

Proceedings

The New Methods for Rapid Exposure and Seismic Vulnerability Assessment. How Do They Adapt to Different Scenarios? [†]

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Abstract: We present a procedure for exposure and vulnerability evaluation that integrates LiDAR, orthophotos, and other ancillary datasets. It comprises three phases: (1) city stratification into homogeneous regions; (2) exposure database compilation; and (3) vulnerability allocation using predictive modelling. We have conducted two applications in Lorca (Spain) and Port-au-Prince (Haiti) and here we compare them. Each phase of the method is subject to variations due mainly to data availability; however, it does not affect the final accuracy that remains high in both scenarios (over 80%). It is a flexible procedure that is able to adapt to the particular features of two different cities.

Keywords: exposure; earthquake vulnerability; LiDAR; orthophoto; machine learning

1. Introduction

Natural disasters have catastrophic impacts on the societies from the economic, social, and environmental point of view. Earthquakes are the most devastating hazard in certain areas of the planet that have to face these events with relatively high frequency. The assessment of seismic risk is the basis for the definition of mitigation measures in the frame of an international Disaster Risk Reduction (DRR) policy. Risk assessment involves two main components: the hazard intensity and the elements exposed to this hazard (such as buildings and people) characterized by their vulnerability and economic value [1]. The results of risk are given in terms of damage to the exposure and economic losses.

The goal of the vulnerability evaluation is to classify the building stock of a city into categories according to their capacity to resist an earthquake shaking. The vulnerability allocation requires a previous characterization of each building in terms of location, construction materials, plan configuration, occupancy rate, height, etc. To this end, inventory databases are implemented with these vulnerability-related attributes following the specifications of any local [2,3] or global [4] building taxonomy.

Commonly, collecting housing and population data for city-level risk analysis is a cumbersome task, as it requires the management of numerous cadaster or census databases, if existent; or the compilation of new datasets through resource-consuming in-field surveys [5]. Thus, innovative procedures have been developed during the last decade that optimize resources to create and update natural risk databases in a time- and cost-effective manner [6]. These procedures (e.g., [7–10]) combine remote sensing data with other sources, such as existing cartography or web-based information, and expert knowledge to create building inventory databases. The vulnerability is

allocated using any type of predictive model that relates the vulnerability class of a building with its attributes. In these studies, different data fusion strategies are presented and compared to others according (mainly) to the final building classification accuracy. However, most of these procedures have been created and validated in one single scenario and hence it is difficult to evaluate till which point they are really globally applicable for the comparison to be valid.

This work is focused on the comparison of the methods that we used for characterizing the built stock of two earthquake-prone cities, namely Lorca (Spain) [6] and Port-au-Prince (Haiti). The goal is to test how the new methodologies for rapid exposure and vulnerability evaluation adapt to different scenarios. Our proposal is to work with open, flexible methodologies that are able to deal with the particular features of different cities.

2. Materials and Methods

The procedure that we propose follows three general phases, as Figure 1 shows, namely (1) stratification of the city; (2) exposure database compilation; and (3) vulnerability allocation. The stratification process divides the city into strata with homogeneous urban configuration under the hypothesis that neighboring buildings share several characteristics (e.g., typology, occupancy, etc.) [11]. The subsequent evaluation of exposure and vulnerability (phases 2 and 3) is easier when working on similar buildings.

Phase 2 is devoted to the implementation of the exposure database in two steps. First, the building footprints are extracted and then, the above mentioned vulnerability-related attributes are computed for each one. The exposure database is used in phase 3 for learning a predictive model to infer the seismic vulnerability of each building. A number of instances are randomly chosen to create the training dataset, which are labeled using ground truth data. Similarly, a testing dataset is compiled for validation in order to measure the accuracy of the method.

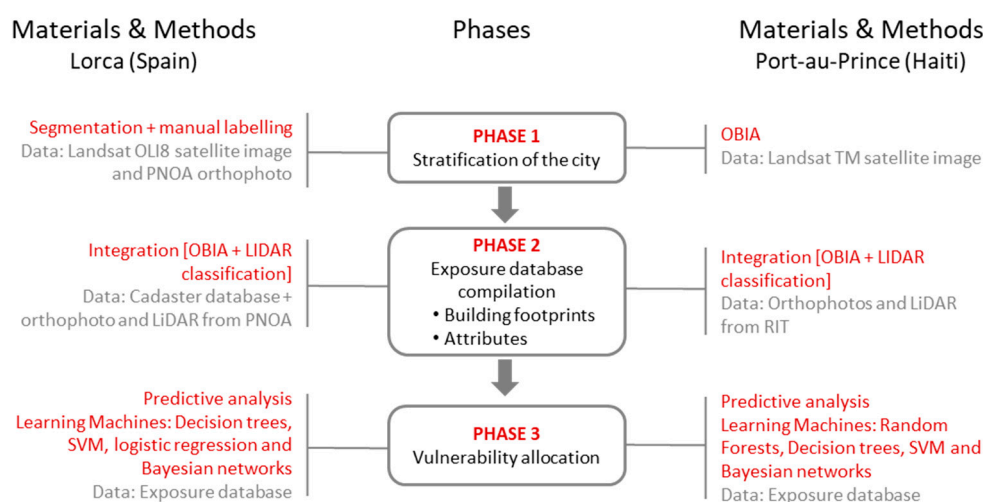


Figure 1. Methodological scheme. Materials and methods are indicated for both scenarios, Lorca (left) and Port-au-Prince (right).

Figure 1 summarizes the materials and methods that we used in each particular city (Lorca [6] and Port-au-Prince). Although they are comparable, still important differences are identified. In phase 1, the stratification of Port-au-Prince was done following a complete Object-Based Image Analysis (OBIA) [11], while in Lorca a segmentation process was used followed by manual labelling of segments given the manageable extend of the city. In both cases, we worked with medium resolution (GSD = 30 m) Landsat images, specifically OLI8 and TM.

We integrated high resolution orthophotos and LiDAR cloud points for phase 2 in both cities. The PNOA data were incorporated in the study for the Spanish scenario. The RGB orthophotos have a GSD of 50cm and the LiDAR cloud has a density of 1 point/m². For the Haitian case, the Rochester

Institute of Technology (RIT) provided the datasets: RGB+SWIR orthophotos with a GSD of 15 cm and LiDAR with a density of 3.4 point/m². The LiDAR points were classified using the MDTopX software. The main difference in this phase is the building footprints data source. In Lorca we could obtain official footprints from the Cadaster, whereas in Port-au-Prince we had to manually digitize the roof contours in absence of any other source of building geometries. In both cases, also an automated image analysis was performed for comparison: segmentation in Lorca and OBIA in Port-au-Prince. The segmentation of Lorca was done with the RGB orthophotos from PNOA. In Haiti, we tried to improve the automated footprint detection in order to provide an alternative to the manual digitization process. To this end, we fused the 4-band RIT orthophotos with the classified LiDAR to incorporate one band of elevations (point elevation over the ground) and another band of intensity values.

Another important difference is related to the roof covering identification. In Port-au-Prince, the roof covering material was extracted from the OBIA analysis as it was conducted for footprint detection. In Lorca, a predictive model was learnt using other attributes: building height, centroid location, and roof slope.

Finally, in phase 3, we configured a number of learning machines that are listed in Figure 1. The six attributes used in Lorca are: centroid location (X,Y), building height, roof slope, roof covering, and floor area. In Port-au-Prince, in addition to those, we considered the plan shape, the building direction, and the location of the building within the block, as they have proved to strongly influence the building seismic performance [4].

3. Results

In Lorca, the study was complete with satisfactory results [6Error! Reference source not found.]. Both, the building attributes and the building vulnerability allocation were validated using a ground truth database provided by Martínez-Cuevas et al. [12]. The vulnerability assessment of the cadastral footprints yielded better results than the assessment of the segmented ones. For the cadastral footprints, the final classification accuracies ranged from 77% to 80% (F1-score) for the four machine learning techniques in the city-center area. In urban sprawl areas, the a priori F1-score varied from 79% to 89%.

In Port-au-Prince, we are obtaining encouraging preliminary results. The OBIA analysis for building detection with characterization of roof covering reaches accuracies of 95% for tin roofs and 99% for concrete roofs, when all the bands are used. The vulnerability allocation has been done in two sample sites, where the estimated distribution of building types matches the actual distribution provided by the Haitian Ministry of Public Works building database (ground truth for this scenario).

4. Conclusions

Novel methodologies for exposure and seismic vulnerability estimation within seismic risk studies integrate remote sensing data with ancillary databases and expert knowledge. The goal is to optimize the traditional procedures and minimize time and budget. Different studies try to design a global, unique approach that reaches the highest building classification accuracies. However, in our opinion, having one single procedure is not suitable since each study needs variations according to the particular features of each city.

Here we have compared two seismic vulnerability studies conducted under a flexible procedure. It has been feasible to adapt it to both scenarios with variations motivated mainly by data availability, but also by other issues, such as the extension of the study area or the particular building types. The high accuracies obtained in both scenarios for building characterization and vulnerability allocation seem to prove the efficiency of this flexible method.

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References

1. UNDRR. Available online: <https://www.unisdr.org/we/inform/terminology> (accessed on 2 May 2019).
2. Milutinovic, Z.V.; Trendafiloski, G.S. *An Advanced Approach to Earthquake Risk Scenarios with Applications to Different European Towns*; WP4: Vulnerability of Current Buildings; European Commissio: Bruxelles/Brussel, Belgium 2003; p. 110.
3. Hazus, M.H. *Multi-hazard Loss Estimation Methodology. Technical Manual*; Federal Emergency Management Agency (FEMA): Washington, DC, USA, 2003; 712p.
4. Silva, V.; Henshaw, P.; Huyck, C.; O'Hara, M. *GED4ALL: Global Exposure Database for Multi-Hazard Risk Analysis*; D5—Final Report; GEM Technical Report 2018-05; GEM Foundation: Pavia, Italy, 2018.
5. Dunbar, P.K.; Bilham, R.G.; Laituri, M.J. Earthquake loss estimation for India based on macroeconomic indicators. *Risk Sci. Sustain. Nato Sci.* **2003**, *112*, 163–180.
6. Torres, Y.; Arranz, J.J.; Gaspar-Escribano, J.M.; Haghi, A.; Martinez-Cuevas, S.; Benito, B.; Ojeda, J.C. Integration of LiDAR and multispectral images for rapid exposure and earthquake vulnerability estimation. Application in Lorca, Spain. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *81*, 161–175.
7. Borfecchia, F.; De Cecco, L.; Pollino, M.; La Porta, L.; Lugari, A.; Martini, S.; L Porta, L.; Ristorante, E.; Pascale, C. Active and passive remote sensing for supporting the evaluation of the urban seismic vulnerability. *Ital. J. Remote Sens.* **2010**, *42*, 129–141.
8. Wieland, M.; Pittore, M.; Parolai, S.; Zschau, J. Exposure estimation from multi-resolution optical satellite imagery for seismic risk assessment. *ISPRS Int. J. Geo-Inf.* **2012**, *1*, 69–88.
9. Geiß, C.; Pelizari, P.A.; Marconcini, M.; Sengara, W.; Edwards, M.; Lakes, T.; Taubenböck, H. Estimation of seismic building structural types using multi-sensor remote sensing and machine learning techniques. *ISPRS J. Photogramm. Remote Sens.* **2015**, *104*, 175–188.
10. Qi, W.; Su, G.; Sun, L.; Yang, F.; Wu, Y. "Internet+" approach to mapping exposure and seismic vulnerability of buildings in a context of rapid socioeconomic growth: A case study in Tangshan, China. *Nat. Hazards* **2017**, *86*, 107–139.
11. Wieland, M.; Torres, Y.; Pittore, M.; Benito, B. Object-based urban structure type pattern recognition from Landsat TM with a Support Vector Machine. *Int. J. Remote Sens.* **2016**, *37*, 4059–4083.
12. Martínez-Cuevas, S.; Benito, M.B.; Cervera, J.; Morillo M.C.; Luna, M. Urban modifiers of seismic vulnerability aimed at Urban Zoning Regulations. *Bull. Earthq. Eng.* **2017**, *15*, 4719–4750. doi:10.1007/s10518-017-0162-2.



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