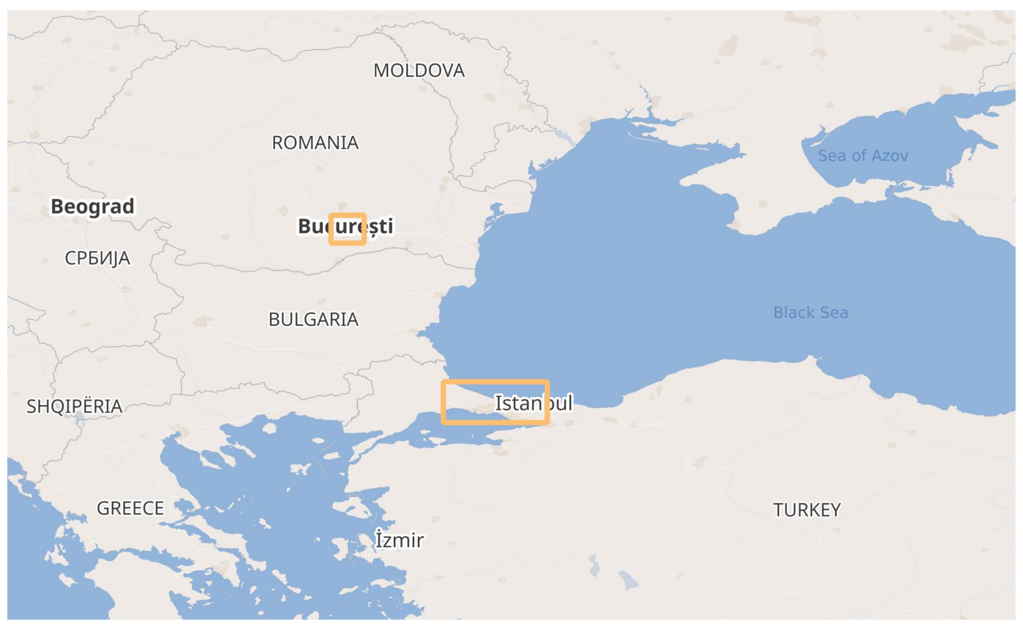
Geospatial extrapolation of time-series data with deep learning

Background

The number of recorded natural hazard events has increased in recent decades. These include earthquakes, fires, floods, and even compounding disasters. Such events have the potential to cause significant losses, particularly in human settlements with high population densities. It can be expected that this situation intensifies in the future as the world's population grows and climate change increases the number of both single and multi-hazard disasters. Consequently, an increasing number of individuals will be exposed to natural hazards in the future, exceeding previous levels. To develop effective mitigation strategies for potential future damage events, it is essential to gain detailed insights into the future spatial distribution of the population and other vulnerable elements. In this context, Earth observation (EO) datasets and innovative artificial intelligence (AI) techniques offer innovative possibilities.

Test Cases

The developed methods will be primarily applied in the Bucharest Metropolitan region (Romania) and the megacity Istanbul (Turkey). Both cities are very highly exposed to droughts, floods and especially earthquakes and landslides. Additionally, Istanbul experienced a huge population growth in the last two centuries from 8 to 15 Million people. [1]



PARATUS Project

An aim of the PARATUS project is to enhance the preparedness of first and second responders to multi-hazard incidents, with the ultimate goal of reducing the risks associated with the multi-sectoral impacts of complex disasters. The principal deliverable is the development of a cloud-based online service platform designed to facilitate the reduction of dynamic risk scenarios and systemic vulnerability resulting from multi-hazard disasters. The will also be assess-ments of the inter-actions of complex hazards and the resulting impacts and the future change. [1]

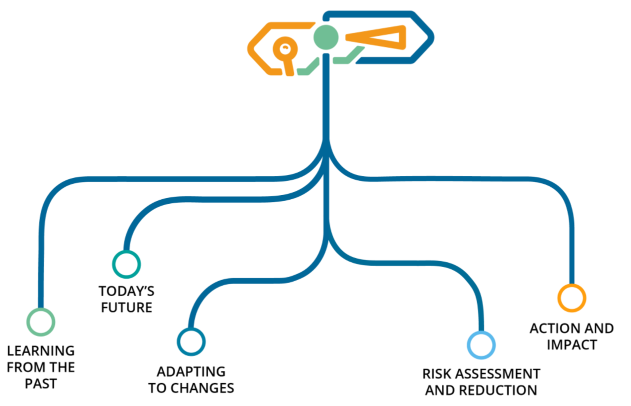


Fig. 1: Project components [1]

Data

Time-variant

Fig. 2: WorldPop Population on a yearly basis from 2000 (l) to 2020 (r) and a spatial resolution of 100 m pixels

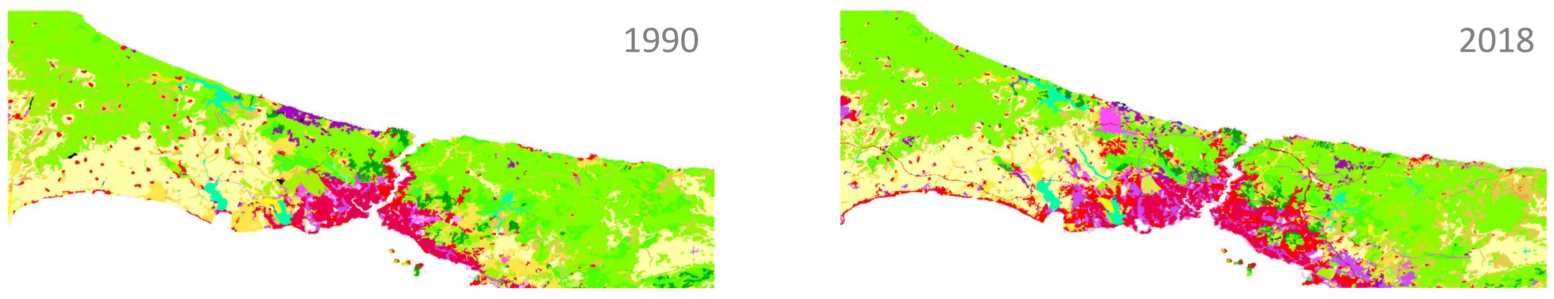


Fig. 3: CORINE land cover almost every 6 years from 1990 (l) to 2020 (r) and a spatial resolution of 100 m pixels

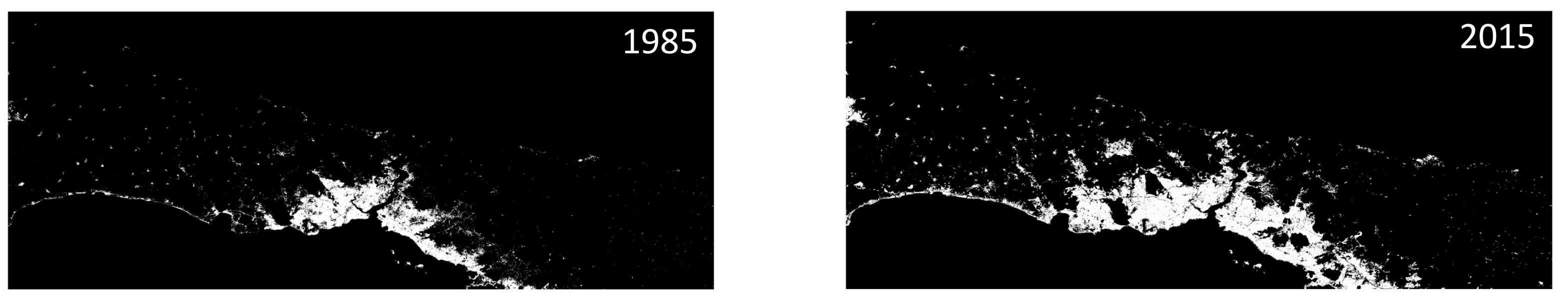


Fig. 4: World Settlement Footprint (WSF) Evolution on a yearly basis from 1985 (top) to 2015 (bottom) and a spatial resolution of 30 m pixels

Driving factors

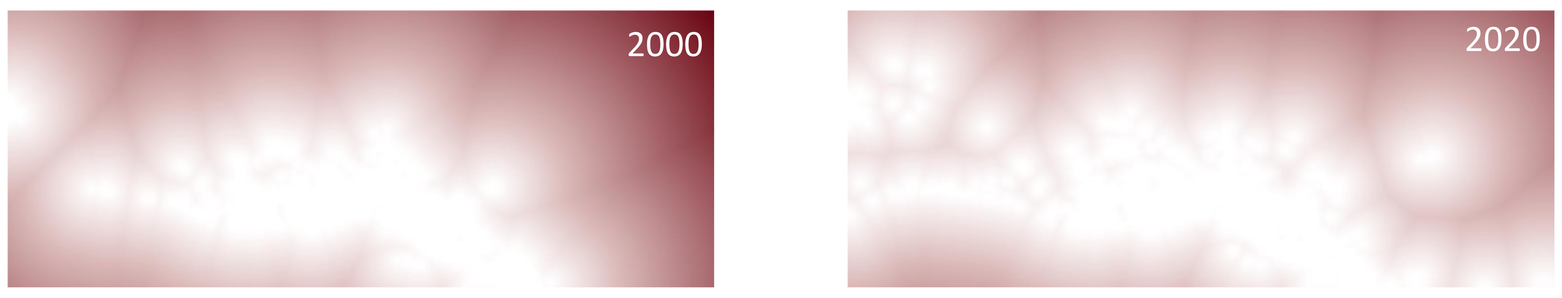


Fig. 5: Distance to urban boundary – derived from WorldPop grid with urban and non-urban values and scaled from 0 to 1

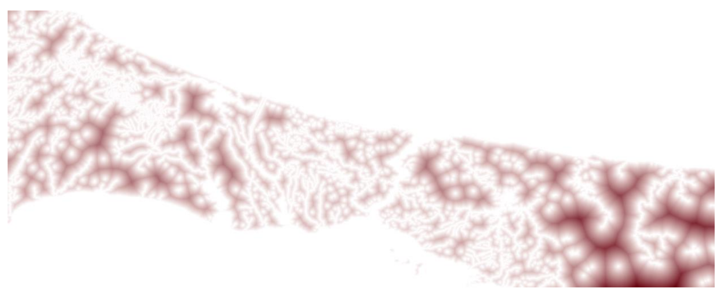


Fig. 6: Distance to water – derived from OSM and DEM water surfaces and scaled from 0 to 1

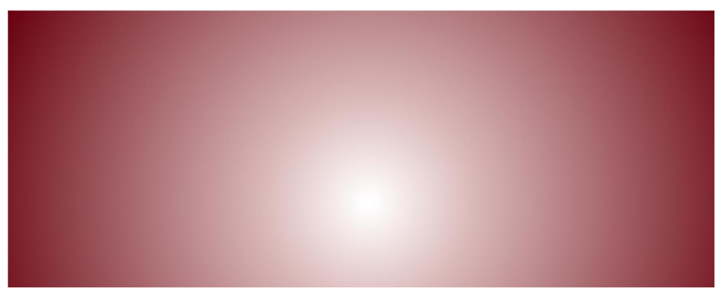


Fig. 7: Distance to city center by using the historical and business city center, scaling it from 0 to 1

Fig. 8: EU-DEM Slope with the slope in degrees and a spatial resolution of 25 m pixels

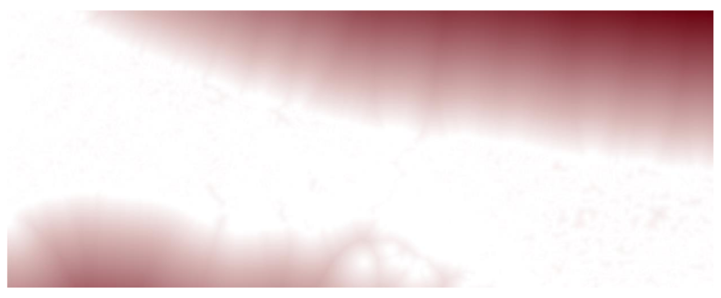


Fig. 9: Distance to roads – derived from OSM and scaled from 0 to 1

Methodology

The current EO datasets, in particular those comprising long time series data with high temporal and thematic resolution, and the new techniques from the field of artificial intelligence (AI), such as the Long Short-Term Memory Cells (LSTM), offer innovative possibilities for the extrapolation of exposure information spatiotemporally [2, 3]. The project comprises the compilation of EO time series data that describe changes in global population and land use land cover (LULC) over the past 20 years, while providing high spatial, temporal, and thematic resolution (see Figures 2 to 4). In conjunction with the driving factors (Fig. 5 to 9), the time series serves as input for a novel multitask LSTM model. This model identifies characteristic change trajectories in the target variables over time and can extrapolate the target variables (population and LULC) correspondingly in spatiotemporal terms into the future. Due to the multitask learning, the tasks are jointly learned, which allows for improved prediction and forecasting performance by encoding the dependencies between the target variables.

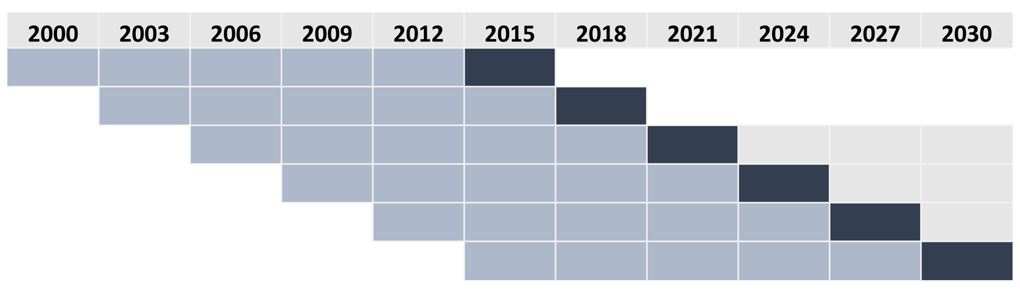


Fig. 11: Training, validation and forecasting time steps for a 3-year interval

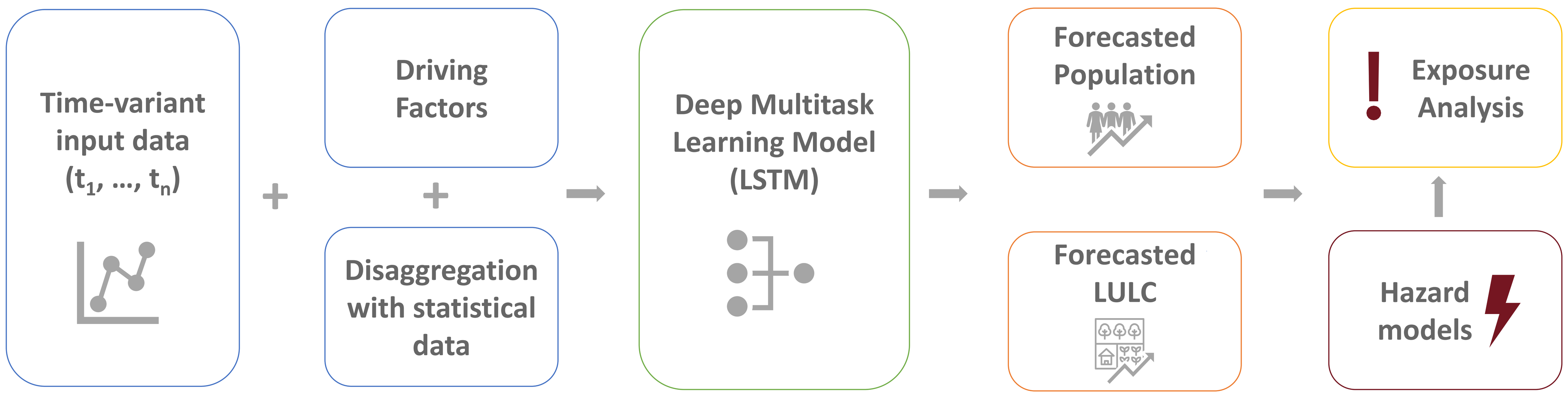


Fig. 10: Methodology overview

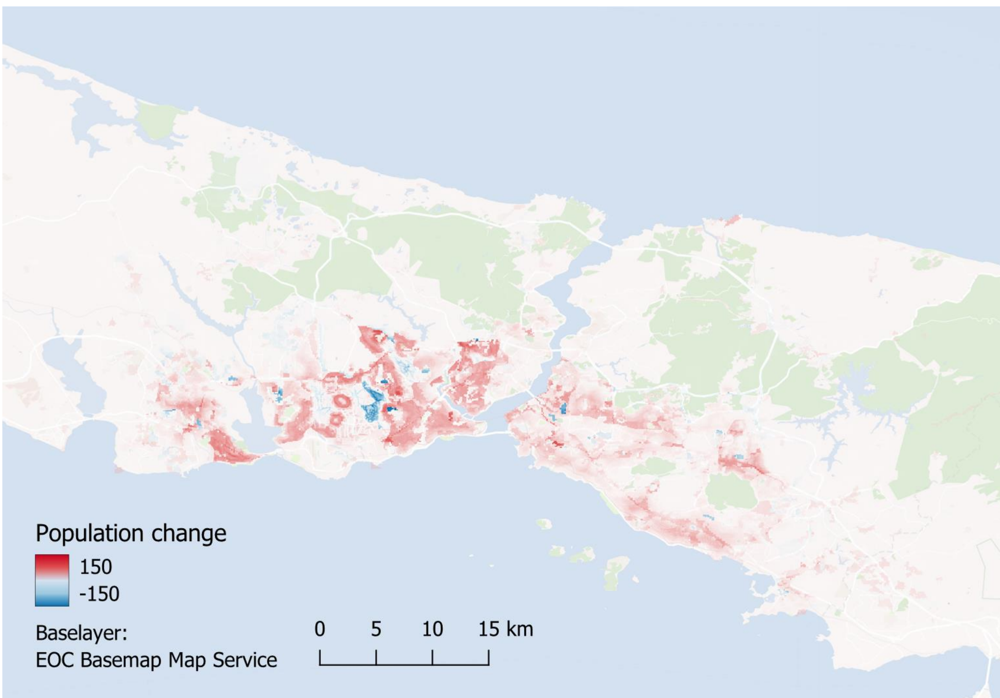


Fig. 12: By comparing the forecasted population distribution for 2030 with the WorldPop values from 2018, areas with population increase and decrease can be identified (preliminary result).

Further research

Additionally, the existing geodata such as population, LULC are augmented with risk-related thematic information, such as building and settlements types. The resulting generated information on future risk-related exposure can then be linked to models of natural hazards to show how many people will be affected by an earthquake, fire, or flood event in the future. Within the PARATUS project this can be done for instance for the highly dynamic megacity of Istanbul, which is exposed to earthquakes and landslides. The resulting exposure datasets can then be used for an early and sustainable urban planning, risk assessment, and risk reduction efforts in the future, as well as for evaluating the systemic risk and vulnerability of human settlements.

Lea Schollerer*[1], Christian Geiß[1], Yue Zhu[2], Jana Maier[3]

[1]German Remote Sensing Data Center, German Aerospace Center, Oberpfaffenhofen, Germany
[2]Department of Civil, Environmental and Geomatic Engineering, ETH Zurich, Zurich, Switzerland
[3]Department of Remote Sensing, Julius-Maximilians-University Würzburg (JMU), Würzburg, Germany
*lea.schollerer@dlr.de

[1] PARATUS (2023). PARATUS Project. https://www.paratus-project.eu/. Accessed 2023-08-06
[2] Zhu, Y., Geiß, C., So, E., and Jin, Y. (2021). Multitemporal relearning with convolutional lstm models for land use classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14.
[3] Geiß, C., Maier, J., So, E., Schoepfer, E., Harig, S., Gomez Zapata, J. C., and Zhu, Y. (2024) Anticipating a risky future: LSTM models for spatiotemporal extrapolation of population data in areas prone to earthquakes and tsunamis in Lima, Peru, EGUsphere