METEOR

Modelling Exposure Through Earth Observation Routines

Tanzania Level-3 Exposure Development

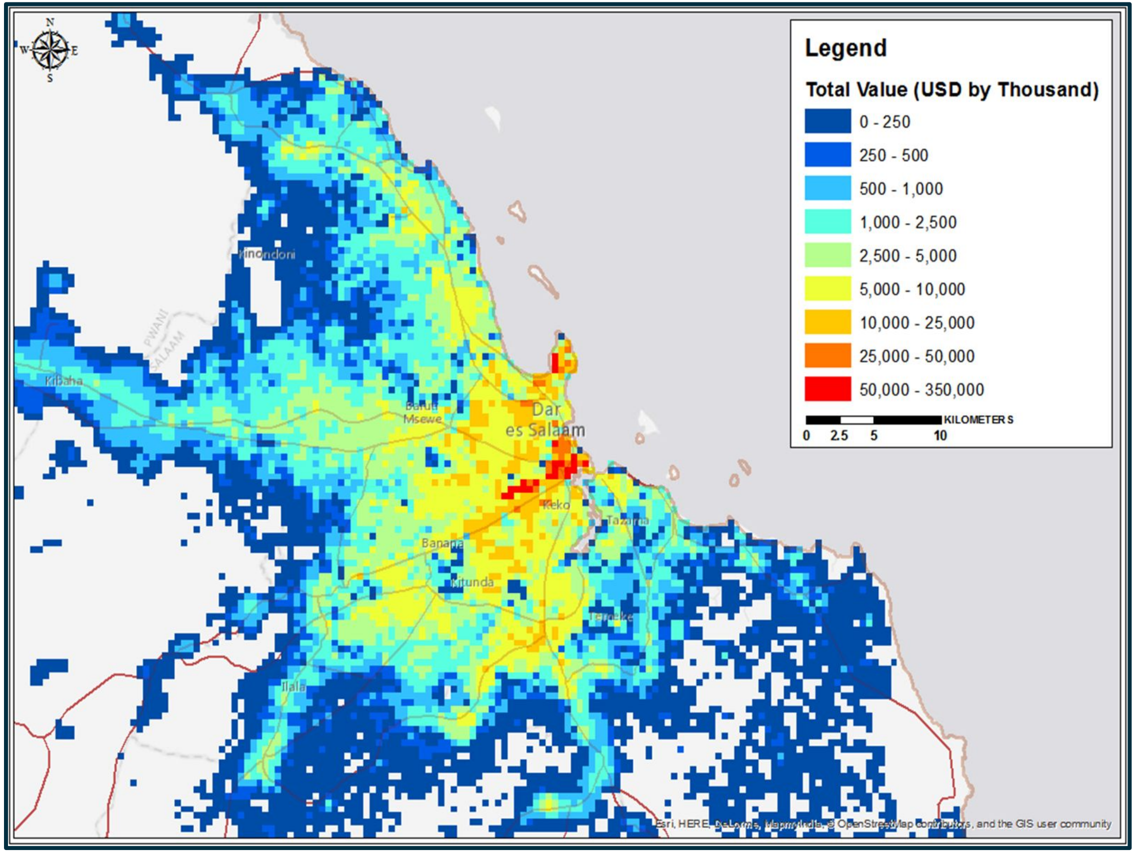
This section will go step-by-step through the Level-3 flowcharts used for gathering data to develop the Level-3 building exposure for Tanzania.

Level 3- Data improvement at the sub-national scale

Examples:

1. Subdividing the country by climate or cultural regions to reflect construction patterns

2. Identifying major urban areas and enhancing building counts or structural mapping schemes in these areas

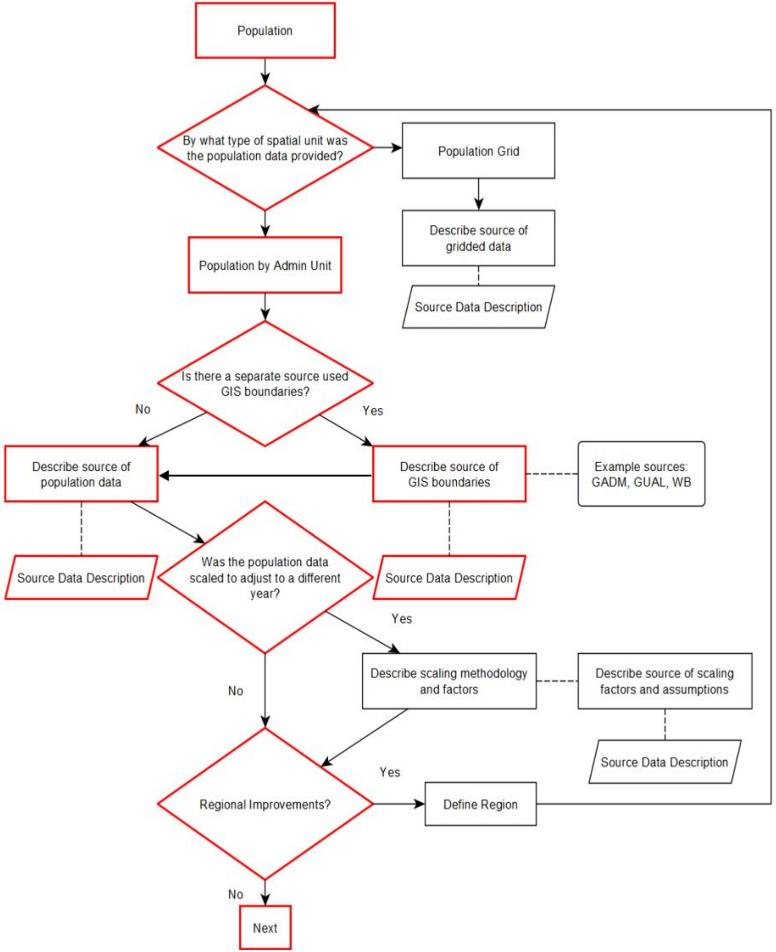


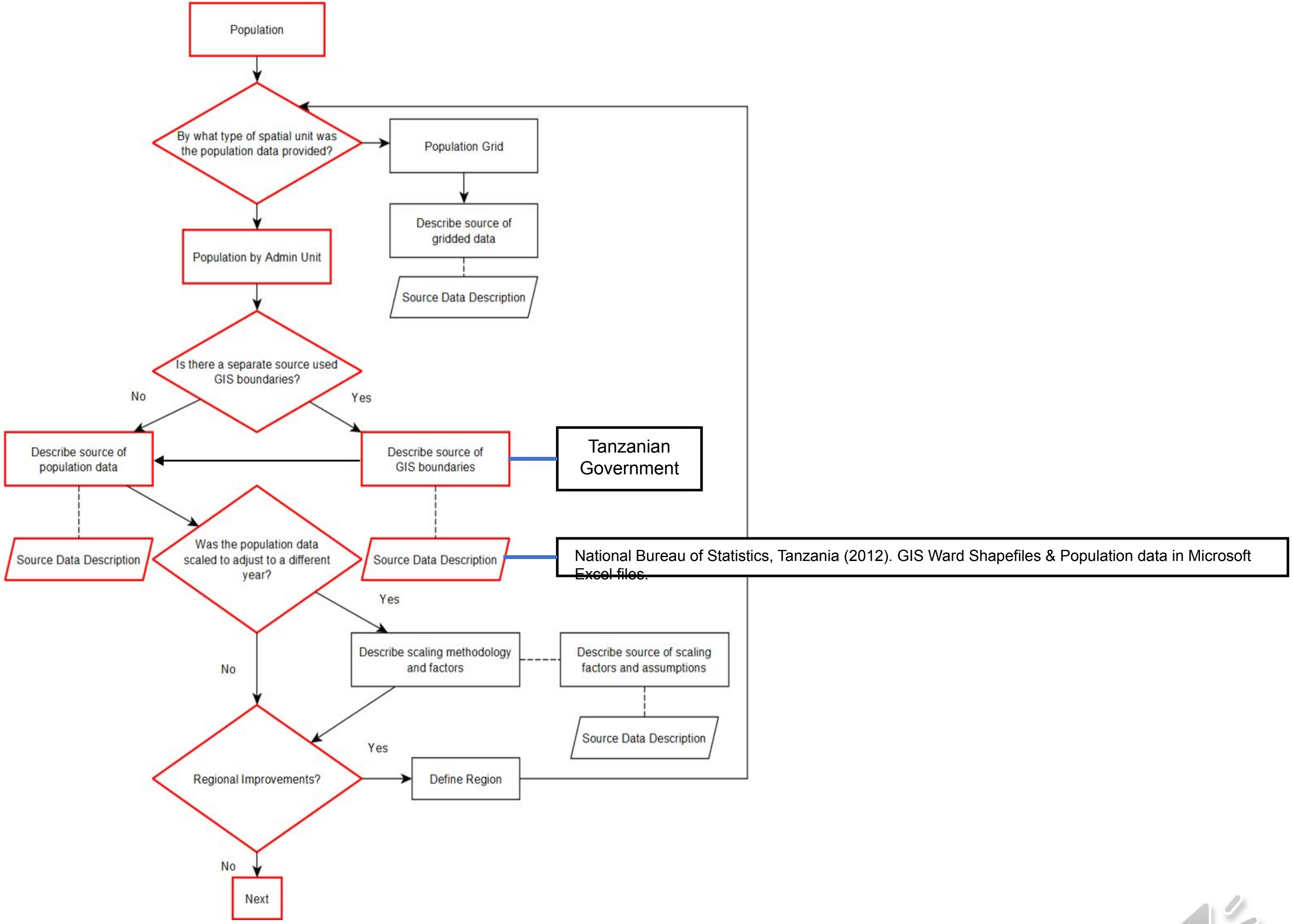
Datasets used to develop the Tanzanian Building Exposure

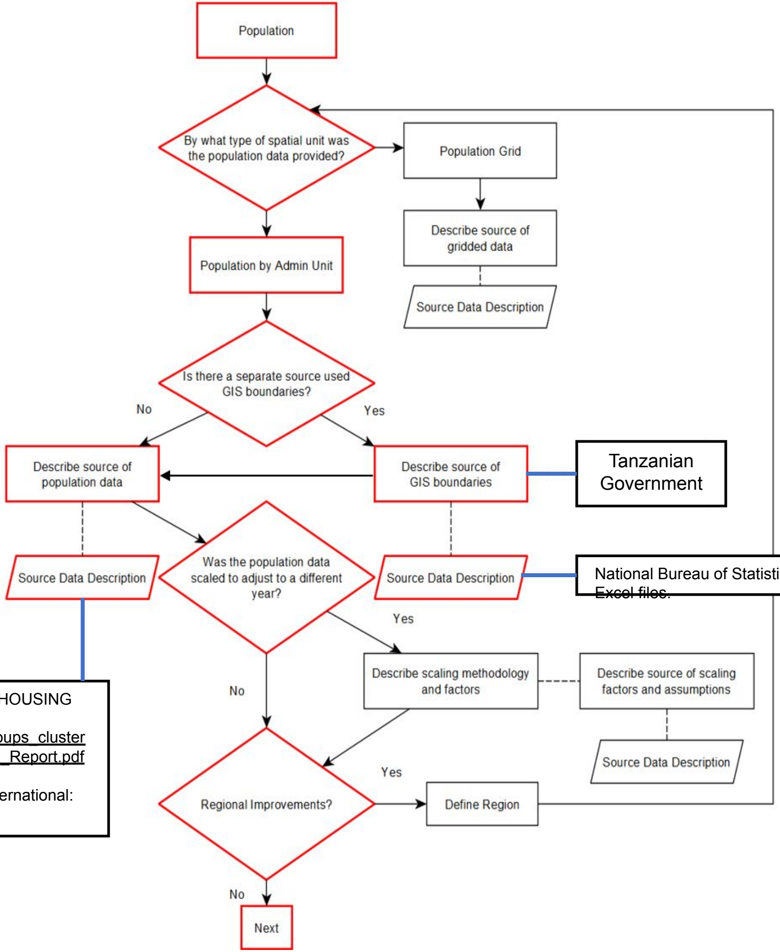
1. AECOM. (2017). Africa Property & Construction Cost Guide 2017, Offering global expertise and tailored local solutions in more than 150 countries.
2. Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001).
3. Breiman, L., Friedman, J.H., Olshen, R., and Stone, C.J. (1984). Classification and Regression Tree. Wadsworth & Brooks/Cole Advanced Books & Software, Pacific California
4. Brzev, S., Scawthorn, C., Charleson, A. W., Allen, L., Greene, M., Jaiswal, K., and Silva, V. (2013). GEM Building Taxonomy (Version 2.0) (No. 2013-02). GEM Foundation. Retrieved from https://storage.globalquakemodel.org/media/publication/EXP-MOD-GEM-Building-Taxonomy-201302-V01_1.pdf
5. Centre for Affordable Housing Finance in Africa. (2016). 2016 Yearbook, Housing Finance in Africa. Accessed October 2017 from https://housingfinanceafrica.org/app/uploads/CAHF_Housing-Finance-in-Africa-Yearbook-2016.09.pdf
6. Center for International Earth Science Information Network - CIESIN - Columbia University, International Food Policy Research Institute - IFPRI, The World Bank, and Centro Internacional de Agricultura Tropical – CIAT. (2011). Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Urban Extents Grid [raster, map, map service]. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). Retrieved from https://sedac.ciesin.columbia.edu/data/set/grump-v1-urban-extents
7. Centre for Affordable Housing Finance in Africa. (2017). Benchmarking Housing Construction Costs in Africa. Accessed November 2017 from http://housingfinanceafrica.org/dashboards/benchmarking-housing-construction-costs-africa/
8. Corbane, C., Florczyk, A., Pesaresi, M., Politis, P. and Syrris, V. (2018). GHS built-up grid, derived from Landsat, multitemporal (1975-1990-2000-2014), R2018A. European Commission, Joint Research Centre (JRC) doi: 10.2905/jrc-ghsl-10007 PID: Retrieved from http://data.europa.eu/89h/jrc-ghsl-10007
9. Corbane, C., Politis, P., Syrris, V. and Pesaresi, M. (2) (2018): GHS built-up grid, derived from Sentinel-1 (2016), R2018A. European Commission, Joint Research Centre (JRC) doi: 10.2905/jrc-ghsl-10008 PID: Retrieved from http://data.europa.eu/89h/jrc-ghsl-10008
10. Deloitte. (2012). Deloitte on Africa, Construction on the African Continent: Opportunities, Risks and Trends.
11. Cortes, C., Vapnik, V. Support-vector networks. Mach Learn 20, 273–297 (1995).
12. DLR Earth Observation Center. (2016). Global Urban Footprint (GUF). Available at https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-11725/20508_read-47944/
13. Earle, P. S., Wald, D. J., Jaiswal, K. S., Allen, T. I., Hearne, M. G., Marano, K. D., Hotovec, A.J., & Fee, J. M. (2009). Prompt Assessment of Global Earthquakes for Response (PAGER): A system for rapidly determining the impact of earthquakes worldwide. US Geological Survey Open-File Report, 1131, 15.
14. Earth Observation Group NOAA-NCEI (2015). Version 1 VIIRS Day/Night Band Nighttime Lights- 2015 Nighttime Light Annual Composite [dataset]: https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html
15. Facebook Connectivity Lab and Center for International Earth Science Information Network - CIESIN - Columbia University. 2016. High Resolution Settlement Layer (HRSL). Source imagery for HRSL © 2016 Digital Globe.
16. GoogleEarth. (n.d.) Tanzania [map]. Available at https://www.google.com/earth/
17. Humanitarian OpenStreetMap Team (2019). In-situ structural building type, height, and footprint area sampling polygons of Tanzania [dataset].
18. Huyck, C.K. and Eguchi, M.T. (2017). GFDRR Africa Disaster Risk Financing-Result Area 5 Exposure Development. Replacement Cost Refinements to the Exposure Data. Prepared for World Bank/GFDRR
19. ImageCat, Inc. (2019). OSM building footprint data aggregation to 3-arcsecond raster grid [dataset]. Unpublished.
20. Jaiswal, K.S. and Wald, D.J. (2011). Rapid estimation of the economic consequences of global earthquakes: U.S. Geological Survey Open-File Report 2011–1116, 47 p.
21. Jaiswal, K. and Wald, D. (2014). PAGER Inventory Database v2.0.xls. Golden, CO: United States Geological Survey (USGS).
22. Jaiswal, K., Wald, D., & Porter, K. (2010). A global building inventory for earthquake loss estimation and risk management. Earthquake Spectra, 26(3), 731-748.
23. Khaled Fawagreh, Mohamed Medhat Gaber & Eyad Elyan (2014) Random forests: from early developments to recent advancements, Systems Science & Control Engineering, 2:1, 602-609
24. Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.2 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D020.V7.2
25. National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA). (2014). SRTM C-BAND DATA Version 2.1, 3 arc second [dataset]. Retrieved from https://dds.cr.usgs.gov/srtm/
26. National Bureau of Statistics, Tanzania (2013). 2012 POPULATION AND HOUSING CENSUS- Population Distribution by Administrative Areas. http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_2/water/WSDP/Background_information/2012_Census_General_Report.pdf
27. National Bureau of Statistics (1), Tanzania. (2012). Population data, Microsoft Excel files. Provided by John Mathias Kiriwai from the Tanzanian Prime Minister's Office.
28. National Bureau of Statistics (2), Tanzania. (2012). GIS Ward Shapefiles. Provided by John Mathias Kiriwai from the Tanzanian Prime Minister's Office.
29. Oak Ridge National Laboratory, Landscan2012: Global Population Data. Oak Ridge, Tennessee: UT Battelle, Department of Energy. Available at http://www.ornl.gov/sci/landscan/landscan_documentation.shtml
30. OpenStreetMap contributors. (2018) Geofabrik Public Server [Tanzania-latest-free.shp]. Retrieved from https://download.geofabrik.de/africa/tanzania.html
31. Pesaresi, Martino; Ehrilch, Daniele; Florczyk, Aneta J.; Freire, Sergio; Julea, Andreea; Kemper, Thomas; Soille, Pierre; Syrris, Vasileios (2015): GHS built-up grid, derived from Landsat, multitemporal (1975, 1990, 2000, 2014). European Commission, Joint Research Centre (JRC) [Dataset] PID: http://data.europa.eu/89h/jrc-ghsl-ghs_built_ldsmt_globe_r2015b
32. Porter K., Hu, Z., Huyck, C. and Bevington, J. (2014), User guide: Field sampling strategies for estimating building inventories, GEM Technical Report 2014-02 V1.0.0, 42 pp., GEM Foundation, Pavia, Italy, doi: 10.13117/GEM.DATA-CAPTURE.TR2014.02.
33. S.E, Michael Eguchi. ImageCat. Tanzania Structural Attribute and Distribution Evaluation: Internal Report. 2018
34. Syrris, V., Corbane, C., Pesaresi, M., & Soille, P. (2018). Mosaicking Copernicus Sentinel-1 Data at Global Scale. IEEE Transactions on Big Data. Retrieved at http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8428406&isnumber=7153538
35. Tanzania, N. B. S. (2012). 2012 Population and Housing Census [dataset]. Provided by IPUMS International.
36. The United Republic of Tanzania, Prime Minister's Office, Regional Administration and Local Government, Dar Rapid Transit Agency, in association with g Dong Engineering Co., Ld and Ambicon Engineering Ltd. (2015). 3.2-1 Resettlement Action Plan Report (Phase 2).
37. Turner & Townsend. (2017). International construction market survey 2017. Accessed November 2017 from http://www.turnerandtownsend.com/en/insights/international-construction-market-survey-2017/
38. V. Syrris, C. Corbane, M. Pesaresi and P. Soille, "Mosaicking Copernicus Sentinel-1 Data at Global Scale," in IEEE Transactions on Big Data. doi: 10.1109/TBDATA.2018.2846265 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8428406&isnumber=7153538
39. WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University (2018). The spatial distribution of population in Tanzania. From the Global High-Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076).
40. Yamazaki, D., Trigg, M. A., & Ikeshima, D. (2015). Development of a global~ 90 m water body map using multi-temporal Landsat images. Remote Sensing of Environment

Level-3 Flowcharts

- Population
- Structural Distribution
- Number of Buildings
- Dasymetric Mapping
- Replacement Cost
- Building Height
- Building Area


Population
By what type of spatial unit was the population data provided?
Population Grid
Describe source of gridded data
Source Data Description
Population by Admin Unit
Is there a separate source used GIS boundaries?
No
Yes
Describe source of population data
Describe source of GIS boundaries
Example sources: GADM, GUAL, WB
Source Data Description
Was the population data scaled to adjust to a different year?
Source Data Description
Yes
Describe scaling methodology and factors
Describe source of scaling factors and assumptions
No
Source Data Description
Yes
Regional Improvements?
Define Region
No
Next


Population
By what type of spatial unit was the population data provided?
Population Grid
Describe source of gridded data
Source Data Description
Population by Admin Unit
Is there a separate source used GIS boundaries?
No
Yes
Describe source of population data
Describe source of GIS boundaries
Tanzanian Government
Source Data Description
Was the population data scaled to adjust to a different year?
Source Data Description
National Bureau of Statistics, Tanzania (2012). GIS Ward Shapefiles & Population data in Microsoft Excel files.
Yes
Describe scaling methodology and factors
Describe source of scaling factors and assumptions
No
Source Data Description
Yes
Regional Improvements?
Define Region
No
Next



Tanzanian Government

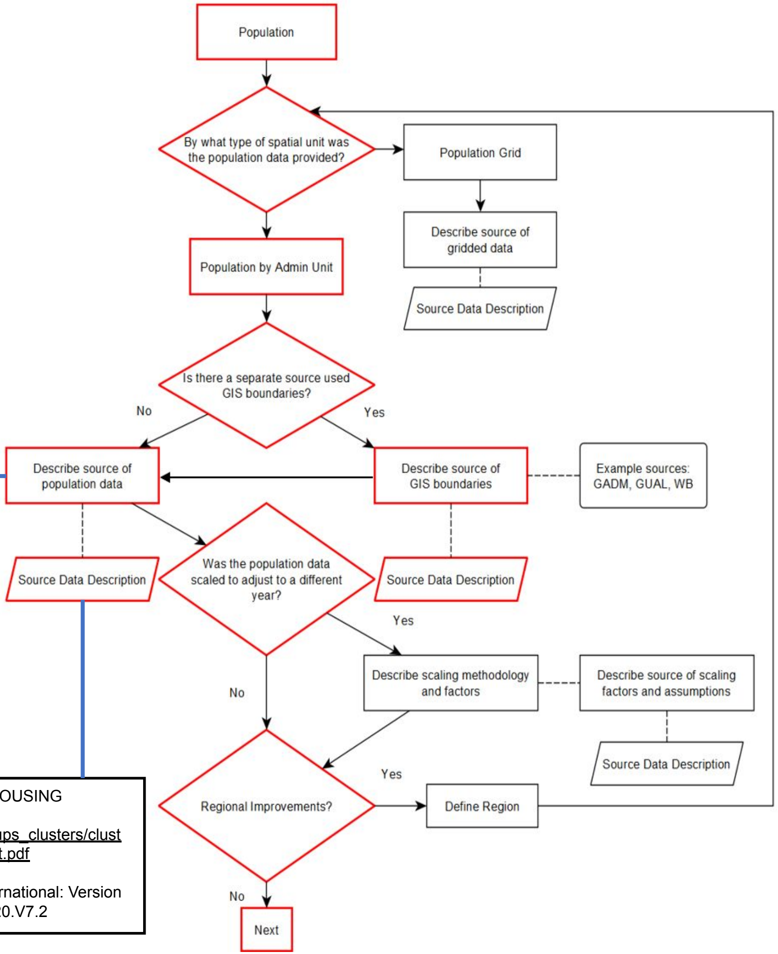
National Bureau of Statistics, Tanzania (2012). GIS Ward Shapefiles & Population data in Microsoft Excel files.

National Bureau of Statistics, Tanzania (2012). 2012 POPULATION AND HOUSING CENSUS- Population Distribution by Administrative Areas. http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_2/water/WSDP/Background_information/2012_Census_General_Report.pdf

Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.2 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D020.V7.2

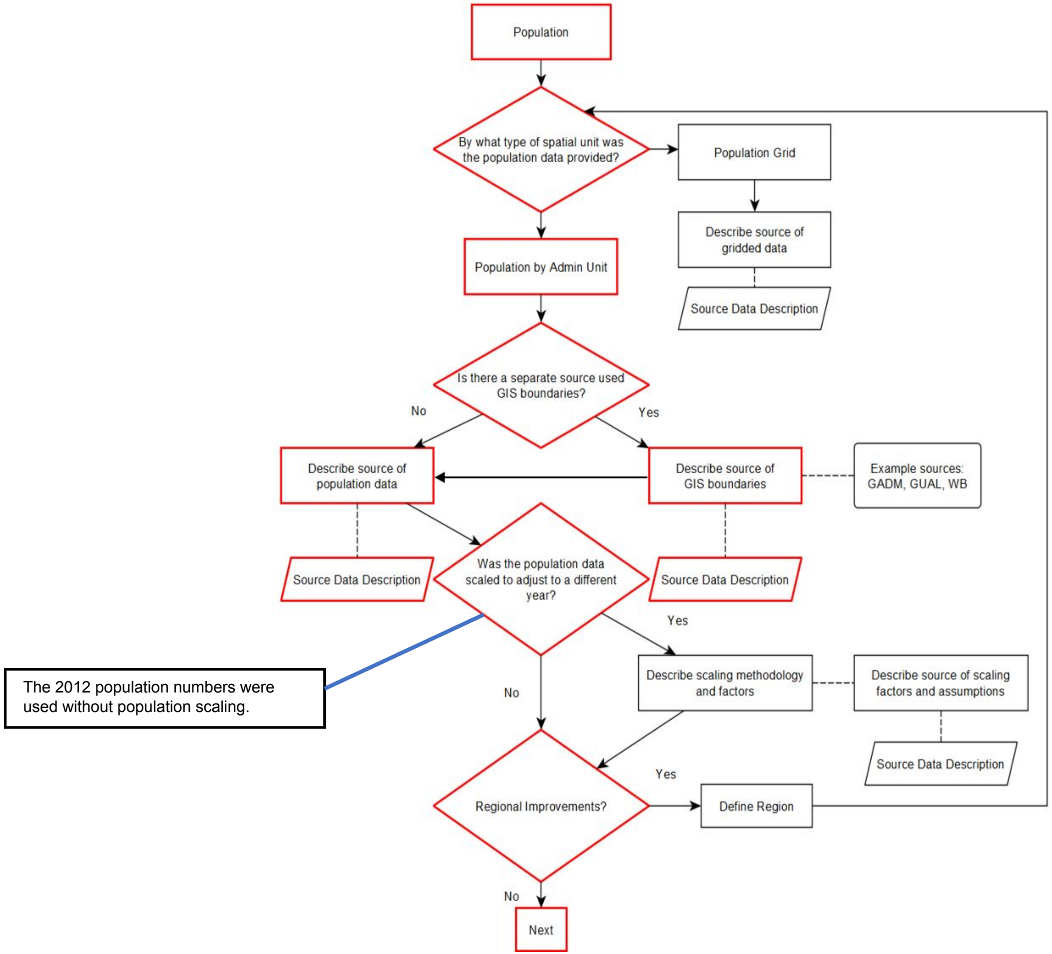
The population information used in Tanzania were the ward-level administrative units to determine population and number of households. The ward GIS data was provided by John Mathias Kiriwai from the Tanzanian Prime Minister's Office (PMO). Along with the GIS shapefiles, PMO provided detailed excel spread sheets of the population counts per ward. The persons per household figures were available at the ward data in the census PDF and matched to the ward level by converting to a word file and matching manually to adjust for variations in spelling and punctuation. All values are from the 2012 National Bureau of Statistics housing and population census.

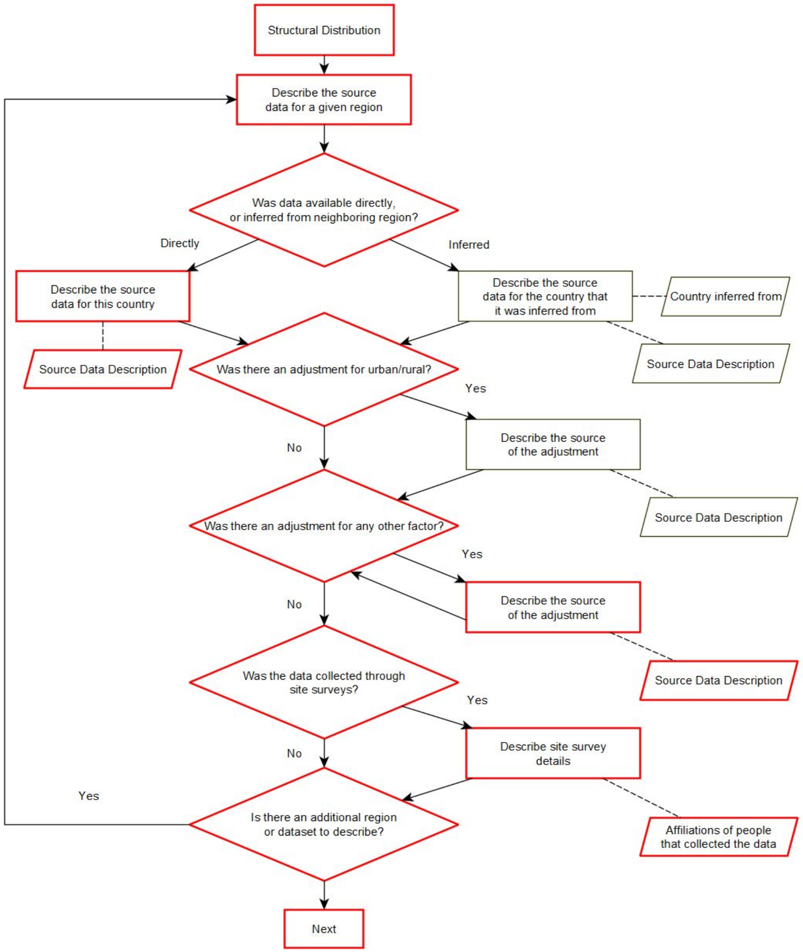
The population and household values are interpolated from the ward level to a 3-arcsecond (~100m) grid cell using various Earth Observation dataset and used to infer the number of buildings.



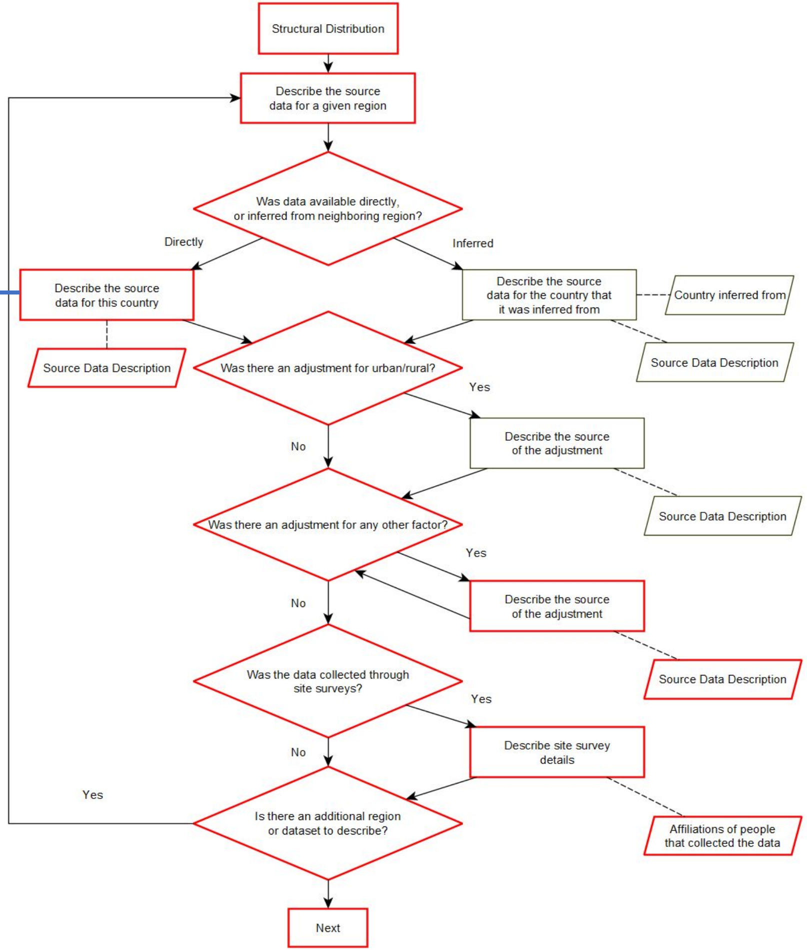
National Bureau of Statistics, Tanzania (2012). 2012 POPULATION AND HOUSING CENSUS- Population Distribution by Administrative Areas. http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_2/water/WSDP/Background_information/2012_Census_General_Report.pdf

Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.2 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D020.V7.2


Population
By what type of spatial unit was the population data provided?
Population Grid
Describe source of gridded data
Source Data Description
Population by Admin Unit
Is there a separate source used GIS boundaries?
No
Yes
Describe source of population data
Describe source of GIS boundaries
Example sources: GADM, GUAL, WB
Source Data Description
Was the population data scaled to adjust to a different year?
Source Data Description
Yes
Describe scaling methodology and factors
Describe source of scaling factors and assumptions
No
Source Data Description
Yes
Regional Improvements?
Define Region
No
Next
The 2012 population numbers were used without population scaling.

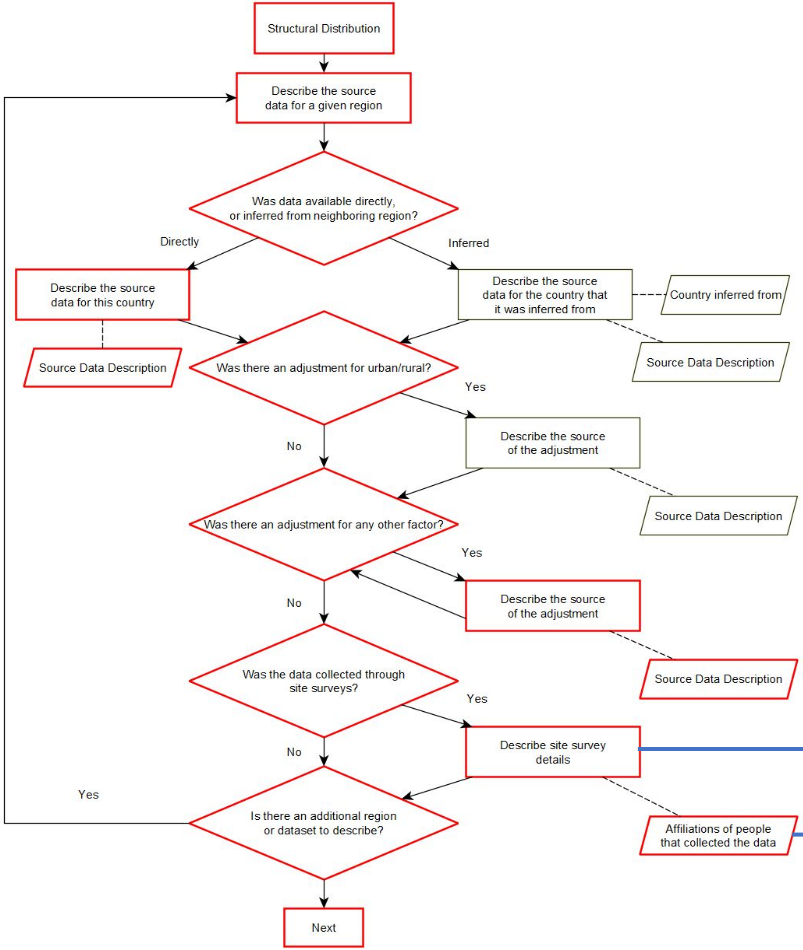

Structural Distribution
Describe the source data for a given region
Was data available directly, or inferred from neighboring region?
Directly
Inferred
Describe the source data for this country
Source Data Description
Describe the source data for the country that it was inferred from
Country inferred from
Source Data Description
Was there an adjustment for urban/rural?
Yes
No
Describe the source of the adjustment
Source Data Description
Was there an adjustment for any other factor?
Yes
No
Describe the source of the adjustment
Source Data Description
Was the data collected through site surveys?
Yes
No
Describe site survey details
Affiliations of people that collected the data
Is there an additional region or dataset to describe?
Yes
Next

IPUMS district census data were used for develop the mapping schemes using a combination of the building wall, roof, and floor material type. Each combination of wall, roof, and floor material type was mapped to a GEM construction type, and the number of households was used to develop a structural distribution by ward. The mapping schemes were developed at the individual ward level. In the few areas where IPUMS district information was not provided, the neighboring district was used as a proxy. The IPUMS wall, floor, roof combinations were mapped to PAGER (USGS, 2008) and GEM (Brzev et al., 2013) classes by ImageCat staff and reviewed by Tanzanian measurement engineer Frank Mushi.



The HOTOSM sampling strategy followed the stratified sampling and Bayesian updating approach (Porter, et al. 2014). Approximately 400 building locations were surveyed in each of the development patterns type (ranging from 240 to 750 per type and approximately 2,900 in total). Photographs of each structure accompanied each assessment. All the mapping schemes were then mapped to the PAGER standard structural types.

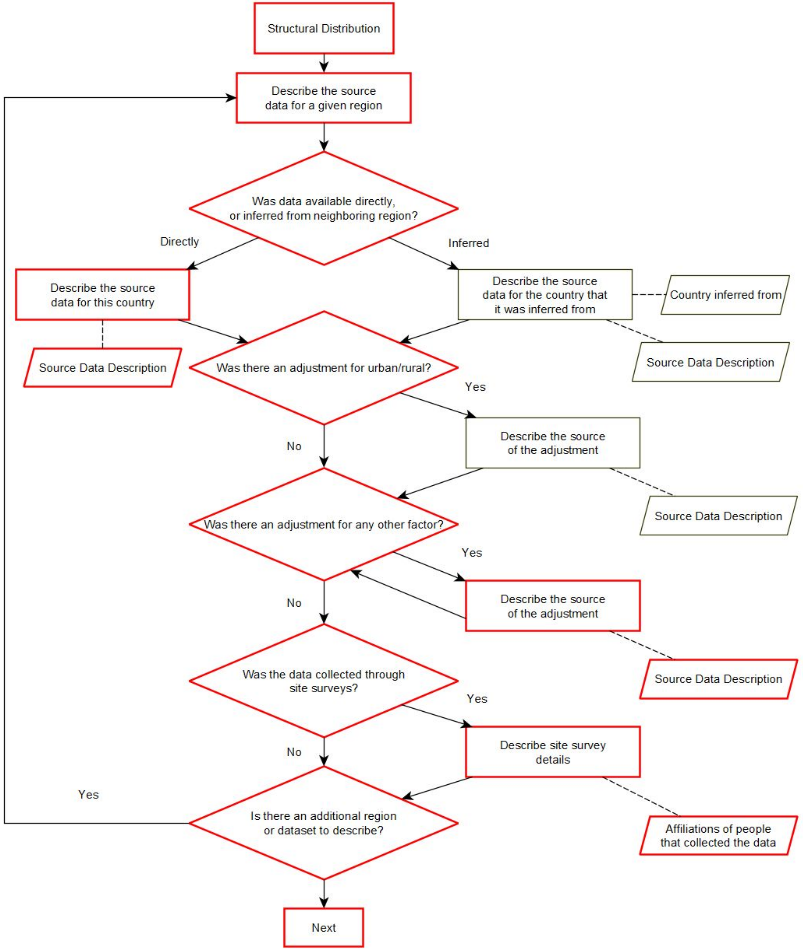
The sites were surveyed using the HOTOSM tools by local staff trained in GIS techniques. Engineers were not present in the initial infield data collection. However, afterwards a second team of 4th year students majoring in Building Economics trained by Frank Mushi, a Measurement Engineer, were present. This team served as validators of the data, whose main aim was to verify the tagging of buildings in priority areas.



PAGER	GEM	DP1	DP2	DP4	DP5	DP6	DP7
UCB	MUR+CB99/HBET:1,3	91.6	82.7	96	52.2	63.8	68.1
W5	W+WWD	5.4	-	-	-	-	0.2
INF	MATO/LN	2.3	0.4	3.6	1.7	3.1	0.7
C1	CR/LFM/HBET:1,3	0.2	0.4	-	2.6	4.4	3.8
W5	W	0.2	0.4	-	-	-	0.5
RS	MUR+STRUB	0.2	-	-	-	-	-
UFB	MUR+CL99	-	15.6	-	-	-	-
C3L	CR/LFINF+DNO/HBET:1,3	-	0.4	0.4	26.3	13.1	12.7
C3M	CR/LFINF+DNO/HBET:4,7	-	-	-	10.2	4.6	1.2
C1	CR/LFM/HBET:8,20	-	-	-	3.2	2.4	-
C3H	CR/LFINF+DNO/HBET:8,20	-	-	-	1.3	4.8	-
UCB	MUR+CB99/HBET:4,7	-	-	-	1.1	0.4	-
C1	CR/LFM/HBET:4,7	-	-	-	0.8	2	0.7
S	S	-	-	-	0.6	1.5	12

Photographs of each structure accompanied each building assessment. The HOTOSM building survey data was verified by an ImageCat engineer (Michael Eguchi) and HOT Mapping Supervisor (Emanuel Kombe). All of the mapping schemes were then mapped to the PAGER standard structural types and overlaid with the development patterns (shown in the next slide) to create a refined mapping scheme.

S.E, Michael Eguchi. ImageCat. Tanzania Structural Attribute and Distribution Evaluation: Internal Report. 2018



The distribution of building structural patterns varies by urban intensity. The development of the distribution of building structural patterns for this project incorporates a stratified sampling technique whereby structural distributions are created for several development patterns. These areas are then used to distribute exposure throughout the region. The following development patterns were identified in Tanzania. Note that these categories represent a means of delineating construction patterns and that the designated purposes (occupancy) of buildings in these areas can vary substantially.

Development Pattern 1
This type of rural development can be found outside of city boundaries and is typically associated with agricultural development. The regions typically consist of small, remote villages with single roads in and out. Buildings are typically spaced far apart and are almost exclusively 1 to 2 stories. Local materials and construction practices are generally used and performed in these areas.

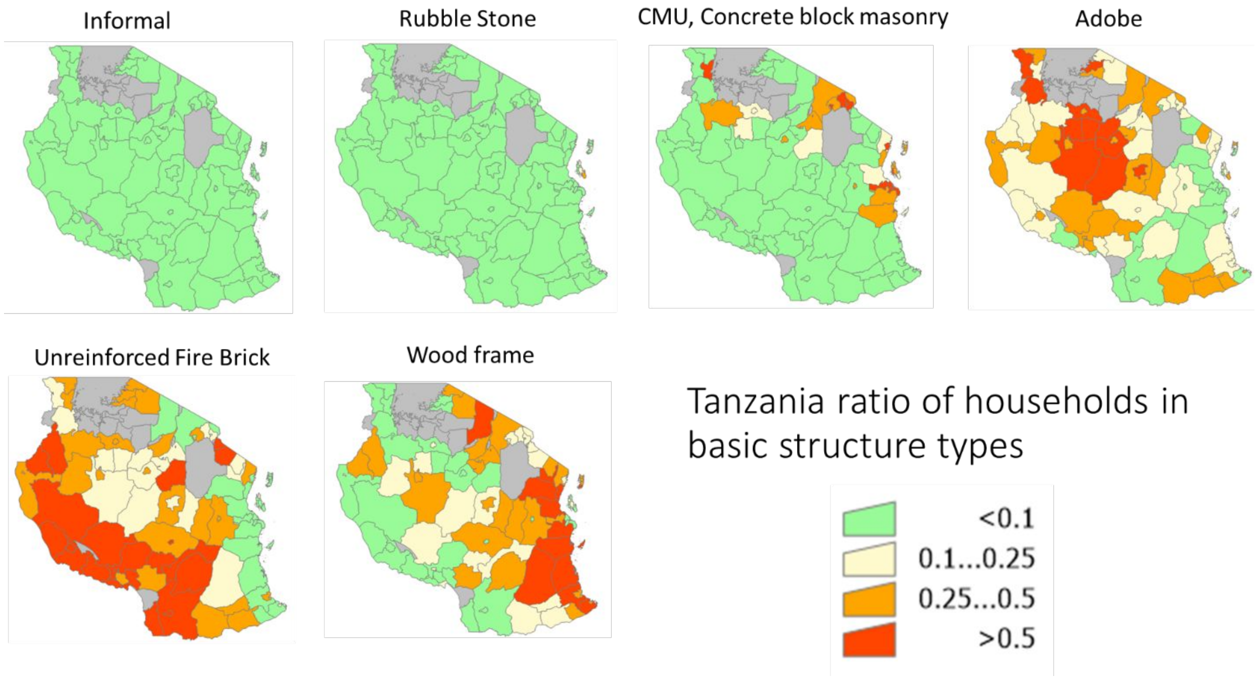
Development Pattern 2
This development pattern reflects areas typically dominated by single-family residential structures. Commercial properties, such as local markets, are present, however residential structures are the primary occupancy. The built-up area is dense, however open land (yards, vacant lots, etc.) are present and can be observed via satellite imagery. All structures are low-rise, with most in the 1 to 2 story range.

Development Pattern 4
This development pattern is typically associated with extremely dense, informal settlements. They are usually found within boundaries of large cities and are typically comprised of very small (<100 sq. m.) standalone structures with little to no space between adjacent buildings. The settlement is unplanned, therefore there is no organization to the configuration of building layouts. Almost all structures are single-story and are typically erected using cheap and accessible local materials. Roof colors will vary from building to building, and even on the same structure. There is very little (to no) space between neighboring buildings. Although most building footprints appear fairly regular (square, rectangular), closer inspection shows that corners are typically not 90 degrees, suggesting buildings were constructed without formal planning. Building footprints are small (<500 sqft) and most are one-story. This development pattern is easy to detect in a satellite image and will be identified manually in this study. Floor area is anticipated to be almost 100% of the built area.

Development Pattern 5
This development pattern is characterized by urban areas predominately occupied by low to mid-rise residential and commercial structures. An occasional high-rise apartment or office building may be present. These developments are typically found near or around major city centers. Buildings are tightly spaced and are regular in shape.

Development Pattern 6
This development pattern is similar to the central business district of any major city. Mid- to high-rise apartments and commercial offices occupy most of the area, but low-rise commercial and residential structures can be situated in between. Typical of an urban area, buildings are spaced relatively close and building layouts of both building and city blocks are structured.

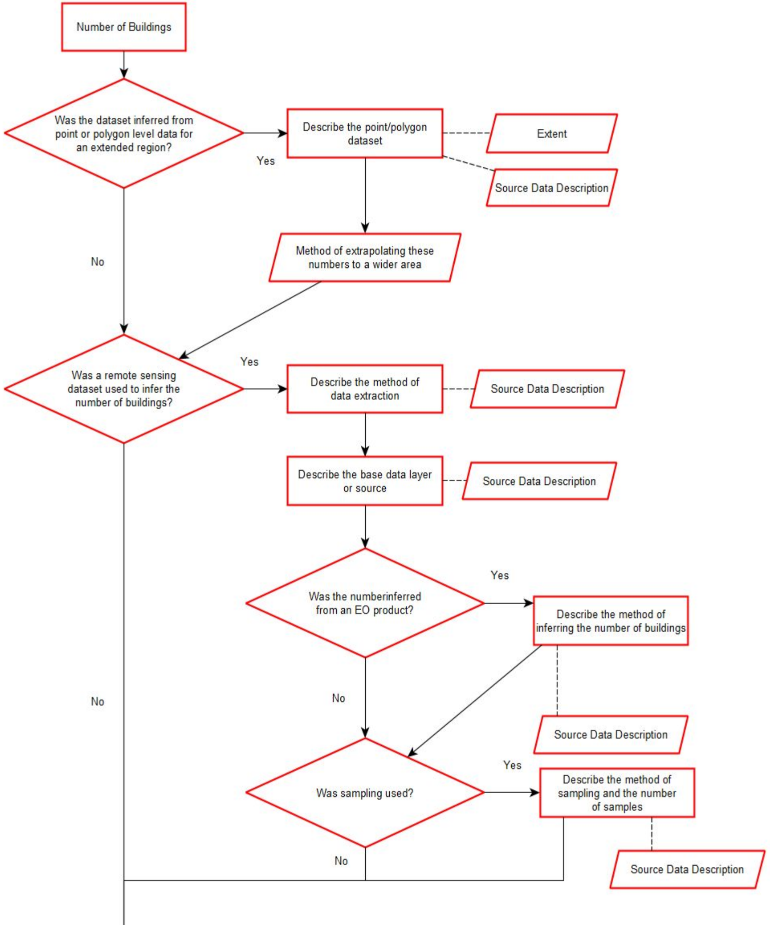
Development Pattern 7
This development pattern is characterized by areas dominated by ports, mining or industrial activities. Structures are typically closely spaced and regular in shape. A majority of buildings within these regions are warehouses, rectangular shape, and single story. Smaller low-rise, office, and commercial structures can also be found on site.



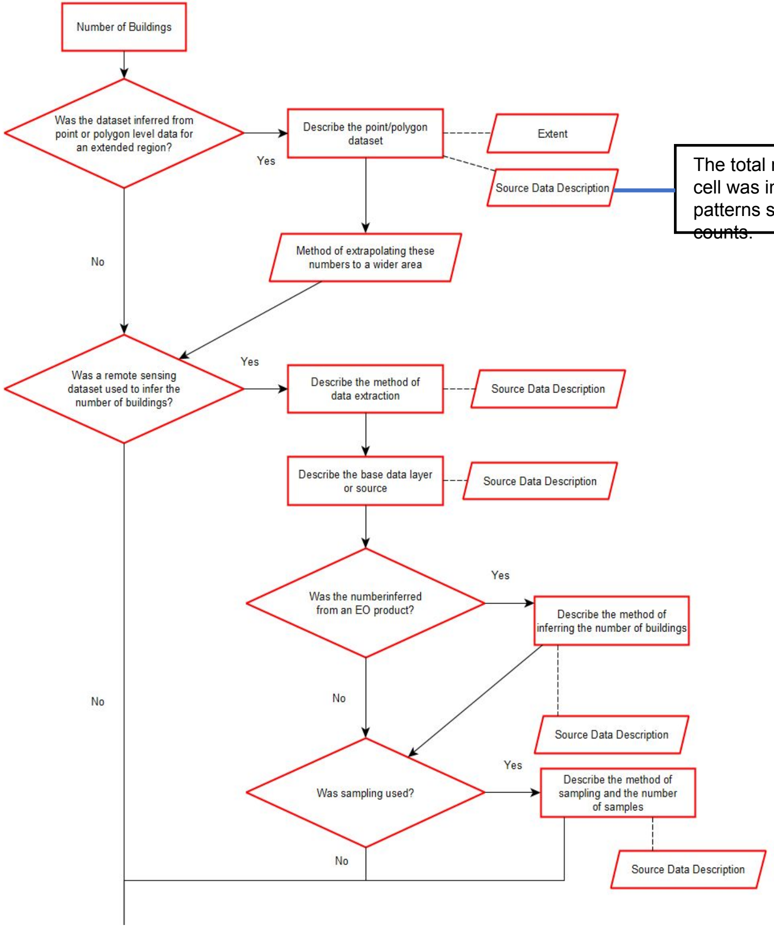
Tanzania ratio of buildings by type from preliminary mapping schemes from IPUMS, 2019

https://meteor-project.org

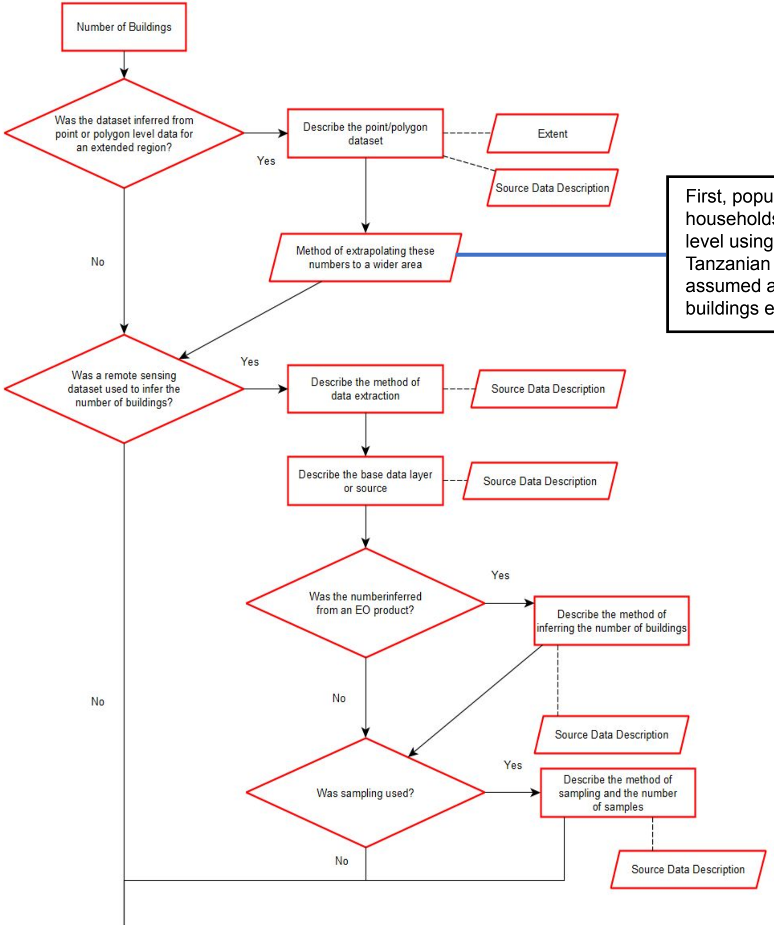
British Geological Survey



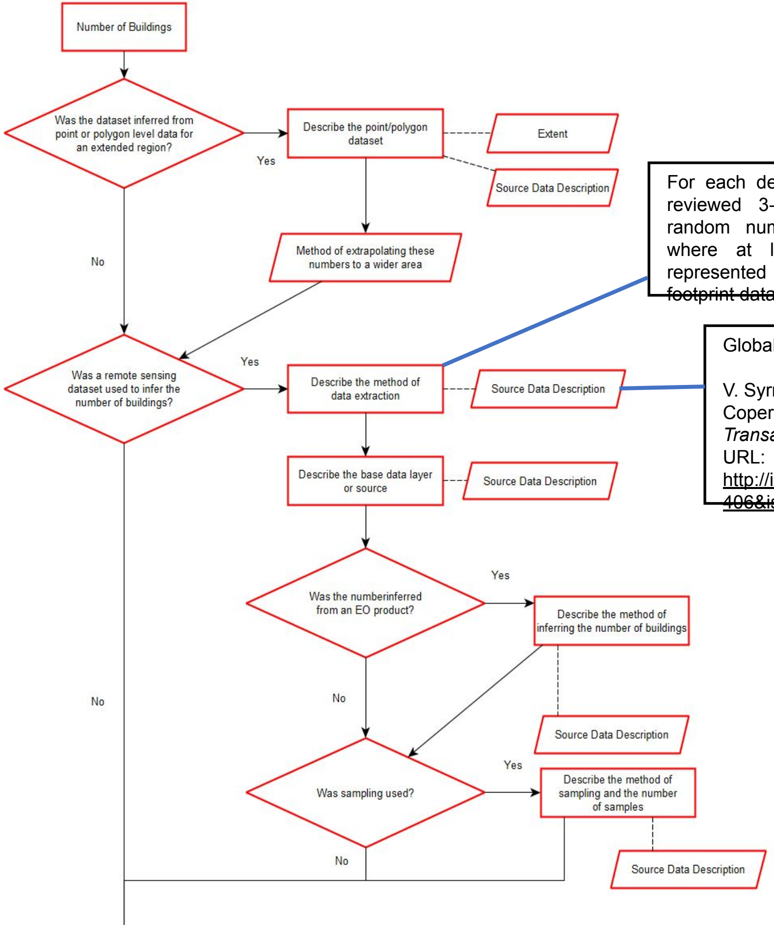
Number of Buildings
Was the dataset inferred from point or polygon level data for an extended region?
Yes
Describe the point/polygon dataset
Extent
Source Data Description
Method of extrapolating these numbers to a wider area
No
Was a remote sensing dataset used to infer the number of buildings?
Yes
Describe the method of data extraction
Source Data Description
Describe the base data layer or source
Source Data Description
No
Was the numberinferred from an EO product?
Yes
Describe the method of inferring the number of buildings
No
Source Data Description
Was sampling used?
Yes
Describe the method of sampling and the number of samples
No
Source Data Description



The total number of buildings per structural class per 3-arcsecond grid cell was inferred using a combination of census data, development patterns samples, building count sample, and aggregated OSM building counts.



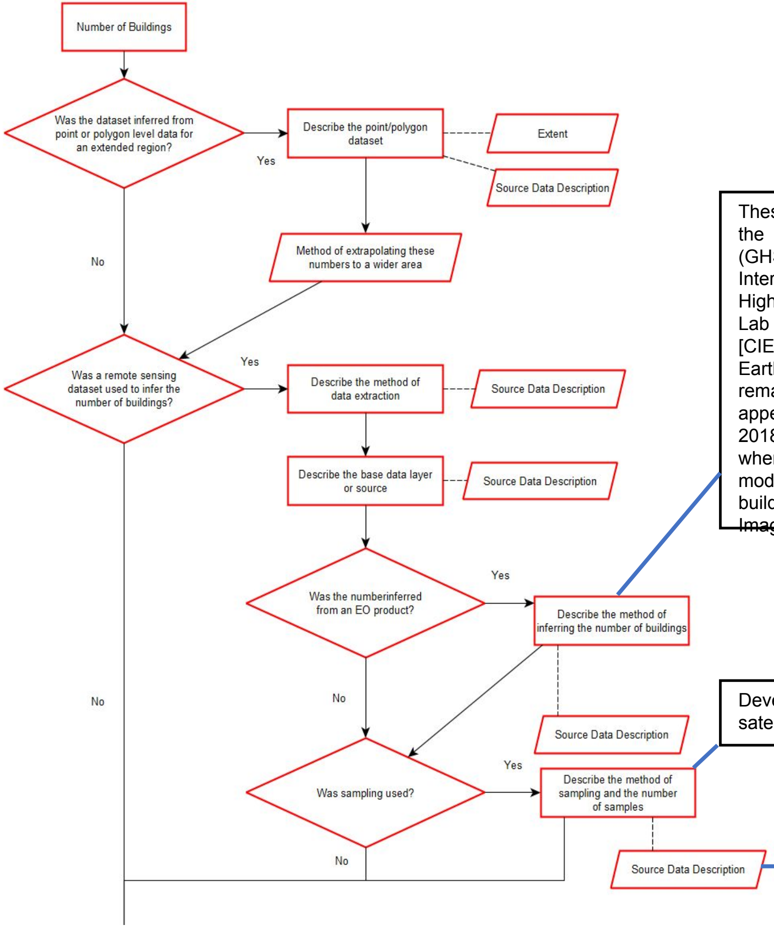
First, population was converted to estimated number of households and disaggregated to the district level from the ward level using the data provided by John Mathias Kiriwai from the Tanzanian Prime Minister’s Office. Ultimately, the number assumed at the district level will equal the estimated number of buildings established by the census.



For each development pattern, a project analyst reviewed 3-arcsecond grids selected using a random number generator and identified cells where at least 90% of the buildings were represented in the OpenStreetMap building footprint data.

Global Urban Footprint (GUF); DLR 2016.

V. Syrris, C. Corbane, M. Pesaresi and P. Soille, "Mosaicking Copernicus Sentinel-1 Data at Global Scale," in *IEEE Transactions on Big Data*. doi: 10.1109/TBDATA.2018.2846265 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8428406&isnumber=7153538



These selected grids were used to train a regression model using the 3-arcsecond Sentinel-1 Global Human Settlement Layer (GHSL-S1). In addition, WorldPop(1) (WorldPop & Center for International Earth Science Information Network [CIESIN], 2018), High Resolution Settlement Layer [HRSL] (Facebook Connectivity Lab & Center for International Earth Science Information Network [CIESIN], 2016), and Global Urban Footprint (GUF) from DLR (DLR Earth Observation Center, 2016) were used to spread the remaining number of buildings, or used in places where the data appeared to be a better indicator than GHSL-S1 (Corbane et al.,(2) 2018). GHSL-S1 proved more effective in highly developed regions, whereas GUF was more effective in rural areas. In addition, the model was constrained using an aggregated 3-arcsecond OSM building count (Humanitarian OpenStreetMap Team, 2019; ImageCat, 2019) as a minimum value.

Development patterns samples and building count sample through satellite imagery reconnaissance.

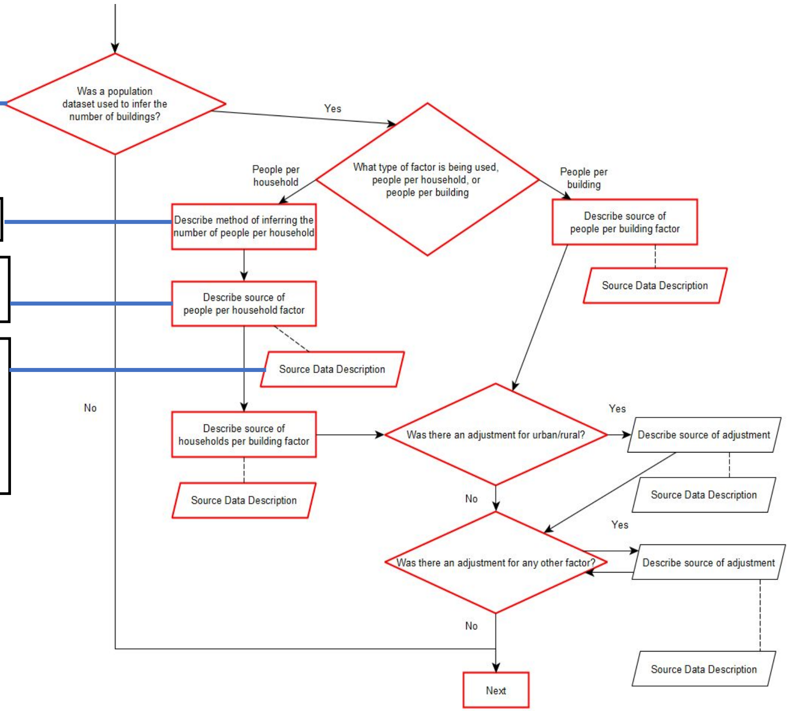
Tanzania.GoogleEarth, 2018. Map
OpenStreetMap contributors. (2018) Geogabrik Public Server [Tanzania-latest-free.shp]. Retrieved from https://download.geofabrik.de/africa/tanzania.html

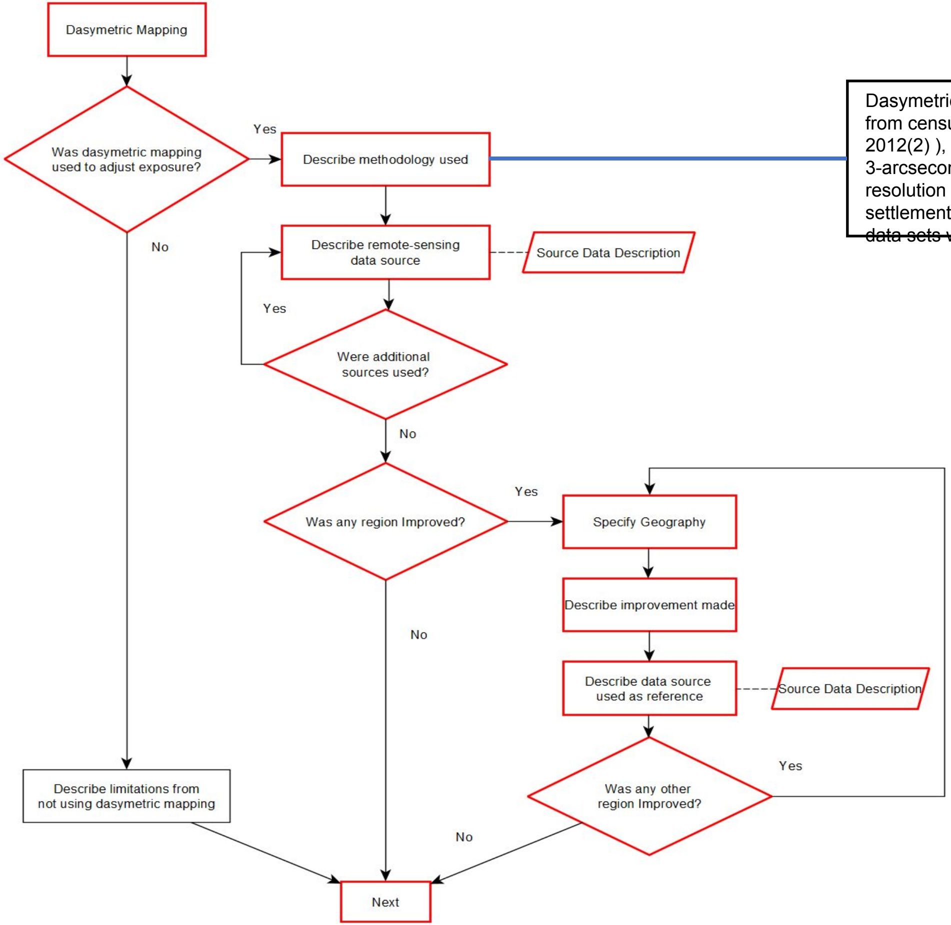
These models are constrained by the aggregated OpenStreetMap building count per 3-arcsecond (100m) grid cell.

Provided directly in census data at the Admin-3, Ward level

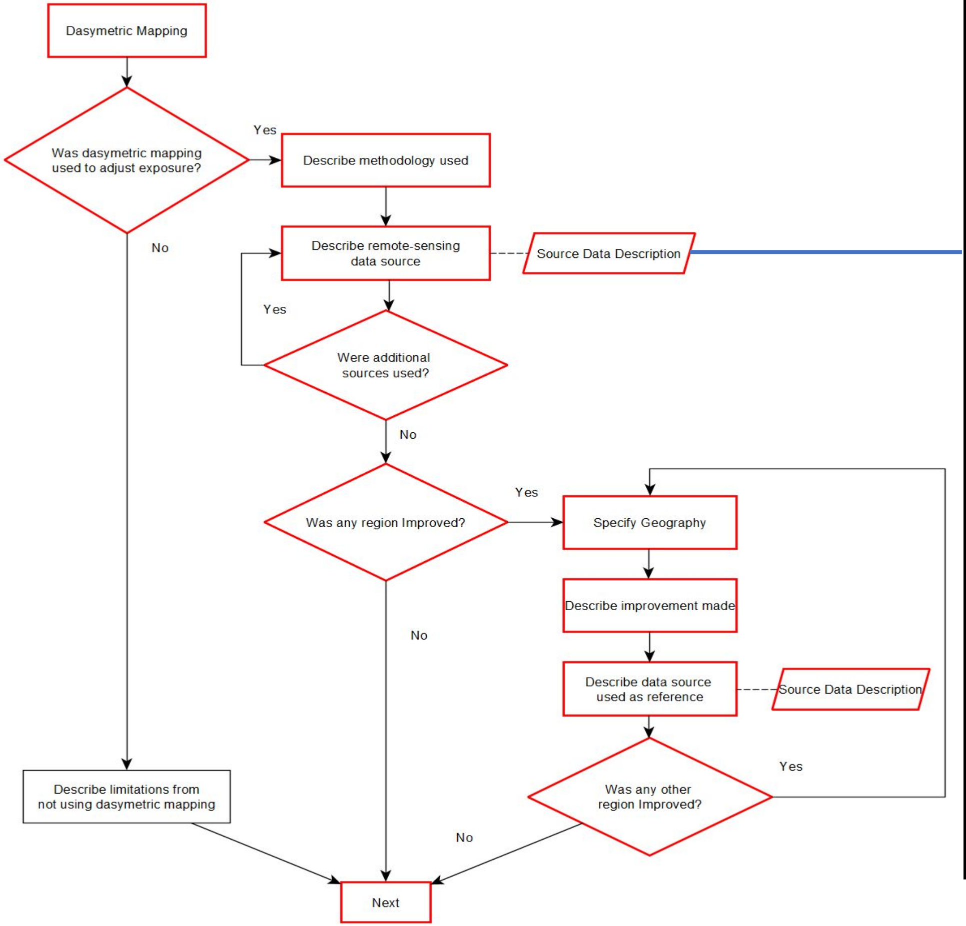
The ward GIS data was provided by John Mathias Kiriwai from the Tanzanian Prime Minister's Office (PMO).

National Bureau of Statistics, Tanzania (2012). 2012 POPULATION AND HOUSING CENSUS- Population Distribution by Administrative Areas. http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_2/water/WSDP/Background_information/2012_Census_General_Report.pdf





Dasymetric mapping was used to spread the number of buildings from census data (Tanzania NBS, 2012(1) and Tanzania NBS, 2012(2)), at the Tanzanian District and Ward census unit level to the 3-arcsecond level, by a statistical assessment of moderate resolution Earth Observation (EO) data. To collect EO indicators of settlements and the density of buildings, various remote sensing data sets were used.



1) NOAA night-time light annual composite (VIIRS) resampled from the 15-arcsecond grid cell to 3-arcsecond (Earth Observation Group NOAA-NCEI (2015))

2) Oak Ridge National Laboratory Landscan ambient population (LSCAN) resampled from the 15-arcsecond grid cell to 3-arcsecond (Oak Ridge National Laboratory. (2012))

3) JRC Global Human Settlement Layer (GHSL-Landsat) derived from Landsat imagery resampled from the 15-arcsecond grid cell to 3-arcsecond (Corbane et al.,(1) 2018)

4) DLR Global Urban Footprint (GUF) resampled from 12-meter grid cells to a 3-arcsecond percentage of human presence raster grid (DLR Earth Observation Center. (2016))

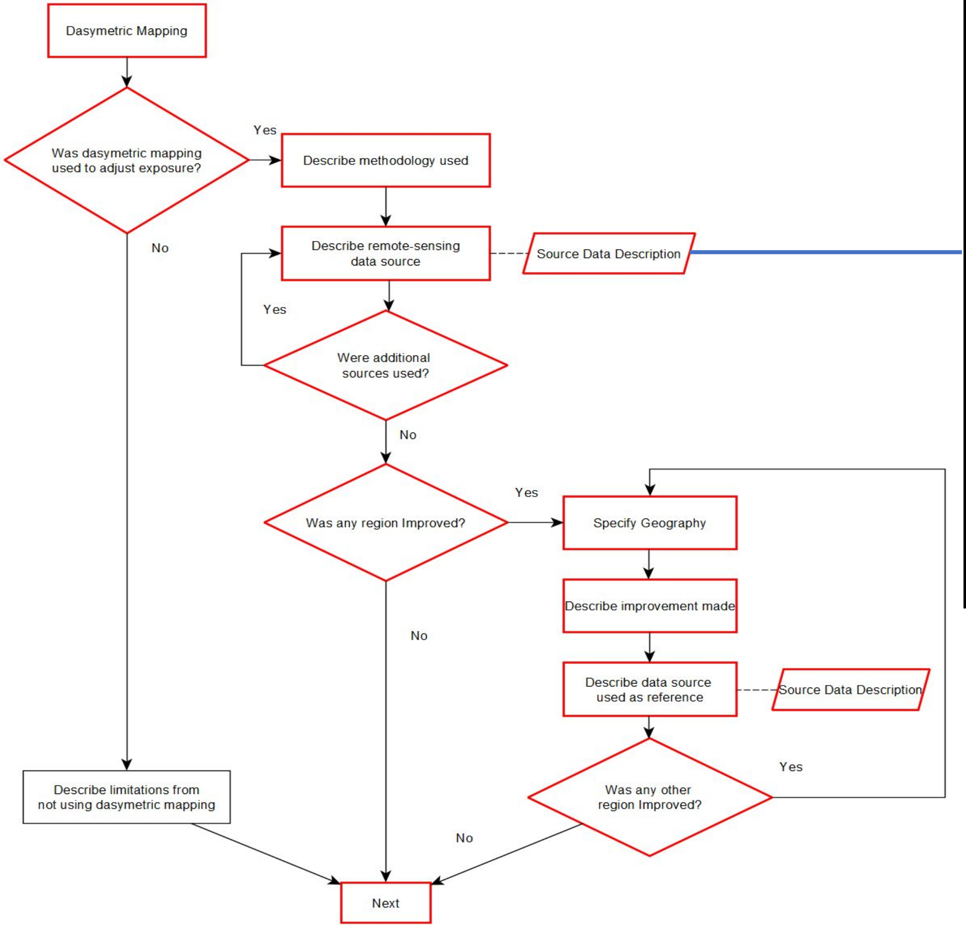
5) JRC GHSL derived from Sentinel-1 SAR (GHSL-SAR) resampled from 20-meter grid cells to a 3-arcsecond percentage of human presence raster grid (Corbane et al.,(2) 2018)

6) CIESIN-Facebook High Resolution Settlement Layer (HRSL) resampled from 1-arcsecond grid cells to a 3-arcsecond percentage of human presence raster grid (Facebook Connectivity Lab and Center for International Earth Science Information Network - CIESIN - Columbia University. (2016))

7) JRC mosaiced Sentinel-1 dual polarization bands (SAR B1, B2, B3) resampled from 20-meter resolution to a 3-arcsecond mean raster grid per band and a maximum mean value of the 3 bands (SAR-MaxMean). (Syrris, V., et. al (2018)

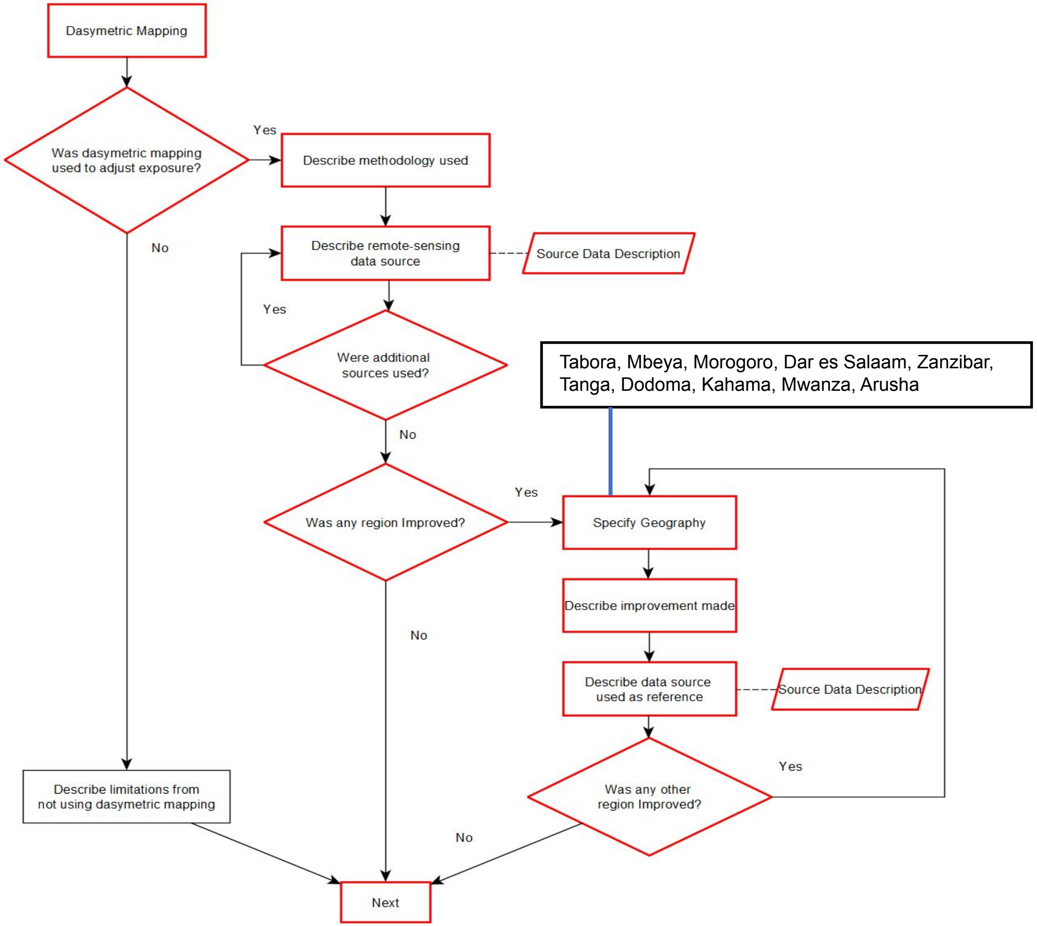
8) Tanzania gridded population from WorldPop 2020 at 3-arcsecond grid cells (WorldPop(2))

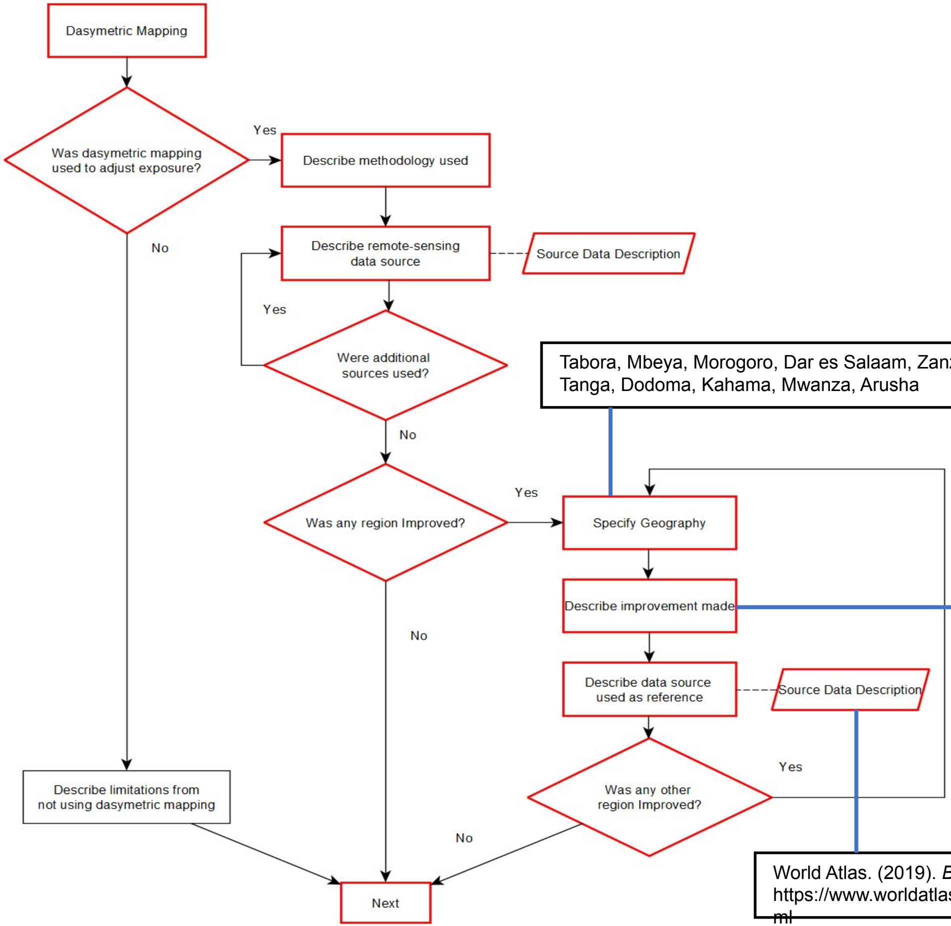
9) An indicator of OSM data throughout the country- building count, area, and maximum building height were calculated from building footprint polygons and aggregated up to create 3-arcsecond grids. (ImageCat, Inc. (2019))



These remotely sensed earth observation products and building footprint aggregates establish the distribution statistics for dispersing buildings by urban density and development pattern type. Each of the EO products, individually or in a combination, act as a weight to disperse the known population per Tanzanian district census level by structural type and determined development pattern to 3-arcsecond grid cells. For determining the weights for distribution within a given district, several machine learning algorithms were run using the EO to develop a prediction model.

To prevent unpopulated areas from being considered as settlements, a mask was created using a minimum threshold value determined by visual inspection of results in Google Earth and with various specific EO datasets, including Sentinel-1 data (Syrris et al., 2018), GUF (DLR Earth Observation Center, 2016), VIIRS (Earth Observation Group NOAA-NCEI, 2015), LandScan (Oak Ridge National Laboratory, 2009), and HRSL (Facebook Connectivity Lab and Center for International Earth Science Information Network [CIESIN], 2016). These minimum values correspond to even the sparsest human presence. This mask was used to subset other high-resolution Sentinel-1 mosaic with dual polarization (Band1 = VH, Band2= linear comparison of VH/VV, Band3 = VV) that goes into the machine learning process to come up with the development patterns. The Global Urban Footprint (GUF), Sentinel-1 SAR based GHSL product, and CIESIN-Facebook High Resolution Settlement Layer (HRSL) were not subset because those data sets were good indicators for locating rural settlements.

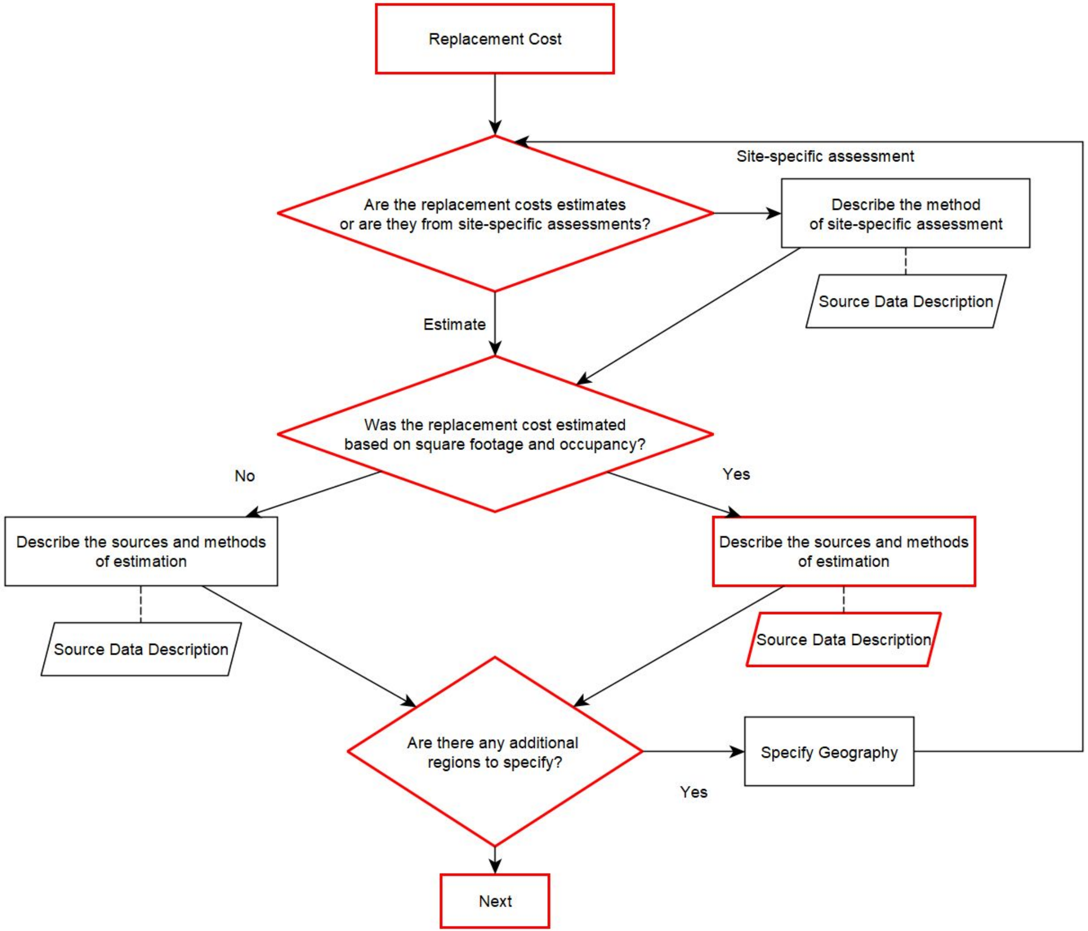

Dasymetric Mapping
Was dasymetric mapping used to adjust exposure?
Yes
Describe methodology used
No
Describe remote-sensing data source
Source Data Description
Yes
Were additional sources used?
Tabora, Mbeya, Morogoro, Dar es Salaam, Zanzibar, Tanga, Dodoma, Kahama, Mwanza, Arusha
No
Yes
Was any region Improved?
Specify Geography
Describe improvement made
No
Describe data source used as reference
Source Data Description
Yes
Describe limitations from not using dasymetric mapping
Was any other region Improved?
No
Next

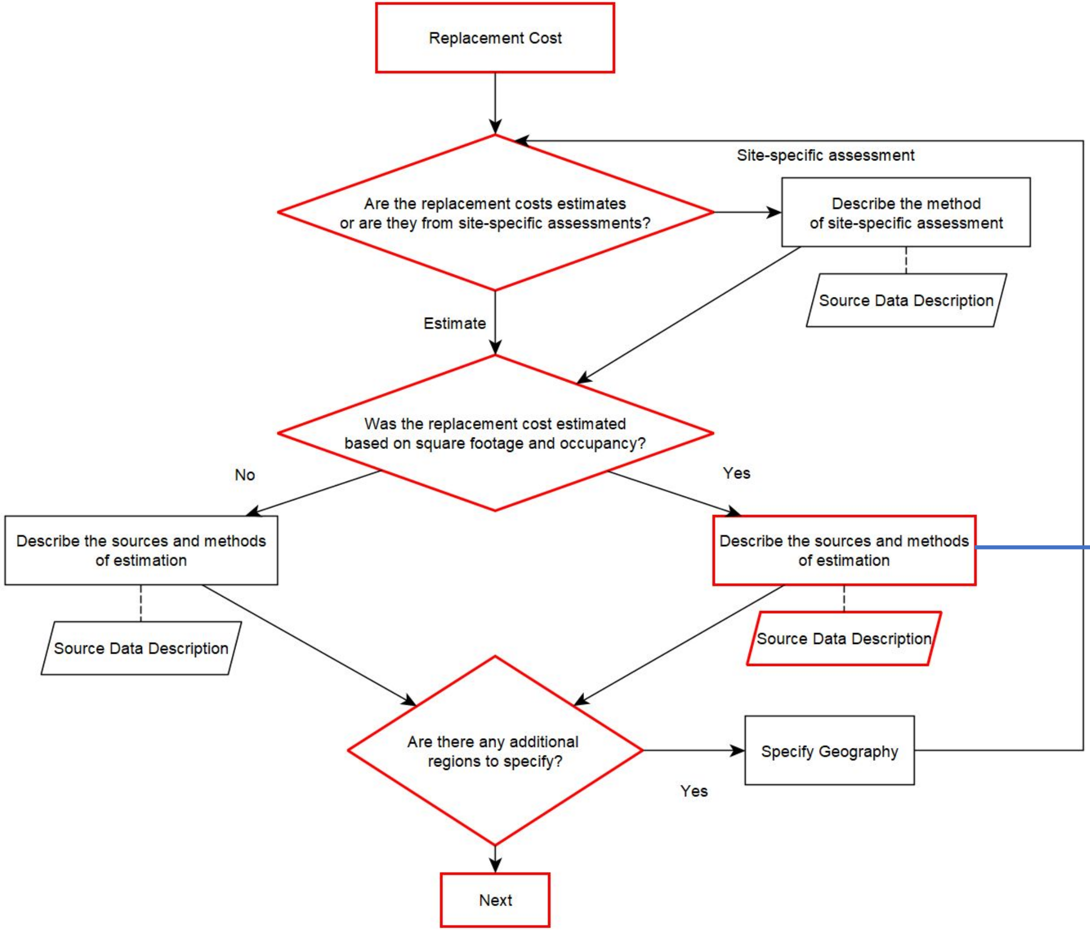


Tabora, Mbeya, Morogoro, Dar es Salaam, Zanzibar, Tanga, Dodoma, Kahama, Mwanza, Arusha

To characterize building density in more populated areas, analysts digitized sample training development pattern polygons in the top 10 most populated cities in the country (World Atlas, 2019; Tabora, Mbeya, Morogoro, Dar es Salaam, Zanzibar, Tanga, Dodoma, Kahama, Mwanza, Arusha). For these cities, the vector data was used directly, rather than the classified development pattern grid. The delineations are digitized using the Google Earth area tool and saved as KMLs. The base map vintage and source vary by region and zoom level. However, the most current high-resolution satellite images are used. The training polygons and the moderate resolution EO products described above are used in a machine learning process (CART algorithm (Breiman et al., 1984; Khaled et al., 2014), Random forest (Breiman, 2001), and Support Vector Networks (Cortes et al., 1995)) for assigning the development patterns throughout the country, which informs the estimated building density. The intensity of urbanity correlates to both the building density and the structural distribution. For Tanzania, the ImageCat engineer characterized 6 development

World Atlas. (2019). *Biggest Cities in Tanzania*. Retrieved from https://www.worldatlas.com/articles/biggest-cities-in-tanzania.html


Replacement Cost
Are the replacement costs estimates or are they from site-specific assessments?
Site-specific assessment
Describe the method of site-specific assessment
Source Data Description
Estimate
Was the replacement cost estimated based on square footage and occupancy?
No
Yes
Describe the sources and methods of estimation
Source Data Description
Describe the sources and methods of estimation
Source Data Description
Are there any additional regions to specify?
Specify Geography
Yes
Next

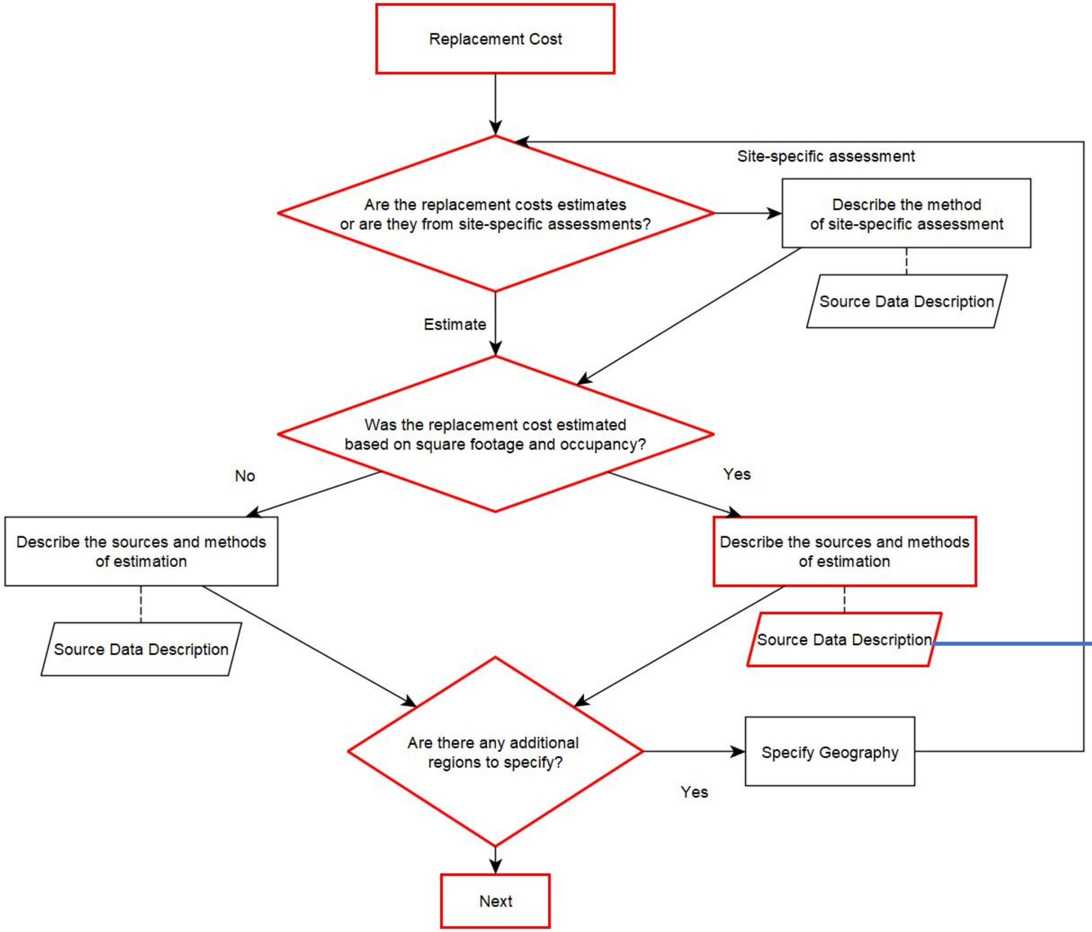


Replacement cost was determined by profiling structural durability by development pattern, as determined remote sensing segmentation and digitization. Structural durability was classified into 3 tiers; temporary, semi-permanent and permanent.

Examples of temporary housing in Tanzania include: earthen, wood frame, and informal structures; semi-permanent includes adobe block, unreinforced masonry; permanent includes reinforced concrete frame and reinforced masonry.

The replacement costs for temporary and semi-permanent structures were gleaned primarily from the resettlement action plans, and the replacement costs for permanent structures were taken from construction cost manuals.

The replacement costs for each development pattern was determined by applying a weight by mapping scheme for each structural type. Work was done under a separate grant for Global Facility for Disaster Reduction and Recovery (GFDRR) and applied to Tanzania (Huyck & Eguchi, 2017).



AECOM. (2017). Africa Property & Construction Cost Guide 2017, Offering global expertise and tailored local solutions in more than 150 countries.

Deloitte. (2012). Deloitte on Africa, Construction on the African Continent: Opportunities, Risks and Trends.

Centre for Affordable Housing Finance in Africa. (2016). 2016 Yearbook, Housing Finance in Africa. Accessed October 2017 from https://housingfinanceafrica.org/app/uploads/CAHF_Housing-Finance-in-Africa-Yearbook-2016.09.pdf

Centre for Affordable Housing Finance in Africa. (2017). Benchmarking Housing Construction Costs in Africa. Accessed November 2017 from http://housingfinanceafrica.org/dashboards/benchmarking-housing-construction-costs-africa/

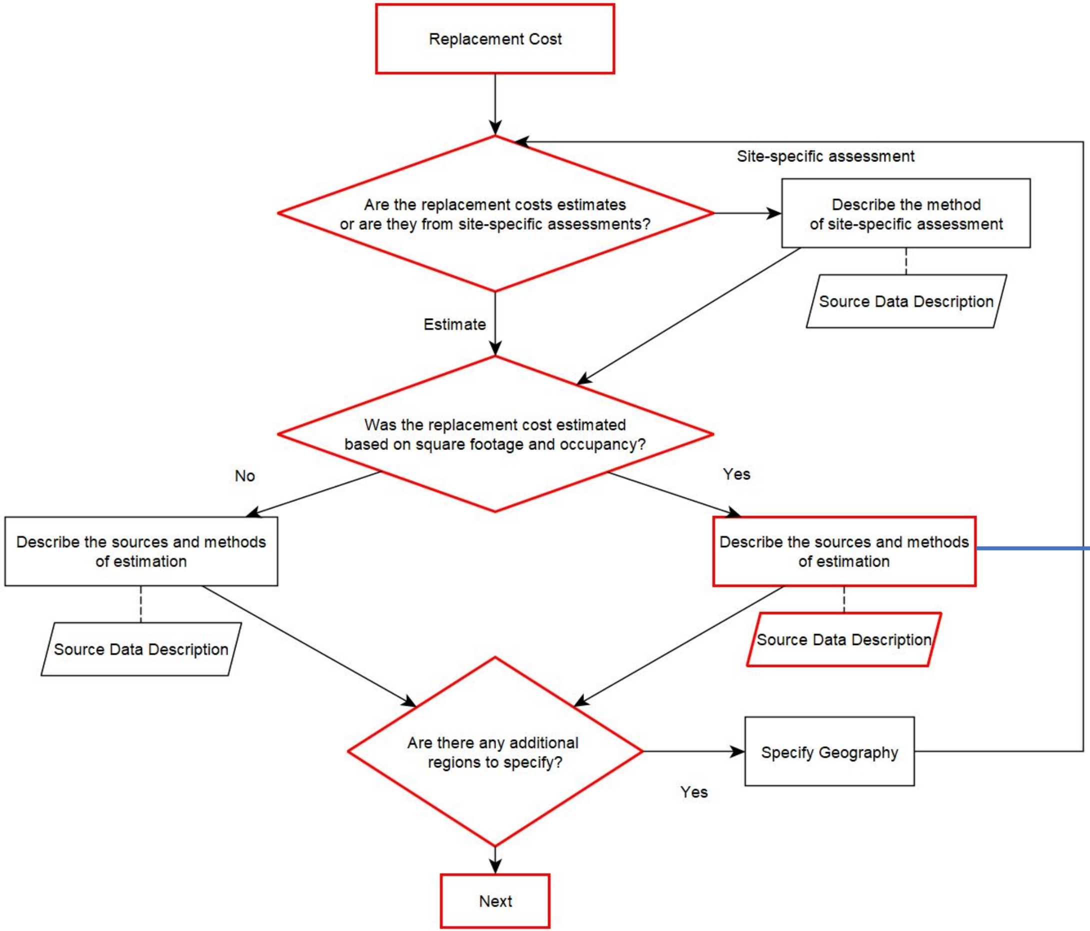
Tanzania National Roads Agency (TANROADS). (2012). Abbreviated Resettlement Action Plan for Properties to be affected by Rehabilitation of Mafinga to Igawa (142km) in Iringa and Mbeya Regions.

Tanzania National Roads Agency (TANROADS) in association with Environmental Benchmark Consulting Engineers. (2012). Abbreviated Resettlement Action Plan for Properties to be affected by rehabilitation of Mafinga to Igawa Road (142 km) in Iringa and Mbeya Regions.

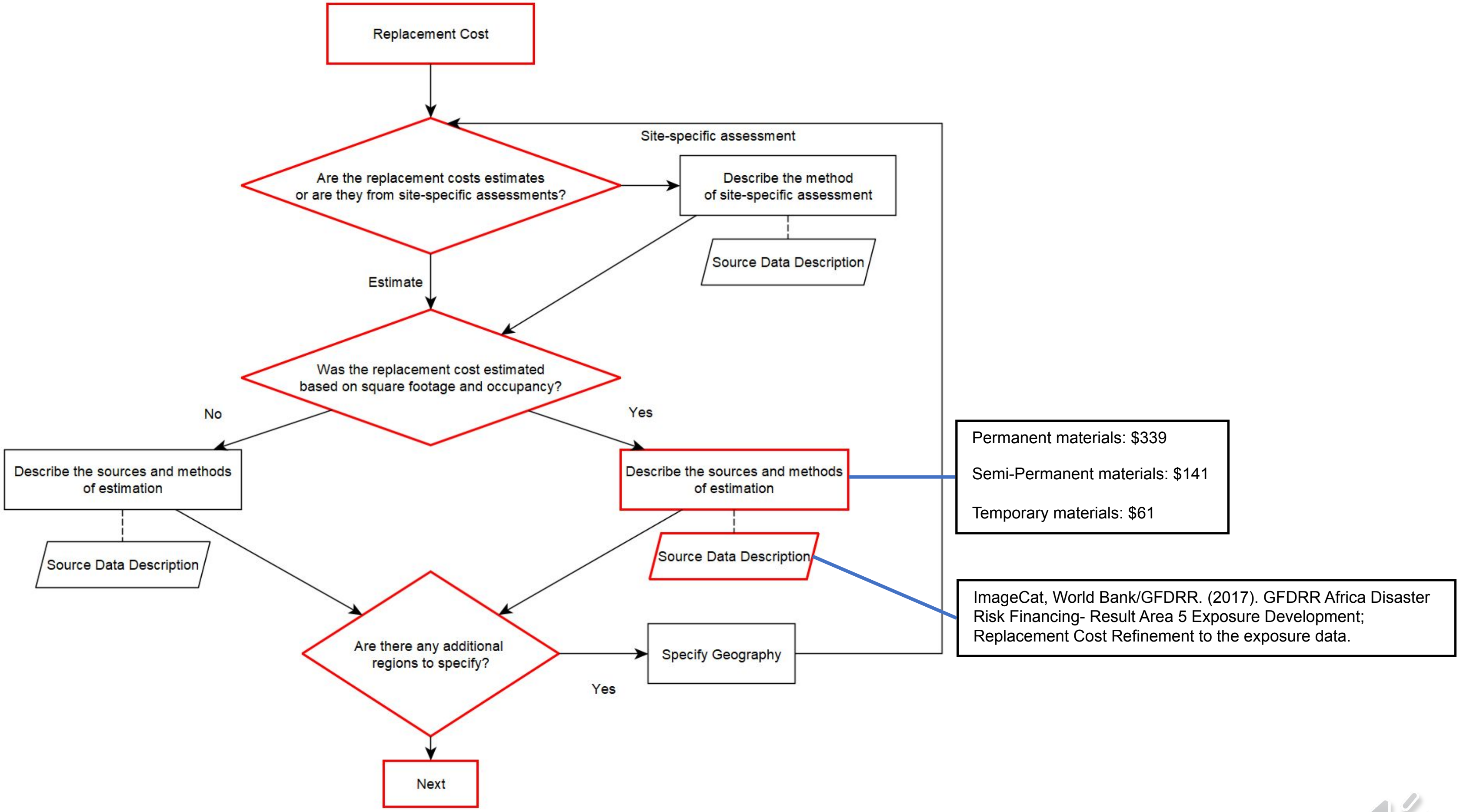
The United Republic of Tanzania, Ministry of Works, TANROADS Regional Manager's Office – Mtwara in association with UWP Consulting, Ltd. (2011). Review and Updating of Environmental and Social Impact Assessment, Economic Valuation and Cost Estimates for the Upgrading of Mangaka-Nanyumbu-Mtambaswala Road (65.5 km) to Bitumen Standard, Resettlement Action plan (RAP).

The United Republic of Tanzania, Prime Minister's Office, Regional Administration and Local Government, Dar Rapid Transit Agency, in association with g Dong Engineering Co., Ltd and Ambicon Engineering Ltd. (2015). 3.2-1 Resettlement Action Plan Report (Phase 2).

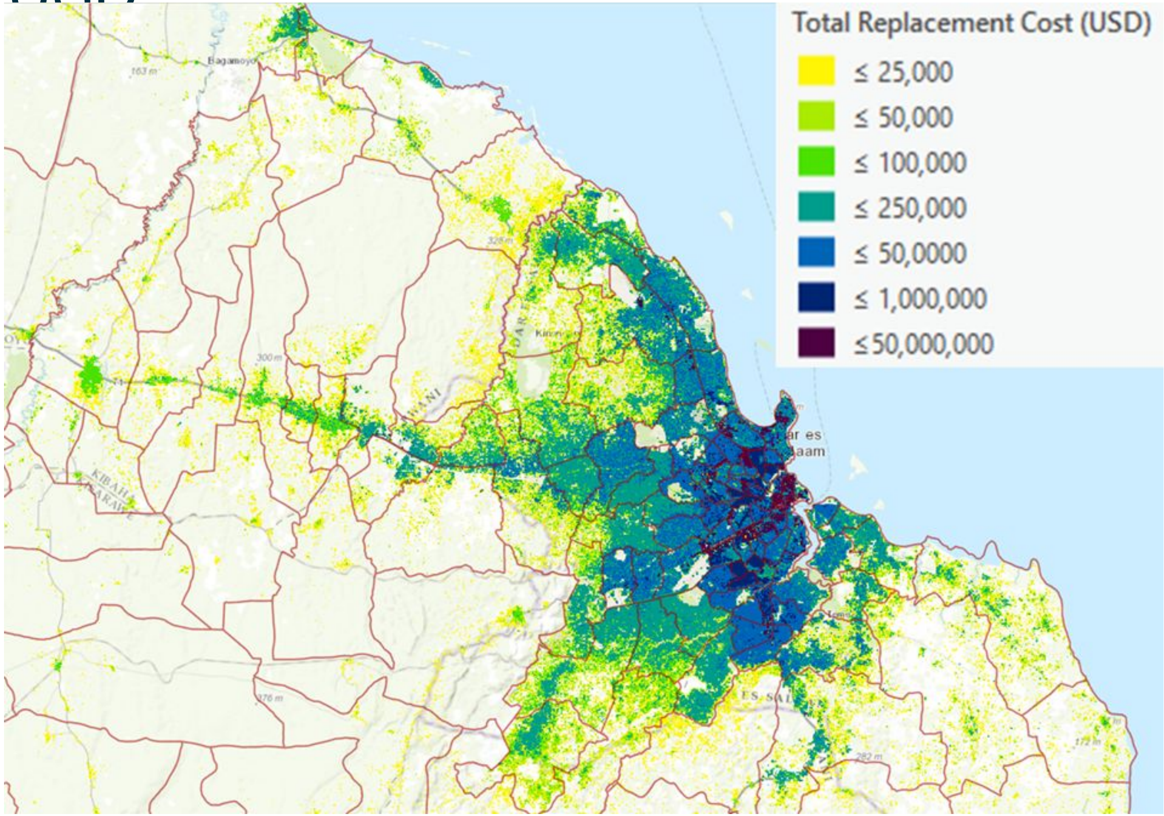
Turner & Townsend. (2017). International construction market survey 2017. Accessed November 2017 from http://www.turnerandtownsend.com/en/insights/international-construction-market-survey-2017/



A ratio was calculated between the durability classes, expressed as a percentage of engineered construction. For example, semi-permanent construction for a given country may represent 40% of the total permanent construction cost, and temporary construction may represent 20% of the total permanent construction cost. The ratio approach is mathematically equivalent to taking the average value by durability class but has the added advantage of providing a basis for comparing the consistency of the approach across countries. Once these prices were established, a matrix of the expected durability class given development pattern was established for all structure types. Typically, these did not vary by development pattern, but in some cases, a structural class such as unreinforced masonry buildings encompass several types of quality and modifying the quality class by development pattern captured the range of quality and replacement cost. These matrices allowed mapping of the new replacement costs to structure class, and by cross-referencing the mapping schemes (percent structure type by country and development pattern), new estimates were produced for replacement cost by country and development pattern.


Replacement Cost
Are the replacement costs estimates or are they from site-specific assessments?
Site-specific assessment
Describe the method of site-specific assessment
Source Data Description
Estimate
Was the replacement cost estimated based on square footage and occupancy?
No
Yes
Describe the sources and methods of estimation
Source Data Description
Describe the sources and methods of estimation
Source Data Description
Permanent materials: $339
Semi-Permanent materials: $141
Temporary materials: $61
ImageCat, World Bank/GFDRR. (2017). GFDRR Africa Disaster Risk Financing- Result Area 5 Exposure Development; Replacement Cost Refinement to the exposure data.
Are there any additional regions to specify?
Specify Geography
Yes
Next

Dar es Salaam Replacement Cost in USD



https://meteor-project.org

BGS British Geological Survey

GEM

HOT

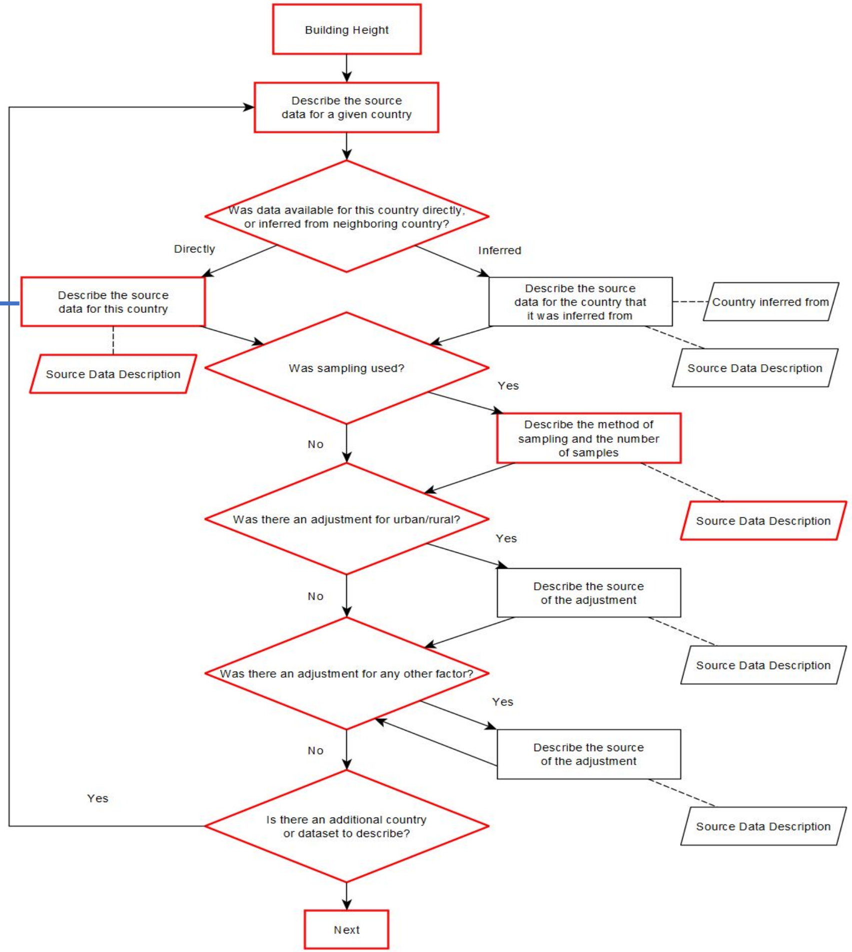
ImageCat

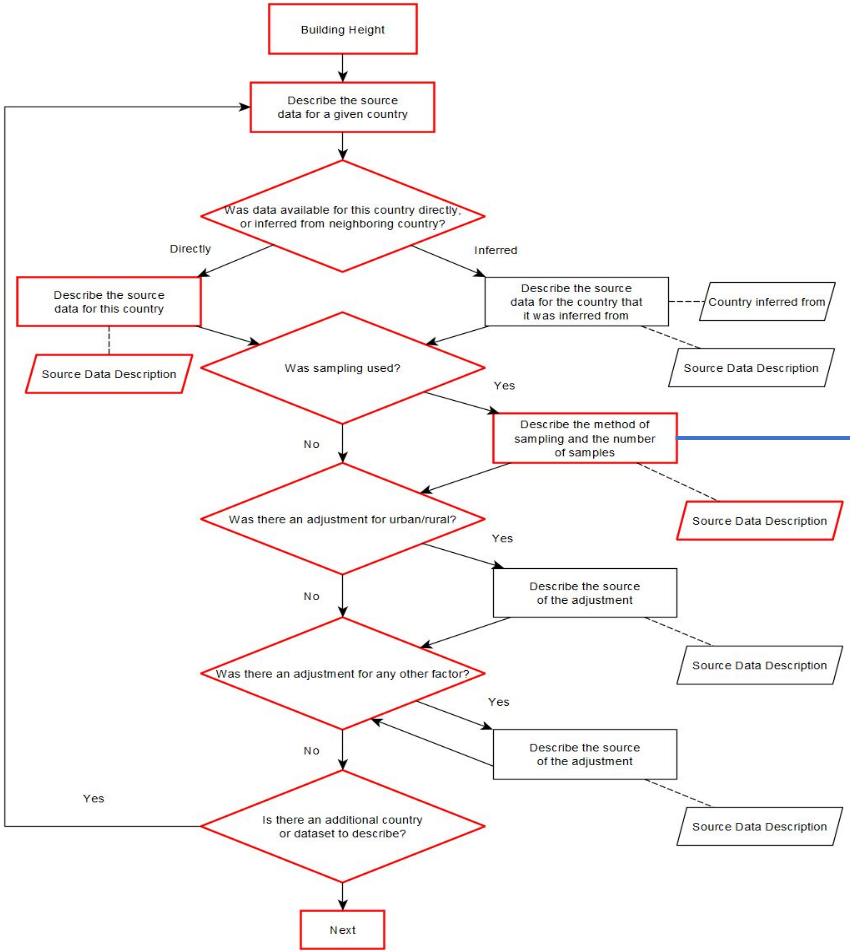
NSET

Oxford Policy Management

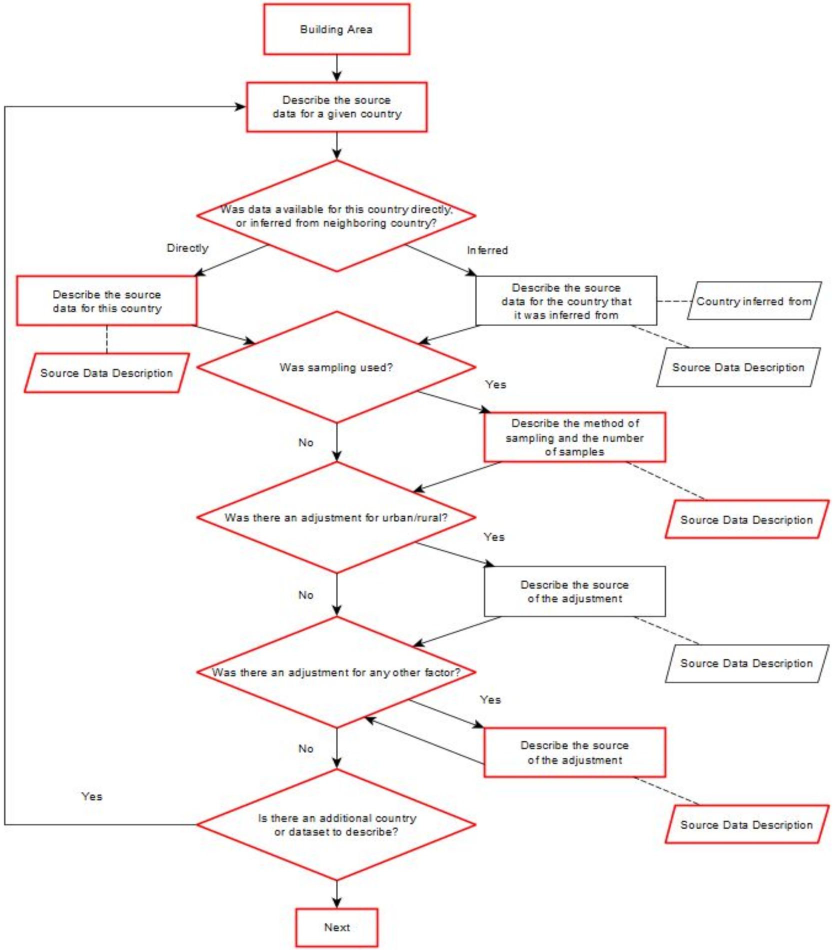
METEOR

The building height values for all development patterns were obtained from the field survey data collected by HOTOSM (Humanitarian OpenStreetMap Team, 2019

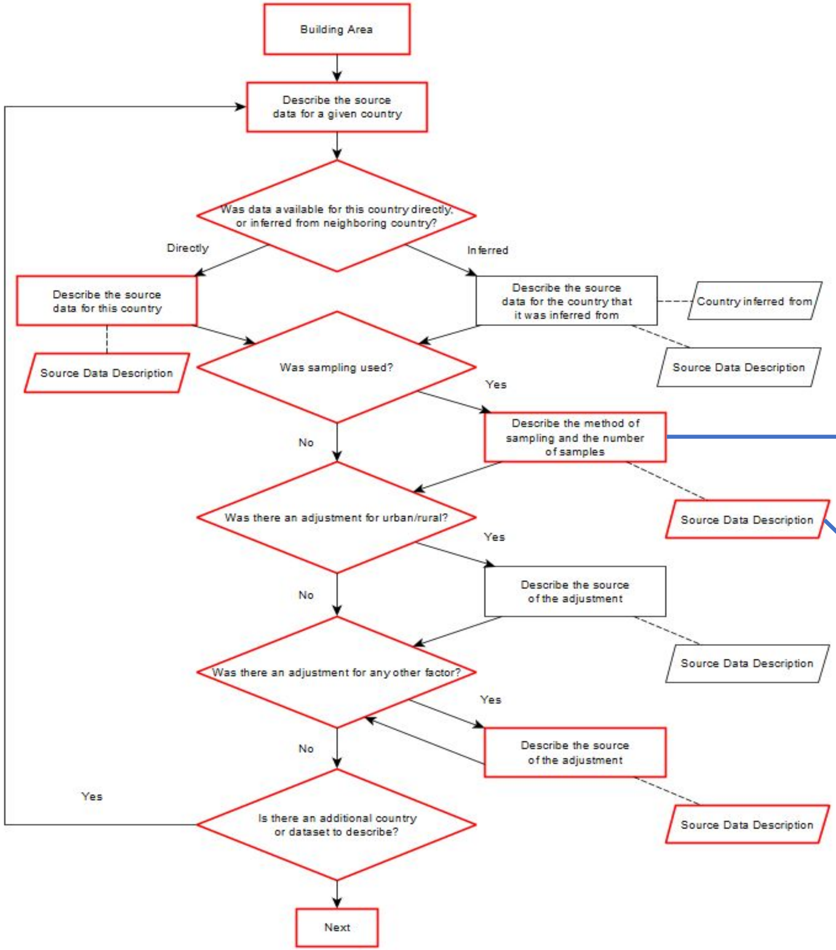




This established the building height by structure type per development pattern type. Rural areas are assumed to be 100% low rise. The HOTOSM survey was reviewed and validated by an in-house engineer using images provided of the individual buildings.



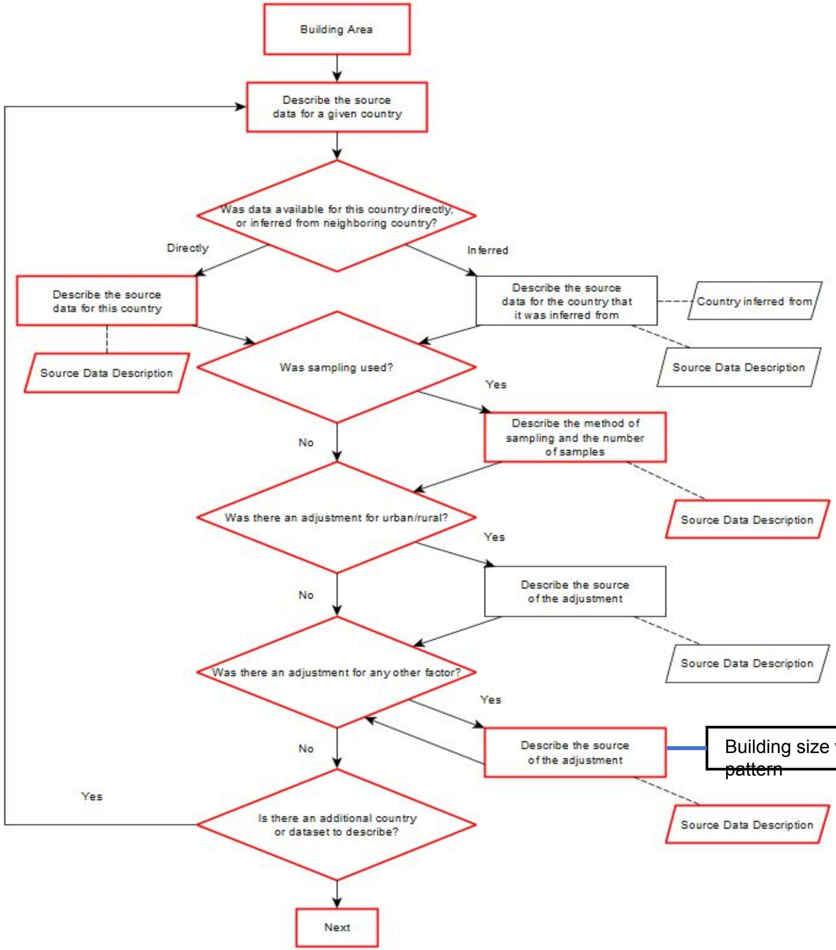
Building Area
Describe the source data for a given country
Was data available for this country directly, or inferred from neighboring country?
Directly
Inferred
Describe the source data for this country
Source Data Description
Describe the source data for the country that it was inferred from
Country inferred from
Source Data Description
Was sampling used?
Yes
No
Describe the method of sampling and the number of samples
Source Data Description
Was there an adjustment for urban/rural?
Yes
No
Describe the source of the adjustment
Source Data Description
Was there an adjustment for any other factor?
Yes
No
Describe the source of the adjustment
Source Data Description
Is there an additional country or dataset to describe?
Yes
Next



The total building area was calculated using a combination of the Humanitarian OpenStreetMap Team (HOTOSM) survey data (Humanitarian OpenStreetMap Team, 2019), and 3-arcsecond aggregated OSM building area raster data sets (ImageCat, Inc., 2019). For the rural development pattern, the average building footprint area from 3-arcsecond aggregated OSM raster was used to determine the average total building area; assuming all rural development are single story. For all delineated development patterns, the HOTOSM in-situ building survey was used to establish the total building area by structure type per development pattern type using the surveyed building footprint and height values.

Humanitarian OpenStreetMap Team (2019). In-situ structural building type, height, and footprint area sampling polygons of Tanzania.

ImageCat, Inc. (2019). OSM building footprint data aggregation to 3-arcsecond raster grid



Building size was adjusted to reflect the urban development pattern

Take-Aways

There is a great deal of information that goes into creating a building exposure database.

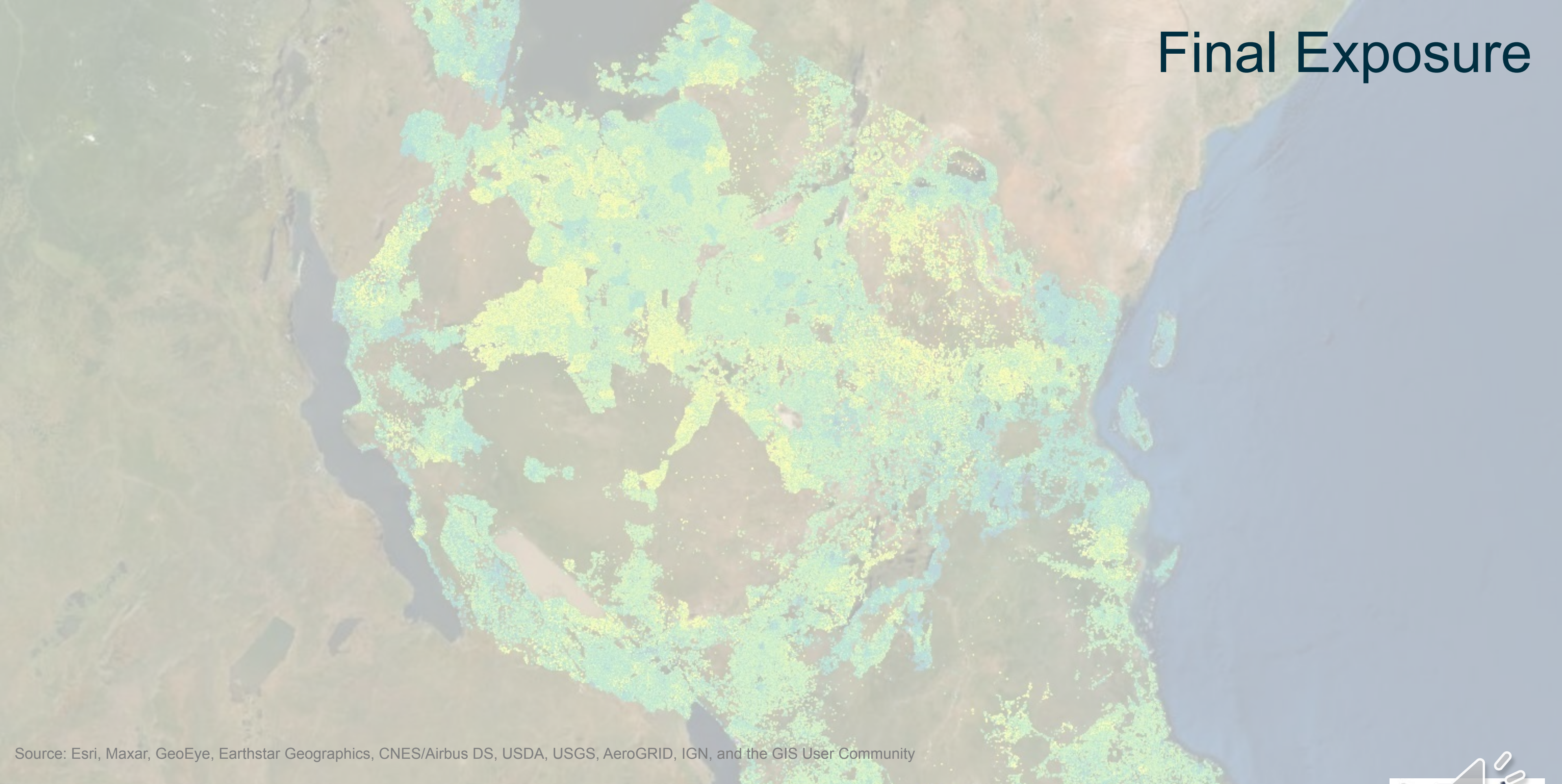
These flowcharts assist in organizing metadata collection and processing step review.

With these flow charts future researchers can update or refine the exposure database as a whole or finely tune an individual section with improved data.

We hope that these flowcharts assist future teams in updating or refining the exposure results.

Source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IG

Final Exposure



Source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

https://meteor-project.org

British Geological Survey

NSET

Oxford Policy Management

METEOR

Source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IG

Thank You

Contact Information: gre@imagecatinc.com

Source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

https://meteor-project.org

British Geological Survey

NSET

Oxford Policy Management

METEOR

Source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IG