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Street-Level Imagery and Deep Learning for Characterization of Exposed Buildings

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Knowledge on the key structural characteristics of exposed buildings is crucial for accurate risk modeling with regard to natural hazards. In risk assessment this information is used to interlink exposed buildings with specific representative vulnerability models and is thus a prerequisite to implement sound risk models. The acquisition of such data by conventional building surveys is usually highly expensive in terms of labor, time, and money. Institutional data bases such as census or tax assessor data provide alternative sources of information. Such data, however, are often inappropriate, out-of-date, or not available. Today, the large-area availability of systematically collected street-level data due to global initiatives such as Google Street View, among others, offers new possibilities for the collection of *in-situ* data. At the same time, developments in machine learning and computer vision – in deep learning in particular – show high accuracy in solving perceptual tasks in the image domain. Thereon, we explore the potential of an automatized and thus efficient collection of vulnerability related building characteristics. To this end, we elaborated a workflow where the inference of building characteristics (e.g., the seismic building structural type, the material of the lateral load resisting system or the building height) from geotagged street-level imagery is tasked to a custom-trained Deep Convolutional Neural Network. The approach is applied and evaluated for the earthquake-prone Chilean capital Santiago de Chile. Experimental results are presented and show high accuracy in the derivation of addressed target variables. This emphasizes the potential of the proposed methodology to contribute to large-area collection of *in-situ* information on exposed buildings.

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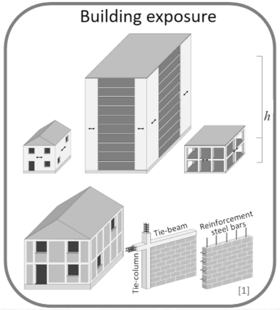
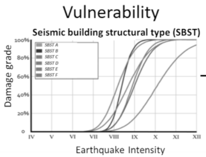
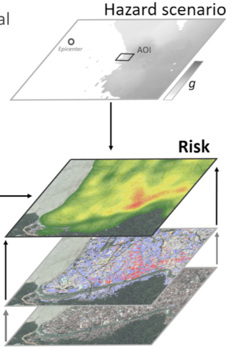
1 BACKGROUND

Natural hazards risk modeling requires knowledge on key structural characteristics of exposed buildings

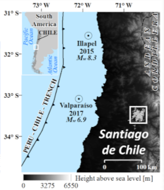






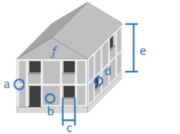
2 DATA & STUDY SITE

Google street-view coverage 2021 [2]



3 BUILDING TAXONOMY DEFINITION

Based on *visual-structural criteria*

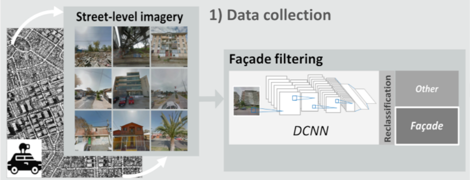


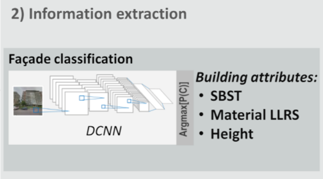
e.g.,
a = tie-bars and columns
b = wall structure
c = opening widths
d = wall thickness
e = no. of storeys
f = design epoch

- 14 Seismic building structural types (SBST),
- 7 Lateral load-resisting system (LLRS) material types,
- 6 height classes

APPLICATION

4 METHOD & SETUP





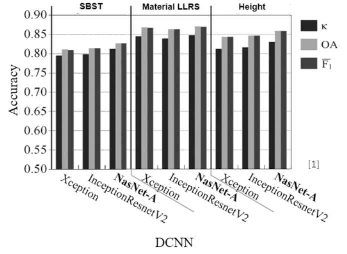
Transfer learning of imageNet [3] pretrained CNNs

Architecture	*# Parameters [M]*
Xception [4]	22.8
InceptionResNet-v2 [5]	55.8
NasNet-A [6]	88.9

- Automated façade image acquisition
- ~30k reference façade images for CNN training and evaluation
- Class balancing and data augmentation strategy

5 RESULTS

Overall accuracy (OA) & Kappa (κ)
> 0.80 for SBST-,
> 0.85 for material type- and height prediction



Automated building characterization

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