Assessing OpenStreetMap roads fitness-for-use for disaster risk assessment applications in developing countries: the case of Burundi

(preprint)

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Abstract

Evidence is showing how disasters caused by extreme weather events are surely becoming more frequent at all latitudes, and are definitely representing an ever growing risk in the floods- and landslides-prone territory of Burundi. The still present inequalities of its society and the vulnerable economy make this African country a very relevant and particularly complex case for hazards risk management. A fundamental step in this task is so correctly map the so-called exposure elements to risk, which most notably comprise the population and households, the critical infrastructure, and the transportation network. In relation to this latter exposure element, this article explains in details the analysis that was undertaken in order to estimate the fitness-for-use of the publicly available OpenStreetMap (OSM) roads network database in the context of a recent multi-hazards risk assessment and mapping exercise on behalf of the International Organization for Migration (IOM).

1. Introduction

As the major, most complete and up-to-date publicly available source of cartographic maps worldwide, OpenStreetMap (OSM) was selected for evaluation of its fitness for use in spatially-explicit risk assessment models in Burundi. Being a crowdsourced Volunteered Geographic Information (VGI) — and despite the guidance and automatic validation triggers that are in place[1] — OSM data accuracy requires to be assessed, especially over a country like Burundi which lacks authoritative reference datasets and where contributions often come as a result of the Humanitarian OSM Team (HOT)[2] intervention from new inexperienced mappers.

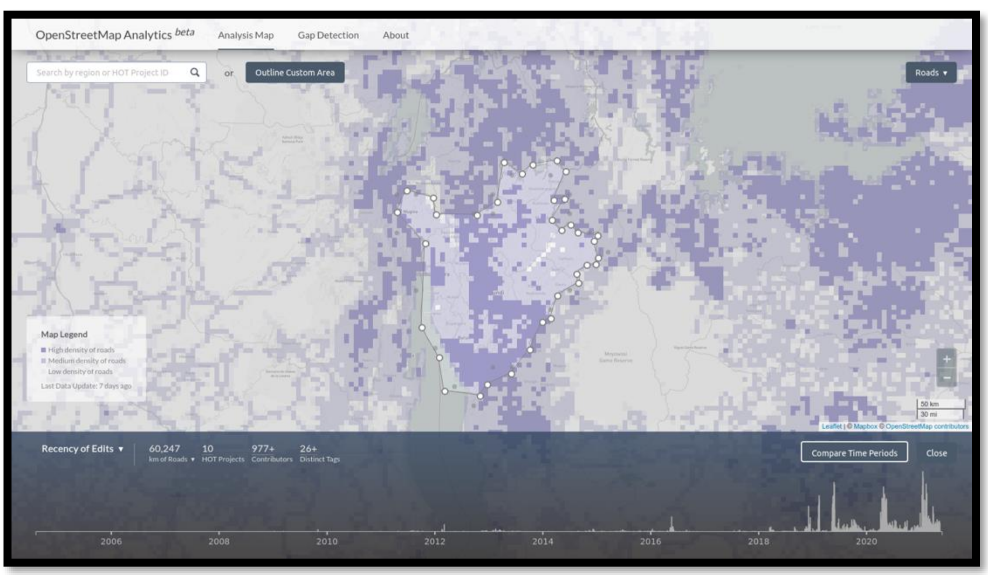
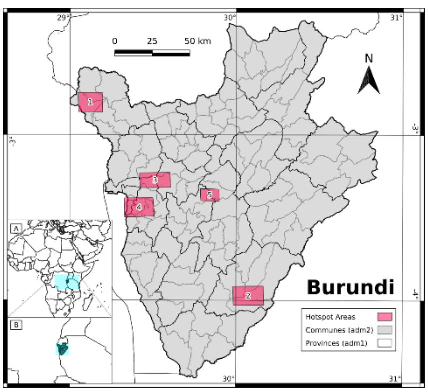


Figure 1 – Density map and timeline of OSM contributions for roads in Burundi. Credits: OSM Analytics.

[1] See *https://wiki.openstreetmap.org/wiki/Tasking_Manager/Validating_data*.
[2] See *https://wiki.openstreetmap.org/wiki/Humanitarian_OSM_Team*.

Data from OSM is not only generally sufficiently accurate (for the scale of our analysis) and publicly available without restrictions, it is also the source of maps which most rapidly reacts to changes, as the case of extreme natural events. As shown in Figure 1, the contributors information from OSM Analytics[3] presents a growing intensity in volunteered participation in the last 2 to 3 years, with an overall high density of roads registered, especially in the area of Bujumbura, the southern provinces of Makamba and Rutana, and the central areas of Mwaro, Muramvya and Kayaza. Most interestingly, the timeline of contributions on the lower part of the image shows us a growing volunteered participation in the last 2-3 years.

Intrinsic quality and completeness indicators are hereby calculated both at both a national level, and at a smaller scale over five selected “hotspot” regions considered of particular importance for their high expected exposure to landslides (see Figure 2).



#	WGS84 BBOX	km²	Description
1	(2°51'40.9"S, 29°03'09.3"E)–(2°44'44.2"S, 29°11'48.8"E)	206	*Rugombo and Mparambo Cities - Cibitoke Province - Nyakagunda River.*
2	(4°01'52.9"S, 29°58'47.2"E)–(3°54'50.8"S, 30°10'03.8"E)	257	*Bukemba City - Rutana Province - Musasa River.*
3	(3°19'04.4"S, 29°25'08.0"E)–(3°13'41.0"S, 29°36'21.6"E)	203	*Kirama Commune, Bujumbura City - Gasenyi River.*
4	(3°29'52.5"S, 29°19'35.7"E)–(3°22'54.9"S, 29°30'32.8"E)	245	*Muha and Kanyosha Communes - Bujumbura Mairie and Bujumbura Rural - Kanyosha River.*
5	(3°23'59.2"S, 29°47'05.2"E)–(3°19'35.8"S, 29°53'55.3"E)	98	*Giheta City - Gitega Province - Ruvyronza River.*

Figure 2 – On the left: the area of study (Burundi), and the five hotspot areas (in red). On the right: description of the selected hotspot areas for landslide analysis in Burundi.

In the next sections we will describe in detail: the underlying technology (Section 2), the data sources used (Section 3), the methodology (Section 4), the results (Section 5), and finally an overall assessment of the results and future work in Section 6; conclusions are drawn in Section 6.

2. Technology

Numerous tools are available online to download, filter and process OSM objects, allowing us to setup cyclic processes of data synchronization and update, so that all OSM datasets can be kept up-to-date in our databases. We chose the *OSMnx* Python package [1] for the purpose of our study: in addition to fine-grained OSM objects filtering capabilities (via Overpass API), the library also enables quantitative analysis of the roads network from a graph theoretic perspective.

[3] *https://osm-analytics.org/*

3. Data

In this section we describe the sources of data that we used in our analysis.

In addition to the “independent” roads data from OSM, we downloaded potential drivers that could help us flag areas with missing roads in Burundi. Such drivers would generally help us also have an idea of the quality of the contributions: there are already several studies [2] indeed that support the correlation of demographic and socio-economic factors with the completeness and accuracy of VGI contributions. Such studies (not surprisingly) suggest that i.e. high population densities and general wealth status positively affect the accuracy of the data.

For this study, we selected the population and settlements densities as demographic indicators, leaving out other drivers like wealth population index as considered not relevant a-priori in a country like Burundi where the deviations in wealth indexes should not vary considerably.

The topographic profile of Burundi is instead considered relevant, as we intuitively assume a minor human presence (hence roads) over areas with high terrain ruggedness.

Finally, metadata about the OSM contributors and contributions (cardinality, user experience, etc.) have already been verified as a covariate of OSM accuracy [3]: for this study we will use them for qualitative analysis over the hotspot areas by means of existing tools, so we did not download any additional data from OSM.

OSM Roads Network

As stated already in Section 2, the OSM streets over Burundi were downloaded by means of the *OSMnx* python library. This tool is particularly useful as it automatically corrects and simplifies the network under the hood: in fact, raw OSM nodes are not only roads intersections and dead-ends, but also include all those nodes which draw the curve of a street. The latter are not *true* nodes in the strict graph-theoretic sense, hence are discarded so to collect meaningful and correct statistics over the network.

For this study we are interested in two different datasets: all available roads data over the country on one side, and all roads that can reasonably be passed by a normal car on the other side. This distinction is thought to be helpful in the development of risk exposure models, as some situations might constraint the interest only on such roads that allow the passage of vehicles like ambulances or other forms of help.

Regarding the filtered “drivable” roads dataset, *OSMnx* offers a set of predefined OSM `[highway]` tag filters for the download, like *drive*, *walk*, *bike*, etc. We extended upon them by adding extra filters that could keep into account the specific state of roads in Africa, as explained by volunteers of the HOT list[4].

For instance, on one side OSM streets are usually classified based on road conditions (eg. paved/unpaved), however this does not hold in Africa, as many *major* roads are unpaved and — during the rainy season — in very poor conditions.

[4] See *https://wiki.openstreetmap.org/wiki/Highway_Tag_Africa*.

In order to keep only viable roads in our area of interest, we added extra constraints based on the [smoothness] tag, which has the following values:

Value	Description
excellent	*Billiards*
good	*Usable with racing bike*
intermediate	*Usable with city bike, sports cars, scooter...*
bad	*Usable with trekking bike, "normal" cars. One can not exclude potholes.*
very_bad	*Usable with car with high clearance. Typically with 404 bachée. "Normal" cars can't go through.*
horrible	*4Wheel drive only.*
very_horrible	*4Wheel drive cars can't go through or it is very difficult, with help of winch. Usable with tractor, ATV, motorcycle, zebu carts.*
impassable	*No wheeled vehicle. Road damaged for instance.*

Table 1 – Values and meanings of the [smoothness] tag of OSM roads.

In addition to viable roads, we are also interested in roads whose availability is not time-constrained over the year: for this case the [seasonal] boolean tag can be exploited to keep only roads that are usable year-round.

The mentioned conditions can be passed on to *OSMnx* by means of custom filters, which are based on the Overpass read-only API provided by OSM[5]. Extending the *OSMnx “drive”* preset filter, we set the following filter:

```
["highway"]["area"!~"yes"]["access"!~"private"]
["highway"!~"abandoned|bridleway|bus_guideway|construction|corridor|cycleway|elevator
|escalator|footway|path|pedestrian|planned|platform|proposed|raceway|steps|track"]
["motor_vehicle"!~"no"]["motorcar"!~"no"]
["service"!~"emergency_access|parking|parking_aisle|private"]
["smoothness"!~"very_bad|horrible|very_horrible|impassable"]
["seasonal"!~"yes"]
```

Listing 1 – The Overpass QL filter used to select the year-round drivable roads of Burundi from the OSM database.

[5] See *https://wiki.openstreetmap.org/wiki/Overpass_API*.

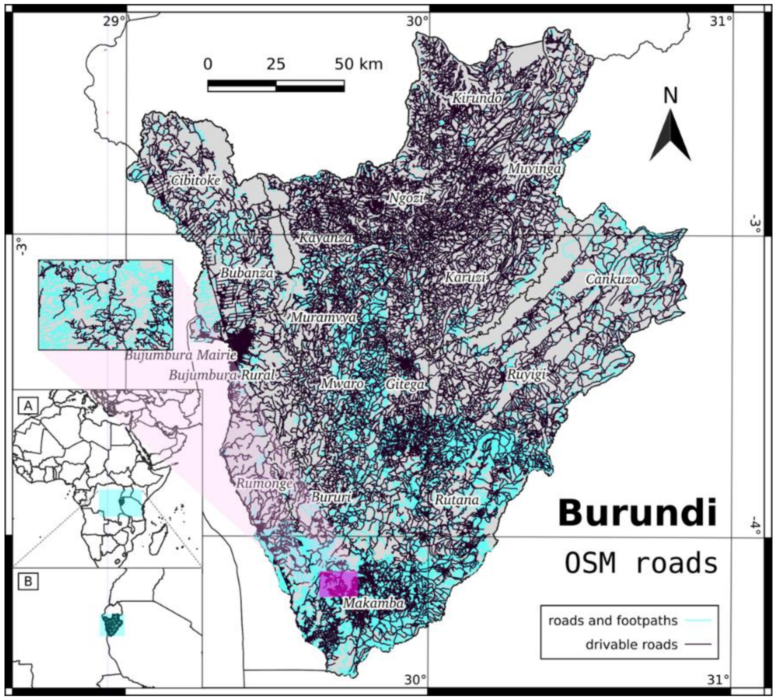


Figure 3 – Complete (light blue) and year-round drivable filtered (purple) OSM roads overlay over Burundi (last update: 03 Jun 2021).

Figure 3 shows the two roads networks that we selected for our purposes: a first complete dataset with all available roads and pathways, and a second one where only the year-round drivable roads were retained. Due to strong hazard-related impacts on roads during the rainy season, both the *seasonal* and the *smoothness* OSM tags where properly tuned in order to get the data, as per OSM recommendations[6]. Looking at the figure, we can see a huge amount of roads marked as seasonal or not passable on a normal car, especially in southern Burundi. Indeed we proceeded to quantify this difference and to derive some basic statistics on the roads networks by defining the following roads categories:

- **PRIMARY**
  OSM *highway* tag ~ motorway|trunk|primary|primary_link
  Main roads and transportation routes among major cities; often paved.

- **SECONDARY**
  OSM *highway* tag ~ secondary|secondary_link
  Transportation routes between cities and large towns; often paved.

[6] *https://wiki.openstreetmap.org/wiki/Highway_Tag_Africa*

- **TERTIARY**
  OSM *highway* tag ~ tertiary|tertiary_link|unclassified
  Transportation routes between towns and villages, minor collector roads; may be paved.

- **OTHER**
  All other (minor) roads not included in the above.
  Access routes to dwellings or agricultural and forestry areas, paths for livestock movements.

The results are shown in Table 1 and show a strong presence of minor roads – mostly those tagged as *path*, *residential*, *track* or *footway* in the OSM database – and tertiary roads. The detailed profile of the tertiary roads classification (not shown here) reveals a major weight of roads classified as *unclassified*, which are minor roads but still passable by 4-wheels vehicles, paved or not.

The number of bridges were also counted, by counting those roads with a *bridge* tag set. A very few non-statistically significant bridges were tagged as *low_water_crossing* – mainly on path roads – meaning that the bridge has a highly seasonal behaviour and is usually submerged during floods or rains.

	GRAND TOTAL	*Primary roads*	*Secondary roads*	*Tertiary roads*	*Other*
Number of roads	***295'896***	*6'191 (~2%)*	*9'952 (~3%)*	*82'398 (~27%)*	*199'251 (~67%)*
Total length [km]	***64'272.5***	*1'871.8 (~3%)*	*3'522.8 (~5.5%)*	*28'765.1 (~45%)*	*30'771.4 (~48%)*
Number of bridges	***1'875***	*220 (~12%)*	*273 (~14.5%)*	*911 (~48.5%)*	*471 (~25%)*

*Table 2. Number of roads, total length [km] and number of bridges found in the OSM roads of Burundi, both at national level and grouped by road type (*highway *tag).*

Comparison with MINESANTE roads dataset

In this section we present a comparison of our filtered OSM roads and an official road dataset from the Ministry of Health of Burundi.

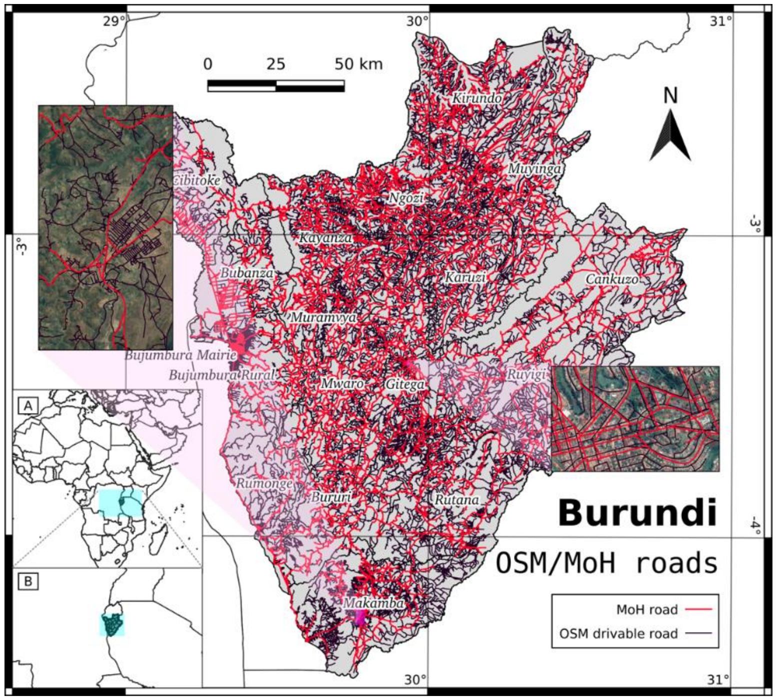


Figure 4 – Visual comparison between our OSM roads dataset and the official roads data from the Ministry of Health of Burundi.

Looking at Figure 4 it is clear how the reference dataset is much less complete than the OSM network: the almost totality of roads in the reference dataset are also tracked in OSM, while there are many more roads available in OSM. With less than 3,000 roads and about 120 km of total length, the reference dataset provides approx. 30 times less data that OSM.

Regarding the accuracy of the data, the small-scale overviews in the figure also show how the accuracy of the authoritative data seems to be generally lower, even though we have to keep in mind that Google Maps satellite images are our truth (field campaigns might help us make a more objective evaluation).

Administrative Boundaries

All quality indicators carried out in this study are based on the same areal unit: the collines (level 3 administrative division). Official collines division of Burundi are taken from the Institute of Statistics and Economic Studies of Burundi (ISTEEBU — *https://www.isteebu.bi/*), and are depicted in Figure 5.

Looking at the figure, the extensions of collines look generally homogeneous throughout the country, so we expect that the MAUP (Modifiable Area Unit Problem) will overall not affect the validity of the statistical analysis of our results.

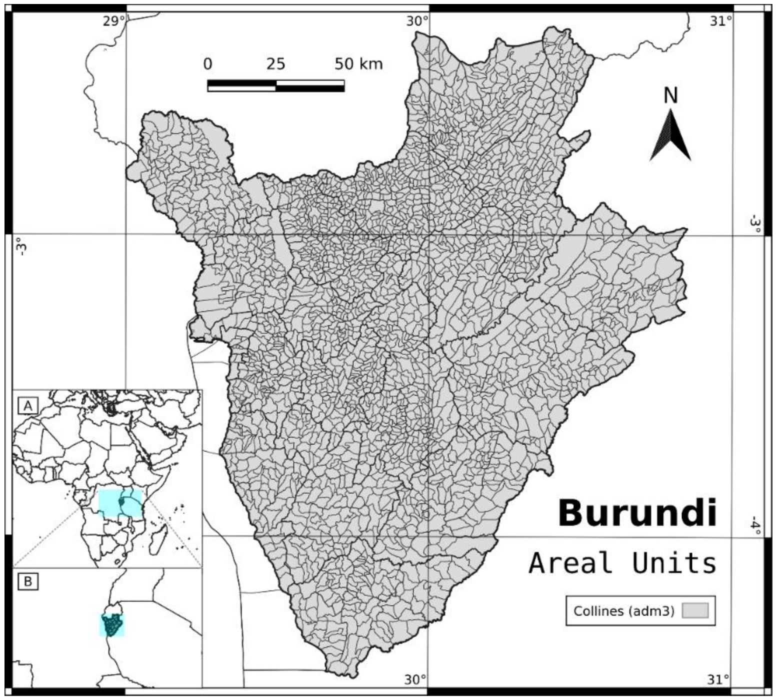


Figure 5 – The areal units of the study: Level-3 administrative boundaries (collines) of Burundi.

Population

Being the population density a potential driver of roads density, in order to support the assessment of the OSM roads network we used a 2021 projection of the population over Burundi downscaled at $100m$ of spatial resolution.

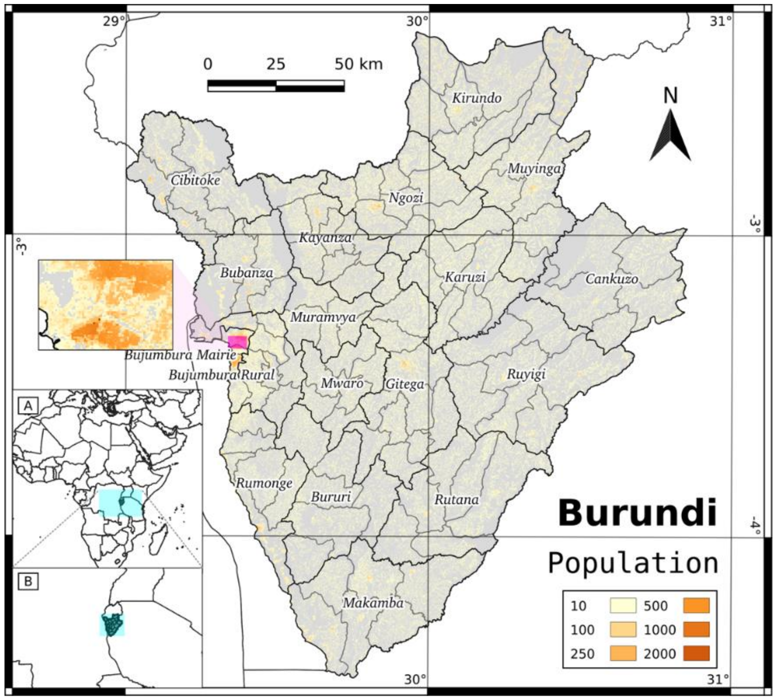


Figure 6 – The population of Burundi at 100 m of spatial resolution downscaled from the ISTEEBU census in 2021.

Human Settlements

Maps of human settlements over Burundi have also been considered of potential value when predicting the presence of roads. Indeed, higher density of roads are usually expected around human settlements. They can also be used for the classification of urban and rural areas.

The datasets that we selected are the taken from the Geo-referenced Infrastructure and Demographic Data for Development (GRID3, *https://grid3.org*) initiative in Burundi.

The data characterizes building density into three classes:

- **Built-up areas** (BUA)
  Generally areas of urbanization with moderately-to-densely-spaced buildings and a visible grid of streets and blocks; built up areas are characterized by contours with an area greater than or equal to 400,000 meters square that maintains a building density of thirteen or more across the entire area.

- **Small settlements** (SSA)
  Settled areas of permanently inhabited structures and compounds of roughly a few hundred to a few thousand inhabitants; the housing pattern in SSAs is an assemblage of family compounds

adjoining other similar habitations; small settlement areas are characterized by having 50 or more buildings and are not a BUA.

- **Hamlets**
  A collection of several compounds or sleeping houses in isolation from small settlements or urban areas; hamlets are characterized as a collection of low-density settlements between one and 50 buildings and falls within 65 meters of one another.

The datasets are shown in Figure 7, Figure 8, and Figure 9.

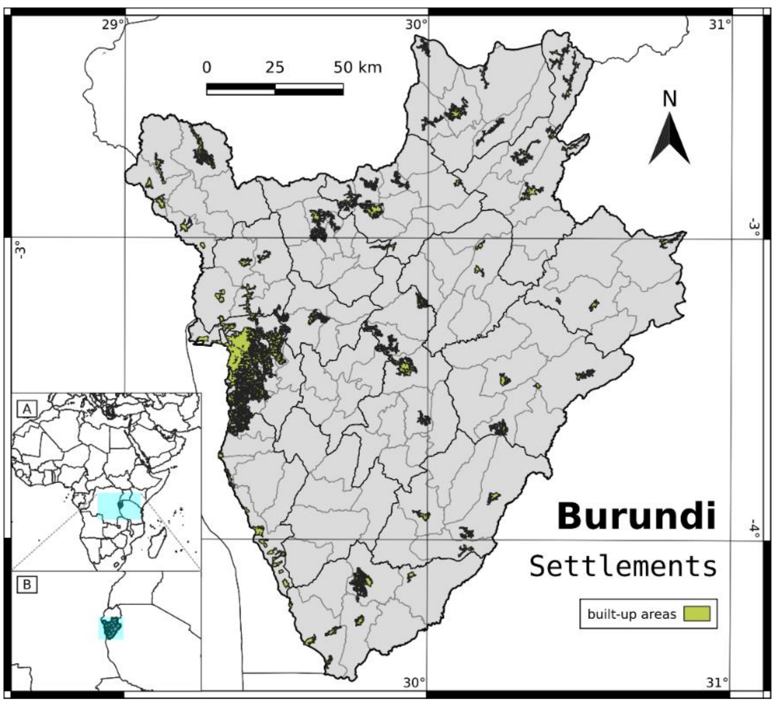


Figure 7 – Human settlements of type "built-up" in Burundi.

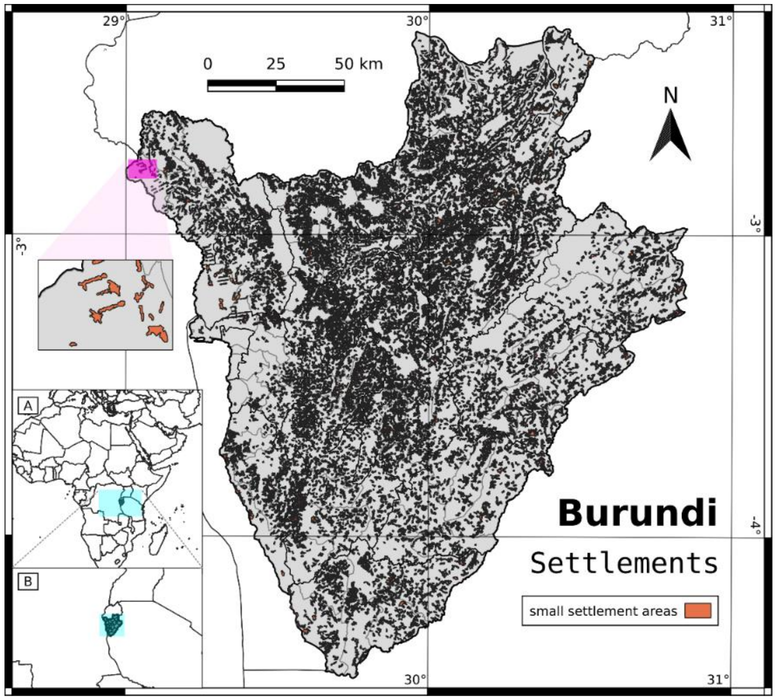


Figure 8 – Human settlements of type "small settlement" in Burundi.

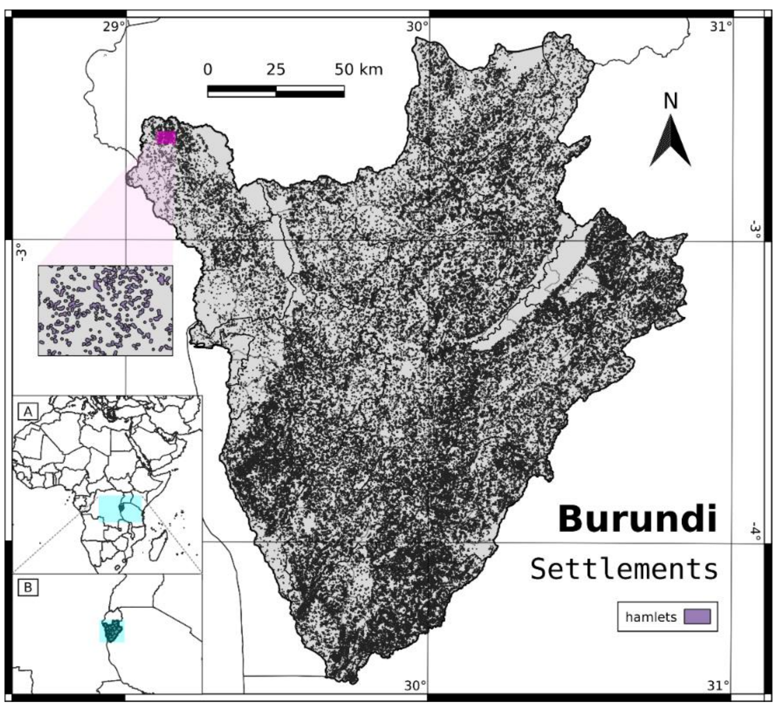


Figure 9 – Human settlements of type "hamlet" in Burundi.

Topography

Elevation standard deviation at 7.5 arc-sec (225 m) of resolution has been extracted from the GMTED2010 (Global Multi-resolution Terrain Elevation Data) global elevation model jointly produced by the United States Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA) [4].

The dataset is openly available online for tile-based download from the GMTED2010 viewer[7]. The data is provided as a GeoTIFF file (one for each tile/feature selection) with WGS84 latitude-longitude coordinates. We downloaded the “Standard Deviation 7.5 arc-sec” feature, and then clipped it to our area of interest, as shown in Figure 10.

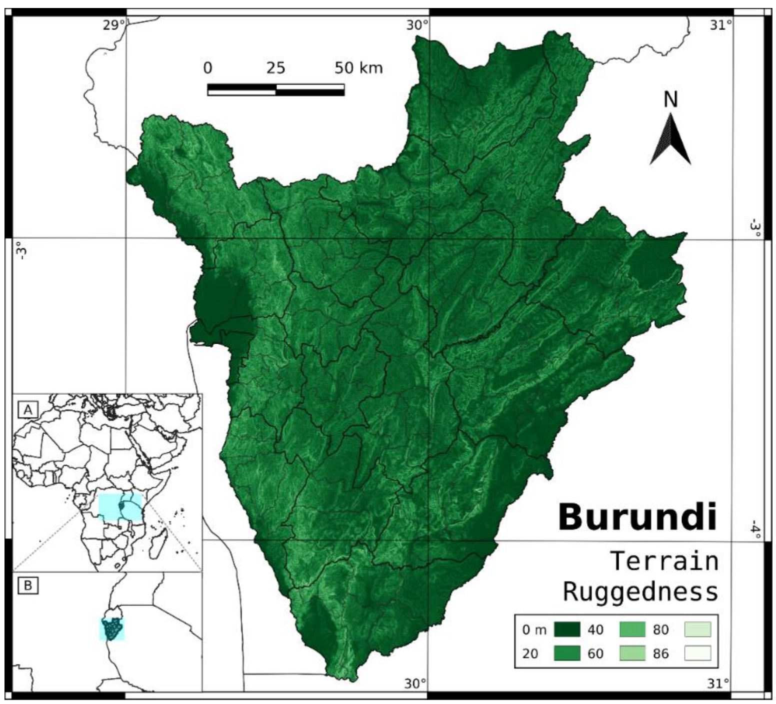


Figure 10 – Elevation standard deviation (terrain ruggedness) over Burundi (source: GMTED2010 dataset).

4. Methodology

In this section we describe the different types of both qualitative and quantitative analysis that we carried out over the OSM roads network and the collected auxiliary variables.

Positional Accuracy

In order to estimate the precision of the OSM dataset over Burundi, we decided to follow the National Standard for Spatial Data Accuracy directives [5] by calculating the Root Mean Square Error (RMSE)

[7] https://topotools.cr.usgs.gov/gmted_viewer/viewer.htm

between a random sample of the topology nodes (road intersections and dead-ends) and correspondent nodes in a reference higher-precision dataset.

To select such reference, we qualitatively compared the tiles from Google Maps and Bing satellite imagery over the 5 hotspots areas, and opted for the former maps provider: Bing maps looked visibly less up-to-date with respect to Google Maps images, where advancements in human built-ups can be appreciated in almost all of the selected areas (full details of the analysis can be found in Annex B – Qualitative correspondence comparison of Bing Vs Google Maps satellite imagery against OSM roads).

In an attempt to identify possible accuracy biases between urban and rural areas [6], [7], the random sampling was implemented as a stratified 20+20 urban/rural selection: we classified a node as urban or rural based on its spatial intersection with major built-up areas (see Figure 7), where we assume most of the population is found.

As a qualitative validation of this approach, we can see from Figure 11 (left side) how all the 10 largest cities/towns of Burundi (listed in Table 3) overlap with our built-up settlements areas dataset.

Largest Cities or Towns in Burundi *(2008 Census)*			
Rank	**Name**	**Province**	**Pop.**
1	Bujumbura	*Bujumbura Mairie*	497,166
2	Gitega	*Gitega*	41,944
3	Ngozi	*Ngozi*	39,884
4	Rumonge	*Bururi*	35,931
5	Cibitoke	*Cibitoke*	23,885
6	Kayanza	*Kayanza*	21,767
7	Bubanza	*Bubanza*	20,031
8	Gatumba	*Bujumbura Rural*	11,700
9	Karuzi	*Karuzi*	10,317
10	Kirundo	*Kirundo*	10,024

Table 3 – The 10 largest cities and villages of Burundi (source: Wikipedia).

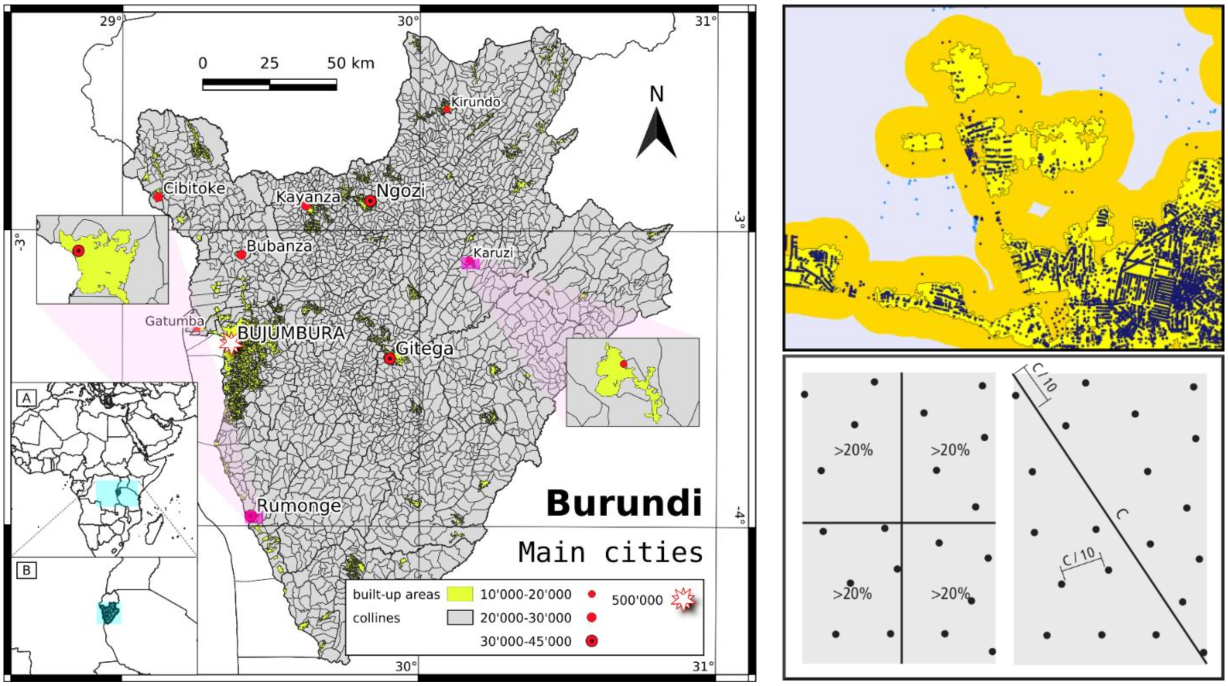


Figure 11 – On sampling the roads intersection for accuracy assessment. Left side) The cities listed in Table 3, overlapped with our available built-up settlements dataset over Burundi (shown in Figure 7). Upper-right corner) Road nodes classification based on overlap on 1-km buffered built-up settlement areas: dark blue nodes are classified as 'urban', light blue ones as 'rural'. Lower-right corner) Ideal spatial distribution of points over an area to be tested for planimetric accuracy: at least 20% of the random samples per quadrant (left side) and minimum distance of a tenth of the ROI's diagonal distance C between each sample (right side) — Credits: Minnesota Governor's Council on Geographic Information and Minnesota Land Management Information Center (LMIC).

As per the number of the random samples, 20 or more test points are enough to conduct a statistically significant accuracy evaluation regardless of the size of the data set or area of coverage [8]. The random selection is constrained in order to adhere to the ideal spatial distribution and spacing of random points over an area, as depicted in Figure 11 (right-hand side).

Finally, since we selected only a subset of the whole population of street nodes in Burundi, we accounted for the error in the RMSE mean statistics by a multiplying it for 1.7308 to achieve a 95% confidence interval statistic, as suggested in [5].

Completeness

Regarding the evaluation of the completeness of the OSM dataset, we attempted to detect gaps in the coverage of the roads network at national level by relying on 2 auxiliary datasets:

I. a 2021 projection of the population in Burundi, starting from the census in 2008, and downscaled to a regular grid of 100m of spatial resolution – the data is updated every year by the *Institut de Statistiques et d'Etudes Economiques du Burundi* (ISTTEBU) [9];

II. elevation standard deviation (also called "terrain ruggedness") at 7.5 arc-sec (225 m) of resolution extracted from the GMTED2010 (Global Multi-resolution Terrain Elevation Data) global elevation model jointly produced by the United States Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA) [4].

Both datasets were used as proxies of supposedly more dense roads networks, as are expected in highly populated and plain areas. We proceeded with a "completeness by discrete classification" algorithm at the *colline*-level and with two gap classification rules based on quartiles:

a. *collines* with road densities below the 1st quartile and population densities over the 3rd quartile, and
b. *collines* with road densities below the 1st quartile and terrain ruggedness below the 1st quartile.

In either case, a *colline* was marked as potentially incomplete.

5. Results

In this section we present all the results of the analysis that were carried out for this study.

Positional Accuracy

We compiled a RMSE table over the 20+20 urban/rural stratified random nodes of our OSM datasets against the equivalent points on the reference Google satellite imagery. The classification yielded 26'131 topology nodes marked as *rural*, and 38'086 as *urban*, with a 40/60 approximate percentage ratio with respect to the overall network.

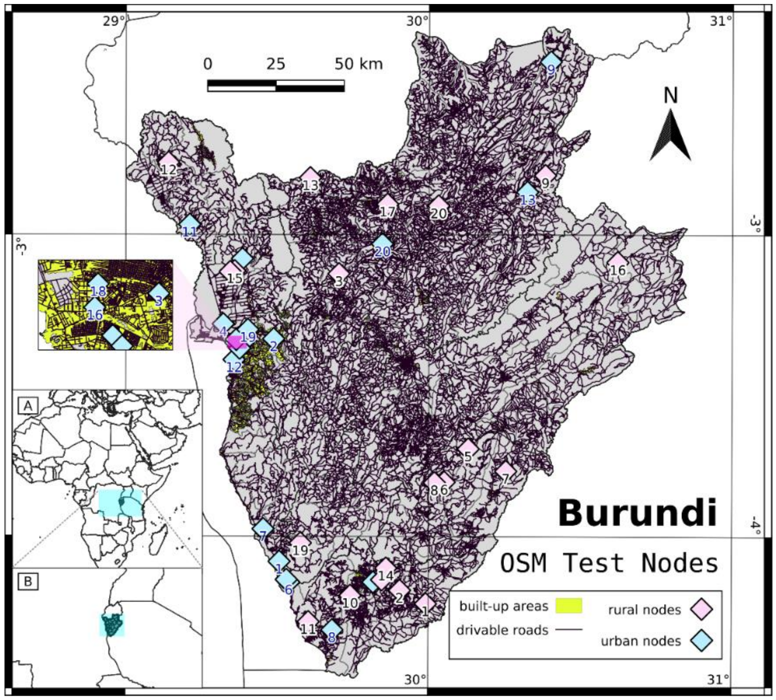


Figure 12 – Selected stratified samples of Burundi nodes (OSM roads intersections and dead-ends) that were used for positional accuracy evaluation.

	Urban	Rural
SUM error [m^2]	691.4	689.3
AVG error [m^2]	34.6	34.5
RMSE [m]	5.9	5.9
NSSDA [m]	10.2	10.2

*Table 4 – Results of the planimetric positional accuracy evaluation of OSM roads in Burundi: i) sum of the squared error (euclidean distances between sample/oracle points), ii) average square error, iii) Root Mean Square Error, and iv) National Standard for Spatial Data Accuracy statistic = 1.7308 * RMSE.*

Table 4 show the complete statistic worksheet that we compiled to calculate the overall planimetric accuracy of the samples (complete statistics detail can be found in "Annex A — Horizontal Positional Accuracy Worksheets". We can see that overall the results look promising, and in line with other studies over other regions of central Africa [10]. Again, following the NSSDA directives [5], we can declare the following statement over the OSM roads in Burundi (averaging urban and rural results):

*Positional Accuracy: Tested **10.2** meters horizontal accuracy at 95% confidence level.*

Such statement should be considered almost as a semi-quantitative result, keeping into account the multiple layers of uncertainties involved in such calculations – including the imprecise truth reference of the Google Maps satellite images, the human error in locating a sample in the ubiquitous unpaved roads of Burundi, on top of the errors of volunteer contributors or OSM automatic algorithms.

The absence of an accuracy bias between urban and rural contexts might be due to the blurred difference between urban and rural areas in a country like Burundi, both from a socio-economic point of view — social welfare differences (an indicator of contribution quality in other areas of the world [11]) are less pronounced than in more developed countries — and also from a technical point of view, since large portions of OSM data are automatically extracted from satellite/aerial imagery digitization anyway.

As a conclusion to this analysis, we believe such results should be taken as a qualitative and general overview of the horizontal accuracy of OSM roads over Burundi. In the first place, the reference data we chose — Google Maps images — are also not exempt of inherent errors (in the range of 10-40 meters of RMSE, depending on location [12]). Secondly, it was not always clear which street crossing (or dead-end) was a random sample pointing to, as most of the roads in Burundi are not paved and their path/borders are not sharp and clear.

Completeness

Regarding the results of the roads completeness analysis, we ran the previously described discrete classification algorithm at the *collines* level, marking each one with a degree of confidence of whether the OSM roads network within the area is potentially incomplete: low/none in case of unexpected gaps; moderate confidence if one – and only one – of the two incompleteness proxy rules were satisfied (blue and yellow *collines* in the map of Figure 13); and high confidence when both rules applied (red *collines* in the map).

On the left side of , the correlation matrix of the three datasets involved in the analysis: the number of OSM roads intersections, the gridded population, and the terrain ruggedness. The data clearly show a very weak covariance/correlation among the variables, which calls for a more detailed and small scale analysis of the reasons behind such unexpected, whether they lie in our hypothesis or in the algorithm data collection. The lack of statistical evidence supporting our hypothesis also removes ground to any conclusion that could be drawn by the discrete classification.

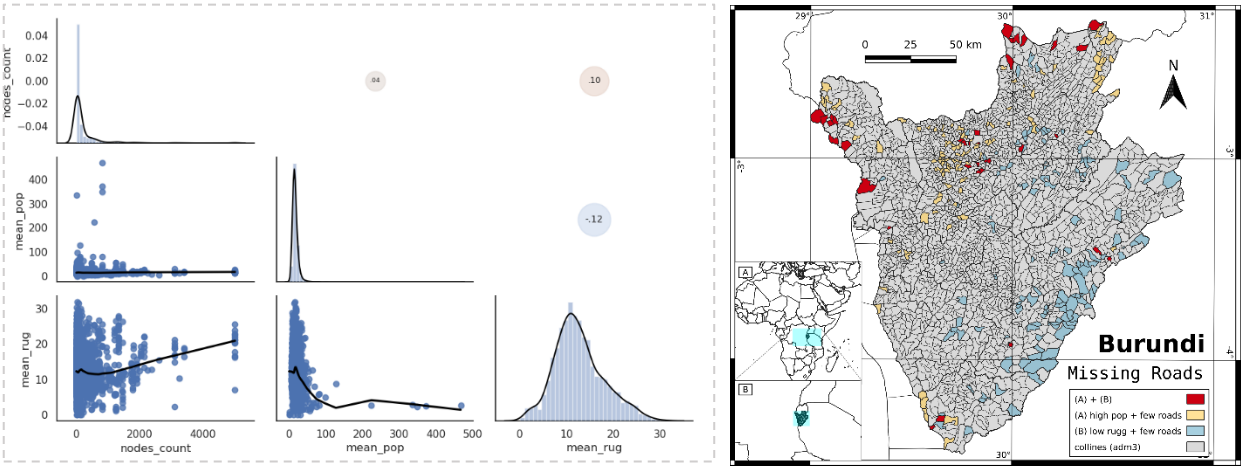


*Figure 13 – On the left: scatterplots, probability density functions and Pearson's r correlation between the variables involved in the Completeness by Discrete Classification analysis of OSM roads, i.e. OSM roads intersections (*nodes_count*), the 2021 gridded population projection (*mean_pop*), and the GMTED2010 terrain ruggedness (*mean_rug*). All variables have been aggregated over collines (L3 administrative boundaries) before computing the statistics. On the right: colline-level roads gap-detection map of Burundi; the classification is based on quartiles rules on the three selected variables: road density, population and terrain ruggedness.*

6. Conclusions

The analysis of roads and their fitness for use in landslide risk management and reduction strategies is surely a key aspect to be considered: roads link disaster areas to hospital facilities, provide access for rescue operations, and a poor topologic structure can imply isolation of sectors of population after a disaster and thus cost lives. The analysis hereby carried out shows an overall good state of the digitization of the roads in Burundi, at all levels: from primary roads, up to footways. Volunteered activity for tracking of roads (and buildings) in the OSM database has been raising substantially in the last few years, bringing the mapping to a satisfactory level of completion in all regions of the country.

A general evaluation of the positional accuracy of the roads has also been carried out, by comparison of random selection of cross-roads in the roads graph and in Google Maps imagery. The result show again a satisfactory level of error (about 10 meters, 95% confidence), even though this might be due to OSM roads being often automatically digitized from Google Maps images themselves. More than high positional precision, it is anyway considered of more importance an analysis on the topology of the roads network, especially in relation to landslide risk. By means of existing Python libraries we also hereby demonstrated the potential for quantitative risk index association to roads – like the betweenness centrality indicator – and accessibility to points of interest like a hospital or a medical aid resource. Such analysis can be extremely useful to visually highlight critical roads or entire network sections, this way identifying vulnerable human settlements to landslides or other hazards. These results can be valuable to decision-makers to possibly trigger actions for an enhanced management of the roads network.

We conclude with an outlook on potential further analysis that are made available by the underlying Python environment, specifically the already mentioned *OSMnx* package, and *pandana* [13]. While the former – built on top of the *NetworkX* graph library [14] – can compute several topology indicators on either the edges (roads) or nodes (roads intersections) of the network, the latter can execute arbitrary optimized spatial queries on such graphs. The maps shown in Figure 14 are an example of possible practical applications of such concepts: i) the *betweenness centrality* indicator analyzes how critical a road is in a network, how likely it is going to carry a higher traffic load due to the topology of the network, and thus can provide decision makers and urban planners a tool to identify sections of higher vulnerability and exposure to risk; ii) on-road accessibility maps with arbitrary edge impedance (from simply the walking distance, to more complex formulas that account for additional factors) to important assets like hospitals can also be produced, as another proxy for population vulnerability studies.

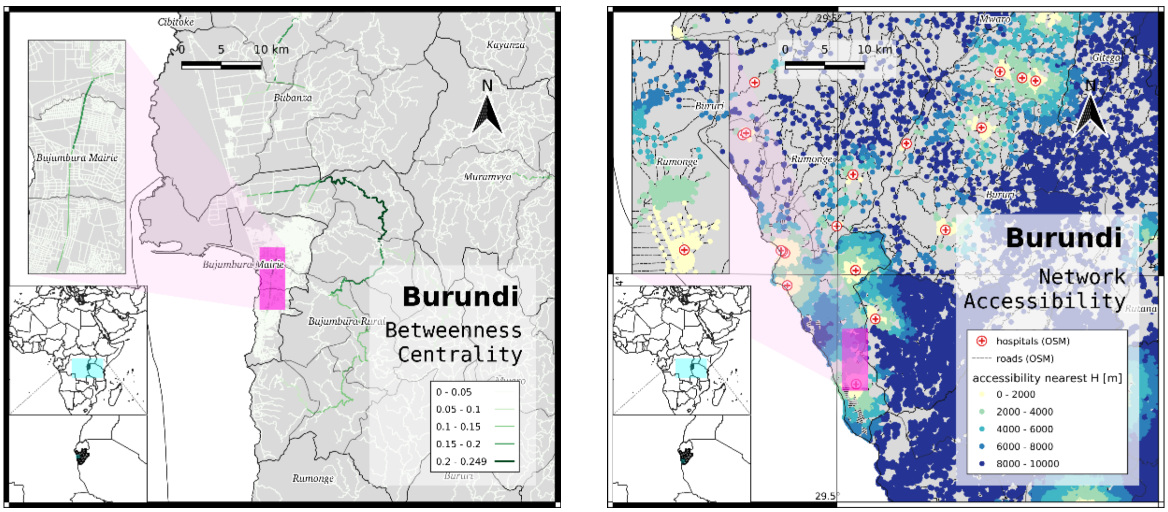


Figure 14 – On the left: a medium-scale view of the "betweenness centrality" topologic indicator computed on Burundi's drivable roads. On the right: hospital accessibility map (distance on roads [m] to nearest hospital).

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CONFLICTS OF INTEREST: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY: All maps shown in this article, along with further exposure, vulnerability and risk related data of Burundi are available at the institution's Web GIS at: *https://maps.eurac.edu/layers/?limit=20&offset=0&group__group_profile__slug__in=burundi*

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Annex A — Horizontal Positional Accuracy Worksheets

This annex shows the detailed results of the positional accuracy analysis of OSM roads carried out over Burundi, as described in Section 4.

The tables show the full list of test (OSM street nodes) and independent (manually extracted "truth" points from Google Maps satellite imagery), stratified over the 2 selected exclusive context: urban and rural areas.

#	Point Description	x (independent)	x (test)	diff in x	(diff in x)^2	y (independent)	y (test)	diff in y	(diff in y)^2	(diff in x)^2+(diff in y)^2
1	URBAN (29.50790840906924 -4.083866372741701)	778452.17	778457.32	-5.14	26.42	-451831.82	-451829.17	-2.65	7.01	33.43
2	URBAN (29.48830519830281 -3.345933322665927)	776504.15	776500.71	3.44	11.82	-370180.98	-370182.15	1.17	1.38	13.2
3	URBAN (29.39287965801869 -3.35268823181139)	765892.21	765892.87	-0.66	0.44	-370901.88	-370901.23	-0.65	0.43	0.87
4	URBAN (29.32178118500192 -3.296849171411414)	758002.01	757995	7.01	49.13	-364705.68	-364708.29	2.61	6.8	55.93
5	URBAN (29.37157018122616 -3.37236639070673)	763517.69	763518.62	-0.93	0.86	-373073.09	-373072.04	-1.05	1.1	1.96
6	URBAN (29.53978372490466 -4.152699734972714)	781969.32	781973.02	-3.7	13.72	-459458.94	-459456.59	-2.35	5.52	19.24
7	URBAN (29.45468576245233 -3.975799415709676)	772575.26	772577.1	-1.85	3.41	-439857.4	-439858.45	1.05	1.11	4.52
8	URBAN (29.68300316518879 -4.310468529930446)	797820.59	797820.19	0.4	0.16	-476969.69	-476969.95	0.26	0.07	0.23
9	URBAN (30.40082795320365 -2.426894455666309)	878312.75	878327.08	-14.33	205.41	-268722.22	-268707.26	-14.95	223.55	428.96
10	URBAN (29.53179299282991 -4.143859991236533)	781084.73	781085.78	-1.05	1.1	-458478.03	-458479.74	1.71	2.92	4.02
11	URBAN (29.21060213037757 -2.967171352787818)	745718.15	745717.35	0.79	0.63	-328209.99	-328210.51	0.52	0.27	0.9
12	URBAN (29.35766598565978 -3.415174291999318)	761960.3	761962.41	-2.11	4.45	-377805.06	-377806.91	1.84	3.39	7.84
13	URBAN (30.32423494811212 -2.858378375621746)	869654.78	869658.74	-3.95	15.62	-316474.53	-316480.33	5.79	33.57	49.19
14	URBAN (29.81805823481121 -4.151666526389003)	812887.65	812888.04	-0.4	0.16	-459449.35	-459448.7	-0.65	0.43	0.59
15	URBAN (29.38464744028414 -3.080460546343983)	765047.3	765043.2	4.1	16.85	-340783.27	-340786.67	3.4	11.59	28.44
16	URBAN (29.36325351707665 -3.359222068228309)	762596.58	762592.22	4.36	19.02	-371616.71	-371617.35	0.65	0.42	19.44
17	URBAN (29.37593880443364 -3.377201345329741)	764002.08	764003.27	-1.19	1.42	-373609.16	-373608.63	-0.52	0.27	1.69
18	URBAN (29.36471294641494 -3.348267831750451)	762761.77	762762.29	-0.52	0.27	-370405.26	-370407.49	2.23	4.98	5.26
19	URBAN (29.40305995801871 -3.315484122335683)	767034.13	767034.79	-0.66	0.43	-366788.72	-366789.91	1.18	1.4	1.83
20	URBAN (29.84631936792524 -3.030938365323274)	816414.3	816411.65	2.65	7.03	-335428.72	-335431.34	2.62	6.86	13.89
									sum	691.42
									average	34.57
									RMSE	5.88
									NSSDA	10.18

Table 5 – Random sample nodes of the Burundi OSM drivable roads network over urban areas selected for accuracy calculation against manual selection of correspondent nodes in Google Maps satellite imagery.

#	Point Description	x (independent)	x (test)	diff in x	(diff in x)^2	y (independent)	y (test)	diff in y	(diff in y)^2	(diff in x)^2+(diff in y)^2
1	RURAL (29.99154827679253 -4.223208655084156)	832136.89	832136.64	0.25	0.06	-467438.91	-467434.97	-3.94	15.5	15.56
2	RURAL (29.9058384501907 -4.17891092813493)	822630.93	822623.52	7.41	54.9	-462500.01	-462503.78	3.78	14.26	69.16
3	RURAL (29.7031551706617 -3.130002666234387)	800459.34	800454.45	4.89	23.89	-346350.01	-346348.68	-1.33	1.76	25.65
4	RURAL (29.84644599556636 -4.143901059002292)	816045.19	816043.98	1.21	1.46	-458601.23	-458606.21	4.98	24.81	26.26
5	RURAL (30.13100960377574 -3.709761844967288)	847850.69	847842.76	7.92	62.8	-410661.32	-410659.85	-1.47	2.17	64.97
6	RURAL (30.05198133754767 -3.819959501169401)	839019.65	839017.81	1.84	3.37	-422828.55	-422824.87	-3.68	13.55	16.93
7	RURAL (30.25510193311403 -3.783451372899952)	861621.39	861618.36	3.03	9.19	-418869.53	-418867.42	-2.11	4.46	13.65
8	RURAL (30.01967633141686 -3.821956872325559)	835427.04	835420.57	6.46	41.78	-423036.95	-423033.91	-3.04	9.25	51.03
9	RURAL (30.38319180886726 -2.803273452509299)	876236.17	876238.56	-2.39	5.71	-310392.16	-310389.67	-2.49	6.2	11.91
10	RURAL (29.74253016688597 -4.1963621858897)	804478.08	804481.13	-3.05	9.3	-464365.97	-464362.31	-3.66	13.41	22.71
11	RURAL (29.604624407828 -4.283571001532104)	789124.42	789132.48	-8.06	64.99	-473963.26	-473960.67	-2.6	6.74	71.72
12	RURAL (29.1402702276411 -2.761368283147229)	737939.26	737940.71	-1.46	2.12	-305430.71	-305429.53	-1.18	1.39	3.51
13	RURAL (29.60820115188787 -2.81195816517332)	789980.72	789976.75	3.97	15.75	-311132.33	-311132.98	0.65	0.42	16.16
14	RURAL (29.86039731773456 -4.105514324160714)	817610.77	817615.53	-4.76	22.66	-454358.44	-454356.88	-1.56	2.42	25.08
15	RURAL (29.35906798292335 -3.120756816321854)	762192.66	762196.99	-4.33	18.79	-345234.8	-345246.75	11.96	142.94	161.73
16	RURAL (30.62240586622809 -3.090643779962737)	902769.35	902763.25	6.1	37.24	-342299.48	-342304.19	4.71	22.19	59.43
17	RURAL (29.86299856962244 -2.899012901866433)	818307.78	818308.56	-0.79	0.62	-320833.24	-320836.27	3.02	9.14	9.76
18	RURAL (29.34416157679251 -3.12369811978341)	760534.27	760534.01	0.26	0.07	-345556.48	-345555.69	-0.79	0.62	0.69
19	RURAL (29.57782322047101 -4.022613680309142)	786241.51	786244.03	-2.52	6.34	-445078.95	-445076.07	-2.88	8.28	14.62
									sum	689.32
									average	34.47
									RMSE	5.87
									NSSDA	10.16

Table 6 – Random sample nodes of the Burundi OSM drivable roads network over rural areas selected for accuracy calculation against manual selection of correspondent nodes in Google Maps satellite imagery.

Annex B – Qualitative correspondence comparison of Bing Vs Google Maps satellite imagery against OSM roads

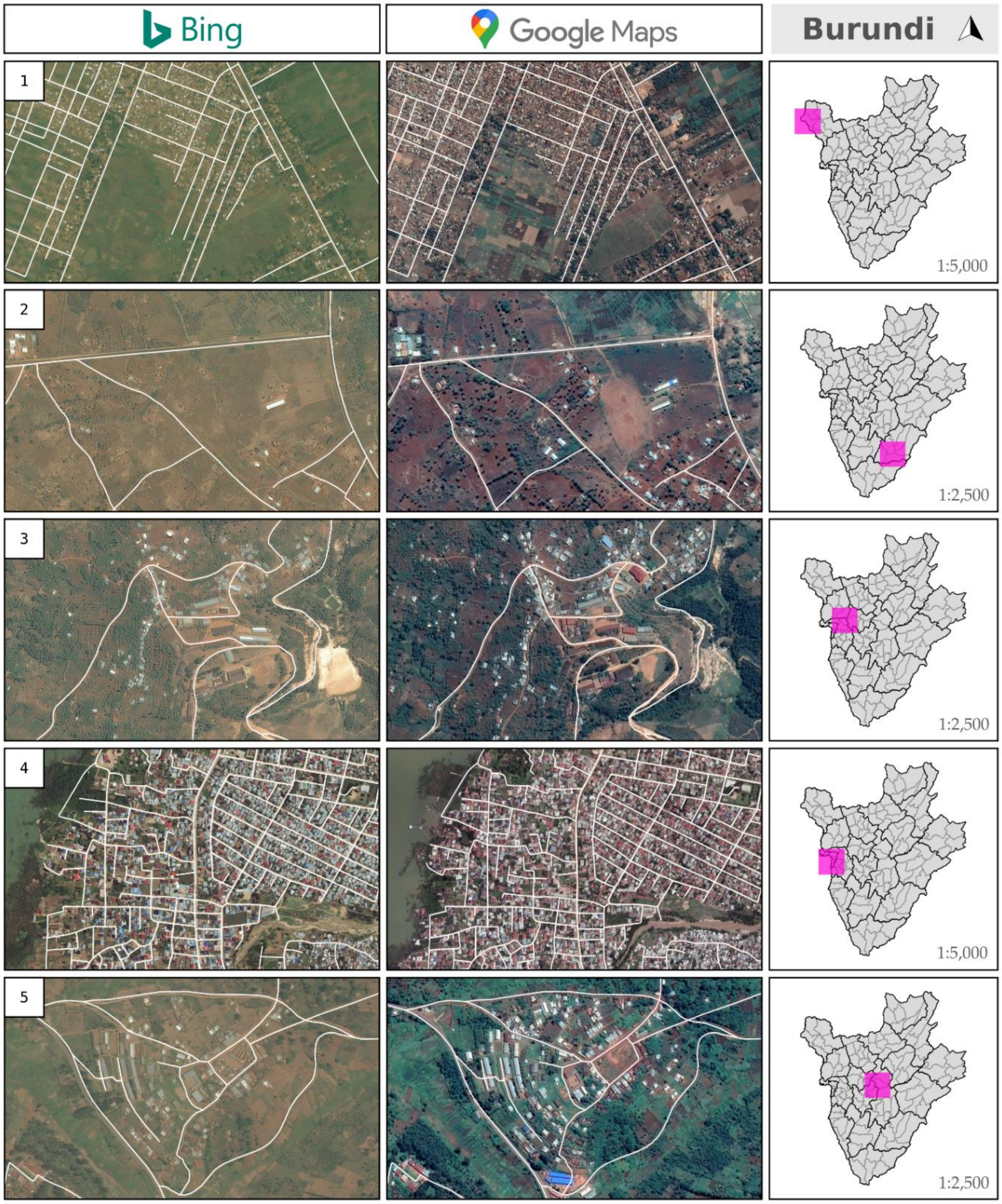

Figure 15 – Comparison of Bing and Google satellite imagery over selected areas of Burundi.

Annex C – Comparison of authoritative versus OSM roads network

Comparison of OpenStreetMap (OSM) year-round drivable roads and the authoritative roads dataset from the Ministry of Health (MoH) of Burundi: the latter, with its 3,000 roads and 12’000 km of total length ca., is approximately 1 order of magnitude smaller than the OSM equivalent, which provides ~100,000 roads with a grand total length of 33’000 km ca.

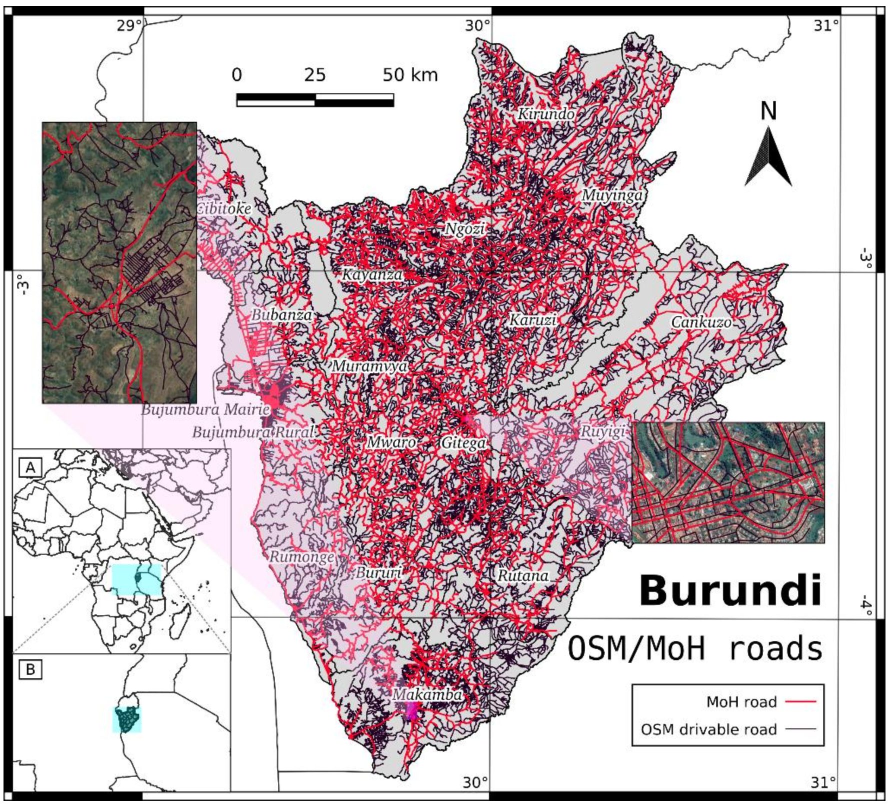

Figure 16 – Visual comparison between OSM roads dataset and the official roads data from the Ministry of Health of Burundi.

OSM	GRAND TOTAL	Primary roads	Secondary roads	Tertiary roads
Number of roads	295’896	6’191 (~2%)	9’952 (~3%)	82’398 (~27%)
Total length [km]	64’272.5	1’871.8 (~3%)	3’522.8 (~5.5%)	28’765.1 (~45%)

MoH	GRAND TOTAL	classe 1	classe 2	classe 3
Number of roads	2’852	48 (~1.6%)	323 (~11.3%)	2’481 (~87%)
Total length [km]	11’783.2	1’379.3 (~12%)	3’903.0 (~33%)	6’501.0 (~55%)

Table 7 –Basic statistics of the national roads datasets of both OpenStreetMap (OSM June 2021, left-hand side) and Ministry of Health (MoH, right-hand side).