This is an excerpt from the thesis "*Anticipating a Risky Future: Deep Neural Networks for Predictive Exposure Modeling*".

Please contact Jana Maier for a full version of the thesis.

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Master Thesis

Anticipating a Risky Future: Deep Neural Networks for Predictive Exposure Modeling

submitted by
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December 22, 2022

Supervision:
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Abstract

Anticipating future geospatial population distribution is essential for numerous applications such as hazard risk assessment, accessibility detection, and other health, economic, and environment-related fields. Existing population forecasts are provided country- or district-wise and are thus not suitable for an exposure analysis on a city level. In this study, freely available population grids are utilized together with machine learning models, that were tailored for time series analysis. In detail, Long Short-Term Memory (LSTM) and Convolutional LSTM (ConvLSTM) networks are trained with WorldPop and ancillary geospatial data to forecast population on a three-year interval for a hazard exposure analysis. The experimental setup is conducted for Peru‘s capital Lima, which features a high population dynamic and a strong seismic activity. To assess the competitive performance of LSTM models for this application, also a Multivariate Linear Regression and Random Forest Regression are implemented for comparison. To gain insight into the influence of different driving factors for population dynamics and the influence of the number of input years on the prediction, the models are trained with different sets of input features and time steps. The results suggest that the LSTM network outperforms the ConvLSTM and the benchmark methods, specifically in terms of lower Root Mean Squared Error (RMSE) and better learning of spatial characteristics. Regions of strong population change are captured much better by the LSTM than by the base models. The included driving factors don't improve the results. On the contrary, models with the population as the only input result in the lowest median absolute error. With the forecasted population grids and a modeled hazard scenario, it was found that the population in the tsunami inundation area is expected to increase by 61% until 2035 and that 70% of the additional population of Lima will accumulate in areas of high earthquake intensities. This comparative analysis underlines the usefulness of the LSTM networks for forecasting gridded population data for exposure assessment.

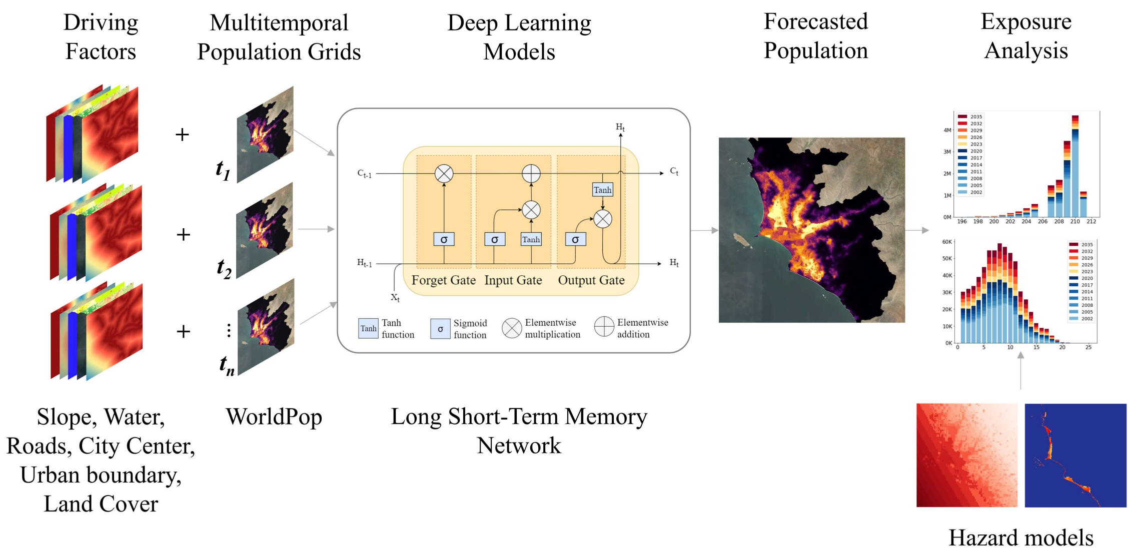

Figure 1: Graphical Abstract

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List of Abbreviations

ANN	Artificial Neural Network
CNN	Convolutional Neural Network
ConvLSTM	Convolutional LSTM
DEM	Digital Elevation Model
DL	Deep Learning
ESA	European Space Agency
GDACS	Global Disaster Alert and Coordination System
GDP	Gross Domestic Product
GHS-POP	Global Human Settlement - Population
GMF	Ground Motion Fields
GPW	Gridded Population of the World
GRID3	Geo-Referenced Infrastructure and Demographic Data for Development
GRUMP	Global Rural Urban Mapping Project
GRU	Gated Recurrent Unit
GWR	Geographically Weighted Regression Method
LMA	Lima Metropolitan Area
LR	Linear Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MedAE	Median Absolute Error
ML	Machine Learning

MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
OSM	OpenStreetMap
ReLU	Rectified Linear Unit
RF	Random Forest
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
UN	United Nations
USGS	United States Geological Survey

1 Introduction

The number of recorded natural disasters experienced a drastic increase in recent decades (EM-DAT, 2022). Such events can cause huge losses, especially in areas with a high population density, where many people are affected. It is expected that in 2050 a share of two-thirds of the world‘s population will live in cities (United Nations, 2018). With this process of urbanization, poorly planned or managed urban expansion very likely lead to uneven intra-urban growth rates and unsustainable development (UN Habitat, 2016), increasing the vulnerability of inhabitants in certain urban areas. To develop mitigation strategies, detailed knowledge about the distribution of the population and their exposure to hazards is needed. For early and sustainable urban planning, estimations of the future population distribution are particularly important.

Until the late 1970s, less than 100 disasters were recorded annually whereas in the last 20 years it were already between 300 and 400 documented disasters. Droughts and floods used to be the most severe hazards and caused by far the most fatalities until 1970. Since 1980, earthquakes and the tsunamis they have triggered, caused nearly half of the deaths related to natural hazards (MunichRE, 2022). The total number of deaths caused by natural disasters decreased over the last century, due to improved disaster management and early warning systems (World Meteorological Organization, 2021). Still, natural hazards caused an average of 45,000 deaths per year in the last decade (Ritchie and Roser, 2014). Even more people are exposed to the hazards, without suffering death. An average of more than 169 million people were affected every year of the last decade. Moreover, not only human but also monetary loss is a consequence, and the economical damage caused by hazards increased even more drastically (Ritchie and Roser, 2014) due to economic development and the increasing accumulation of capital assets (Bouwer, 2019). It is therefore important to understand the relationship between urban dynamics and hazard probabilities, for effective exposure modeling.

The world’s population reaches 8 billion soon and is projected to grow up to 9.7 billion in 2050 (United Nations, 2022). Already today 55% of the world’s population is residing in urban areas, whereas in 1950 it were only 30%. Northern America, Latin America and Europe are the regions with the highest urbanization of rates close to

80% (United Nations, 2018). The United Nations further state:

> "As the world continues to urbanize, sustainable development depends increasingly on the successful management of urban growth, especially in low-income and lower-middle-income countries where the most rapid urbanization is expected between now and 2050."

One of these fast-growing cities in Latin America is Lima, the capital of Peru. In the last 80 years, it grew from only 7% of today's population, a bit more than half a million people, up to 8,5 million. In 1981 Lima still only consisted of half of its today's inhabitants (INEI, 2018). Since then, the annual growth rate decreased but is still relatively high with 1.2% over the last 20 years (United Nations, 2018).

Urban growth is a complex socio-economic process. "Well-managed urbanization (among other factors), informed by an understanding of population trends over the long run, can help [...] minimizing [...] potential adverse impacts of a growing number of city dwellers." (United Nations, 2018). This knowledge about population trends is essential and should be provided objectively, timely, and with high quality. Population density estimations are beneficial for many aspects of urban planning, as it is a basis to estimate the demand for land, public facilities, and infrastructure and support the planning for public and private sectors, investments, and emergency management (Amer et al., 2020; Wang et al., 2021; Xue et al., 2020). Most importantly, spatial population dynamics are crucial information for natural hazard risk assessment (Geiß et al., 2022).

With rapid urbanization but poor planning, multiple subsequent problems come along, especially in low-income countries. Inadequate housing, urban poverty, absence of proper land use policies are consequences and further contribute to urban sprawling and the emergence of slums (Dewan and Yamaguchi, 2009). Slums are usually characterized by a high population density and unstable building constructions, that further increase the threat of hazards and the vulnerability of the residents. As a result of rapid urbanization, where natural hazards affected only a small amount of people living in sparsely populated places, today hit millions of people in urban areas (Bilham, 2009; He et al., 2017). To asses the exposure of population to future perils, detailed information about the spatiotemporal distribution of the population and natural hazards, and the magnitude of strength of these events is necessary. With this information, the exposure of the population can be quantified with a high resolution and a high level of automatization as done by Geiß et al. (2017). The higher the population density and the higher the hazard magnitude, the greater is also the risk and the associated loss.

Knowledge about past natural hazards exists and is available from several institutions such as the Earthquake catalogue from the United States Geological Survey (USGS) (2022), the Global Disaster Alert and Coordination System (GDACS) (2022) or EM-DAT (2022). Generalized hazard models such as the Ground Motion Fields (GMF) provided by the Web Processing Service Shakyground V.1.0 (Weatherill et al., 2021) are based on data from past events, and can be used to assess potential future events. Also, population distributions are known in most places of the world. Historically, censuses and surveys were the main sources for population estimation and are still widely used to map spatial distributions. However, census counts only reflect the population for a time in the past, are often provided with a low frequency, and are thus of limited use for long-term planning. To be able to anticipate future exposure, forecasts of population data are needed. Some future population estimations do exist, such as the global forecasts of the United Nations for all years until 2100 (United Nations, 2022). These estimations, though, are only provided country-wise. Therefore, it is not possible to determine the exposure on a city level, which could then be utilized to assess human exposure to hazards. Consequently, there is a clear need for methods to create future spatial distribution estimations for the population on a city level.

To fill that gap, this research study aims to create a future exposure estimation by evaluating different model setups for population prediction. The resulting small-scale spatial population forecasts are used for risk assessment. The goal is to analyze the possibility to forecast population distribution for urban areas using Deep Learning (DL) models. More specifically, the following objectives are in focus:

- To utilize Deep Learning methods for population distribution forecasting
- To assess if the Deep Learning models result in better predictions than machine learning base models
- To evaluate the influence of ancillary geospatial data
- To quantify the predicted population that will be exposed to multiple natural hazards

These objectives serve to answer the overarching research question:

Are Neural Networks a suitable tool to forecast population distribution for exposure modeling?

This thesis is divided into 8 chapters. Chapter 2 covers the theoretical background of population modeling, population forecasting, and the concept of Neural Networks. a focus is set on Convolutional, Recurrent, and Long Short-Term Memory (LSTM) Networks, which were utilized in this study. In chapter 3, the study area and input data are described in detail. This is followed by the methods in chapter 4, and the experimental setup in chapter 5. In that chapter all trained models will be described, and how the hyper-parameters and network architecture were defined. In chapter 6, all results will be shown and described, the discussion will follow in chapter 7. An overall conclusion and outlook in the last chapter 8 rounds the research up.

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