4% of the 2008/9 stock of which were demolished without replacement (compared to 1% of 'villas' and 'modern apartments') (Fig. 16).

Findings Regarding Methodological Challenges

For the 2015 classification, an 'automated' building classification was able to correctly classify about 85% of buildings. A process of more costly, time-consuming, and less transparent, manual revision was then required to correct the remaining 15% of buildings. This manual revision was equal to approximately 200 hours from students trained in basic GIS techniques.

These results are promising for the use of such techniques for monitoring the urban environment in data-poor cities, such as for urban planning and property tax purposes. However, although this is a high share of correct classification, it should be considered against the fact that approximately 80% of the building stock is rudimentary in Kigail. Thus, if an algorithm were simple to categorise all buildings as rudimentary, it would have only a slightly lower level of accuracy. The researchers believe that final accuracy is near 100%, following manual correction, however.

The three key issues for the automated detection and classification of buildings in Kigali were:

- The spectral properties ('colours') of rooves are often similar to those of ground surface materials like soil or asphalt. For example, rusted tin rooves appear very similar to much of Kigali's sandy-coloured soil. This required manual correction.

- Adjacent buildings in densely built-up areas are often detected as a single large building. This was addressed through the automated splitting of large rudimentary building clusters, to achieve realistic building sizes but incorrect shapes, as described below.

- In addition, Kigali's undulating ground (with concave and convex slopes), dense settlements, and considerable foliage, obscure building *heights*. Building heights were estimated but remain unreliable.

The largest share of buildings not correctly *detected* through the semi-automated process were low-income, 'rudimentary'. These are typically exempt from property taxes, lessening challenges for the use of remote sensing for purposes such as valuation and tax enforcement.

These challenges show that the use of high-resolution data is a prerequisite for reliable results in such densely built-up areas; however, very high resolutions (for example as obtained by drones) also introduce serious challenges of computing power.
It is anticipated that proximate improvements to remote sensing methodologies, such as through machine learning, offer a high likelihood of raising the share of properties correctly classified automatically above 85%. Finally, manual corrections may be faster and more accurate when performed by local employees (given adequate training), due to greater familiarity with local building typologies and urban form; labour costs may also be reduced.

For the 2008/9 aerial images, no automatic building detection and classification was applied because of the low image quality available (spectral properties). A manual identification was conducted, which was based on the existing 2015 dataset. This manual digitisation and classification was equal to approximately 230 hours from students trained in basic GIS techniques.

1. METHOD

The analysis is based on remote sensing images and manual correction. A dataset of building footprints, including the classification in building archetypes, has been computed with a Pléiades stereoscopic satellite image and was made available of the University of Tuebingen for the year 2015. In this study, buildings in aerial images of Kigali of the years 2008 / 2009 were interpreted and trends of the housing market analyzed.

The study area is the central part of Kigali (Fig. 1).

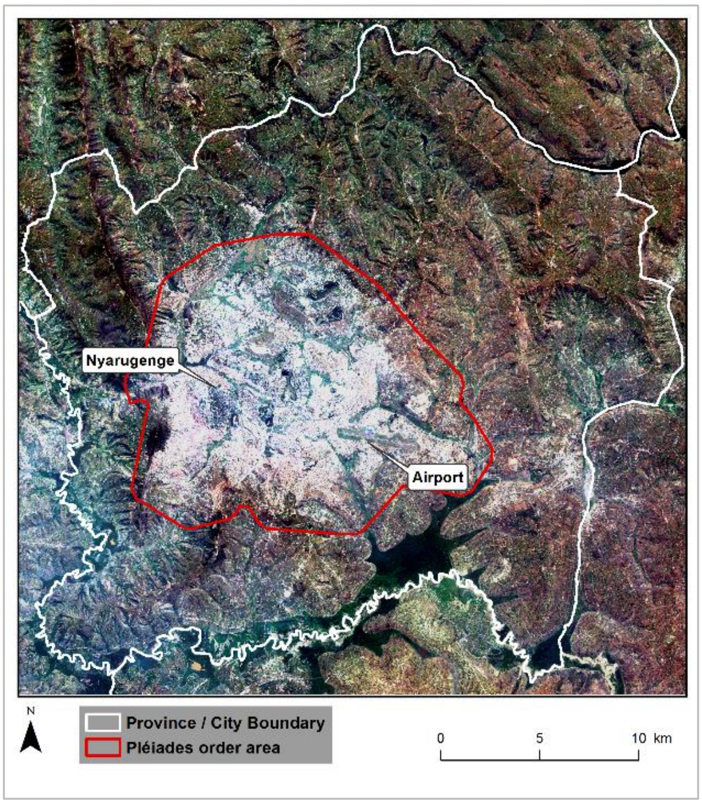


Fig. 1: Study area.

1.1. THE PLÉIADES 2015 DATASET

A Pléiades tri-stereoscopic satellite image (2015-08-09) is the base data for the analysis. The two satellites of the Pléiades mission (1A and 1B) were launched in 2011 and 2012. The satellite constellation provides images with a resolution of 70 cm for the panchromatic channel and 2.8 m for the 4 multispectral channels. The physical resolution is resampled to 50 cm and 2m ground resolution.

The processing was conducted within the RapidPlanning project by the University of Tuebingen. The satellite image processing was conducted with the software eCognition, which allows object-oriented image analysis (OBIA). The processing resulted in preliminary automatic and rulebased delineation of building footprints, which had to be corrected manually.

1.2. BUILDING ARCHETYPES

Buildings in the dataset were distinguished as one of the following building archetypes.

1. Rudimentary

Definition:
Small, single family dwellings. Low-rise (1-2 floors). Often very dense built-up areas, with informal or unplanned character. Constructed of basic building materials.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	10 m^2 (!< MMU) / 80 m^2
Minimum / Maximum height	2 m / 4 m
Number of dwellings	1 – 6
Number of storeys	1

Reference Pictures	Satellite Images
Kigali (UTM 36S – E 184,146; S 9,790,321)	
	

Challenges in identification:

Differentiation to "Bungalow-Type", "Hall" and "Outbuilding". In Kigali, also the type "Local-Type Building" holds structural similarities.

2. Local Type

Definition:
Describes a small building with a local architecture type. Densely built-up compound or block structure. In most cases with a commercial usage. Often found in the CBD or in central areas with a high road density. One to three floors.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	50 m^2 / 600 m^2
Minimum / Maximum height	2.5 m – 25 m
Number of dwellings	Mostly commercial usage
Number of storeys	1 - 2

Reference Pictures	Satellite Images
Kigali (UTM 36S – E 172,874; S 9,784,689)	
	

Challenges in identification:

Differentiation with the classes “Rudimentary Building” and “Hall”.

3. Bungalow

Definition:
Single to two family building. Mostly detached, but also semi-detached and terraced building patterns. Often with a gabled roof and with greening and/or courtyard. Qualitative construction and qualitative building materials.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	70 m^2 / 250 m^2
Minimum / Maximum height	2 m / 8 m
Number of dwellings	1 - 2
Number of storeys	1 - 2

Reference Pictures	Satellite Images
Kigali (UTM 36S – E 171,636; S 9,781,294)	
	

Challenges in identification:

Differentiation to "Local-Type Building" and "Villa-Type".

4. Villa

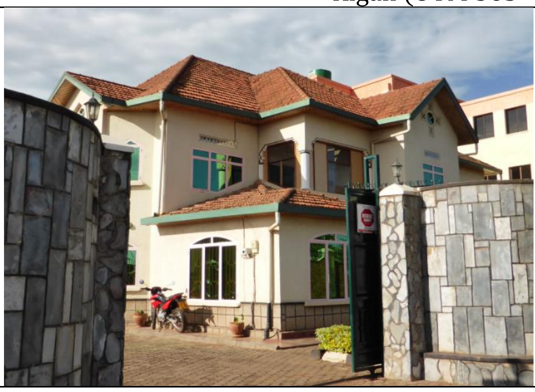
Definition:
Single or two-family building. Detached building pattern. Size of the building and property is extraordinary. High quality construction materials. In most cases with complex roof structures and greenery and/or courtyard.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	100 m^2 / 500 m^2
Minimum / Maximum height	4 m / 18 m
Number of dwellings	1 - 2
Number of storeys	1 – 3

Reference Pictures	Satellite Images

Kigali (UTM 36S – E 179,059; S 9,784,023)



Challenges in identification:

Differentiation to "Bungalow-type" building.

5. Local Apartment

Definition:
Multi-storey/multi-unit apartments with more than two units. The building type often show lack of maintenance and a local architecture type. A commercial and/ or public usage is possible.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	150 m^2 / 1600 m^2
Minimum / Maximum height	4 m / 100 m
Number of dwellings	3 - ~
Number of storeys	1 – 20?

Reference Pictures	Satellite Images
Kigali (UTM 36S – E 178,644; S 9,783,505)	
	

Challenges in identification:

Differentiation to “Modern Apartment” and “Hall”.

6. Modern Apartment

Definition:
Multi-storey/multi-unit apartments with more than three units. A commercial and/ or public usage is possible.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	200 m^2 / 2500 m^2
Minimum / Maximum height	4 m / 200 m
Number of dwellings	3 - ~
Number of storeys	1 - >50

Reference Pictures	Satellite Images
Kigali (UTM 36S – E 172,846; S 9,784,548)	
	

Challenges in identification:

Differentiation to "Local-Type Apartment" and "Halls".

7. Hall

Definition:

Non-residential. Mostly commercial (market) or industrial (warehouse) usage. Large ground floor area higher than 100 m^2. In some cases smaller buildings adjacent to large "Halls".

Building characteristics used for the automatic building classification:

Minimum / Maximum area	100 m^2 / ~
Minimum / Maximum height	3 m / ~
Number of dwellings	0
Number of storeys	1 - 3

Reference Pictures	Satellite Images
Kigali (UTM 36S – E 174,890; S 9,783,205)	
	

Challenges in identification:

N/A

8. Outbuilding

Definition:
A small, usually rundown, non-residential building or an outbuilding with non-residential usage, or sometimes a 'shack'.

Building characteristics used for the automatic building classification:

Minimum / Maximum area	5 m^2 (!< MMU) / 100 m^2
Minimum / Maximum height	1.5 m / 5 m
Number of dwellings	0
Number of storeys	1 - 2

Reference Pictures	Satellite Images

Kigali (UTM 36S – E)

Challenges / Difficulties:

The morphology of these buildings may vary. Differentiation to type 1 "Rudimentary Building".

9. Special

Definition:
Mostly – non-residential, but public/ commercial/ cultural or industrial usage.
Examples: Religious building with a special morphology, buildings with extraordinary architecture.
Industrial examples: power plants, refineries, traffo-stations, silos, antennas.

Building characteristics used for the automatic building classification:

	Kigali
Minimum / Maximum area	25 m^2 / ~
Minimum / Maximum height	2 m / ~
Number of dwellings	-
Number of storeys	-

Reference Pictures	Satellite Images

Kigali (UTM 36S – E 183,577; S 9,784,165)

Challenges in Identification:

Shape and characteristics vary and make it impossible to define a ruleset for automatic classification.

1.3. PLÉIADES PROCESSING

1.3.1. IDENTIFICATION AND CLASSIFICATION OF BUILDINGS

The processing was conducted with the software eCognition, which allows object-oriented image analysis (OBIA).

As input datasets served:

- Pleiades spectral bands (red, green, blue, near-infrared) pan-sharpened with the panchromatic dataset to 0.5 m resolution. The FuzeGo pansharpening algorithm was applied
- A normalized difference vegetation index (NDVI) from the Pleiades dataset
- The first three components of a principle component analysis (PCA)
- A layer with edges derived by the Canny Edge Operator (computed with Matlab)

The process can be summarised as follows:

Step 1: Derive Building Footprints

I. Creation of rules to automatically identify building footprints from above image data.
    - E.g. Colours, identifying complete shapes…
    - This is an iterative process: Rules are adapted flexibly to improve accuracy. As a result, the final 'formula' is not very transparent even for experts.
    - A challenge at this stage was that some dense buildings were detected as one large building.

II. Parcel shapefiles were overlaid, and these building 'clusters' separated, with the assumption that one unit does not span a plot boundary.

III. Building edges were 'sharpened', to better reflect likely building shapes.

IV. Manual correction was applied, for example in cases of:
    - Buildings with roof colours too similar to the ground to be detected automatically.
    - Large buildings with complex rooves identified incorrectly as several buildings.

V. Proximate buildings on one parcel remain unsplit at this stage.
    - If these were rudimentary, a rule-based splitting was applied, which results in more accurate building sizes but incorrect shapes.
    - Manual correction was applied for other (less common) building types.

Each of the above steps and challenges is next described in more detail, with examples.

1.3.2. GEOMETRIC CORRECTION / 'SHARPENING'

The automatic and manual correction of misclassification are necessary post-processing steps. After a visual inspection and manual correction, the building objects were generalized to produce segments that are more compact and non-build-up landcover was reclassified (Fig. 2 & Fig. 3).

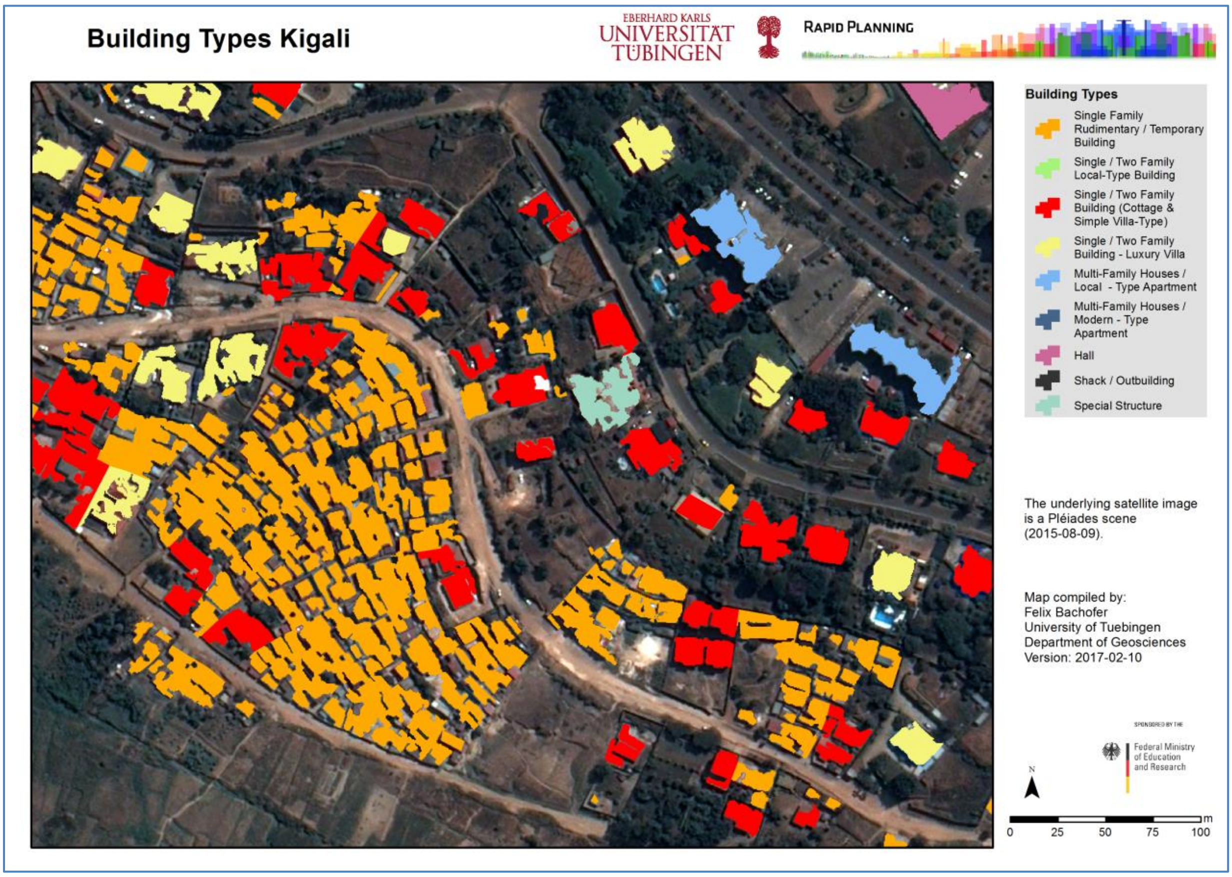


Fig. 2: Original building footprints.

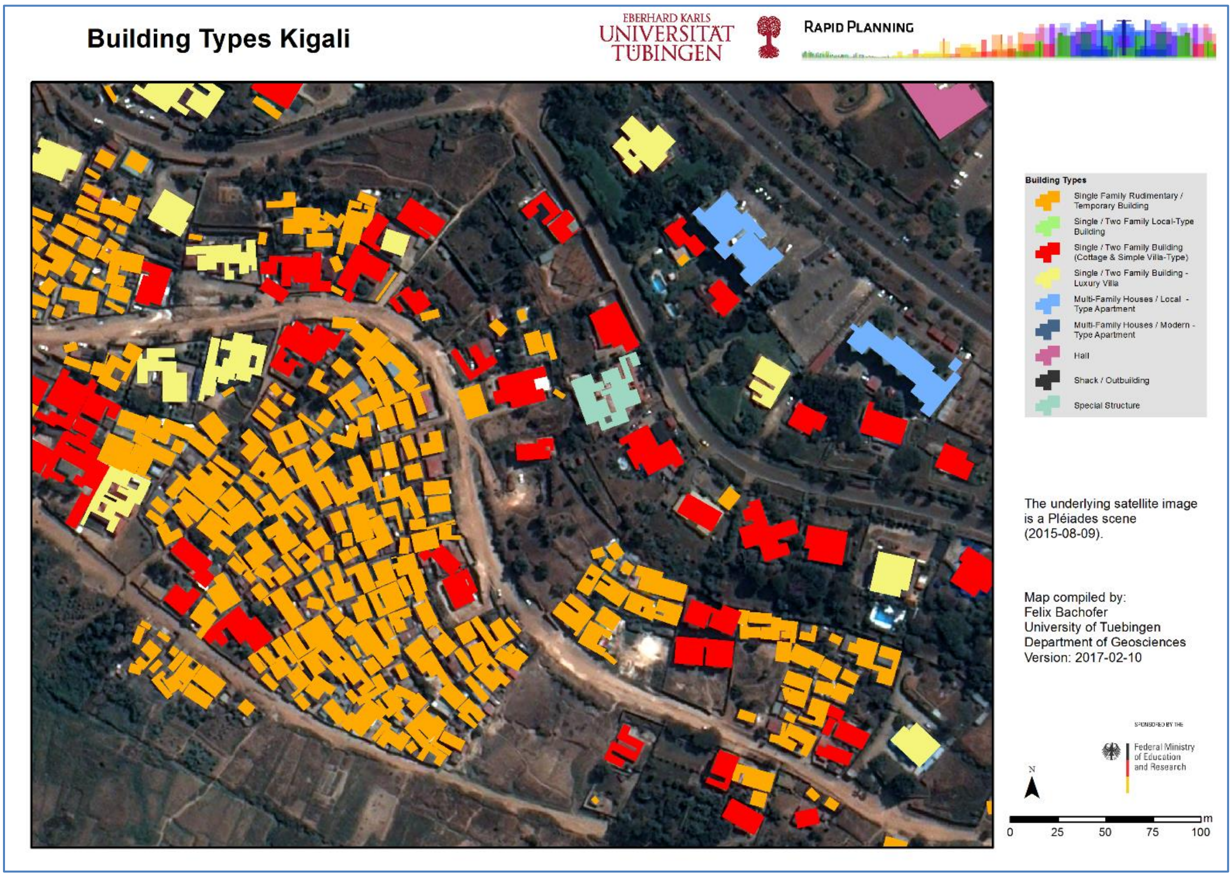


Fig. 3: Generalized building footprints.

1.3.3. Known problems

For the interpretation of the Pléiades derived building footprints and classification of building archetypes, it is necessary to consider several complications. The manual post-processing solved some of the striking problems. However, under consideration of the effort of manual editing not all issues were tackled. We give examples of problems and challenges with the interpretation of the Pléiades result.

1. Adjacent Dense Buildings

One of the most relevant problems occurs in slum areas with “rudimentary” buildings, which are densely built-up. Most roofs appear adjacent, meaning several small close buildings are detected as a single large object. For example in image 1b, several houses are clearly detected as one by the automated process. In image 3b, some buildings are distinguished, whereas other detected outlines contain a large number of buildings.

Image Before Building Detection	**Building Outlines Detected (Without Cadastral Parcel Shape Data)**
1-a) 	1-b) 
2-a) 	2-b) 
3-a) 	3-b) 

In some cases, also other building types like "villa" face the same problem (4-a and 4-b).

4-a)

4-b)

Partly, this was solved by intersecting the building footprints with the cadastral data (Parcel outlines). The remaining objects mostly contain 1 to 3 buildings. In the images above, all buildings in a polygon are on a single parcel, so cadastral data could not improve the accuracy of building outlines. A figure below also shows both parcel outlines (black) and detected building outlines (blue) (Fig. 4).

We then correct for remaining pooled buildings. The median ground floor area of the 1,162 manually digitized rudimentary reference buildings is 75.2 m^2 (Table 1). After a visual inspection of the results, as well as taking into account the statistics, we decided to apply areas up to the doubled median size as single building and beginning from 150.4 m^2 to add a further building every 75.2 m^2 using a look-up-table (LUT) (Table 2). The new geometries do not represent the real shape, size, and location of the buildings within the plot (Fig. 5). Given the inexactness of this method, these buildings are marked with "1" in the column "Model" of the attribute table of the spatial dataset. 60,149 of the 151,217 rudimentary buildings are modelled with this procedure (39.8 %).

Table 1: Statistics of reference building for the "Rudimentary" building type (Pléiades area, from 1,162 reference rudimentary buildings)

Statistic	Building Area
MEDIAN	75.2 m^2
MEAN	86.3 m^2
STANDARD DEVIATION	49.45 m^2
MINIMUM	9.79 m^2
MAXIMUM	531.31 m^2

Table 2: LUT to correct the number of "Rudimentary" buildings of the Pleiades result

Range object area (m^2)	New number of buildings
0 – 150.4	1
150.4 – 225.6	2
225.6 – 300.8	3
300.8 - 376	4
376 – 426.2	5
426.2 – 501.4	6
501.4 - 531.31	7

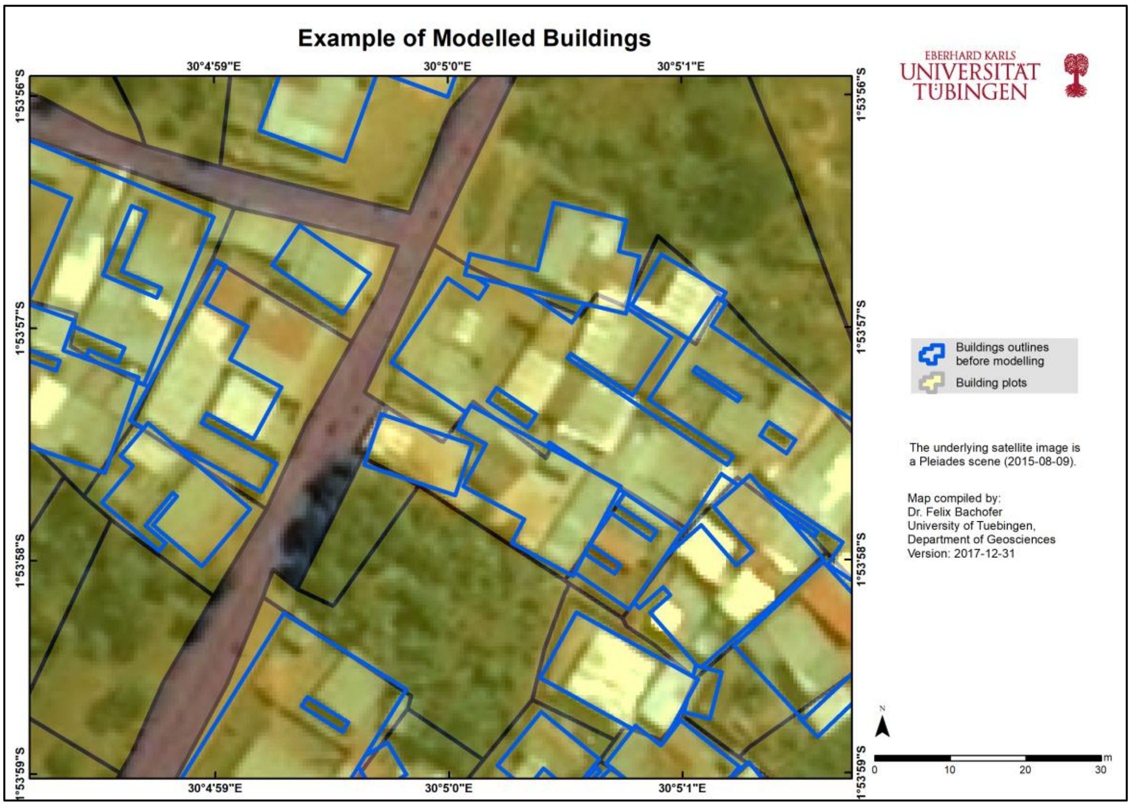


Fig. 4: Automatically detected and generalized buildings. The example shows adjacent buildings treated as single objects.

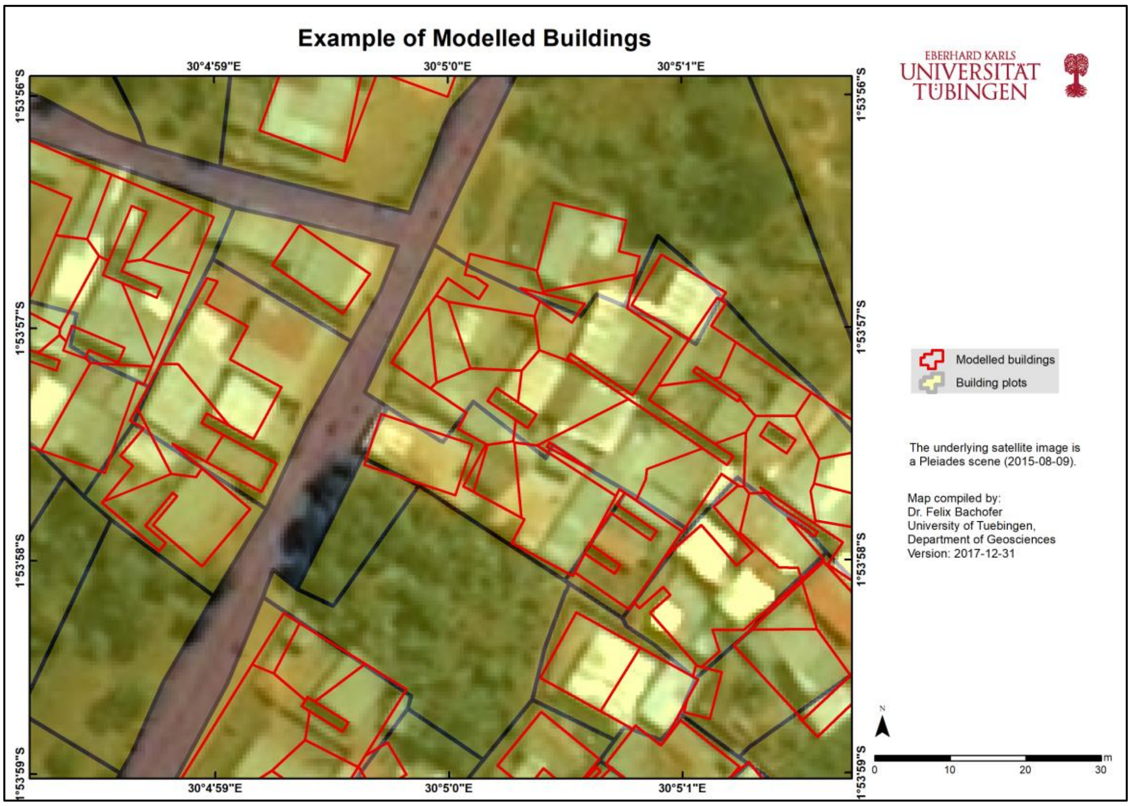


Fig. 5: Modelled buildings following the proposed methodology.

2. Roof Colours Similar to Adjacent Ground

In some cases, roofs have the spectral properties, which are similar to the adjacent ground surfaces. This complicates to retrieve adequate geometries, or even to detect the buildings (5-a. 5-b, 6-a, 7-a). With manual editing, many issues were solved.

5-a) 	5-b) 
6-a) 	7-a) 

3. Semi-detached Dwellings

Semi-detached bungalows and villas were typically detected as a single dwelling unit. These were separated by manual editing process when it was obvious that two dwelling units are present (8-a and 8-b).

8-a) 	8-b) 

4. Complex Rooves

Complex roofs often produce several objects with the automatic building detection (9-a and 9-b). Without editing the result would show four generalized building objects for the semi-detached building (9-c). With manual editing, we receive two buildings (9-d). Probably, not all cases were identified by the visual inspection.

9-a) 	9-b) 	9-c) 	9-d) 

5. Object heights

A Digital Surface Model (DSM) could be derived from the tri-stereoscopic Pléiades data. The use of object height information for the classification of building types and to derive the gross floor area was not successful in Kigali. While the building height for objects in flat areas (like the CBD) were determined, building heights in densely built-up areas and areas on slopes could not be derived with the necessary accuracy. The problem was that the bare earth elevation could not be retrieved for the entire study area because only a few points could be identified automatically. The concave and convex slopes, as well as the high building density were the main causes for the inaccurate bare earth model. Without an accurate bare earth model, it was not possible to calculate objects heights.

Fig. 6: DSM of the CBD in Kigali. Wide roads and a flat terrain at the CBD in the Nyarugenge sector led to good results in this part of the city.

1.4. RESULTS OF THE PLÉIADES ANALYSIS 2015: BUILDING SUPPLY

189,875 building objects were detected in the central part of Kigali, which is covered by the Pleiades satellite scene. 79% of the buildings are "rudimentary" buildings. Bungalow-type buildings are with 13.5% the second biggest class (Fig. 7, Table 3).

Table 3: Number of buildings per building type 2015.

Class Name	Code / Type	Number of buildings	Percentage of buildings	Mean ground cover area in m²
Rudimentary	1	151,214	79.64 %	72.4
Local building	2	1,184	0.62 %	287.6
Bungalow	3	25,586	13.48 %	200.3
Villa	4	5,709	3.01 %	271.4
Local apartment	5	861	0.45 %	536.9
Modern apartment	6	224	0.12 %	882.3
Hall	7	4,763	2.51 %	531.4
Outbuilding	8	157	0.08 %	36.0
Special	9	175	0.09 %	302.9
SUM		189,871	100.00 %	111.8

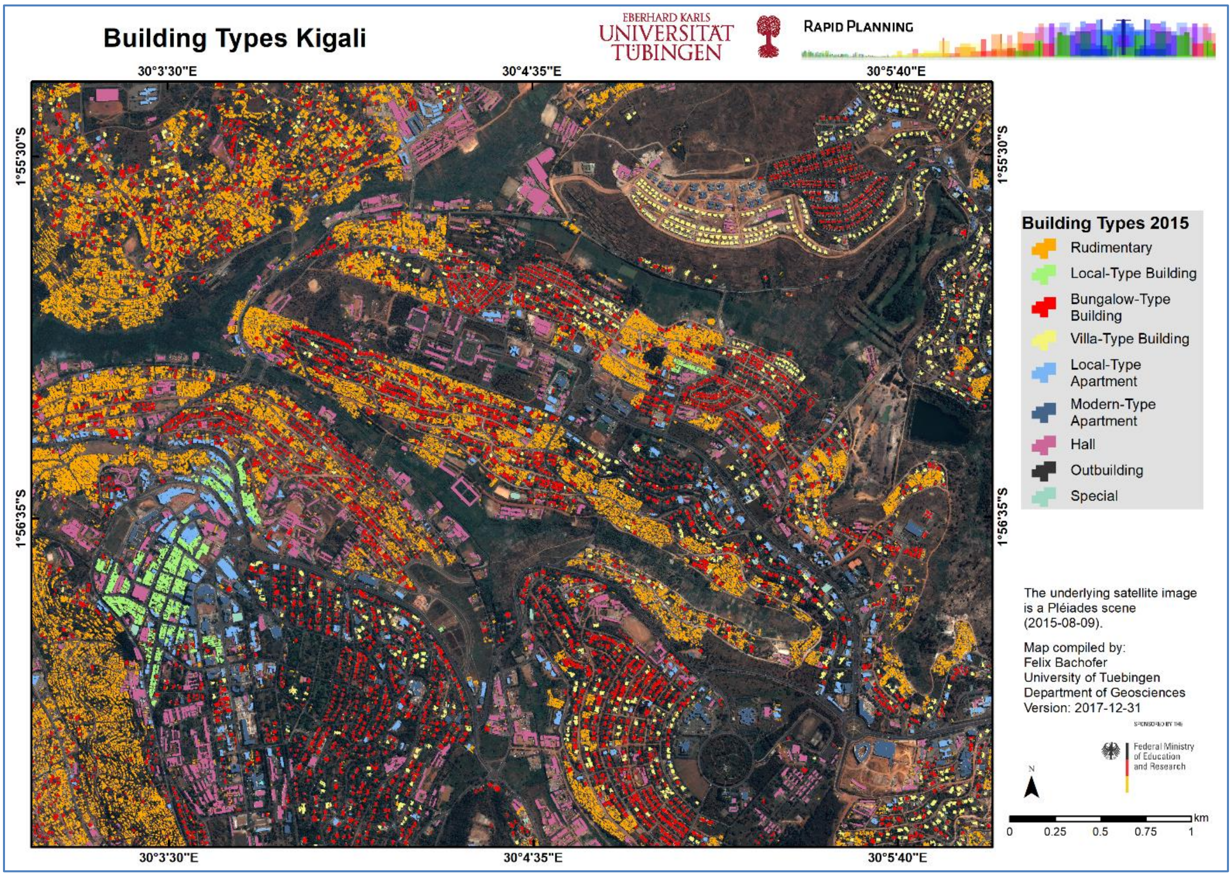


Fig. 7: Building types 2015 (subset area).

1.5. THE AERIAL IMAGES OF 2008 / 2009

96% of the Rwandan landmass was mapped with aerial images in the summer of 2008 and 2009. The resolution of the images is 25 cm and only visual spectral bands (blue, green and red) were taken. Furthermore, the colour of the images was also adjusted with unknown parameters. These weaknesses seriously limit the possibilities for an automated remote sensing analysis.

Therefore, a manual visual mapping of the change between the 2009 images and 2015 footprints and classification was conducted.

The analysis shows that the total number of buildings increased by over 40,000 to reach the 190,000 buildings in 2015 (Table 4).

Table 4: Number of buildings per building type 2008/2009.

Class Name	Code / Type	Number of buildings	Percentage of buildings	Mean ground cover area in m²
Rudimentary	1	123,218	82.80 %	81.6
Local building	2	1,172	0.79 %	288.8
Bungalow	3	18,034	12.12 %	205.3
Villa	4	1,939	1.30 %	296.7
Local apartment	5	544	0.37 %	530.9
Modern apartment	6	98	0.07 %	941.6
Hall	7	3,616	2.43 %	543.0
Outbuilding	8	62	0.04 %	35.3
Special	9	140	0.09 %	277.2
SUM		148,823	100.00	114.6

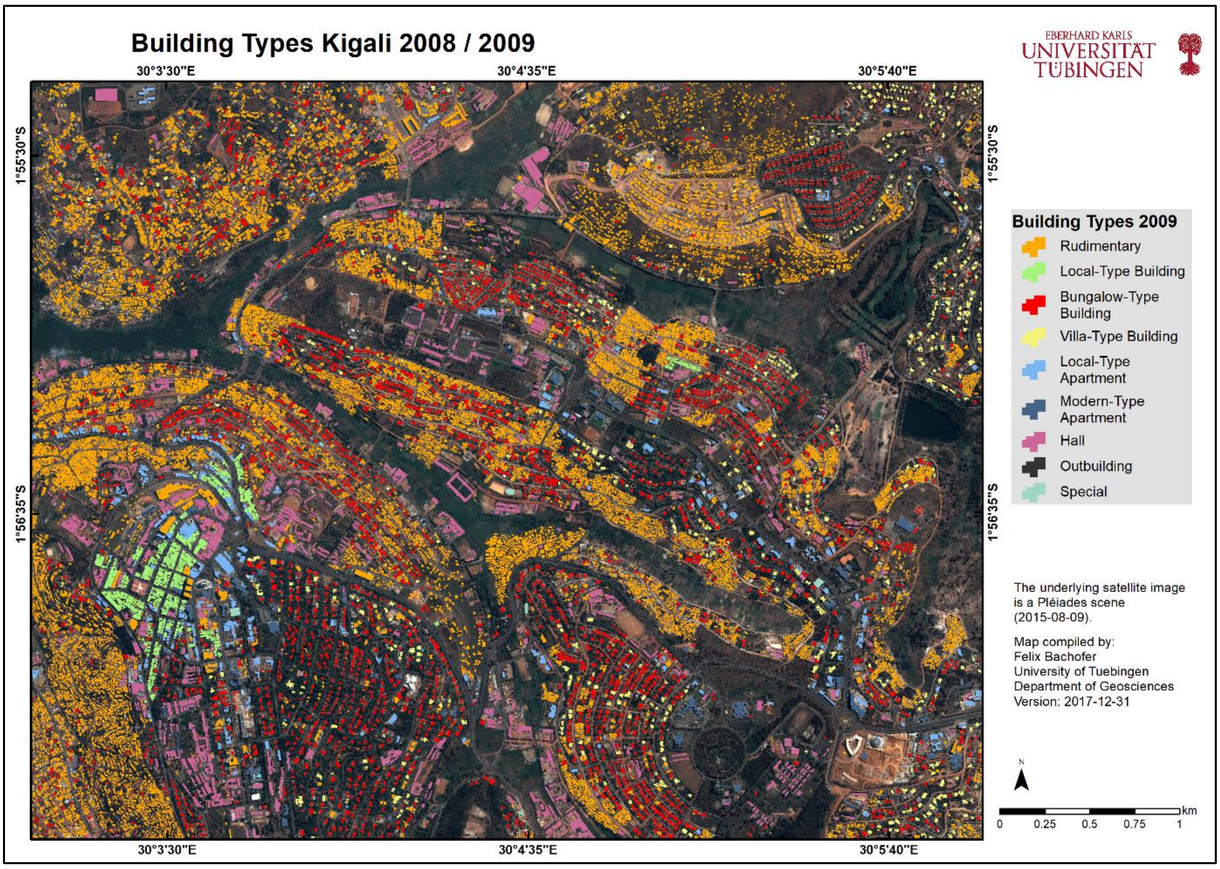


Fig. 8: Building types 2008 / 09 (subset area).

2. Results of the change analysis

The following tables illustrate the changes of the building supply by building typology in the study area between 2008 / 2009 and 2015. Table 5 shows the *number* of buildings in each period (by typology, and Table 6 shows the *ground cover* (m2) of buildings in each period.

Table 5: Number of buildings per building type 2008/2009 and 2015.

Building Class	Number of buildings 2008 / 2009	% of 2008/9 buildings	Number of buildings 2015	% of 2015 buildings	Total increase in % 2008/9 to 2015	% point increase in share (2008/9 to 2015)
Rudimentary	123,218	82.80 %	151,214	79.64 %	22.72	-3.16 %
Local building	1,172	0.79 %	1,184	0.62 %	1.28	-0.16 %
Bungalow	18,034	12.12 %	25,586	13.48 %	41.88	1.36 %
Villa	1,939	1.30 %	5,709	3.01 %	194.43	1.70 %
Local apartment	544	0.37 %	861	0.45 %	58.27	0.09 %
Modern apartment	98	0.07 %	224	0.12 %	128.57	0.05 %
Hall	3,616	2.43 %	4,763	2.51 %	31.72	0.08 %
Outbuilding	62	0.04 %	157	0.08 %	153.23	0.04 %
Special	140	0.09 %	175	0.09 %	25.00	0.00 %
SUM	148,823	100.00 %	189,871	100.00 %	27.58	

Table 6: Ground cover area of buildings per building type 2008/2009 and 2015.

Building Class	Ground cover area in m² 2008 / 2009	% of 2008/9 buildings	Ground cover area in m² 2015	% of 2015 buildings	Total increase in % 2008/9 to 2015	% point increase in share (2008/9 to 2015)
Rudimentary	10,051,347	58.94%	10,958,277	51.63%	9%	-7.31%
Local building	338,416	1.98%	340,567	1.60%	0.6%	-0.38%
Bungalow	3,702,784	21.71%	5,125,494	24.15%	38.4%	2.44%
Villa	575,355	3.37%	1,549,589	7.30%	169%	3.93%
Local apartment	288,808	1.69%	462,329	2.18%	60.1%	0.48%
Modern apartment	92,278	0.54%	197,631	0.93%	114.2%	0.39%
Hall	1,963,319	11.51%	2,531,031	11.93%	28.9%	0.41%
Outbuilding	2,187	0.01%	5,649	0.03%	158.3%	0.01%
Special	38,805	0.23%	52,999	0.25%	36.6%	0.02%
SUM	17,053,299	100.00%	21,223,566	100.00%	24.5%	

The following changes to ground cover for each building, between 2008 / 2009 and 2015, were then mapped:

1) No change
2) Newly built building (on a previously unbuilt area)
3) Improvements (roof, structure) of an existing building

   or

   rebuilt WITHOUT a change of the building class

   or the building was under construction in 2008 / 2009
4) Building demolished and newly built

   or

   building upgraded WITH a change of the building class
5) Building demolished

The following figure (Fig. 10) shows an example of a change in a building without the change of the building class (code: 3 above). The bungalow-type building of 1-a appears to have been demolished and newly built, or the roof was upgraded. Yet, the building class remained "bungalow-type". The rudimentary building 'A' in image 2-a got a new roof between 2009 and 2015, but remained in the class "rudimentary". On the contrary, the rudimentary building 'B' was rebuilt and upgraded to the building class "bungalow-type".

2008 / 2009	2015
	
1-a	1-b

	
2-a	2-b

Fig. 9: Examples for improvements / change of a building without the change of the building class (Code: 3).

The following figure (Fig. 10) shows examples of upgrades to a new building class (code: 4). The rudimentary-type building of 3-a was demolished and newly built up as bungalow-type building (3-b). The rudimentary building in figure 4-a was rebuilt as "villa-type" building (4-b).

2008 / 2009	2015
	
3-a	3-b

	
4-a	4-b

Fig. 10: Examples of upgraded or newly built buildings with the change of the building class (Code: 4).

The change analysis shows a trend of increasing building quality in Kigali over the period. The share of rudimentary buildings fell by three percentage points, while the share of villas increased by 1.7 percentage points from a low base (the *number* of villas tripled). There was also a 1.4 percentage point increase in the share of bungalows in the building stock.

New building was heavily concentrated in peripheral areas, such as the more rural North-Eastern Kigali. Building upgrades were more common in suburbs. However, it is notable that very little change in the building stock occurred in central areas, despite a high share of still lower-grade housing typologies (Figs 11-15). This suggests that regulations and/or inadequate infrastructure provision in central areas is preventing the expected upgrading, and leading to a rapidly sprawling urban development.

Table 7: Type of change between 2008/2009 and 2015.

Number of buildings	Area in m²	Change code	Type of change
127,237	14,017,928	1	No change
46,395	4,729,034	2	Newly built (on a previously unbuilt area)
11,914	1,463,584	3	Improvements (roof, structure) of an existing building or rebuilt WITHOUT a change of the building class
4,325	1,012,579	4	Building demolished and newly built or building upgraded WITH a change of the building class
5,347	559,210	5	Building demolished

Table 8: Buildings with no change between 2008/2009 and 2015.

	[1] - Buildings with no change, 2008/9 to 2015		
Building Class	**Number**	**No. as % of 2008/9 buildings**	**No. as % of 2015 buildings**
Rudimentary	103,771	84%	69%
Local building	1,050	90%	89%

Bungalow	1,6742	93%	65%
Villa	1,802	93%	32%
Local apartment	462	85%	54%
Modern apartment	84	86%	38%
Hall	3,133	87%	66%
Outbuilding	57	92%	36%
Special	136	97%	78%
SUM	127,237	85%	67%

Table 9: Newly built between 2008/2009 and 2015.

	[2] - Newly built buildings, 2008/9 to 2015		
Building Class	**Number**	**No. as % of 2008/9 buildings**	**No. as % of 2015 buildings**
Rudimentary	37,269	30%	25%
Local building	15	1%	1%
Bungalow	4,372	24%	17%
Villa	3,131	161%	55%
Local apartment	214	39%	25%
Modern apartment	61	62%	27%
Hall	1,202	33%	25%
Outbuilding	97	156%	62%
Special	34	24%	19%
SUM	46,395	31%	24%

Table 10: Improvements without class change between 2008/2009 and 2015.

	[3] - Improved with no change in class, 2008/9 to 2015		
Building Class	**Number**	**No. as % of 2008/9 buildings**	**No. as % of 2015 buildings**
Rudimentary	10,174	8%	7%
Local building	119	10%	10%
Bungalow	1,114	6%	4%
Villa	123	6%	2%
Local apartment	69	13%	8%
Modern apartment	13	13%	6%
Hall	296	8%	6%

Outbuilding	3	5%	2%
Special	3	2%	2%
SUM	11,914	8%	6%

Table 11: Demolished and newly built or upgraded with class change between 2008/2009 and 2015.

	[4] - Improved or rebuilt *with* change in class, 2008/9 to 2015	
Building Class (2015)	**Number**	**No. as % of 2015 buildings**
Rudimentary	0	0%
Local building	0	0%
Bungalow	3,358	13%
Villa	653	11%
Local apartment	116	13%
Modern apartment	66	29%
Hall	130	3%
Outbuilding	0	0%
Special	2	1%
SUM	4,325	2%

Table 12: Demolished buildings between 2008/2009 and 2015.

	[5] - Demolished since 2008/9	
Building Class (2008/9)	**Number**	**No. as % of 2008/9 buildings**
Rudimentary	4,951	4%
Local building	0	0%
Bungalow	178	1%
Villa	14	1%
Local apartment	13	2%
Modern apartment	1	1%
Hall	187	5%
Outbuilding	2	3%
Special	1	1%
SUM	5,347	4%

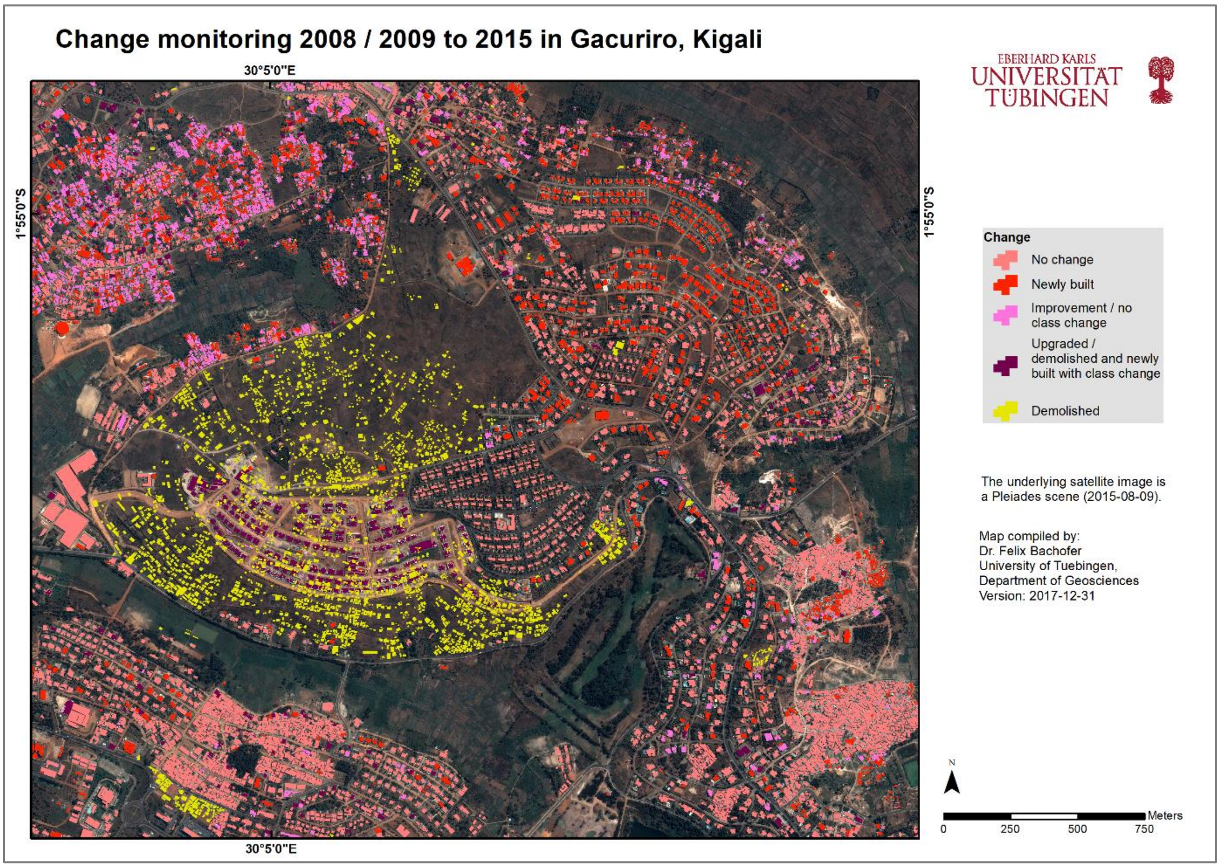


Fig. 11: Example: Change Monitoring in Gacuriro (Suburban Residential area)

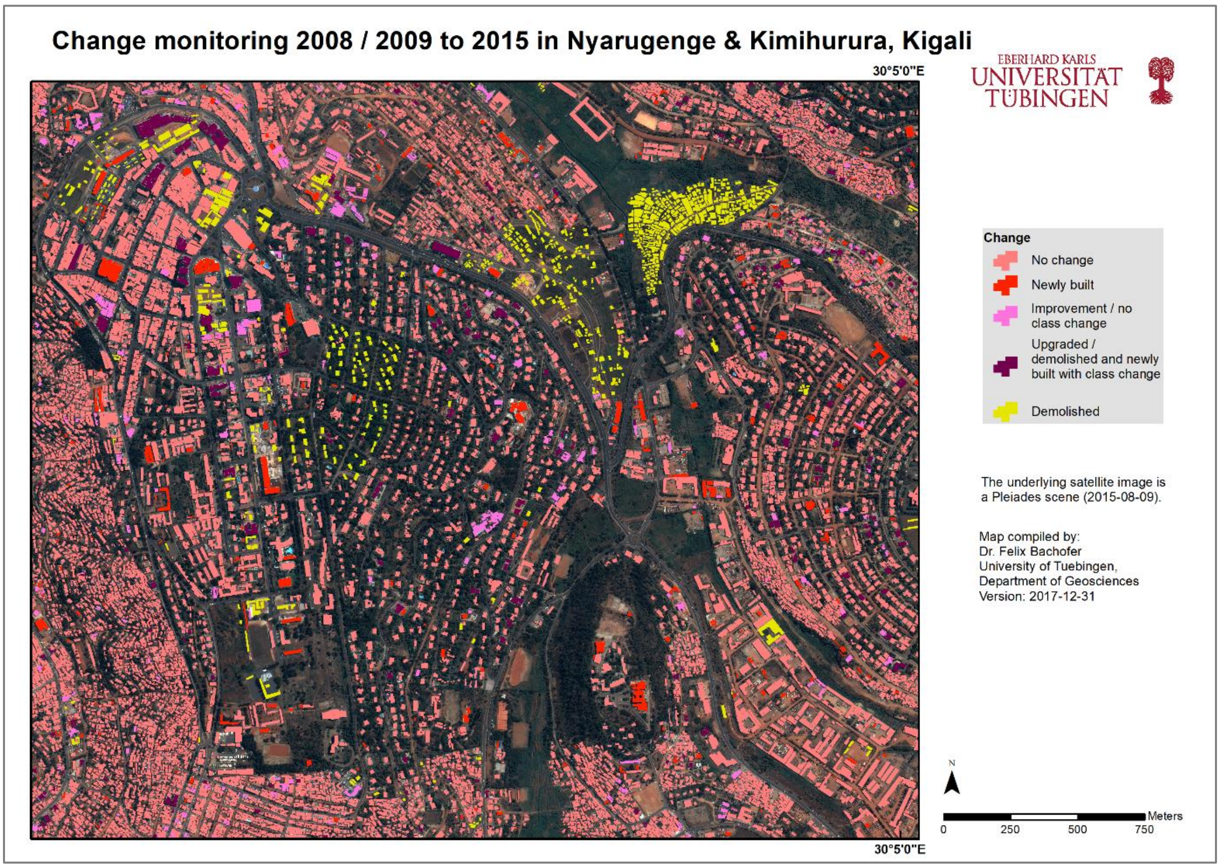


Fig. 12: Example: Change monitoring Nyarugenge & Kimihurura (CBD area)

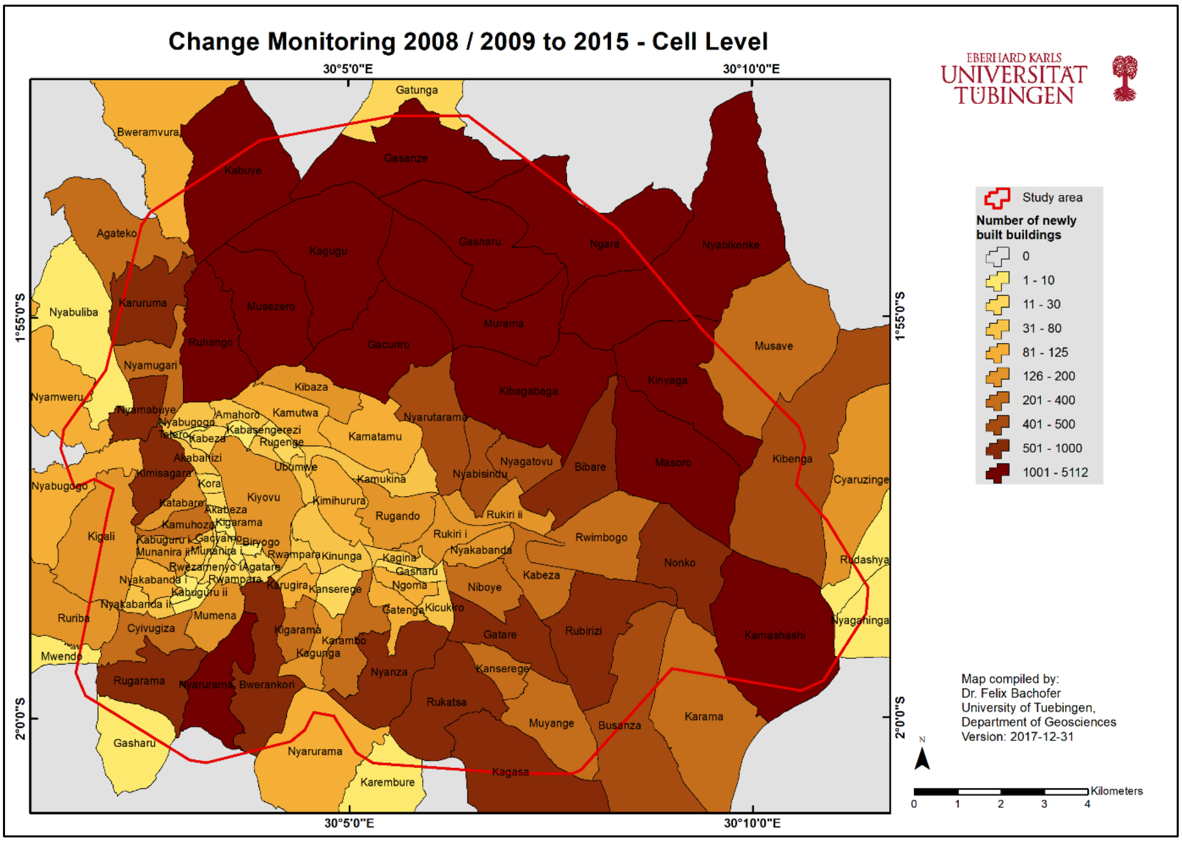


Fig. 13: Number of new buildings at the sector level

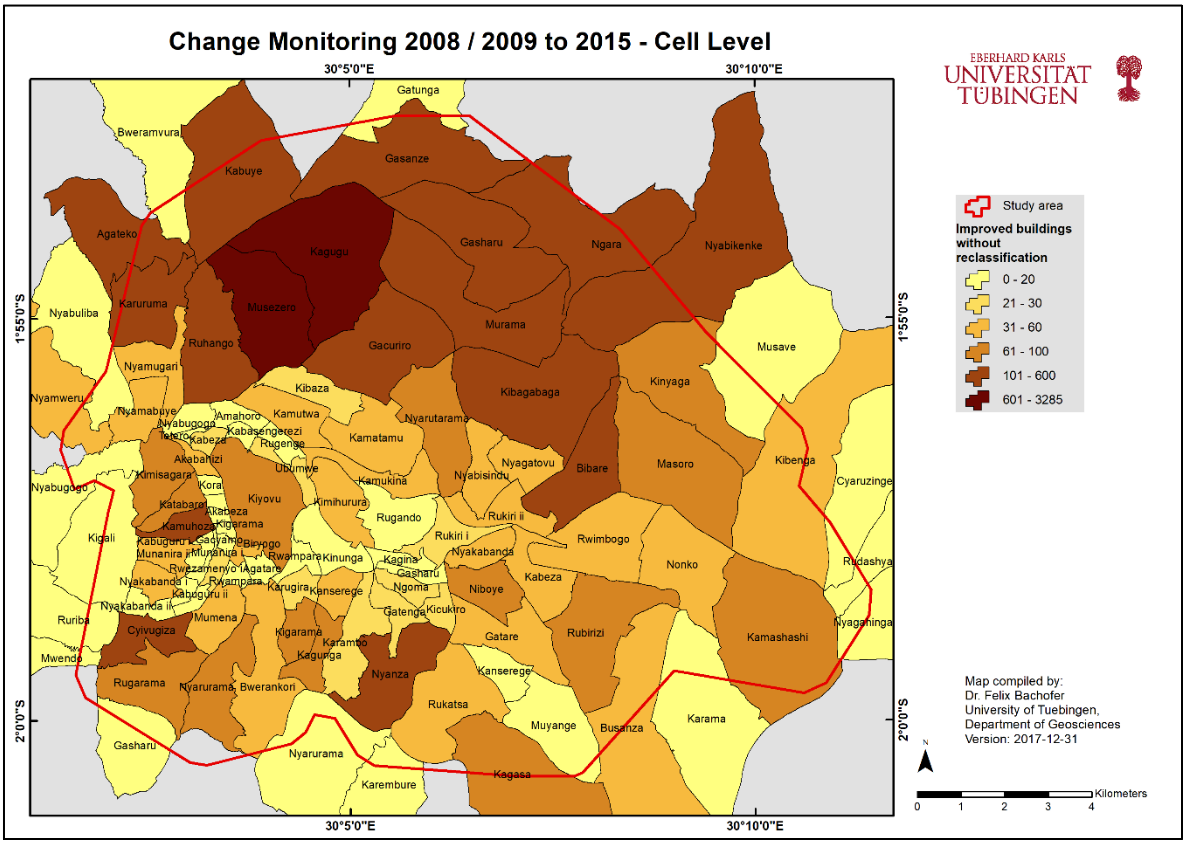


Fig. 14: Improved building without reclassification.

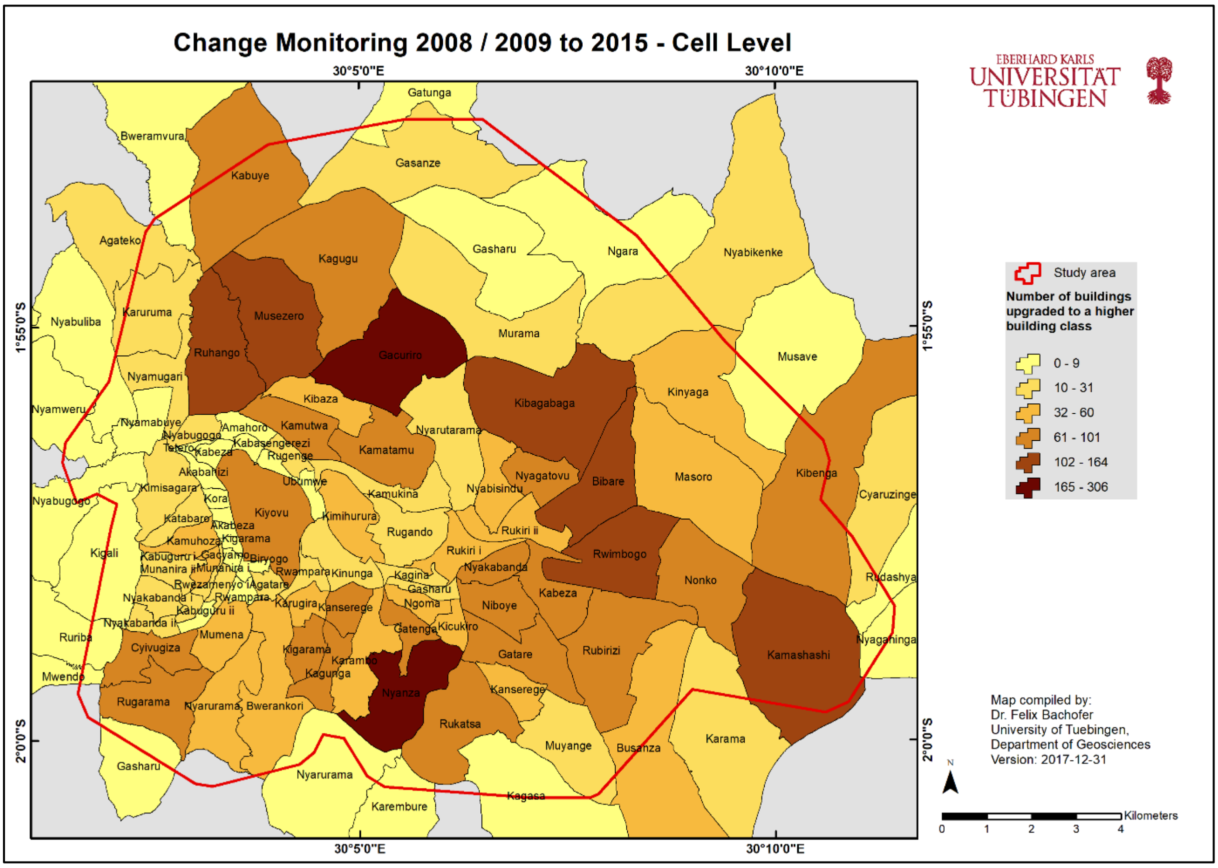


Fig. 15: Number of upgraded buildings at the sector level

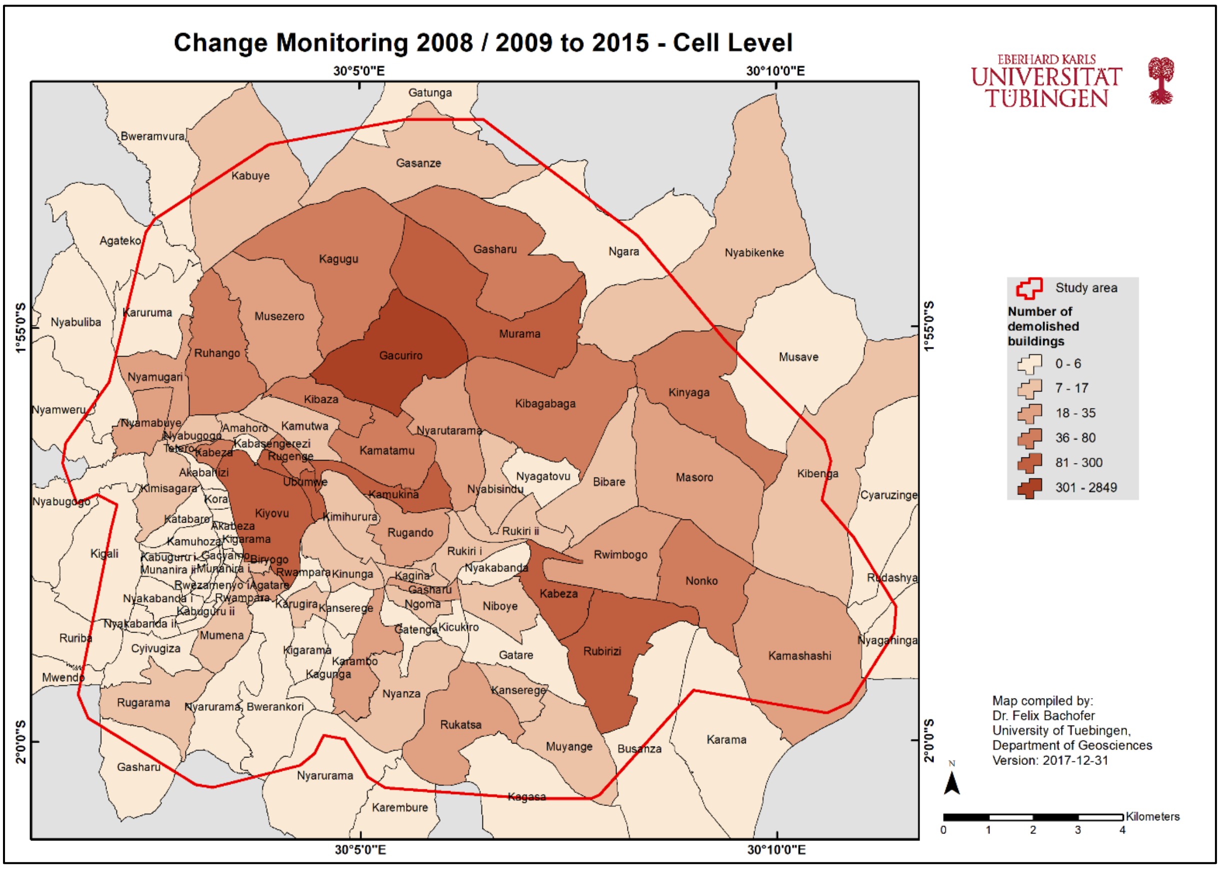


Fig. 16: Number of buildings demolished without replacement at the sector level

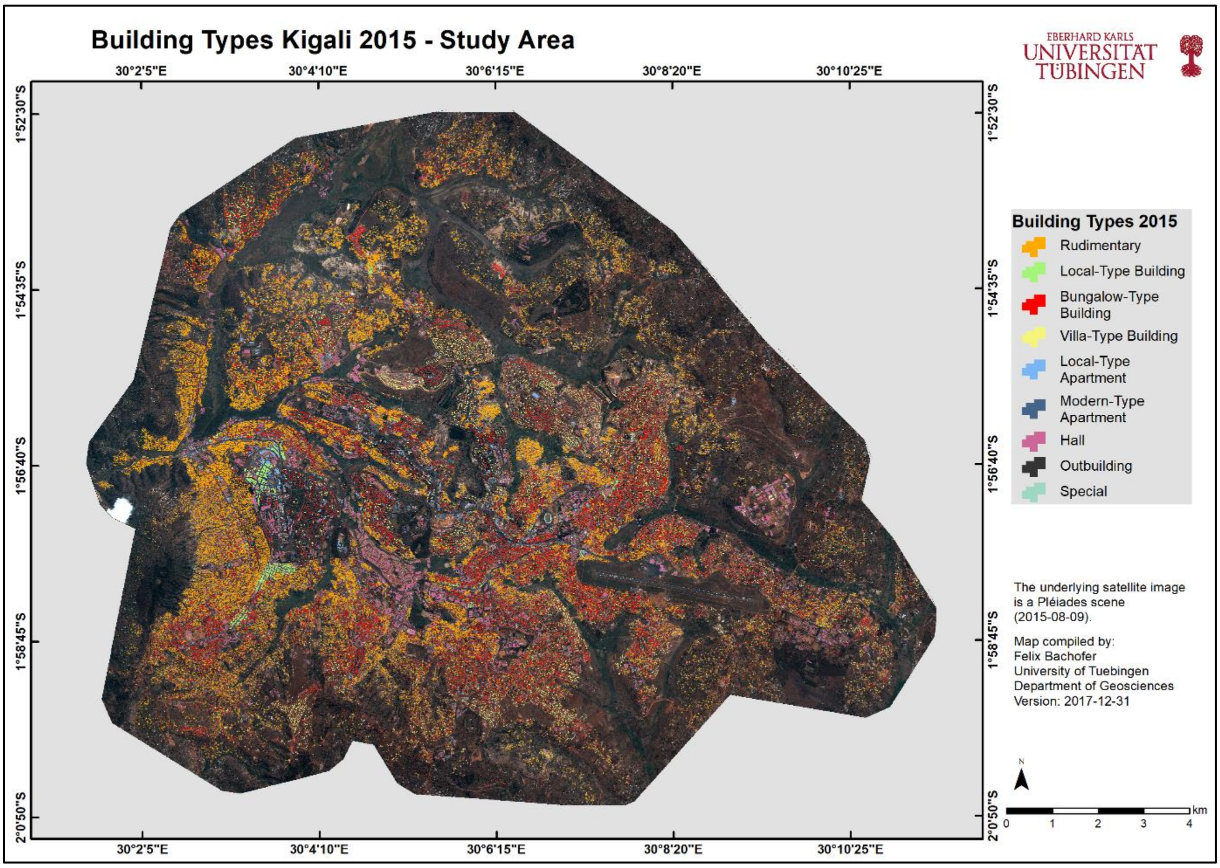


Fig. 17: Result of the building type classification for the study area (2015).

3. Looking Forwards

Anticipated Uses of the Study Datasets

Going forwards, the data will be used to support two concrete ongoing studies. The first is a study of the housing market in Kigali, in which the data will be used to study the impact of factors like infrastructure and building regulations on the evolution of building supply, density, and typologies over time, as well as simply how effectively supply is meeting demand. The second will combine the building supply data with a dataset of parcel transaction prices, to analyse the determinants of land and property prices. This will test the whether such relatively cheap housing supply data, combined with machine learning approaches, can cost-effectively produce land and property valuations usable for tax purposes, extending analyses like that in Glaeser's 'Big Data and Big Cities' to a developing country, data-poor, context. In both cases, this is a critical contribution, as previous analyses lacked access to comprehensive data on the *buildings* on plots.

We anticipate that this data will have many other uses to improve our ability to understand and manage cities. The City of Kigali have expressed a strong interest in the data and building such systems 'in house', in order to cost-effectively monitor and manage building supply in their city. When presenting preliminary results to local stakeholders, they expressed particular interest in:

1. Extending the analysis to the rural parts of Kigali;
2. Using more recent 2017 / 2018 satellite images for further monitoring;
3. Studying masterplan compliance challenges;
4. Classification of more detailed building footprints.

Possible Improvements to the Methodology

With the existing dataset, future analysis can be processed more efficiently. The methodology can be improved by with existing methods:

1) By spending more time on the manual editing on the building footprints. That way, it would not be necessary to automatically model the number of buildings when several adjacent buildings are on a single plot.
2) By including wore stereoscopic satellite images, it will be possible to improve the object height model of the buildings in Kigali. With this information, it would be possible to improve the automatic building classification by using the building height / volume, as well as to use data on building volume rather than simply ground floor area.
3) Recent satellite sensors like WorldView-3 have a spatial resolution of 30 cm. With such high resolution, for images close to the Nadir, the identification of building footprints could be improved.

There are also promising new methods, which have to be investigated and developed to solve the research question [Mboga *et al.* 2017, Yu *et al.* 2017]. Those methods are based on Neural Networks (Deep Learning). These methods are successfully applied in various image analysis applications. For Kigali to pursue this would mean establishing a library of classified building images, which can be used by the algorithm as training samples. The algorithm searches for similar patterns and provides probabilities for the occurrence of buildings (or even building types). This would allow a continuous and automated mapping, as soon as new satellite image acquisitions are available.

REFERENCES

1 Mboga, N., Persello, C., Bergado, J. & Stein, A., 2017 - *Detection of Informal Settlements from VHR Images Using Convolutional Neural Networks*. Remote Sensing, Vol: 9 (11):

2 Yu, X., Wu, X., Luo, C. & Ren, P., 2017 - *Deep learning in remote sensing scene classification: a data augmentation enhanced convolutional neural network framework*. Giscience & Remote Sensing, Vol: 54 (5): 741-758.

ANNEX: THE STRUCTURE OF THE DATASET

The spatial datasets are ESRI polygon shapefiles (*.shp), which can be read by common Geoinformation Systems (GIS) (e.g. ESRI ArcGIS, QGIS, etc.).

All shapefiles have attribute tables, which stores all necessary information of the change analysis for each building polygon.

Kigali_buildings_2009_2015.shp: stores the polygon geometries and attributes of single buildings.

- Column "Shape Area": displays the area of each polygon in sqm.
- Column "Model": Indicates if the geometry, exact position and total number of this entity is an estimate (see section 2.3.3).
- Column "Change": Indicates the type of change between 2008 / 2009 and 2015.

Table 13: Type of change between 2008/2009 and 2015.

Change code	Type of change
1	No change
2	Newly built (on a previously unbuilt area)
3	Improvements (roof, structure) of an existing building or rebuilt WITHOUT a change of the building class
4	Building demolished and newly built or building upgraded WITH a change of the building class
5	Building demolished

- Columns "2015_ty" and "2009_ty": Indicates the building archetype by code for the respective period.
- Columns "2015_name" and "2009_name": Indicates the building archetype for the respective period.

Table 14: Naming of building archetypes.

Class name	Class Name (short)	Code / Type
Rudimentary / Basic or Unplanned Building	rudimentary	1
Local-Type Building	localbuilding	2
Bungalow-Type Building	bungalow	3
Villa-Type Building	villa	4
Local –Type Apartment	localtype	5
Modern -Type Apartment	modernapartment	6
Hall	hall	7
Shack	outbuilding	8
Special Structure	special	9

Kigali_buildings_2009_2015_point.shp: stores point geometries and attributes of single buildings. This shapefile is meant for further analyses like the intersection with administrative units.

Table 15: Attribute table content of *Kigali_buildings_2009_2015_point.shp.*

Column name	Content
"Shape Area" "Model" "Change" "2015_ty" "2009_ty" "2015_name" "2009_name"	Same as in *Kigali_buildings_2009_2015.shp*
The following rows are filled with binary values (0, 1). Objects with 0 fulfil not the affiliation indicated by the column name. Objects with 1 fulfil the affiliation indicated by the column name.	
C1	No change
C2	Newly built (on a previously unbuilt area)
C3	Improvements (roof, structure) of an existing building or rebuilt WITHOUT a change of the building class
C4	Building demolished and newly built or building upgraded WITH a change of the building class
C5	Building demolished
2009_1	Rudimentary in 2009
2009_2	Localbuilding in 2009
2009_3	Bungalow in 2009
2009_4	Villa in 2009
2009_5	Localtype in 2009
2009_6	Modernapartment in 2009
2009_7	Hall in 2009
2009_8	Outbuilding in 2009
2009_9	Special in 2009
2015_1	Rudimentary in 2015
2015_2	Localbuilding in 2015
2015_3	Bungalow in 2015
2015_4	Villa in 2015
2015_5	Localtype in 2015
2015_6	Modernapartment in 2015
2015_7	Hall in 2015
2015_8	Outbuilding in 2015
2015_9	Special in 2015

Kigali_Cell_2009_2015.shp: stores polygon geometries and attributes of the administrative cell level and statistical information on the building stock.

Table 16: Attribute table content of *Kigali_Cell_2009_2015.shp.*

Column name	Content
Join_Count	Number of objects intersected with *Kigali_buildings_2009_2015_point.shp*
Dist_ID	Official Rwandan district ID number
District	District name
Sect_ID	Official Rwandan sector ID number

Sector	Sector name
Cell_ID	Official Rwandan cell ID number
Cell	Cell name
Shape_Area	Cell area
C1	No change
C2	Newly built (on a previously unbuilt area)
C3	Improvements (roof, structure) of an existing building or rebuilt WITHOUT a change of the building class
C4	Building demolished and newly built or building upgraded WITH a change of the building class
C5	Building demolished
F2009_1	Number of “Rudimentary” in 2009
F2009_2	Number of “Localbuilding” in 2009
F2009_3	Number of “Bungalow” in 2009
F2009_4	Number of “Villa” in 2009
F2009_5	Number of “Localtype” in 2009
F2009_6	Number of “Modernapartment” in 2009
F2009_7	Number of “Hall” in 2009
F2009_8	Number of “Outbuilding” in 2009
F2009_9	Number of “Special” in 2009
F2015_1	Number of “Rudimentary” in 2015
F2015_2	Number of “Localbuilding” in 2015
F2015_3	Number of “Bungalow” in 2015
F2015_4	Number of “Villa” in 2015
F2015_5	Number of “Localtype” in 2015
F2015_6	Number of “Modernapartment” in 2015
F2015_7	Number of “Hall” in 2015
F2015_8	Number of “Outbuilding” in 2015
F2015_9	Number of “Special” in 2015
Sum_2009	Total number of buildings 2009
Sum_2015	Total number of buildings 2015

The International Growth Centre (IGC) aims to promote sustainable growth in developing countries by providing demand-led policy advice based on frontier research.

Find out more about our work on our website www.theigc.org

For media or communications enquiries, please contact mail@theigc.org

Subscribe to our newsletter and topic updates www.theigc.org/newsletter

Follow us on Twitter @the_igc

Contact us
International Growth Centre,
London School of Economic and Political Science,
Houghton Street,
London WC2A 2AE

International Growth Centre

DIRECTED BY

LSE

UNIVERSITY OF OXFORD

FUNDED BY

UKaid from the British people

Designed by soapbox.co.uk