# *Author Comment to RREFEREE 2*

# *Interactive* comment on “Enhancement of large-scale flood damage assessments using building-material-based vulnerability curves for an object-based approach” by J. Englhardt et al.

*[RC2_1]: This is a very good paper, focusing on the importance of using building-material-based information in the exposure, vulnerability components of large-scale (global) flood modelling efforts.*

[Our response]: We would like to thank the referee for the time put into the reviewing and the very valuable feedback that helped to improve the manuscript. We are pleased that the reviewer finds it a very good paper.

*[RC2_2]: The paper demonstrates clearly how such work is making significant improvements in flood risk assessment. Another important part is the discussion of spatial capture of urban-rural areas. This merits to also be included in the paper’s title.*

[Our response]: We thank the referee for this comment. We will follow the referee’s suggestion to highlight the distinction of risk in urban and rural areas as an important part of our study and adjust the title to “Enhancement of large-scale flood risk assessments using building-material-based vulnerability curves for an object-based approach in urban and rural areas” (see here also our reply to comment RC1_2 of referee 1).

*[RC2_3]: My review focused more on this aspect of the paper’s content. Please see my comments in the attached PDF file.*

[Our response]: We thank the referee for the feedback. All comments have been numbered and copied into this response document for ease of replying to them.

*[RC2_4]: I am concerned that the estimation of the replacement value of the buildings in Ethiopia shows a big urban-rural divide (buildings per capita exposure being 32 times greater in the urban areas vs the rural areas).*

[Our response]: Please see our reply to comment RC2_A19 of referee 2.

*[RC2_5]: Since this paper is applying the proposed methodology to Ethiopia it is very important to use Ethiopia data. It is necessary to revise the entire section "Object-based exposure data" to include review of the 2007 Ethiopia census.*

[Our response]: The data for the last Ethiopian census were collected in May and November 2007 in both urban and rural areas and since then has seen considerable economic growth (World Bank, 2019a), but unfortunately the already delayed 2017 census was recently further postponed (Reuters, 2019). Two types of questionnaires were used in 2007, whereby a long questionnaire including housing characteristics was administered to 20% of randomly selected households (CSA, 2012). According to the census, the majority of all housing units in Ethiopia were of 'wood and mud' wall material (73.9%), followed by 'wood and thatch / wood only' (13.0%), 'stone and mud' (7.1%), and only minor shares by several other wall materials. As pointed out by the reviewer in comment RC2_A3, this amounted to about 80% of urban units assigned to the mud and wood type of wall materials compared to 72.5% in rural areas where also a large portion (15.5%) of units are of the wood and thatch / wood only type (CSA, 2010). It is part of the ImageCat methodology to apply census-based data which is redistributed and derived to a finer resolution given earth-observation (EO) indicators. EO is used to segment the region into various development patterns which are used for stratified sampling of building characteristics. This approach provides both spatial focusing of assets beyond the census level, which is required for flood risk analysis, and a characterization of the spatial distribution of building characteristics beyond what is typically available in the data (Huyck and Eguchi, 2017).

In all Ethiopian censuses, however, urban areas are defined as localities with 2,000 or more inhabitants, plus the capitals of all regions and sub-zones and further all localities with at least 1,000 people who are primarily engaged in non-agricultural activities as well as other areas declared urban by administrative officials (Schmidt and Kedir, 2009). Therefore, also many smaller settlements are included as urban in the census and different definitions such as thresholds of built-up or population density, or a methodology using building stock like our approach can affect the urban-rural classifications and thus the distributions in these areas. Regarding the entire Ethiopian building stock, ImageCat estimates for the building structure types were initially developed through interviews with local professionals; and confirmed, cross-checked and adjusted with site surveys, scholarly journals (e.g. WHE), visual assessments/sampling process from satellite imagery. Information from the GEM Foundation were provided by the Earthquake Risk Consortium and were also used to "sanity check" the estimates. Obtaining the housing data can be more difficult than the population data - and a consistent approach between countries was a goal of the ImageCat project. If we compare for example class I and II constructions in the ImageCat data (71.6% of the total building stock) to the 2007 census (approximately 97%), the differences are not surprising: Masonry construction is minimal in the 2007 census (2.4%), and reinforced concrete seems non-existent (perhaps included in the "others" category, which accounts for 0.4% of the total building stock), but as observed in the ImageCat project such construction make up the majority in large cities. Furthermore, Ethiopia experienced "strong, broad-based-growth averaging 10.3% [GDP growth] a year from 2006/07 to 2016/17" which appears to coincide with a growth in the construction industry (World Bank, 2019b). For example, based on online imagery and ground observations in the ImageCat project, the sprawl observed through historic satellite imagery since 2007 in Addis Ababa, appears to be a majority of class III and IV. We acknowledge the different results compared to the 2007 census data, and reasons for that discussed here, need to be better highlighted and we will include some information in the revised manuscript (p.22 l.27ff.) (please see also our reply to comment RC2_6).

p.22 l.27ff.

"Nonetheless, as previously discussed in section 3.1, exposure of an area can vary depending on the applied dataset. Using ImageCat data, over half of the construction types in Ethiopia belong to class I, and about 14% towards each of the other classes (see Table 10). However, according to data from the last census in Ethiopia from 2007, 73.9% of all housing units in Ethiopia were of 'wood and mud' wall material, with 80% of the urban units and 72.5% of rural units, whereas a large share of rural units were built with wood (and thatch) walls (15.5%). Compared to the ImageCat data, the Ethiopian building stock appears to be less diverse and shows a different distribution of urban and rural constructions, which is also affected by the applied definition of urban in the census. Since the 2007 census, Ethiopia has experienced considerable economic growth that appears to coincide with growth in the Ethiopian construction industry (World Bank, 2019). Furthermore, census data are aggregated to administrative levels and thus cannot be applied in the approach developed in this paper, for which an object-based dataset is required that is also comparable between countries, such as the ImageCat data. With different methodologies in exposure datasets, future research should explore how flood risk assessments that are based on building-material-based vulnerability are affected by the applied building stock dataset and their different scales."

*[RC2_6]: Once this is done it will be also apparent that the section "3.2. Flood risk assessment" also needs to be revised because the building stock distributions of classes I to IV in Ethiopia are quite different to what the authors have probably assumed. In this section a Table of classes I, II, III, III2 and IV distribution of the building footprints in urban and rural Ethiopia used in the model is not shown and this is an important omission.*
*This part of the work, i.e. the passing from census data to classification of the building vulnerability classes and the building footprints needs to be much more clearly explained than it is in the present version with some additional references for the ImageCat methodology.*

[Our response]: Our study presents an approach for using building-material-based vulnerability in large-scale flood risk assessments. As described in the introduction chapter, traditional models aggregate the exposed elements into land-use categories, whereas in our alternative approach we are using the object-based data from ImageCat. As such, the Ethiopian census data that the reviewer suggests cannot be directly applied and has several disadvantages. For example, compared to the ImageCat data, the census data are aggregated to administrative levels that have different spatial extents and are not comparable throughout the country. In our flood risk assessment, we can overlay the inundation maps with the finer resolution dataset from ImageCat to identify exposed areas. Moreover, the Ethiopian census follows a methodology set out by the country's statistical agency, meaning that the definitions of urban and rural areas are different to those in other countries, which is contradicting to one of the aims of this study to develop a methodology that could also be used in other regions. Furthermore, using census data for a building-material-based approach would require going back to a model setup up similar to land-use-based flood risk models due to the aggregation in the census data. In our manuscript Ethiopia is an example to which we apply the approach we developed. Using large-scale datasets that have a consistent methodology to provide exposure data for many countries such as the object-based ImageCat data allows us to analyse flood risk based on building material vulnerability outside of resource-intensive local studies and apply one approach in order to achieve comparability between countries. In combination with the adjustments to the manuscript in response to comment RC2_5, more information will be included on the differences between datasets and an overview of the building stock distribution in the ImageCat data (p. 22 l.27ff. and Table 10). Finally, we like to point out that we are currently working on a follow-up paper which focuses on analysing different approaches and compares flood risk assessments for several countries using different building exposure datasets. Regarding the building footprints, Table 10 in combination with the overview in Table 3 allows the reader the reproduction of building footprints per class and land use. We will also add some more information regarding the ImageCat estimation of building area to the manuscript. (See here also comment RC2_A1).

p.23 l.16

**“Table 101 Ethiopian building stock according to ImageCat data”**

| Type | Description | % total building stock | Class | % urban building stock | % rural building stock |
|---|---|---|---|---|---|
| ADB | URM adobe building | 4.1 | I | 3.4 | 72.0 |
| ERTH | Earthen building | 3.9 | | | |
| INF | Informal building | 9.4 | | | |
| WWD | Wattle & daub building | 39.7 | | | |
| WLI | Light wood building | 1.0 | II | 2.0 | 18.0 |
| WS | Solid wood building | 13.5 | | | |
| BRK | URM brick building | 6.1 | III | 29.9 | 10.0 |
| STN | URM stone building | 8.2 | | | |
| RC | Reinforced concrete frame with URM infill building | 13.9 | IV | 64.8 | 0.03 |

*See RC2 supplement https://www.nat-hazards-earth-syst-sci-discuss.net/nhess-2019-32/nhess-2019-32-RC2-supplement.pdf [RC2_A1]: Census data usually report the number of housing units (incl. in Ethiopia). Some explanation as to how these data have been used to derive information on the number of residential and non-residential "buildings" is needed.*

[Our response]: We thank the reviewer for the comment. Given that most of the residential building stock is single family housing, the number of housing units is used directly from the census data in the ImageCat data and in there, apart from the development patterns, not further differentiated. We will include this in combination with further information on the ImageCat methodology (p.9 l.5ff.). (See here also comments RC2_6).

p.9 l.5ff.

"For the building numbers the Ethiopian census data on housing units was used directly in most regions as the building stock is mostly single family housing. The living area was gleaned from sampling building footprint data, and as with structural characteristics, varies by development pattern. For a predominantly commercial pattern, building stock data is adjusted with exposure derived from building footprint data. The number of floors can vary by development pattern, but for the vast number of buildings is single story for most of the country. For highly urbanized areas the number of stories was adjusted through expert opinion of several country-based structural engineers (Huyck and Eguchi, 2017)."

*[RC2_A2]: This Reference is missing*

[Our response]: We apologize for the oversight and will include the reference.

*[RC2_A3]: In the 2007 census of Ethiopia the most common wall-type is "Mud and Wood" forming 80% of houses in Urban & 72.5% in Rural. In rural areas the next most common are "Wood and Thatch / Wood only" (15.5%).*

[Our response]: Please see the response to comment RC2_5.

*[RC2_A4]: In future, if the data allow, differentiating vulnerability between clay bricks, stones and concrete blocks should be considered.*

[Our response]: We agree with the reviewer that future research would benefit from further differentiation within the current vulnerability classes, if and when sufficient data becomes available. We will add this suggestion to the manuscript in combination with our response to comment RC2_A5.

*[RC2_A5]: These buildings tend to have more non-structural elements that can be vulnerable to flooding especially in Africa's Urban areas e.g. air conditioning units, partition walls, mechanical & electrical components, etc. that would need to be considered both in terms of their contribution to the overall building replacement value and their vulnerability. At a future stage.*

[Our response]: While the focus of our study is the structural vulnerability, we agree that future flood risk assessments would benefit from including further components of the buildings and will add this to the recommendations for future research (p.24. l.28ff.).

p.24 l.28ff.

"Furthermore, if the data allows in the future, vulnerabilities within the classes could be further refined such as between clay, stone and concrete brick/block construction or regarding non-structural elements like electrical components and partition walls."

*[RC2_A6]: This needs a Reference and brief explanation of how it was developed. In particular how the number of floors was estimated.*

[Our response]: Please see our response to comment RC2_A1.

*[RC2_A7]: As use is also made of PAGE v2.0 classification system, an additional column is needed to map the ImageCat classes to the PAGER classes.*

[Our response]: We thank the reviewer for this comment, and we will add an overview of assigned classes to the PAGER typology and include further information on the different construction types to the revised supplements (see supplementary section 1 and supplementary table 1) and add a note to that at table 2.

*[RC2_A8]: URM = unreinforced masonry, RC = reinforced concrete - must be added for the benefit of those less familiar with these acronyms*

[Our response]: Please see our response to comment RC2_A7.

*[RC2_A9]: DS & STN are similar. Briefly explain their differences.*

[Our response]: Please see our response to comment RC2_A7.

*[RC2_A10]: RC and C3 are similar Briefly explain their differences.*

[Our response]: Please see our response to comment RC2_A7.

*[RC2_A11]: "Earthen", "Mud walls", "Rammed earth", "Adobe" are very similar typologies. Briefly explain their differences.*

[Our response]: Please see our response to comment RC2_A7.

*[RC2_A12]: URM stands for "unreinforced masonry". BRK, CB, are very similar UFB, UCB respectively. Briefly explain their differences.*

[Our response]: Please see our response to comment RC2_A7.

*[RC2_A13]: Add also this Ref: Jaiswal, K. S., Wald, D. J., and Porter, K. A. (2010a). A Global Building Inventory for Earthquake Loss Estimation and Risk Management. Earthquake Spectra*

[Our response]: We will include the suggested reference.

*[RC2_A14]: In PAGER for Africa there is the problem that only 19 of the 56 countries have original data (and of these 6 are from 1993), the rest are based on "neighbor country". Also these data are primarily distributions of the housing units, not the Residential + Non-Residential buildings, and in urban areas the building distributions would be quite different due to many houses being in apartment buildings. Also differentiation for Urban-Rural and Residential-Non-Residential exists only for 2 countries (Algeria & Morocco). The value of 2% in Urban is for Algeria. In rural Algeria this value is 15%. In the 2007 Ethiopia Housing census the ratio of class I & II in Urban is 89% (81% in Addis Ababa) which would challenge the rural hypothesis (>50%)..Since this paper is examining Ethiopia it would be better to use the data from the 2007 Ethiopia Census (also available in PAGER v2) that gives distributions of the housing units in urban and rural areas or use the distributions of Ethiopia in PAGER (though they do not differentiate urban-rural).*

[Our response]: We thank the reviewer for the comment and further clarified PAGER and the selection in the manuscript (p.10 l.4ff.). The literature provides only little information on differences between building stock in urban and rural areas, usually the focus is on one of the areas and/or housing durables and quality. However, the PAGER dataset provides estimates of building stock inventory on a global scale. The information basis for these estimates is better for some countries than others and for many African countries the estimates are based on neighbouring countries. Therefore, we included in Figure 3 not only the distribution of class I and II construction types in urban and rural areas for Africa, but also for different income groups. The average class I and II share in urban areas is higher (10%) for the low and lower middle income countries than the African average (2%), however there is a clear difference to rural areas with (36% class I and II in lower and lower middle income countries and 22% for African countries). This information in PAGER indicates that there are distinct differences between the built environment in urban and rural areas. The threshold we set in our approach is set even higher (>50% class I and II), which means that an area classified as rural is dominated by more traditional and less expensive housing. We acknowledge in the manuscript that the presented approach to differentiate urban and rural can be applied if the building stock is more heterogeneous, but similarly to other products additional indicators for example population density could be further incorporated to refine the approach (p.18 l.18ff., p.24 l.21ff.). Furthermore, as we showed in section 3.1, the urban-rural map derived with our approach is comparable to other maps that are classified from remote sensing data and/or using several input parameters.

p.10 l.4ff.

"To check the assumption that the share of class I and II buildings in developing countries is higher in rural areas compared to urban areas, we examined these shares in the PAGER dataset (Jaiswal and Wald, 2008; Jaiswal et al., 2010). PAGER is a global residential and non-residential building inventory at the country level (usually but not exclusively expressed in proportions of people living or working in particular building structure typologies in urban and rural areas respectively), which is often used in earthquake research. PAGER provides information at a country level on the construction types that make up the total urban and rural building stock., though the information quality is varying between countries. First, we reclassified the PAGER construction types into the four flood vulnerability classes used in our study (see Supplementary table 1). Then, we calculated the percentage of buildings in PAGER's total urban and rural building stocks that are categorised as class I and II (Figure 3). The building stock differences between urban and rural areas can be found to a changing degree in all groups. While there is a distinct gap suggested for Africa, PAGER has to rely there on very limited information (i.e. only 2 of the countries differentiate urban and rural building stock without judging on information from neighbouring countries). Nevertheless, the data for urban and rural building stock distribution compared by income level also indicates this differences in the built environment. In low and lower middle income countries, the percentage of buildings in class I and II is indeed much higher in rural areas (36%) than in urban areas (10%). These differences are far less pronounced for higher income countries. The chosen threshold to identify rural areas in the ImageCat dataset (>50%) is larger than the average share we find in PAGER (Figure 3). This means that cells identified as rural using the ImageCat data information about the built environment with the chosen threshold are quite likely to indeed be rural."

*[RC2_A15]: Add in the Supplementary References: Congalon, 1991*

[Our response]: We apologize for the oversight and will include the reference.

*[RC2_A16]: This reference is a GFDRR report, but "Replacement Cost Refinements to the Exposure data" is not included. As it is a crucial reference, it would be good to include a Reference where this would be explained. The same stands for the reference ImageCat et al. (2017), "Exposure Development for 5 Sub-Saharan African countries"*

[Our response]: ImageCat et al. (2017) and Huyck and Eguchi (2017) are both included in the reference list. The Huyck and Eguchi (2017) reference is a report not yet published by GFDRR, about the ImageCat data for several African countries. This report also covers the ImageCat approach to estimate replacement costs. Further information then provided in these references or given in accompanying articles (see for example references used on p.3 l.26ff.) is proprietary information of ImageCat.

*[RC2_A17]: Please provide more explanation as to why "Class II 2 floors" has nearly 5.6 times greater footprint than "Class II 1 floor".*

[Our response]: We know from the ImageCat data that most of the buildings in these classes are larger, which is further confirmed by the ImageCat description for Ethiopia of the typical building stock in different areas which reports that those buildings are predominantly found in urban environments with for example many apartment blocks instead of single family buildings. We will adjust the building footprint description in the manuscript to reflect the difference and its explanation (p.13 l.13ff.).

p.13 l.13ff.

"The buildings of class III and IV with multiple floors have a much greater footprint than the one assigned to the other classes. While buildings with smaller footprints are primarily single family residential structures or within informal settlements, the buildings of the last two classes are mainly found in urban environments, with many of them being long apartment blocks with very large building footprints leading to a larger average footprint. The resulting building footprints for Ethiopia can be seen in Table 3."

*[RC2_A18]: ditto*

[Our response]: Please see our response to comment RC2_A17.

*[RC2_A19]: These values when summed would suggest that the replacement value of Ethiopia's building stock is assessed at 384% of 2016 GDP. The per capita buildings exposure would be ca 11,730USD in Urban & 360USD in Rural, i.e. a factor of 32 in per capita exposure between Urban & Rural. Both of these indicators are big and need to be corroborated by other socio-economic evidence given that most ETH houses are "mud & brick" type. The differences in urban and rural housing in Ethiopia need to be investigated to gain more insights. The 2007 census gives data on type of outer walls, roof cover, floor, ceiling but also other factors that influence the RV of a house. For the time being the only available resource is the 2007 Census, as the 2019 Census was indefinitely postponed.*

[Our response]: We thank the reviewer for this comment. In this paper we present a large-scale flood risk assessment approach that is particularly interesting for areas where there is a large variation in construction types, and provide the application in Ethiopia as an example. Therefore, when calculating the maximum damage values, we are using the Huizinga et al. (2017) dataset of country-specific construction costs based on a globally consistent process for a non-biased comparison between different countries and differentiate from it maximum damage values for our vulnerability classes. Huizinga et al. (2017) describe in their report that information available about flood damage and construction cost values in Africa to inform their approach is very sparse. Consequently, for many countries, especially low income countries, it is more difficult to reproduce the construction costs and they applied non-linear regression for better representation.

We acknowledge that the difference in the total values we calculate for urban and rural areas is high. Firstly, this can in part be attributed to the fact that urban areas are defined in our approach by a greater proportion of higher value buildings (class III and IV). As we discuss in the manuscript (p.18 l.20ff., p.24 l.22ff.), this can lead to a higher exposed value of the urban built environment, as for example urban slums could be misclassified as rural areas. As pointed out by the reviewer, the Ethiopian building stock value in our study surpasses its 2016 GDP. However, a country's building stock is created over decades and continuously developed and can therefore exceed GDP. For example, when taking the 2016 GDP and value of all dwellings from the Dutch statistical office, even in the Netherlands the residential building stock has a value of 245% of the country's GDP and the per capita exposure is 102,000USD (CBS, 2019). We might also look at GDP exceeding damage and losses from natural disasters, according to IWF studies for example events on the pacific islands such as cyclone Nigel in Vanuatu with damage of 131% of the country's GDP in 1985 or in the Caribbean like the 2010 Haiti earthquake with about 120% (Cabezon et al., 2015; Lee et al., 2018). Secondly, while there is no data that would be sufficient to quantify gaps in urban and rural exposure, some information can indicate the level of difference in urban and rural areas. According to the census data the rural population in Ethiopia is 5 times the urban population, and out of the 90% of the rural housing units that own livestock, in more than half of them the livestock spend the nights in a room with people. Furthermore, considering household size the difference between urban and rural is already reduced to factor 25 as more people live in rural households, with an average rural household size at 4.9 persons (urban 3.8) (CSA, 2010). Literature about indicators that might inform differentiations between urban and rural housing are mostly surveyed for households in urban areas (e.g. Adeoye, 2016; Gulyani et al., 2018), or regarding low-cost and informal living in urban areas (e.g. Govender et al., 2011; Simiyu et al., 2018), and/or are focused on the living conditions in terms of health and sanitation (e.g. Ashebir et al., 2013; Sahiledengle et al., 2018). The Demographic and Health Survey for Ethiopia also showed large differences for flooring material in urban and rural households which was the only structural characteristic surveyed: While about 67% of urban households have higher quality floors[1], only about 4% of rural floors are of these types (CSA and ICF, 2016). Also the 2007 census shows that over 86% of urban housing units get their drinking water from taps in- or outside the house or compound compared to only 15% for rural ones which otherwise use wells, springs, river, etc. as their source; similarly, 75% of rural housing units have no toilet facility which is the case for 28% in urban settings (CSA, 2010). Such differences in drinking water, sanitation and floor material illustrate that there are large differences for the living conditions in the two areas and give an indication about the difference in exposed value.

In order to better illustrate the urban and rural gap, we will include information about housing quality to the end of section 2.3 (p.14 l.10ff.).

p.14 l. 10ff.

"Similarly, there is also a large gap between the living standard in rural and urban areas. The last Ethiopian census in 2007 (CSA, 2010) and the 2016 DHS report (CSA and ICF, 2016) provide some indications for rural and urban households that show huge differences in household durables and quality, for example more than half of the rural household with livestock share at night the room with the animals, or high quality floors in two thirds of urban households compared to only 4% of floors in rural households. The contrasts shown there in housing characteristics such as sanitation, drinking water and flooring material illustrate that there are large differences in living conditions which indicate similar differences in exposed urban and rural value."

*[RC2_A20]: Please add the statement mentioned in the Supplement i.e. "The inundation associated with each return period is assumed to occur everywhere simultaneously".*

[Our response]: We will include the statement in the revised manuscript (p.14 l.18).

[1] Parquet or polished wood, vinyl or asphalt strips, ceramic tiles, cement, carpet

*[RC2_A21]: This would be expected to differ in urban and rural parts?*

[Our response]: While urban areas often seem to have better flood protection than rural areas, Scussolini et al. (2016) do not differentiate their data and no further information on protection standards is available.

*[RC2_A22]: More recent datasets suggest: UN World Urban Prospects report (for 2014) Ethiopia Urban Popul. 19%, World Bank's 2016 estimate is at 19.9%.*

[Our response]: We will adjust the statement to include more recent urban population estimates (p.15 l.19).

p.15 l.16ff
"The area in Ethiopia categorized as urban or built-up is relatively low in all data sources and is in accordance with Ethiopia being one of the least urbanized countries in Sub Saharan Africa, with the share of urban population being according to Schmidt and Kedir (2009) only between 11% and 16%, or according to more recent data from the World Bank (2016) at about 20%."

*[RC2_A23]: This may not be the case in Ethiopia as suggested by the 2007 housing census*

[Our response]: Please see our response to comment RC2_5, RC2_6 and RC2_A14.

[Our response to referee's grammatical/typo corrections and rephrasing]: We like to thank the referee for pointing out parts of the text that needed corrections or where additional information was suggested to provide for further clarification for the reader. The manuscript was adjusted where necessary.

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# Enhancement of large-scale flood ~~damage~~ risk assessments using building-material-based vulnerability curves for an object-based approach in urban and rural areas

Johanna Englhardt[1], Hans de Moel[1], Charles K. Huyck[2], Marleen C. de Ruiter[1], Jeroen C. J. H. Aerts[1], Philip J. Ward[1]

[1]Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, De Boelelaan 1087, 1081HV Amsterdam, The Netherlands
[2]ImageCat Inc., Long Beach, CA 90802, USA

*Correspondence to*: Johanna Englhardt (j.englhardt@vu.nl)

**Abstract.** In this study, we developed an enhanced approach for large-scale flood damage and risk assessments that uses characteristics of buildings and the built environment as object-based information to represent exposure and vulnerability to flooding. Most current large-scale assessments use an aggregated land-use category to represent the exposure, treating all exposed elements the same. For large areas where previously only coarse information existed such as in Africa, more detailed exposure data ~~is~~ are becoming available. For our approach, a direct relation between the construction type and building material of the exposed elements is used to develop vulnerability curves. We further present a method to differentiate flood risk in urban and rural areas based on characteristics of the built environment. We applied the model to Ethiopia, and found that rural flood risk accounts for about 22% of simulated damage~~s~~; rural damage~~s are~~ is generally neglected in the typical land-use-based damage models particularly at this scale. Our approach is particularly interesting for studies in areas where there is a large variation in construction types in the building stock, such as developing countries. ~~It also enables comparison across different natural hazard types that also use material-based vulnerability, paving the way to the enhancement of multi-risk assessments.~~

## 1. Introduction

Globally, floods are one of the main natural hazards in terms of socioeconomic impacts, causing billions of dollars of damage each year. For example, between 1980 and 2013, global flood damage~~s~~ exceeded $1 trillion, and resulted in ca. 220,000 fatalities (Dottori et al., 2016). Reducing disaster risk, such as from flooding, is globally very high on the political agenda. For example, it is an important aspect of both the Sendai Framework for Disaster Risk Reduction (UNISDR, 2015) and the Warsaw International Mechanism for Loss and Damage Associated with Climate Change Impacts (UNFCCC, 2013). To achieve this reduction in risk at the global scale requires methods to quantitatively assess global flood risk (Mechler et al., 2014). Here, flood risk is defined as a function of three components: hazard (e.g. flood extent and depth), exposure (assets and people exposed), and vulnerability (factors that determine the susceptibility of the exposed assets to the hazard) (UNISDR, 2015).

Global flood risk assessments are increasingly used in decision-making and practice, and have been useful for identifying flood risk hotspots (e.g. Ward et al., 2015). In an ideal situation, such flood risk assessment models could use detailed, high-resolution data for all locations around the globe (Jonkman, 2013). In practice, data and resources required for such models rarely exist, and therefore global flood risk models have been developed. Current global flood risk models often use resolutions between 30” x 30” and 0.5° x 0.5° to assess the exposed assets (e.g. Alfieri et al., 2013; Arnell and Gosling, 2016; Ward et al., 2013). Recently, much effort has been put into improving global risk models, mainly by improving the hazard component (e.g. Dottori et al., 2016; Ikeuchi et al., 2017; Sampson et al., 2015; e.g. Trigg et al., 2016). However, much less attention has been given to improvements in the representation of exposure and vulnerability, despite the fact that their overall contribution to uncertainty is large (de Moel and Aerts, 2010).

In large-scale assessments, i.e. regional to global levels, exposure is generally represented based on aggregated land-use categories, especially in regions where only limited data are available, such as Africa (de Moel et al., 2015). Whilst using such data provides a useful first assessment of large-scale damage~~s~~ and risk (e.g. Feyen et al., 2011; Hall et al., 2005; Ward et al., 2013), more detailed information of the exposed objects could improve these assessments. Vulnerability is mostly represented using stage-damage functions, also known as vulnerability curves, which describe the relationship between the potential damage~~s~~ of the exposed elements for different levels of the hazard (usually water depth). These functions can represent physical vulnerability, which we refer to in this paper, however not social vulnerability (i.e. characteristics that influence a person’s or group’s capability of dealing with the impact of a natural hazard), or other vulnerability dimensions (e.g. institutional, economic, environmental) (Fuchs, 2009; Papathoma-Köhle et al., 2017). For large-scale studies, a vulnerability curve is generally developed for each of the aggregated land-use categories used to represent exposure (Ward et al., 2013).

Whilst aggregated land-use categories may be a suitable option to represent exposure if data are limited, they cannot reflect the (spatial) heterogeneity within each land-use category (Wünsch et al., 2009). For instance, large-scale flood risk models usually focus on an ‘urban’ category that aggregates exposed elements of various types (e.g. houses, infrastructure, shops, green areas etc.) into one land-use class (Ward et al., 2015). Since an aggregated land-use category like ‘urban’ is coupled to one ‘urban’ vulnerability curve, these curves generalise the relationship between flood depth and damage across all of the diverse exposed element types within that category. Without a more direct relation between these types of exposed elements and the impact of flood waters, large uncertainties exist in the simulated damage~~s~~ (de Moel and Aerts, 2010). More detailed information on the specific land use, its extent, and the vulnerability of the exposed elements could improve large-scale assessments, for example by using high-resolution remote sensing products (Goldblatt et al., 2018; Myint et al., 2011) or information as used in local~~-~~-scale flood damage~~s~~ studies at an object level (individual buildings, businesses, infrastructure objects, etc.) (de Moel et al., 2015; Merz et al., 2010). In our approach, we therefore utilize information about the composition of an area’s building stock and the characteristics of exposed objects, particularly construction types and materials. Applying ~~these~~such object-based information, which is not to be confused with object based image analysis in remote sensing, is contrasting to the common land-use-based approach in large-scale flood risk assessments.

The literature distinguishes flood vulnerability of buildings according to different structural factors (such as building type, quality, height, and material), as well as occupancy type (such as residential, commercial, industrial, etc.). The latter is a commonly used factor for determining ~~the~~ vulnerability (de Ruiter et al., 2017), with much fewer studies relating potential losses to the structural factors. Reasons for this are the paucity of information and the huge effort it takes to obtain information on the damage incurred by individual objects and the structural components (Wahab and Tiong, 2016). Studies or models that do include information on these factors are mostly based on surveys and ~~were~~ have therefore only been feasible on smaller scales. FLEMOps (Thieken et al., 2008) is an example of a model that uses survey data on flood damage~~s~~ in Germany, and includes factors such as building type and quality. The study by de Villiers et al. (2007) is one of the few assessments (see also World Bank, 2000) within Africa, but uses size and content value of houses to determine flood damage and does not go into detail on structural features. Studies that focus on construction type and building material to assess the flood damage show that these characteristics, together with ground floor elevation and number of floors, are important features in determining the vulnerability of different building types to floods (e.g. Godfrey et al., 2015; Neubert et al., 2008; Schwarz and Maiwald, 2008; Zhai et al., 2005).

Furthermore, building characteristics are essential components of physical vulnerability and risk assessment ~~Compared to risk assessments~~ in the earthquake domain~~ where they are essential components~~ (de Ruiter et al., 2017)~~, or in local-scale studies focusing on physical vulnerability~~, as well as for other flood types such as flash floods in mountain areas and ~~to~~ debris flows. For such studies on the local-scale aspects can even include for example features of the building envelope such as layout of openings and wall dimensions, flow direction, sediment load and surrounding buildings; these elements are sometimes evaluated via laboratory experiments and on-site data collection (e.g. Godfrey et al., 2015; Milanesi et al., 2018; Sturm et al., 2018).~~(Papathoma-Köhle et al., 2017), construction types and building materials have only played a minor role as~~ There is a gap in applying such indicators in ~~for flood vulnerability. L~~large-scale flood risk assessments, which could be improved by using object-based characteristics to represent exposure and vulnerability, particularly in developing countries with a diverse structural building stock.

Recently, a building exposure dataset has been developed for several African countries as part of the Building Disaster Resilience program for the World Bank's Africa Disaster Risk Financing Initiative by ImageCat (ImageCat et al., 2017). ImageCat uses a stratified sampling technique that infers the number of buildings in a region from census data and then uses image processing tools to identify development patterns (Hu et al., 2014). The construction practices are then characterized through a review of the literature, interviews, review of VHR images, in situ video, and in some cases site visits (Silva et al., 2018). This characterization of development patterns is used for dasymetric mapping of building counts to a 15" grid. Estimates are supplemented with total estimates of floor area, and replacement values based on construction practices observed in each development pattern (Huyck and Eguchi, 2017). Compared to the methods employed in current large-scale flood risk models, the information about the built environment of an area and its characteristics as provided in such datasets enables a differentiation between the exposed objects in terms of vulnerability to flood waters and exposed value.

Furthermore, a greater level of detail opens up the possibility to address the issue of distinguishing urban and rural flood risk. This is commonly neglected in land-use-based flood risk assessment, due to the focus on higher value urban damage~~s~~. Moreover, land-use classification studies have difficulties in assessing urban and rural differences. This is because the resolution in previous land-use and land-cover products was not sufficient to identify smaller settlements, and the characteristics of urban and rural areas are very different and can be difficult to grasp in land-use classification studies (Dijkstra and Poelman, 2014). Internationally there is no agreed way to distinguish urban from rural areas. For example, according to the national census ~~in~~of Ethiopia, localities of 2,000 or more inhabitants are considered urban, whereas the urban definition for Niger only includes capitals of departments and districts (UNSD, 2016). Another traditional distinction is that urban areas provide a different way of life and usually a higher living standard (UNSD, 2017). Compared to developed countries, the building stock in rural areas of developing countries is often constructed from more traditional and less expensive building materials, which makes them more vulnerable to flooding. In this regard, urban settlements in the context of this study are defined as geographic units with built-up area that are more developed and have a higher built-up density than rural settlements.

The aim of this paper is to develop an approach for assessing large-scale river flood risk in urban and rural areas using object-based data from ImageCat to represent exposure, and to develop vulnerability curves for different building classes. The approach draws upon common practices in earthquake risk assessments, and relates damage by flood waters more directly to the vulnerability of buildings based on the building materials. We test the suitability of this approach for the case of Ethiopia, comparing our results with those using a more traditional large-scale flood ~~damage~~risk modelling approach, examining how the increased detail influences risk estimates. In addition to river floods, Ethiopia has experienced flash flood events in the past such as in 2006 with several casualties and millions of property damage in Dire Dawa (Billi et al., 2015). However, these kinds of floods are not included in this analysis.

## 2. Data and Methods

The approach used in this study is composed of the following main four steps, and shown in Figure 1:

1) development of **vulnerability classes and curves** for different construction types and building materials based on a literature review of previous studies;

2) classification of an **object-based exposure** dataset using input data from ImageCat;

3) derivation of **maximum damage values** and

4) **risk assessment** by combining the aforementioned vulnerability and exposure with hazard data.

Each of these steps is described in more detail in the following subsections.

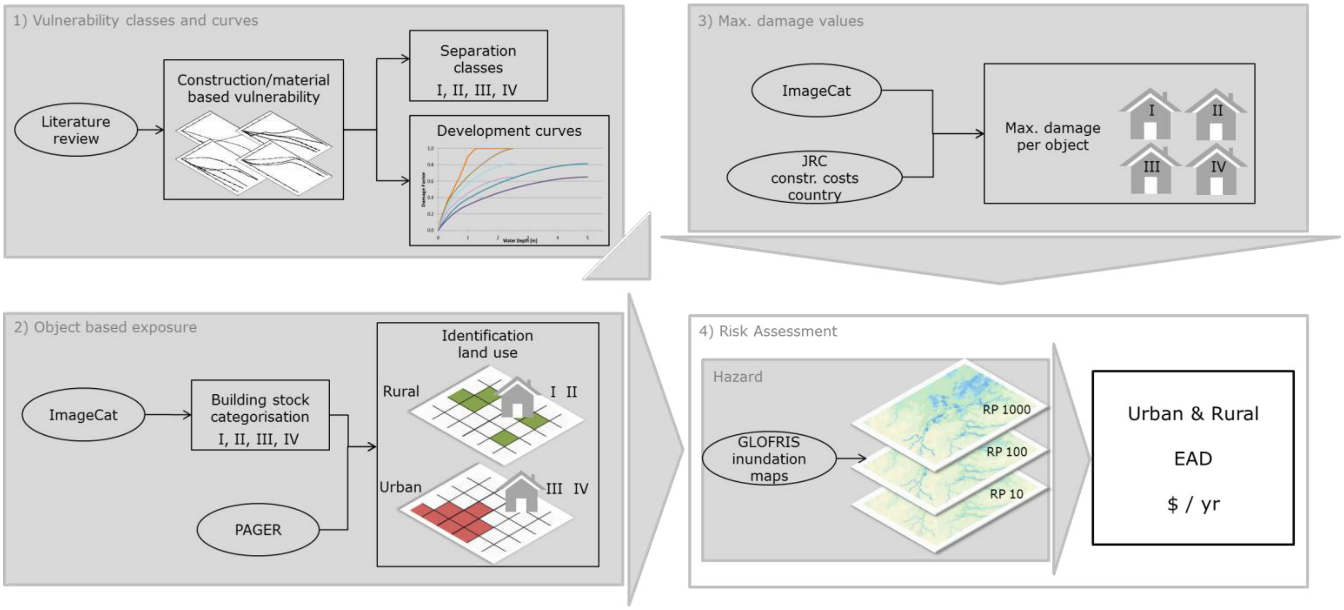


**Figure 1 Flowchart for large-scale flood risk assessment using object-based data with a building-material-based vulnerability approach.**

### 2.1. Vulnerability classes and curves

As a first step (Figure 1), an extensive literature review was conducted to develop flood vulnerability classes and associated curves based on construction types and building materials (Table 1). An increasing number of studies investigate multi-parameter damage models (e.g. Chinh et al., 2016; Wagenaar et al., 2018), but given the large amount of data required to apply such models, we here only consider studies on river floods that apply stage-damage curves. For the class and curve development, we use studies from different regions that have focused on the vulnerability of individual construction types or building materials, and which are preferably based on actual event data. Some additional studies, often more qualitative in nature, were used to further refine the flood vulnerability classifications of the different building materials and construction types (e.g. Kappes et al., 2012; Laudan et al., 2017; Neubert et al., 2008; Zhai et al., 2005). Apart from reviewing the literature, experts with a structural engineering background were consulted to confirm the coherence of the final classification and vulnerability curves.

**Table 1 Overview of studies used to derive construction type and building-~~–~~material-based vulnerability classes and curves. The four classes are: (I) non-engineer~~structur~~ed buildings created by compacted mud, adobe blocks or informal buildings; (II) wooden buildings; (III) unreinforced masonry/concrete buildings; and (IV) reinforced masonry/concrete and steel buildings**

| Vuln. class | Country | Source | Data basis | Main structural~~.~~ type / bldg. material | Event / applied area |
|---|---|---|---|---|---|
| I | India | Dhillon (2008) | Field survey | Mud structurs~~.~~ | Birupa River basin in Orissa after the 2006 flood |
| I | India | Maiti (2007) | Household interviews | Mud wall buildings~~.~~ | Rural areas in Oriss~~i~~a after the 2003 flood |
| I | China | Li et al. (2016) | Interviews, questionnaires, field investigation | Wood-earth structures~~.~~ | Taining county town, Fujian province |
| I | Malawi | Rudari et al. (2016) | To generic Malawi housing typology adjusted CAPRA | Traditional (mud walls), semi-permanent (sun-dried bricks) typologies | Based on data for Northern and Central Malawi |
| II | India | Dhillon (2008) | Field survey | Wooden structures~~.~~ | Birupa River basin in Orissa after the 2006 flood |
| II | Germany | Buck (2007) | Expert seminar | Wood structures~~.~~ | Bldgs. in flood prone areas of Greifswald |
| II | New Zealand | Reese and Ramsay (2010) | Based on international~~.~~ studies and adjusted by post-event surveys | Timber buildings~~.~~ | Hutt Valley flood risk case study using major flood events in 2004 and 2007 |
| II | Australia | Hasanzadeh Nafari et al. (2016) | Derived data of extreme events and other models | Timber wall structures~~.~~ | Q~~O~~ueensland 2013 |
| II | Japan | Dutta et al. (2003) | Function derived from post flood event data | Wooden structures~~.~~ | Applied to case study area in Chiba prefecture |
| II | Guatemala | Peters Guarín et al. (2005) | Field survey, interviews | Wood frame and board construction | Flood in Samalá River tributaries related to precipitation of hurricane Mitch 1998 |
| II | Philippines | Sagala (2006) | Field survey, household interviews | Wood, bamboo structures~~.~~ | Floods in 1995 and 2004 at Naga and Bicol River in Sabang and Igualdad Barangay, Naga City |
| II | Romania | Godfrey et al. (2015) | Expert weighted vuln. index and curves from other studies | Wooden buildings~~.~~ | Applied to case study in Nehoiu Valley |
| III | India | Dhillon (2008) | Field survey | Brick, cement structures~~.~~ | Birupa River basin in Orissa after the 2006 flood |
| III | Australia | Hasanzadeh Nafari et al. (2016) | Derived data of extreme events and other models | Masonry buildings~~.~~ | Q~~O~~ueensland 2013 |
| III | Bangladesh | Islam (1997) | Household and expert interviews | Brick buildings~~.~~ | Floods between 1988 and 1993 in urban areas |
| III | China | Li et al. (2016) | Interviews, questionnaires, field investigation | Brick-wood and masonry structures~~.~~ | 2010 flood in Taining county town, Fujian province |
| III | Australia | Middelmann-Fernandes (2010) | Based on quantity surveyor data | Brick-veneer structures~~.~~ | Swan River system in Perth, Western Australia |
| III | Malawi | Rudari et al. (2016) | To generic Malawi housing typology adjusted CAPRA | Permanent (burnt bricks, concrete, stone walls) typologies | Based on data for Northern and Central Malawi |
| III | Philippines | Sagala (2006) | Field survey, household interviews | Concrete structures~~.~~ | Floods in 1995 and 2004 at Naga and Bicol River in Sabang and Igualdad Barangay, Naga City |
| IV | China | Li et al. (2016) | Interviews, questionnaires, field investigation | Steel-reinforced concrete structures~~.~~ | 2010 flood in Taining county town, Fujian province |
| IV | India | Maiti (2007) | Household interviews | RCC structures~~.~~ | Rural areas in Oriss~~i~~a after the 2003 flood |
| IV | Germany | Buck (2007) | Expert seminar | Reinforced masonry / concrete structures~~.~~ | Bldgs. in flood prone areas of Greifswald |
| IV | Japan | Dutta et al. (2003) | Function derived from post flood event data | RC concrete buildings~~.~~ | Applied to case study area in Chiba prefecture |

Table 1 summarises the studies used to derive construction type and building-~~–~~material-based vulnerability classes and curves. In all of these studies, the construction type or (dominant) building material is clearly specified, and is either the only indicator, or one of the primary indicators, for the description of the flood vulnerability. Four vulnerability classes can be identified from this literature, of which each class consists of similar construction types and building materials with comparable behaviour towards flooding. The four classes are: (I) non-~~structured~~engineered buildings built ~~of~~with materials such as compacted mud and adobe block or informal buildings; (II) wooden buildings; (III) unreinforced masonry/concrete buildings with walls of burnt bricks or stone or concrete blocks; and (IV) reinforced masonry/concrete and steel buildings.

From the literature described in Table 1, we identified information to develop the stage-damage curve for each of these vulnerability classes. The stage-damage curves in most of the studies are concave, increasing steeply at low water depths (especially for the buildings made with more vulnerable materials), and with a decreasing slope at higher water depths. This overall concave shape was differentiated into curves for each of the four vulnerability classes, shown in Figure 2, using information on threshold levels (e.g. the water depth at which most damage was incurred) from the studies in Table 1. We distinguish curves that go up to 2.5m and up to 5m (for buildings with 1- and 2-floors) as flood levels rarely reach higher levels. Housing built through informal channels dominate in Africa (World Bank, 2015), and self-constructed buildings using inexpensive materials and traditional manufacturing techniques are still very common (Alagbe and Opoko, 2013; Collier and Venables, 2015). Buildings of class I and II belong to this group and are assumed to be one floor only, as multiple story buildings would require higher quality materials and hiring a professional construction crew. The four vulnerability classes are described below:

*Class I* are non-engineer~~structur~~ed buildings built with materials such as compacted~~created by~~ mud, (non-cemented) adobe blocks and other traditional materials found in the natural environment or informal buildings (often using natural or scrap materials for the walls and roof covers). Buildings in this class can ~~dissolve~~disintegrate and collapse easily when impacted by flood waters~~. These~~ and thus are the most vulnerable to flooding. Literature shows that mud walls ~~will~~can collapse when flooded by about a meter of water (Maiti, 2007), and submersion tests illustrate that most adobe bricks completely dissolve when submerged for 24 hours (Chen, 2009). Depending on the material mixture and mortar for example by adding cement the stability of these buildings can be increased. However, with the high level of the cement prices in Africa (Schmidt et al., 2012) this is rather consideration for class I buildings in other regions. ~~These b~~Buildings of class I are assumed to be one floor only.

*Class II* consists of wooden buildings. Theoretically, these are far less vulnerable to collapsing than class I, when held together by joinery or nailing and straps into a structural frame and have durable wall and roof cover materials, but if wood frames become wet, they often have to be replaced, or finishing needs to be removed for drying (and replaced afterwards). In a study carried out in Germany, Buck (2007) showed that the damage~~s~~ can be ~35%-50% higher for wood frame homes than for masonry/concrete homes. However, the value and quality of the wooden buildings in Ethiopia is much lower and they seem to be predominantly present in rural areas with more informal, less durable building material. Therefore, we decided to let the curve progress up to damage factor 1 (total loss due to destruction or need for demolition) at flood depth of 2.5 m (i.e.

damage can reach full building value, unlike masonry and concrete constructions). Buildings that are based on wood construction types can account for a large proportion of overall building stock in some countries (e.g. USA, Japan and Ethiopia). The quality of these constructions and the building's value can vary considerably. For large-scale assessments outside of Africa, adjustment towards a greater flood resistance is recommended.

*Class III* are unreinforced masonry/concrete buildings with walls of burnt bricks or stone or concrete blocks. These buildings are more vulnerable than those in class IV (reinforced masonry/concrete or steel). This is related to the fact that unreinforced walls are less able to resist the pressure of flood water exerted on walls. However, damage potential is assumed to be less than class II, as ~~masonry~~ bricks, stone and concrete blocks are more durable and less likely to disintegrate or need replacement after being flooded compared to wood. Nonetheless, as described in Li et al. (2016), brick masonry buildings are less resilient than steel-reinforced structures. Therefore, a curve between class II and class IV was created for both one and two storey buildings of this class~~floors~~.

*Class IV* represents engineered reinforced masonry/concrete and steel buildings. These types of buildings are engineered and basically standard in most western countries and large cities in Africa. Overall, they constitute the most resistant class to flooding. Many studies (e.g. Buck, 2007; Li et al., 2016; Maiti, 2007) show that vulnerability curves for these types of buildings do not go up to a damage factor of 1, as some elements do not need replacement after a flood (e.g. the foundation or ~~carrying~~the structural walls or the frames). This is similar to the values from Dutta et al. (2003) and HAZUS-MH (Scawthorn et al., 2006), who show examples of curves that go up to 0.6-0.7 damage ratio. Therefore, in this study it is chosen to let this curve go up to 0.65. Both reinforced masonry and reinforced concrete and steel are put in the same class.

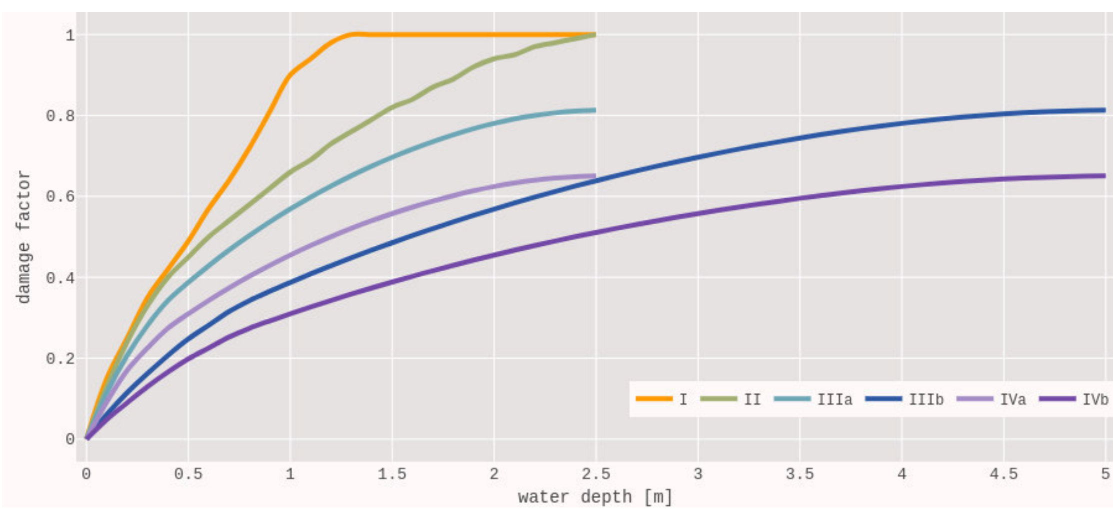


**Figure 2 Stage-damage curves for four building-material-based vulnerability classes. For class III and IV the one and two floor curve are denoted by (a) and (b).**

### 2.2. Object-based exposure data

In step 2 (Figure 1), we reclassify the objects identified in the ImageCat database into the four vulnerability classes, and distinguish between urban- and rural areas. The exposure data developed by ImageCat are available on a 15” x 15” grid for several African countries. Each grid cell contains building counts for different construction types, as well as the total floor area and total building value of the cell’s building stock. For the building numbers the Ethiopian census data on housing units was used directly in most regions as the building stock is mostly single family housing. The living area was gleaned from sampling building footprint data, and as with structural characteristics varies by development pattern. For a predominantly commercial pattern, building stock data is adjusted with exposure derived from building footprint data. The number of floors can vary by development pattern, but for the vast number of buildings is single story for most of the country. For highly urbanized areas the number of stories was adjusted through expert opinion of several country-based structural engineers (Huyck and Eguchi, 2017). In total, 22 construction types are differentiated in the ImageCat data. Table 2 shows how these can be reclassified into the four vulnerability classes used in our study. Further description of the construction types can be found in supplementary section 1. In the Ethiopian data nine of the~~se~~ types from Table 2 occur.

**Table 2 Construction types of the ImageCat building exposure data with their respective flood vulnerability class.**

| Type | Description | Vuln. class | Type | Description | Vuln. class |
|---|---|---|---|---|---|
| ADB | URM adobe building~~.~~ | I | DS | Stone masonry building~~.~~ | III |
| ERTH | Earthen building~~.~~ | I | STN | URM stone building~~.~~ | III |
| INF | Informal building~~.~~ | I | UCB | Unreinforced concrete block building~~.~~ | III |
| M | Mud walls building~~.~~ | I | UFB | Unreinforced fired brick masonry building~~.~~ | III |
| RE | Rammed earth building~~.~~ | I | BTLR | ~~Butler bldg. (s~~Steel frame with bracing~~ed~~ rods~~)~~ (Butler) building | IV |
| WWD | Wattle & daub building~~.~~ | I | C2 | Reinforced concrete shear wall building~~.~~ | IV |
| W2 | Wood frame building~~.~~ | II | C3 | Non-ductile RC frame with masonry infill walls building~~.~~ | IV |
| WLI | Light wood building~~.~~ | II | MCF | Confined masonry building~~.~~ | IV |
| WS | Solid wood building~~.~~ | II | RC | Reinforced concrete frame with URM infill building~~.~~ | IV |
| BRK | URM brick building~~.~~ | III | RM | Reinforced masonry brick building~~.~~ | IV |
| CB | URM concrete block building~~.~~ | III | S | Steel building~~.~~ | IV |

Most large-scale flood assessments focus on urban areas ~~as~~ due to the availability of data and high potential damage~~s~~. In countries with large differences between urban and rural living standards, such as developing countries, it can be expected that the share of more vulnerable buildings (i.e. class I and II) is higher in rural areas compared to urban areas (e.g. Fiadzo, 2004). To account for these differences, we classify each cell as urban or rural. If more than 50% of the ImageCat objects in a cell belong to vulnerability class I or II, the area is assumed to be predominantly rural.

To check the assumption that the share of class I and II buildings in developing countries is higher in rural areas compared to urban areas, we examined these shares in the PAGER dataset (Jaiswal and Wald, 2008; Jaiswal et al., 2010). PAGER is a global residential and non-residential building inventory at the country level (usually but not exclusively expressed in proportions of people living or working in particular building structure typologies in urban and rural areas respectively), which is often used in earthquake research. PAGER provides information at a country level on the construction types that make up the total urban and rural building stock~~.~~, though the information quality is varying between countries. First, we reclassified the PAGER construction types into the four flood vulnerability classes used in our study (~~similar to Table 2~~see Supplementary table 1). Then, we calculated the percentage of buildings in PAGER's total urban and rural building stocks that are categorised as class I and II (Figure 3). The building stock differences between urban and rural areas can be found to a changing degree in all groups. While there is a distinct gap suggested for Africa, PAGER has to rely there on very limited information (i.e. only 2 of the countries differentiate urban and rural building stock without judging on information from neighbouring countries). Nevertheless, the data for urban and rural building stock distribution compared by income level also indicates this differences in the built environment. In low and lower middle income countries, the percentage of buildings in class I and II is indeed much higher in rural areas (36%) than in urban areas (10%). These differences are far less pronounced for higher income countries. The chosen threshold to identify rural areas in the ImageCat dataset (>50%) is larger than the average share we find in PAGER (Figure 3). This means that cells identified as rural using the ImageCat data information about the built environment with the chosen threshold are quite likely to indeed be rural.

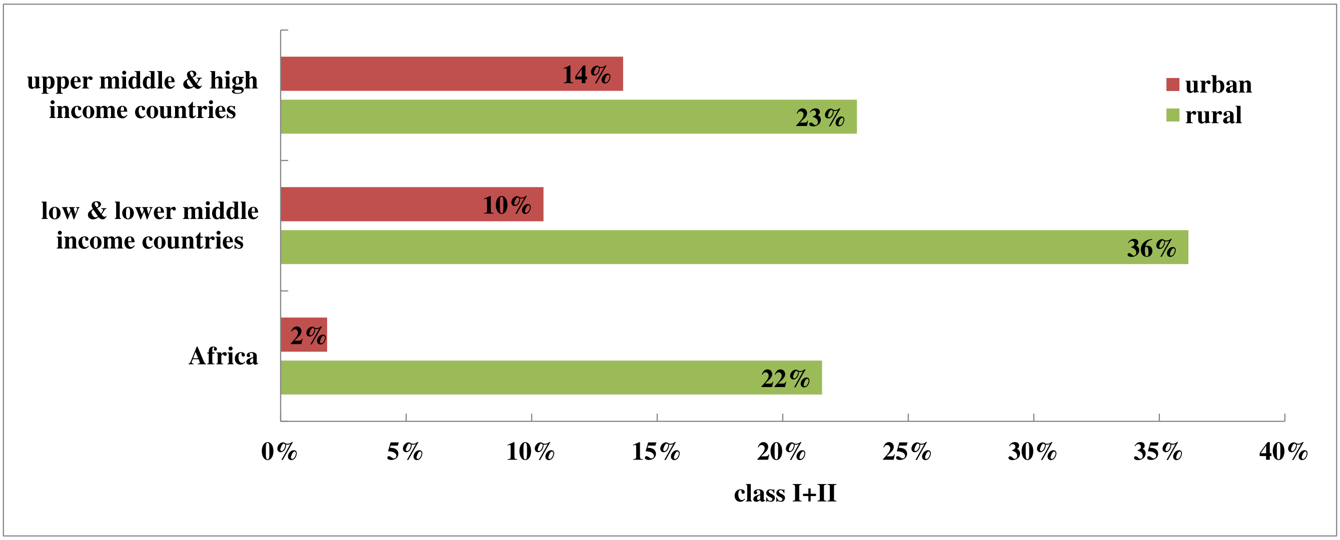


**Figure 3 Average percentage of urban and rural buildings belonging to vulnerability classes I and II for different income groups and Africa according to PAGER for countries with different urban-rural inventory.**

In remote sensing or land-use studies, accuracy assessments determine a process' accomplishment of classifying an image (e.g. satellite data, aerial photos). Such an assessment requires reference values that represent the ground truth of the region of interest. Preferably these values are from ground collected data or hand-labelled high-resolution imagery validated by multiple interpreters (e.g. Goldblatt et al., 2018; Miyazaki et al., 2011). With these options out of the scope of this study, we examine the similarity between existing land-use products and classified areas in our approach. Compared to a strict accuracy assessment this holds the limitation of comparing already classified products. However, by benchmarking the classified ImageCat data against established and recently published products, we provide an assessment of how well areas are identified in comparison. To this end, we reviewed the quality of the urban-rural ImageCat map by visual comparison with satellite imagery and by overlap with other classification products, visually and by quantifying the agreement between classified areas of the ImageCat data and other products (section 3.1). Two comparisons are made, one for urban and rural areas, and one ~~for~~ only for urban areas. Similar to an accuracy assessment, we express the performance of this overlap by calculating common comparison metrics from a confusion matrix such as overall accuracy, kappa coefficient, and producer's and user's accuracy for the sampling cells as described in Supplementary figure 1. Overall accuracy and kappa coefficient are metrics indicating the general agreement between the reference and comparison dataset. The latter two refer to the accuracy of individual classes of which the producer's accuracy describes the probability that, for example, an urban pixel is correctly classified, and the user's accuracy that a pixel classified as urban is actually urban.

For Ethiopia, the comparison maps are from several global land-use datasets as there are no other maps on national scale available for the country. For the reference map, the ImageCat data are assigned the reference categories 'urban', 'rural', and 'other land use' for cells outside of settlements. From the comparison maps, GHS-SMOD is the only other product that also considers rural settlements, allowing for a comparison of both urban and rural classifications. GHS-SMOD~~It~~ is a relatively new product based on the high-resolution European Joint Research Centre's Global Human Settlement layer (Pesaresi and Freire, 2016). For GHS-SMOD, built-up areas are combined with population grids to differentiate between three settlement classes: urban centres, urban clusters, and rural (Pesaresi and Freire, 2016). In order to compare to the ImageCat reference, the GHS-SMOD's urban centre and cluster cells were reassigned into a single urban class and rural cells were kept as is.

More products are available that provide a classification limited to urban areas, but largely overlook rural areas, such as: GRUMP (CIESIN, 2011), MOD500 (Schneider et al., 2009), the Global Urban Footprint (GUF) (Esch et al., 2017), and HBASE (Global Human Built-up And Settlement Extent) (Wang et al., 2017). GRUMP and MOD500 are widely used land cover/use datasets, with GRUMP being a 30" x 30" grid of urban extent and MOD500 based on MODIS satellite data with a 500m x 500m resolution. GUF represents built-up area based on satellite imagery with a 12m x 12m spatial resolution. HBASE is a 30m x 30m Landsat derived dataset of the extent of built-up area and settlements. All these products are used in the second comparison, in which only the 'urban' classified ImageCat settlements remain in the reference map and all cells outside of these settlements are reassigned to 'other land use'. From GHS-SMOD, the urban centre and cluster cells are again combined, but rural GHS-SMOD areas are excluded in this assessment.

Both the urban-rural and the sole urban classification comparisons between the ImageCat data and the other products follow a class defined stratified random sampling scheme, meaning that per class 10,000 sample points were randomly placed over the cells in each reference class. As the original maps do not all share a common geospatial model, they were reprojected to a 15" x 15" raster, using the WGS-84 datum. The results of the assessments ~~can be found~~are discussed in section 3.1.

### 2.3. Maximum damage values

In step 3 (Figure 1), we determine the maximum damage of buildings in each vulnerability class. For a coherent set of input values, we use depreciated country-specific structural maximum damage estimates per square meter as provided by the JRC report of Huizinga et al. (2017), in which residential construction costs are estimated per country using a non-linear relationship between construction costs and GDP per capita. This maximum damage value needs to be further differentiated between the four different vulnerability classes used in our study, and then multiplied by an estimate of the building footprint area per cell. This is achieved by applying the following formula for each cell:

$$D_i = \sum_{1}^{k} S \cdot N_{k,i} \cdot A_{k,i} \cdot F_k$$

Where

$D_i$ is total structural maximum damage in a given cell ($i$), $S$ is structural maximum damage per square metre in Ethiopia, $N$ is the number of buildings belonging to vulnerability class $k$ and cell $i$, $A$ is the object area, meaning the building footprint for each vulnerability class $k$ and cell $i$, and $F$ is the maximum damage adjustment factor for vulnerability class $k$.

The factors $A$ and $F$ are derived as follows:

*Building footprint area (A)*

As data on the footprint of different building types are not directly available, we estimated these based on floor area and number of floors derived from the ImageCat data. ImageCat provides estimates of floor areas for each construction type, based on sampling of building footprints, OSM data, interviews with local contractors and experts and literature review (Huyck and Eguchi, 2017). The country data descriptions also provide information on the typical number of floors, based on sampling. For each construction type, we divided the average floor area from the ImageCat data with the number of floors, and calculated the footprint area per class ($A$) as the average from the construction types belonging to each class.

Our assumptions on the number of floors are derived from information in the ImageCat country data descriptions. Since buildings of construction types belonging to vulnerability class I or II rarely exceed one floor, we assumed them to have one floor in both urban and rural areas. The construction of class III and IV buildings with more than one floor requires a higher skill level, mainly found in professional construction workers available in urban areas. Considering these characteristics, most class III buildings can be assumed to ~~be~~have one floor in rural areas. However, as most buildings in urban areas have more than one floor, we assumed class III buildings in urban areas to have two floors. Class IV buildings are assumed to be multiple floors in all areas. The buildings of class III and IV with multiple floors have a much greater footprint than the one assigned to the other classes. While buildings with smaller footprints are primarily single family residential structures or within informal settlements, the buildings of the last two classes are mainly found in urban environments, with many of them being long apartment blocks with very large building footprints leading to a larger average footprint. The resulting building footprints for Ethiopia can be ~~found~~seen in Table 3.

**Table 3 Building footprints derived for Ethiopia from the ImageCat data.**

| Vuln. class | Building footprint [m$^2$] |
|---|---|
| I | 37 |
| II | 43 |
| III 1 floor | 46 |
| III 2 floors | 256 |
| IV | 467 |

*Maximum damage adjustment factor (F)*

The maximum damage values of Huizinga et al. (2017) are depreciated country-specific structural maximum damage estimates, averaged across various building types. Therefore, we differentiated these into maximum damage values for the four different vulnerability classes used in our study. Huyck and Eguchi (2017) provides estimates of replacement costs for different structures, based on factors such as ~~input~~construction material and whether the structure is owner-built or engineered using professional contractors. We used these to calculate the average replacement costs for each of the four vulnerability classes, for example the average for vulnerability class I in Ethiopia is about 95 $/sqm. In order to apply comparable maximum damage values based on a coherent dataset, these average costs per vulnerability class are then put in ratio to the country-specific values from Huizinga et al. (2017), resulting in adjustment factors (*F*) for each vulnerability class (see Table 4) to arrive at maximum damage estimates.

**Table 4 Construction cost based on Huizinga et al. (2017) and adjustment factors derived from the ImageCat data for Ethiopia.**

| Ethiopia construction costs | 671 $/sqm |
|---|---|
| Vulnerability class | Adjustment factor |
| I | 0.14 |
| II | 0.11 |
| III 1 floor | 0.18 |
| III 2 floors | 0.33 |
| IV | 0.48 |

A detailed example of the maximum damage value can be found in Supplementary figure 2. The overall Ethiopian building stock is according to the ImageCat data comprised of over 16.8mln buildings. With the described approach, the total value exposed in urban areas amounts to about $250bln compared to almost $30bln in rural areas. Similarly, there is also a large gap between the living standard in rural and urban areas. The last Ethiopian census in 2007 (CSA, 2010) and the 2016 DHS report (CSA and ICF, 2016) provide some indications for rural and urban households that show huge differences in household durables and quality, for example more than half of the rural household with livestock share at night the room with the animals, or high quality floors in two thirds of urban households compared to only 4% of floors in rural households. The contrasts shown there in housing characteristics such as sanitation, drinking water and flooring material illustrate that there are large differences in living conditions which indicate similar differences in exposed urban and rural value.

### 2.4. Damage and ~~R~~risk assessment

To calculate the damage, we combine the new exposure and vulnerability data described above, with existing hazard maps derived from the GLOFRIS global flood risk model (WRI, 2018). These maps show inundation extent and depth at a horizontal resolution of 30’’ x 30’’ for different return periods. The original model setup of GLOFRIS is described in Ward et al. (2013) and Winsemius et al. (2013). The maps used in this study are those developed for the current time-period in Winsemius et al. (2015), which have been further benchmarked against observations and high-resolution local models in

Ward et al. (2017). In doing so, we estimate damage for the return periods 2, 5, 10, 25, 50, 100, 250, 500 and 1000 years. The inundation associated with each return period is assumed to occur everywhere simultaneously and w

~~W~~e expressed flood risk using the commonly used metric of expected annual damage (EAD). This is estimated as the integral of the flood damage curve over all exceedance probabilities (e.g. Ward et al., 2013). A source of uncertainty in flood risk assessment is the level of incorporated flood protection. Here, we use the modelled protection standard for Ethiopia taken from the FLOPROS database, a global database of flood protection standards developed by Scussolini et al. (2016), namely 2 years.

## 3. Results and discussion

The third chapter is organized as follows: Section 3.1 discusses the urban-rural exposure in the comparison between the ImageCat data and other products. In section 3.2, we present the results of the Ethiopian flood risk assessment using our approach and compare them in 3.3 to the results of a traditional model. In section 3.4, the sensitivity of our flood risk results is discussed for different model parameter.

### 3.1. Urban-rural identification

The results of our classification of ImageCat cells for Ethiopia into urban or rural are shown in Table 5, along with summaries of data from other data sources. For rural areas, our result (7.2%) is similar to that of GHS-SMOD (6.4%), which is the only other data source among the products that has a specific value for rural areas. The area in Ethiopia categorized as urban or built-up is relatively low in all data sources ~~which~~and is in accordance with Ethiopia being one of the least urbanized countries in Sub Saharan Africa, with the share of urban population being according to Schmidt and Kedir (2009) only between 11% and 16%, or according to more recent data from the World Bank (2016) at about 20%.

**Table 5 Cell areal extent of different land-use categories in Ethiopia as a percentage of the country area according to different products (original dataset projections).**

| Dataset | % of country |
|---|---|
| ImageCat | urban 0.6%, rural 7.2% |
| GHS-SMOD | urban centre 0.4%, urban clusters 1.1%, rural 6.4% |
| GRUMP | urban extent 0.5% |
| MOD500 | urban extent 0.1% |
| GUF | built-up area 0.1% |
| HBASE | built-up area and settlements 0.1% |

*Visual comparison*

Our urban-rural classification is shown spatially in the example of Figure 4, in which we compare different land-use products for an area near the City of Awasa. The urban and rural areas identified in GHS-SMOD and our classified ImageCat data show a more detailed and differentiated representation of the settlements than the coarse resolution GRUMP and MOD500 products. All products overlap in the location of main urban areas, although their extent varies. Locations of built-up areas with medium extent, for example in GUF, are hardly or not detected in HBASE, MOD500, and GRUMP, but are also seen with GHS-SMOD and our ImageCat classification.

Using our classification method, some smaller settlements are labelled urban with the ImageCat data, because their building stocks have high shares of class III and IV buildings, whilst GHS-SMOD classifies them as urban clusters or rural. Examples are the areas around Shashemene (see circled examples in Figure 4a). By visual inspection of Google Earth ~~data~~, these seem to be areas of urban-rural transition. They have a more densely built environment than rural areas and a higher number of class III and IV buildings, which leads to the urban ~~label~~classification in our method. Areas where cells from the ImageCat data get classified as rural are also rural in GHS-SMOD or to some extent urban clusters due to a higher population density in the surrounding cells. However, the overlap of these settlements is more about the general area and less regarding a cell by cell ~~basis~~comparison. In addition, visual inspection ~~also~~ showed that the small, more widespread settlements such as east of Awasa and Shashemene are correctly detected in the ImageCat data (rural areas in Figure 4a) but are not displayed in GHS-SMOD (Figure 4b). As a consequence of these issues, it ~~can be~~is expected that ~~the performance of~~ the classified ImageCat data and GHS-SMOD overlap is lower for rural than urban settlements.

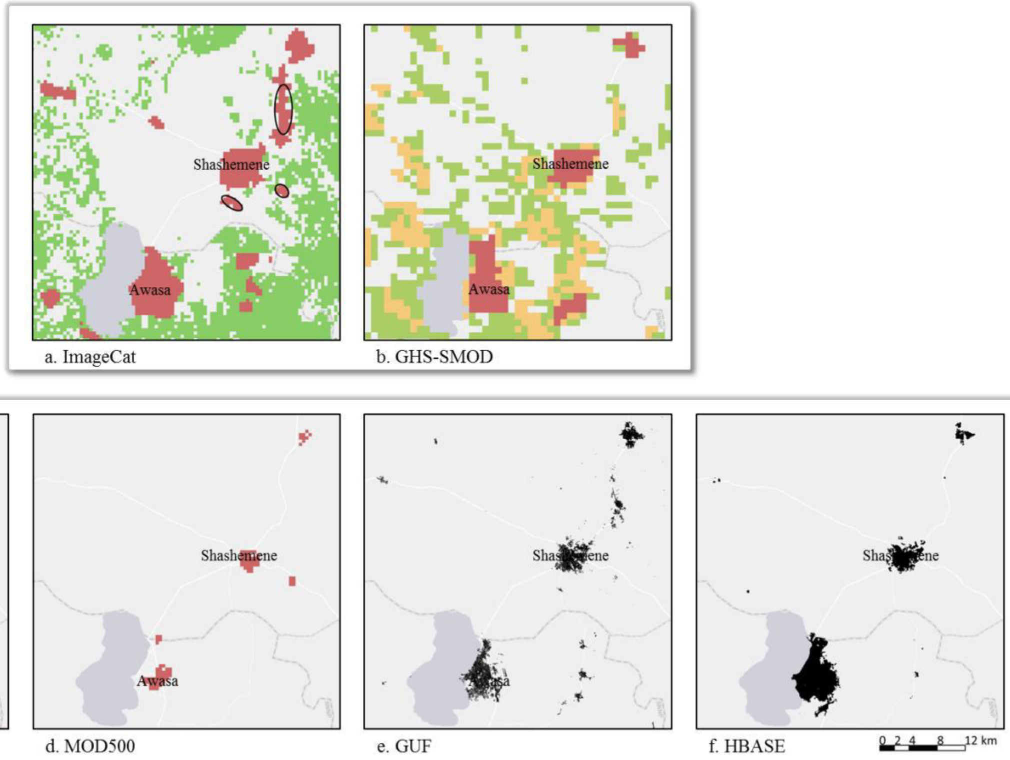


**Figure 4 Illustration of urban-rural land use in the greater Awasa area in Ethiopia: (a) Urban (red) and rural (green) classified ImageCat data, (b) GHS-SMOD urban centre (red), urban cluster (yellow), rural (green), (c) GRUMP urban extent (red), (d) MOD500 urban extent (red), (e) GUF built~~d~~-up area (black), (f) HBASE built~~d~~-up area and settlements (black); original dataset projections.**

*Map agreement analyses*

Map agreement has been assessed for urban-other classes, and urban-rural-other classes using confusion matrices (see supplementary table ~~1~~2 and supplementary table ~~2~~3). When comparing the urban areas (supplementary table ~~3~~4), we see that urban and built-up area cells in the GRUMP, MOD500, GUF and HBASE almost always correspond with urban cells in the ImageCat map (urban user's accuracy ~99-100%). This confirms the observations from the visual comparison (Figure 4) where we see that the general location of the main urban areas are similar between the datasets. However, with the ImageCat data more medium-sized urban areas are detected which are often not in the other datasets, resulting in the low producer's accuracy (~6-26%), again confirming the visual comparison of the Awasa region.

When including rural settlements in the assessment, only GHS-SMOD and the ImageCat classification can be compared (Table 6), as they are the only datasets which distinguish rural areas. This comparison is complicated by the fact that GHS-SMOD has three categories (urban centres, urban clusters and rural). Visual comparison with satellite imagery reveals that the middle class of urban clusters are sometimes an extension of urban centres, but can also refer to higher density settlements areas in rural areas. Nevertheless, for the map agreement analysis of urban-rural-other classes we grouped these urban clusters with the urban centres to form the urban class. We find that urban cells in the GHS-SMOD have a high probability to also be urban areas in the ImageCat map (urban user's accuracy of 86.3%). However, urban cells from the ImageCat data have a much lower probability to be urban in GHS-SMOD (urban producer's accuracy of 48.7%). This implies that there are various urban settlements in the ImageCat map, which are not present ~~in~~ in the urban group (centres and clusters) of the GHS-SMOD.

The agreement of rural cells is less good as compared to the urban cells, with considerably lower user's and producer's accuracies (31.3% and 11.0% respectively). Classifications of the built-up land from remote sensing based products inherently have lower accuracy levels in less developed regions and rural settings. Even high resolution products still omit large shares of built-up areas and have to improve their performance in arid regions ~~in~~of Africa and areas where settlements are more scattered (Klotz et al., 2016; Leyk et al., 2018). We can also observe this in the visual comparison (Figure 4) where the high resolution GUF and HBASE datasets omit many of the scattered settlements that are found in the ImageCat data or GHS-SMOD. Because of these difficulties in detecting such scattered settlements, the agreement between rural areas from the ImageCat classification and in GHS-SMOD is adversely affected as one dataset might indicate rural areas that are not identified in the other.

Comparability of classified maps remains an issue. For example, it has been illustrated in the literature that the total urban land in global maps varies by an order of magnitude between early global earth observation products and GRUMP. Likewise, there is about a factor 5 difference between MOD500 and GRUMP (Potere et al., 2009), and the global built-up area in the high resolution GUF product is 35% less than in GHS built-up (Esch et al., 2017). ImageCat data is more specific to the African context as the other maps are based on global classification algorithms.

The ~~on~~ construction types based ImageCat classification is a distinctly different approach as compared to most classifications, which use population and/or built-up densities. This can also cause some mismatches, for instance in informal settlements in or around cities which are classified as urban when looking at densities, but would be classified as rural when looking at construction types. Our analysis showed, however, that the classification from ImageCat data is overall reasonably~~e~~ similar to existing datasets, and it includes ~~compared to~~unlike other land-use products rural settlements, and~~ is~~ as such a good alternative for flood risk assessments as it provides the option for more detailed building-material-based vulnerability curves in the analysis.

**Table 6 Results of map agreement for Ethiopia using the ImageCat data classified to urban, rural, and other land use as the reference map.**

| | Urban | | Rural | | Other land use | | | |
|---|---|---|---|---|---|---|---|---|
| Urban-Rural Map | Producer's Accuracy (%) | User's Accuracy (%) | Producer's Accuracy (%) | User's Accuracy (%) | Producer's Accuracy (%) | User's Accuracy (%) | Overall Accuracy (%) | Kappa |
| GHS-SMOD | 48.7 | 86.3 | 11.0 | 31.3 | 94.8 | 45.5 | 51.5 | 0.27 |

### 3.2. Flood risk assessment

Modelled flood damage~~s~~ for the different return periods and risk for urban and rural areas are shown in Table 7. For 2-year return periods the damage~~s are~~ is always zero as it is assumed that these flood events would not cause overbank flooding. As can be expected, the damage~~s~~ in urban areas ~~are~~is higher, as it is a more densely concentrated built-up environment and the value of the buildings is higher. On the other hand, the majority of exposed buildings are in rural areas. To illustrate, about 88,000 buildings in urban areas are exposed to a 100-year flood event, compared to more than four times as many rural buildings.

**Table 7 Simulated flood damage~~s~~ (in Million $ 2016) to building structures in urban and rural areas of Ethiopia, for different return periods (RP) .**

| | RP 2 | RP 5 | RP 10 | RP 25 | RP 50 | RP 100 | RP 250 | RP 500 | RP 1000 |
|---|---|---|---|---|---|---|---|---|---|
| Rural | 0 | 92.2 | 145.5 | 208.7 | 252.8 | 293.5 | 339.6 | 368.9 | 395.3 |
| Urban | 0 | 351.2 | 522.9 | 706.0 | 819.7 | 924.7 | 1,054.5 | 1,142.7 | 1,226.5 |

Table 8 shows the damage~~s~~ per return period for the different vulnerability classes. These results show that most of the damage in rural areas results from damage to buildings of class I, which are buildings with the highest vulnerability. In urban areas, the largest share of the damage results from damage to buildings of class IV; these are the buildings with the highest exposed values. In addition, this class also makes up a large share of the exposed urban buildings, about 57,000 for a 100-year flood event which is more than twice as many buildings of class III. In total more than 464,000 buildings are simulated to be affected for events with this return period, but most are in rural areas with the majority belonging to class I (58.3%) (class II 14.6%, class III 8.1%).

**Table 8 Simulated flood damage~~s~~ (in Million $ 2016) to building structures by vulnerability class in urban and rural areas of Ethiopia, for different return periods (RP).**

| | | RP 2 | RP 5 | RP 10 | RP 25 | RP 50 | RP 100 | RP 250 | RP 500 | RP 1000 |
|---|---|---|---|---|---|---|---|---|---|---|
| Rural | I | 0 | 58.9 | 96.6 | 144.2 | 178.2 | 209.6 | 244.9 | 266.9 | 286.5 |
| | II | 0 | 17.7 | 26.0 | 34.3 | 39.6 | 44.5 | 50.4 | 54.3 | 58.0 |
| | III | 0 | 15.6 | 22.9 | 30.3 | 35.0 | 39.3 | 44.4 | 47.8 | 50.9 |
| | IV | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Urban | I | 0 | 0.6 | 0.9 | 1.3 | 1.6 | 1.9 | 2.2 | 2.4 | 2.5 |
| | II | 0 | 0.5 | 0.7 | 0.8 | 1.0 | 1.1 | 1.2 | 1.3 | 1.4 |
| | III | 0 | 62.8 | 93.5 | 126.3 | 146.6 | 165.4 | 188.6 | 204.4 | 219.4 |
| | IV | 0 | 287.3 | 427.7 | 577.5 | 670.5 | 756.3 | 862.5 | 934.6 | 1,003.2 |

The overall flood risk in Ethiopia (i.e. expected annual damage, EAD), is about $213.2mln/yr; 78% of the total EAD is in urban areas. Whilst the rural EAD is below the EAD in urban areas, it is still high in absolute terms ($46.7mln/yr). This demonstrates that neglecting damage~~s~~ to rural buildings in large-scale assessments may lead to a severe underestimation of total damage values. Furthermore, the flood damage~~s~~ in urban and rural areas have to be considered in the context of the coping capacity of the population in the respective areas. The flood vulnerability of people below the poverty line is higher, as a larger proportion of their wealth could be affected during a flood event (Winsemius et al., 2018). While this is also true for the urban poor, the livelihoods of rural people are more susceptible where services and infrastructure are limited (Komi et al., 2016).

### 3.3. Comparison with Aqueduct

Compared to a traditional land-use-based model, the total simulated damage~~s~~ in our approach ~~are~~is somewhat higher, but similar in magnitude. For example, the new version of the GLOFRIS model used for the Aqueduct Global Floods tool (WRI, 2018) applies the same inundation data as used in this study, but follows the common approach of using land-use-based exposure and vulnerability data, resulting in EAD for Ethiopia of $182mln/yr. The results from our approach contain much more detail on the exposed elements and their vulnerability and allow us to examine damage in urban and rural areas. Damage in urban and rural areas cannot be distinguished in GLOFRIS as it uses HYDE data (Klein Goldewijk et al., 2011) to represent exposure, which represents the urban built-up fraction per grid cell. Moreover, Figure 5 compares the land use exposure map using classified ImageCat data and HYDE for the example of Addis Ababa. As for the rest of the country, it demonstrates that datasets like the ImageCat exposure data can provide more spatial detail than the commonly used exposure maps such as HYDE used in land-use~~-~~-based flood risk models. Settlement extent and outlines are more distinctive, resulting in an overall better representation of affected settlement areas in the risk assessment of our approach.

Further comparison with reported losses as well as flood protection can be found in supplementary section ~~1~~2.

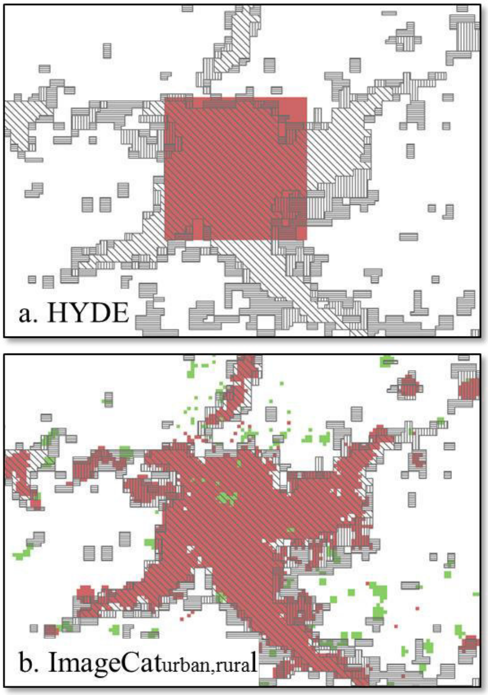


**Figure 5 Addis Ababa mapped by a. HYDE as used in GLOFRIS with above 0% urban built-up (red); b. classified ImageCat data urban (red), rural (green); GHS-SMOD rural (horizontal), urban cluster (vertical), urban centre (diagonal) as background boundary reference.**

### 3.4. Sensitivity analysis

Given the uncertainty in the input datasets and methods used in our approach, we perform a one-at-a-time sensitivity analysis to assess how the simulated EAD is affected by our assumptions on the: (a) structural maximum damage values; (b) threshold used in the urban/rural classification; (c) object area; and (d) stage-damage curves.

To assess the sensitivity of the results to the assumed values for maximum damage, we used the 90% confidence interval of estimated construction costs for residential buildings reported by Huizinga et al. (2017). These state that construction costs can be between 28% lower and 53% higher than the estimates used in this paper. For sensitivity to the threshold used in the urban/rural classification, we used thresholds of 20% and 80% for classifying urban areas, instead of the 50% used in the earlier analysis. Object areas can be very diverse between and within countries and depend on the characteristics of the housing market. For example, the Centre for ~~a~~Affordable Housing Finance in Africa yearbooks include some indication on the average house size and price per country. However, the used sample sizes for example are very small and the average value covers only the minimum size that formal developers in urban areas are prepared to build, therefore neglecting selfbuilt houses. Furthermore, no differentiation between building types or constructions is given (CAHF, 2017). For the sensitivity analysis, instead of calculating the footprint areas from average floor areas across the construction types per vulnerability class, we used the most frequent floor area size per type in the ImageCat data. The building footprint sizes most affected by this are those for classes II and III (see supplementary table ~~4~~5), as the size decreased ~~with~~by 5 to 11m$^2$. The state-damage curves in this study show a wide range of vulnerability (see Figure 2). Nonetheless, this as well as a comparable shape can also be found in the for different continents identified residential curves by Huizinga et al. (2017) as for example their damage ratios at 1m range between 38% to 71%. While our vulnerability functions show high degrees of damage particularly for class I and II (mud/adobe and wooden buildings), other functions that consider building structure such as in the CAPRA project (CAPRA, 2012; Wright, 2016) display similar behaviour for these types of buildings. The sensitivity regarding the vulnerability curves is analysed by applying like most traditional flood risk models only one vulnerability curve, thus neglecting the differentiation our model makes toward material-based vulnerability. To this end, we selected the residential stage-damage curve used in GLOFRIS, for which the degree of damage progresses slightly below the class III one floor curve.

**Table 9 Expected annual damage~~s~~ (in Million $ 2016~~ per year~~) compared for the normal model setup and the modified parameters used in the sensitivity analysis.**

| | Normal Run | Sensitivity Analysis | | | | | |
|---|---|---|---|---|---|---|---|
| | | Max. Damage | | Urban-Rural | | Object Area | Vuln. Curve |
| | | lower | upper | 20% | 80% | | |
| Rural | 46.7 | 33.6 | 71.4 | 46.7 | 46.7 | 41.5 | 37.4 |
| Urban | 166.6 | 119.9 | 254.8 | 166.6 | 166.6 | 165.8 | 264.1 |
| Total | 213.2 | 153.5 | 326.2 | 213.2 | 213.2 | 207.3 | 301.5 |

Results of the sensitivity analysis are summarised in Table 9. Clearly, the flood risk estimate is very sensitive to the applied maximum damage values, as the EAD scales linearly with maximum damage changes. The results also show the EAD to be sensitive to the applied vulnerability curve. Using the single curve from GLOFRIS leads to a higher total estimate of risk by 41%. Therefore, the~~ correct~~ estimation of maximum damage values and improved representation of vulnerability are important considerations for large-scale flood risk modelling. Our approach improves the incorporation of vulnerability in the risk assessment by differentiating ~~the~~a built environment into classes that characterise the vulnerability of a building stock even on large scales. The EAD is very insensitive to the threshold used in the urban/rural classification. Even with the wide range of thresholds used in the sensitivity analysis, influence on the urban-rural distribution is minimal, confirming that the urban and rural built environment in Ethiopia is very distinct in terms of what materials and construction types are applied. Nonetheless, as previously discussed in section 3.1, exposure of an area can vary depending on the applied dataset.

Using ImageCat data, over half of the construction types in Ethiopia belong to class I, and about 14% towards each of the other classes (see Table 10). However, according to data from the last census in Ethiopia from 2007, 73.9% of all housing units in Ethiopia have been assigned the ‘wood and mud’ wall material, with 80% of the urban units and 72.5% of rural units, whereas a large share of rural units were built with wood (and thatch) walls (15.5%). Compared to the ImageCat data, the Ethiopian building stock appears to be less diverse and shows a different distribution of urban and rural constructions, which is also affected by the applied definition of urban in the census. Since the 2007 census, Ethiopia has experienced considerable economic growth that appears to coincide with growth in the Ethiopian construction industry (World Bank, 2019). Furthermore, census data are aggregated to administrative levels and thus cannot be applied in the approach developed in this paper, for which an object-based dataset is required that is comparable between countries, such as the ImageCat data. With different methodologies in exposure datasets, future research should explore how flood risk assessments that are based on building-material-based vulnerability are affected by the applied building stock dataset and their different scales.

In our sensitivity analysis, the assumptions made on the object areas have little influence on the EAD, with overall slightly lower EAD when using alternative footprint sizes. Even though the effect of the object areas is small ~~here~~, it must be noted that these are estimated sizes and in reality building layouts are very diverse.

**Table 10 Ethiopian building stock according to ImageCat data**

| Type | Description | % total building stock | Class | % urban building stock | % rural building stock |
|---|---|---|---|---|---|
| ADB | URM adobe building | 4.1 | I | 3.4 | 72.0 |
| ERTH | Earthen building | 3.9 | | | |
| INF | Informal building | 9.4 | | | |
| WWD | Wattle & daub building | 39.7 | | | |
| WLI | Light wood building | 1.0 | II | 2.0 | 18.0 |
| WS | Solid wood building | 13.5 | | | |
| BRK | URM brick building | 6.1 | III | 29.9 | 10.0 |
| STN | URM stone building | 8.2 | | | |
| RC | Reinforced concrete frame with URM infill building | 13.9 | IV | 64.8 | 0.03 |

## 4. Conclusions and recommendations

In this paper, we investigated how characteristics of the built environment can be used to assess flood impacts on large~~-~~ scales. To this end, we developed flood vulnerability classes and stage-damage curves that are based on construction types and building materials. In contrast to other large-scale flood risk models that ~~work with~~employ aggregated land-use categories and vulnerability curves, our approach takes advantage of detailed information of the exposed elements ~~and~~to differentiate~~s~~ their vulnerabilit~~ies of these~~y.

Showing that the predominant types of buildings are different in urban and rural areas, particularly in developing countries, the settlements' land use can be identified by the characteristics of their building stock. By distinguishing the urban and rural built environment using our vulnerability classes, we opened up the possibility to analyse flood impacts outside of the typical focus on urban areas of large-scale flood assessments. We used it to show how flood damage~~s~~ to buildings differ and assessed flood risk in urban and rural areas ~~in~~of Ethiopia. Although EAD in urban areas exceeds EAD in rural areas, the rural flood risk of $46.7mln/yr (over 20% of total risk) is nevertheless significant. Moreover, far more buildings are affected in rural as opposed to urban areas. As low water depths can already cause major damage to the types of buildings that predominantly exist in rural settings in Africa, differentiation between flood damage in urban and rural settings could also be invaluable to studies related to poverty and flooding.

We examined the effects of parameter uncertainty and found that the model is insensitive to the applied threshold identifying urban and rural areas from the object-based information about the characteristics of building stock in the study area using our material-based vulnerability classes. Consistent with other studies (e.g. de Moel and Aerts, 2010; Merz et al., 2010), the sensitivity analysis showed that the replacement value of the exposed buildings deserves considerable attention as we see large differences in the model output. The results further showed that aggregated vulnerability as used in large-scale land-use-based models affects the results to a great extent. In our model, vulnerability is addressed in greater detail as it reflects the behaviour of different types of buildings ~~to~~during floods according to their structural characteristics. Therefore, it provides a more direct relation between physical damaging processes and flood impact on different structural types.

This approach is of particular importance for studies where there is a large variation in construction types, such as large-scale studies or studies in developing countries for which the urban and rural building stock is much more differentiated. Large informal settlement areas in cities are not specifically addressed in the current setup and would be classified as rural. To acknowledge this, the urban-rural classification could be extended to highlight such areas and ones where none of the typically urban or rural building types clearly prevail. Lastly, it has to be noted that maintenance can influence the quality of the construction over the years, thus the structural vulnerability would further increase with building age. Future research would benefit including these indicators or similar ones such as building laws and practices, given that sufficient data becomes available, to highlight differences between regions. Furthermore, if the data allows in the future, vulnerabilities within the classes could be further refined such as between clay, stone and concrete brick/block construction or regarding non-structural elements like electrical components and partition walls.

Besides improving the accuracy in estimating direct flood damage~~s~~, the use of building-material-based vulnerability curves also paves the road to the enhancement of multi-risk assessments as the method enables the comparison of vulnerability across different natural hazard types that also use building-material-based vulnerability.

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**Supplementary Material**

**Supplementary section 1 Construction typology**

In general, for the mapping of construction types, the materials used for the structural frame and the bearing walls are a main factor in order to differentiate between individual types. Furthermore, the characteristics of each type are for example also influenced by local building practices, building codes and other materials used. Therefore there are often similarities between construction types and depending on the available information further subtypes can be differentiated. For example unreinforced masonry (URM) is a general description of buildings with bearing walls made from individual units of some masonry material typically bound together by some form of mortar. With more available information on attributes such as the size of brick, the used material (e.g. clay, stone, concrete), or the type of mortar (mud or cement based), subtypes can be separated (for example the ImageCat data differentiates BRK (URM brick building), CB (URM concrete block building), UFB (unreinforced fired brick masonry building) and UCB (unreinforced concrete block building)). Similarly the very traditional buildings such as ERTH (earthen building), M (mud walls building), RE (rammed earth building), and ADB (URM adobe building) are made from soil materials mixed for example with straw and cement. The material can then be formed into bricks and sun-dried, whereas for RE buildings the soil is rammed using wooden molds. The ImageCat structure DS (stone masonry) is similar to buildings made from rubble stones. More information can be found in supplementary table 1 containing the PAGER typology or further in the descriptions of the World Housing Encyclopedia[1].

**Supplementary section ~~1~~2 Comparison to reported damage~~s~~**

Risk is defined as the product of hazard, exposure and vulnerability and expressed as the expected annual damage (EAD) in this paper. The hazard component is comprised of layers of inundation extent and depth for nine return periods (50% to 0.1% annual exceedance probability). The inundation associated with each return period is assumed to occur everywhere simultaneously and we calculate the expected annual damage as the integral of the exceedance probability-impact curve. With this probabilistic analysis the total EAD for Ethiopia in our model is $213.2mln/yr ($46.7mln/yr for rural and $166.6mln/yr for urban areas).

The validation of risk values is difficult as publicly available losses for flood events especially in developing countries, are, if observed at all, rough estimates and often limited to low-frequency, high-impact events. However, we believe that it is important to show the order of magnitude of the losses from the model compared to those in loss databases, even though this is difficult. Therefore, we compared our results with losses reported in the NatCatSERVICE provided by MunichRe (Munich

[1] http://www.db.world-housing.net/

Re, 2016). The NatCatSERVICE database covers global flood loss information from 1980 to 2016. After normalizing those values to 2016 by accounting for inflation and changes of population and wealth since the year of the event, the average damage for Ethiopia is $83mln/yr. It should be stressed that this is simply the average damage per year of the period 1980 to 2016, rather than begin based on a probabilistic approach. Therefore, the modelled and observed metrics are different, since the reported losses do not include information on all flood probabilities. Notwithstanding, the average of the reported losses is significantly lower than our estimated EAD, although they are of a similar order of magnitude. It is to be expected that simulated values are higher than reported values, as not all flood events are recorded in the NatCatSERVICE database (Kron et al., 2012). Generating the flood events and their damage~~s~~ stochastically would be a different approach to calculate the risk or might be used to support a dataset of reported losses as the synthetic realizations could extend missing parts of the exceedance probability-impact curve. However, this also would raise the question of the validation of those risk results and validation of the stochastic generated hazard layer of the events.

In our flood risk assessment we assume that Ethiopia is only protected against floods with a return period of 2 years, whilst in reality there may be higher flood protection in place for the most flood-prone areas, especially in the main urban areas. Estimates of EAD are very sensitive to the assumed protection standard (Ward et al., 2017). For example, if we assumed that Ethiopia was protected against floods with a return period of 5 years, the EAD would fall to $124.5mln/yr ($96.3mln/yr urban, $28.2mln/yr rural) which is similar to the country's flood risk ($135.5mln) in the 2015 Global Assessment Report (UNISDR, 2015) .

**Supplementary table 1 Pager construction types with assigned flood vulnerability classes.**

| PAGER | Description | Vuln. Class | PAGER | Description | Vuln. Class | PAGER | Description | Vuln. Class |
|---|---|---|---|---|---|---|---|---|
| W5 | Wattle and Daub (Walls with bamboo/light timber log/reed mesh and post). | I | UFB5 | Unreinforced fired brick masonry, cement mortar, but with reinforced concrete floor and roof slabs | III | C4 | Nonductile reinforced concrete frame without masonry infill walls | IV |
| M | Mud walls | I | UCB | Concrete block unreinforced masonry with lime or cement mortar | III | C4L | Nonductile reinforced concrete frame without masonry infill walls low-rise | IV |
| M1 | Mud walls without horizontal wood elements | I | MS | Massive stone masonry in lime or cement mortar | III | C4M | Nonductile reinforced concrete frame without masonry infill walls mid-rise | IV |
| M2 | Mud walls with horizontal wood elements | I | UNK | Not specified (unknown/default) | III | C4H | Nonductile reinforced concrete frame without masonry infill walls high-rise | IV |
| A | Adobe blocks (unbaked sundried mud block) walls | I | S | Steel | IV | C5 | Steel reinforced concrete (Steel members encased in reinforced concrete) | IV |
| A1 | Adobe block, mud mortar, wood roof and floors | I | S1 | Steel moment frame | IV | C5L | Steel reinforced concrete (Steel members encased in reinforced concrete) low-rise | IV |
| A2 | Adobe block, mud mortar, bamboo, straw, and thatch roof | I | S1L | Steel moment frame low-rise | IV | C5M | Steel reinforced concrete (Steel members encased in reinforced concrete) mid-rise | IV |
| A3 | Adobe block, straw, and thatch roof cement-sand mortar | I | S1M | Steel moment frame mid-rise | IV | C5H | Steel reinforced concrete (Steel members encased in reinforced concrete) high-rise | IV |
| A4 | Adobe block, mud mortar, reinforced concrete bond beam, cane and mud roof | I | S1H | Steel moment frame high-rise | IV | C6 | Concrete moment resisting frame with shear wall - dual system | IV |
| A5 | Adobe block, mud mortar, with bamboo or rope reinforcement | I | S2 | Steel braced frame | IV | C6L | Concrete moment resisting frame with shear wall - dual system low-rise | IV |
| RE | Rammed Earth/Pneumatically impacted stabilized earth | I | S2L | Steel braced frame low-rise | IV | C6M | Concrete moment resisting frame with shear wall - dual system mid-rise | IV |
| INF | Informal constructions. | I | S2M | Steel braced frame mid-rise | IV | C6H | Concrete moment resisting frame with shear wall - dual system high-rise | IV |
| W | Wood | II | S2H | Steel braced frame high-rise | IV | C7 | Flat slab structure | IV |
| W1 | Wood stud-wall frame with plywood/gypsum board sheathing. | II | S3 | Steel light frame | IV | PC1 | Precast concrete tilt-up walls | IV |
| W2 | Wood frame, heavy members (with area > 5000 sq. ft.) | II | S4 | Steel frame with cast-in-place concrete shear walls | IV | PC2 | Precast concrete frames with concrete shear walls | IV |
| W3 | Wood light unbraced post and beam frame. | II | S4L | Steel frame with cast-in-place concrete shear walls low-rise | IV | PC2L | Precast concrete frames with concrete shear walls low-rise | IV |
| W4 | Wood panel or log construction. | II | S4M | Steel frame with cast-in-place concrete shear walls mid-rise | IV | PC2M | Precast concrete frames with concrete shear walls mid-rise | IV |
| W6 | Wood unbraced heavy post and beam frame with mud or other infill material. | II | S4H | Steel frame with cast-in-place concrete shear walls high-rise | IV | PC2H | Precast concrete frames with concrete shear walls high-rise | IV |
| W7 | Wood braced frame with load-bearing infill wall system. | II | S5 | Steel frame with unreinforced masonry infill walls | IV | PC3 | Precast reinforced concrete moment resisting frame with masonry infill walls | IV |
| MH | Mobile homes | II | S5L | Steel frame with unreinforced masonry infill walls low-rise | IV | PC3L | Precast reinforced concrete moment resisting frame with masonry infill walls low-rise | IV |
| RS | Rubble stone (field stone) masonry | III | S5M | Steel frame with unreinforced masonry infill walls mid-rise | IV | PC3M | Precast reinforced concrete moment resisting frame with masonry infill walls mid-rise | IV |
| RS1 | Local field stones dry stacked (no mortar) with timber floors, earth, or metal roof. | III | S5H | Steel frame with unreinforced masonry infill walls high-rise | IV | PC3H | Precast reinforced concrete moment resisting frame with masonry infill walls high-rise | IV |
| RS2 | Local field stones with mud mortar. | III | C | Reinforced concrete | IV | PC4 | Precast panels (wall made of number of horizontal precast panels, construction from former Soviet Union countries) | IV |
| RS3 | Local field stones with lime mortar. | III | C1 | Ductile reinforced concrete moment frame with or without infill | IV | RM | Reinforced masonry | IV |
| RS4 | Local field stones with cement mortar, vaulted brick roof and floors | III | C1L | Ductile reinforced concrete moment frame with or without infill low-rise | IV | RM1 | Reinforced masonry bearing walls with wood or metal deck diaphragms | IV |
| RS5 | Local field stones with cement mortar and reinforced concrete bond beam. | III | C1M | Ductile reinforced concrete moment frame with or without infill mid-rise | IV | RM1L | Reinforced masonry bearing walls with wood or metal deck diaphragms low-rise | IV |
| DS | Rectangular cut-stone masonry block | III | C1H | Ductile reinforced concrete moment frame with or without infill high-rise | IV | RM1M | Reinforced masonry bearing walls with wood or metal deck diaphragms mid-rise (4+ stories) | IV |
| DS1 | Rectangular cut stone masonry block with mud mortar, timber roof and floors | III | C2 | Reinforced concrete shear walls | IV | RM2 | Reinforced masonry bearing walls with concrete diaphragms | IV |
| DS2 | Rectangular cut stone masonry block with lime mortar | III | C2L | Reinforced concrete shear walls low-rise | IV | RM2L | Reinforced masonry bearing walls with concrete diaphragms low-rise | IV |
| DS3 | Rectangular cut stone masonry block with cement mortar | III | C2M | Reinforced concrete shear walls mid-rise | IV | RM2M | Reinforced masonry bearing walls with concrete diaphragms mid-rise | IV |
| DS4 | Rectangular cut stone masonry block with reinforced concrete floors and roof | III | C2H | Reinforced concrete shear walls high-rise | IV | RM2H | Reinforced masonry bearing walls with concrete diaphragms high-rise | IV |
| UFB | Unreinforced fired brick masonry | III | C3 | Nonductile reinforced concrete frame with masonry infill walls | IV | CM | Confined masonry | IV |
| UFB1 | Unreinforced brick masonry in mud mortar without timber posts | III | C3L | Nonductile reinforced concrete frame with masonry infill walls low-rise | IV | CML | Confined masonry low-rise | IV |
| UFB2 | Unreinforced brick masonry in mud mortar with timber posts | III | C3M | Nonductile reinforced concrete frame with masonry infill walls mid-rise | IV | CMM | Confined masonry mid-rise | IV |
| UFB3 | Unreinforced brick masonry in lime mortar | III | C3H | Nonductile reinforced concrete frame with masonry infill walls high-rise | IV | CMH | Confined masonry high-rise | IV |
| UFB4 | Unreinforced fired brick masonry, cement mortar. | III | | | | | | |

**Supplementary table 2 Confusion matrix of urban settlement map of the ImageCat data as reference with different classification maps.**

| | | ImageCat | |
|---|---|---|---|
| | | Other land use | Settlement (urban) |
| GRUMP | Other land use | 9,967 | 7,363 |
| | Settlement | 33 | 2,637 |
| MOD500 | Other land use | 9,995 | 9,403 |
| | Settlement | 5 | 597 |
| GUF | Other land use | 9,997 | 8,792 |
| | Settlement | 3 | 1,208 |
| HBASE | Other land use | 9,999 | 8,618 |
| | Settlement | 1 | 1,382 |
| GHS-SMOD | Other land use | 9,855 | 5,150 |
| | Settlement (urban centre/cluster) | 145 | 4,850 |
| GHS-SMOD | Other land use | 9,855 | 5,150 |
| | Settlement (urban centre) | 145 | 4,850 |

**Supplementary table 3 Confusion matrix of urban-rural map of the ImageCat data as reference with GHS-SMOD as classification maps.**

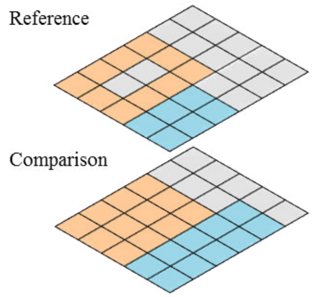
| | | ImageCat | | |
|---|---|---|---|---|
| | | Other land use | Rural | Urban |
| GHS-SMOD | Other land use | 9,484 | 8,231 | 3,123 |
| | Rural | 411 | 1,101 | 2,004 |
| | Urban (centre/cluster) | 105 | 668 | 4,873 |

**Supplementary table 4 Results of agreement for Ethiopia using the ImageCat data classified to urban settlement and other land use as the reference map.**

| | Settlement (urban) | | Other land use | | Overall Accuracy (%) | Kappa |
|---|---|---|---|---|---|---|
| Settlement Map | Producer's Accuracy (%) | User's Accuracy (%) | Producer's Accuracy (%) | User's Accuracy (%) | | |
| GRUMP | 26.4 | 98.8 | 99.7 | 57.5 | 63.0 | 0.26 |
| MOD500 | 6.0 | 99.2 | 100.0 | 51.5 | 53.0 | 0.06 |
| GUF | 12.1 | 99.8 | 100.0 | 53.2 | 56.0 | 0.12 |
| HBASE | 13.8 | 99.9 | 100.0 | 53.7 | 56.9 | 0.14 |
| GHS-SMOD (urban centre/cluster) | 48.5 | 97.1 | 98.6 | 65.7 | 73.5 | 0.47 |
| GHS-SMOD (urban centre) | 25.0 | 99.2 | 99.8 | 57.1 | 62.4 | 0.25 |

**Supplementary table 5 Building footprints for sensitivity analysis derived from the ImageCat data of flood risk assessment for Ethiopia.**

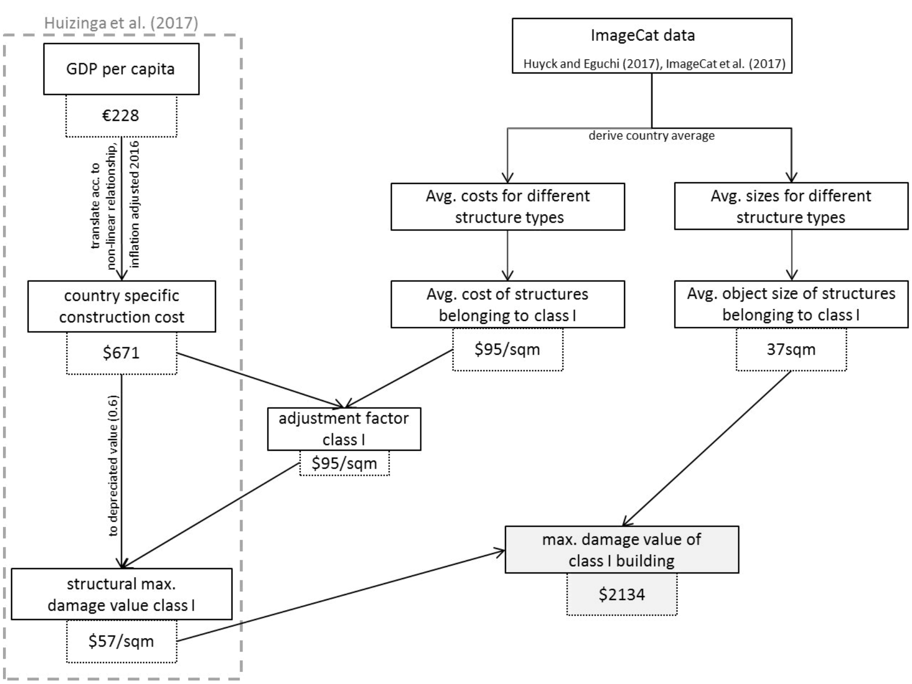
| Vuln. class | Building footprint [$m^2$] |
|---|---|
| I | 35 |
| II | 35 |
| III 1 floor | 35 |
| III 2 floors | 251 |
| IV | 467 |




| | | Reference | | | |
|---|---|---|---|---|---|
| | | Class 1 | Class 2 | Class 3 | Sum |
| Comparison | Class 1 | $p_{11}$ | $p_{12}$ | $p_{13}$ | $p_{1\_}$ |
| | Class 2 | $p_{21}$ | $p_{22}$ | $p_{23}$ | $p_{2\_}$ |
| | Class 3 | $p_{31}$ | $p_{32}$ | $p_{33}$ | $p_{3\_}$ |
| | Sum | $p_{\_1}$ | $p_{\_2}$ | $p_{\_3}$ | 1 |

| Metric | Equation | Short Explanation |
|---|---|---|
| Overall accuracy | $OA = \sum_{j=1}^{q} p_{jj}$ | proportion of samples classified correctly; refers to the probability that a randomly selected location on the comparison map is classified correctly |
| Kappa | see Congalton (1991) | agreement between the maps, corrected for the agreement as can be expected from random allocation of classes |
| Producer's accuracy | $P_j = p_{jj} / p_{\_j}$ | proportion of the samples of reference class j that is mapped as class j; probability that class j in the reference is mapped as the same class |
| User's accuracy | $U_i = p_{ii} / p_{i\_}$ | proportion of the samples mapped as class i that has reference class i; probability that an area of class i on the comparison map is also that class in the reference |

**Supplementary figure 1 Example accuracy assessment using a confusion matrix of q classes and $p_{ij}$ representing the proportion of samples that has classification class i and reference class j.**




**Supplementary figure 2 Process of calculating the maximum damage value for the example of a class I building.**

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