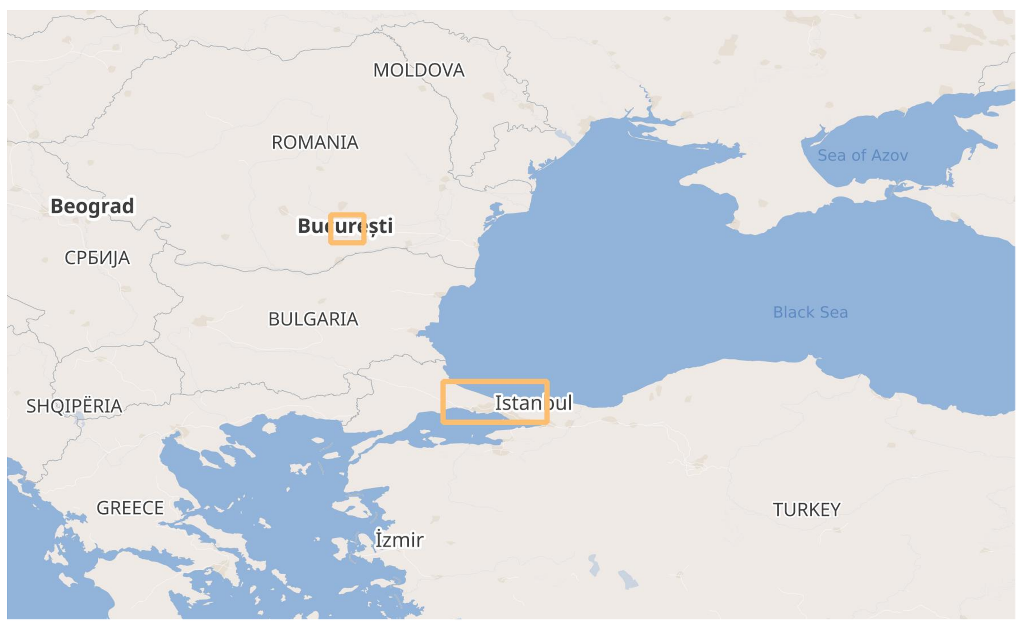
Geospatial extrapolation of time-series data with deep learning

Background

There has been an increase in the number of recorded **natural hazard events** in the last decades, including for instance earthquakes, fires, floods, and even compounding disasters. Such events can cause huge losses, especially 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. As a result, **more people will be exposed to natural hazards in the future** than ever before. In order to develop **mitigation strategies** for possible future damage events, detailed information on the future spatial distribution of the population and further exposed elements are required. Here Earth observation (EO) datasets and new 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 improve the preparedness of first and second responders to multi-hazard events and to reduce the risks associated with the multi-sectoral impacts of complex disasters. The main deliverable is the development of a cloud-based online service Platform to support the reduction of dynamic risk scenarios and systemic vulnerability caused by multi-hazard disasters. Within the project there will also be assessments of the interactions of complex hazards and the resulting impacts and the future change. [1]

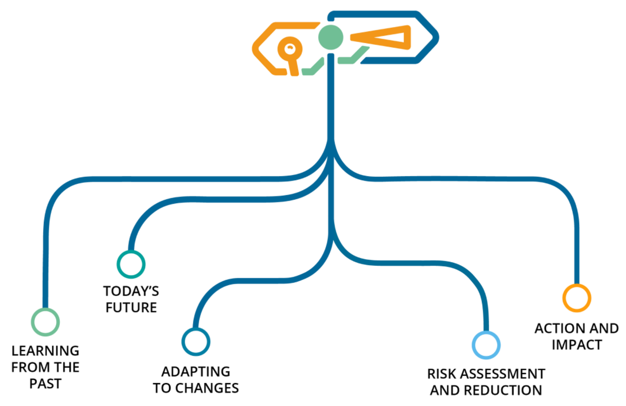


Fig. 1: Project components [1]

Data

Time-variant

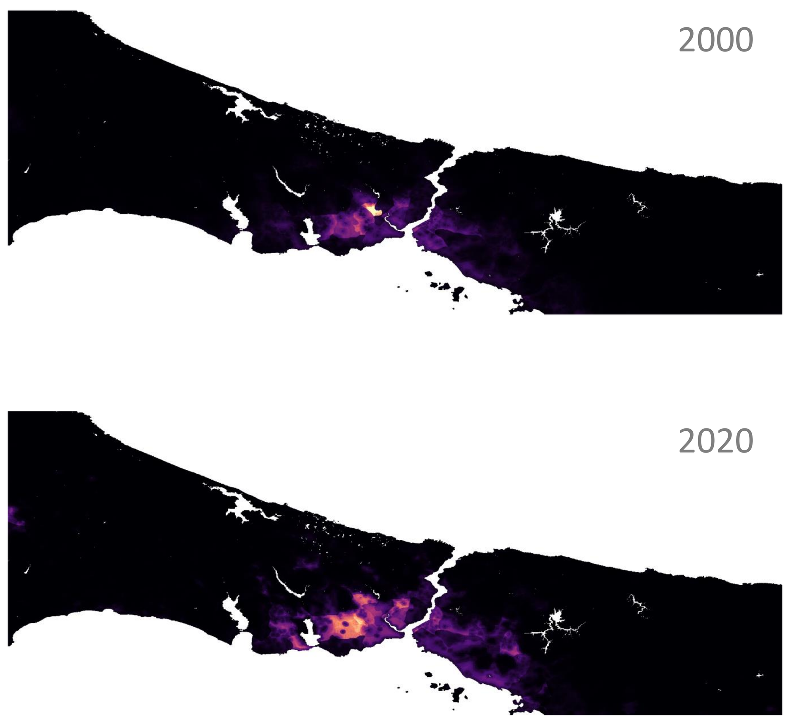


Fig. 2: WorldPop Population grid on a yearly basis from 2000 (top) to 2020 (bottom) and a spatial resolution of 100 m pixels

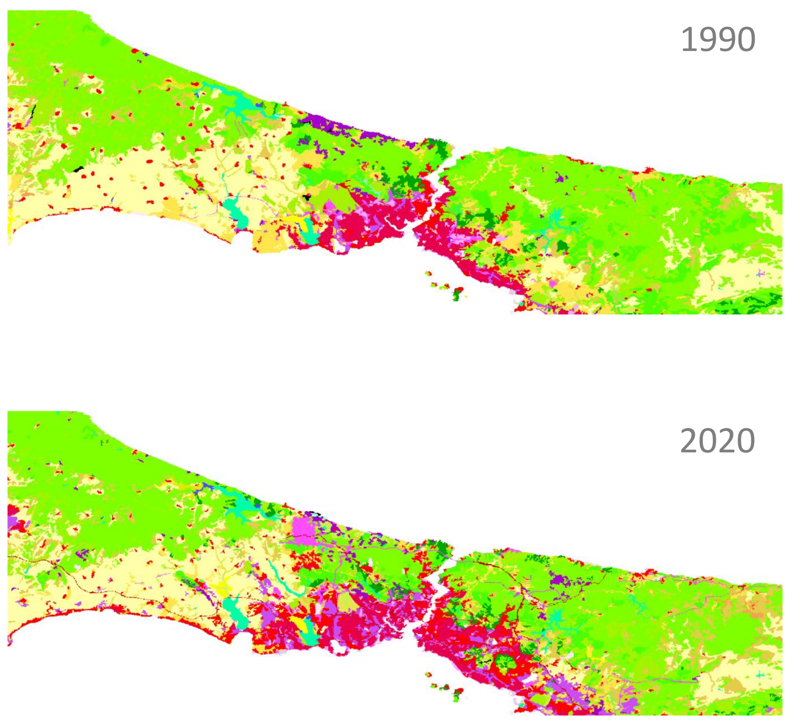


Fig. 3: CORINE land cover raster almost every 6 years from 1990 (top) to 2020 (bottom) and a spatial resolution of 100 m pixels

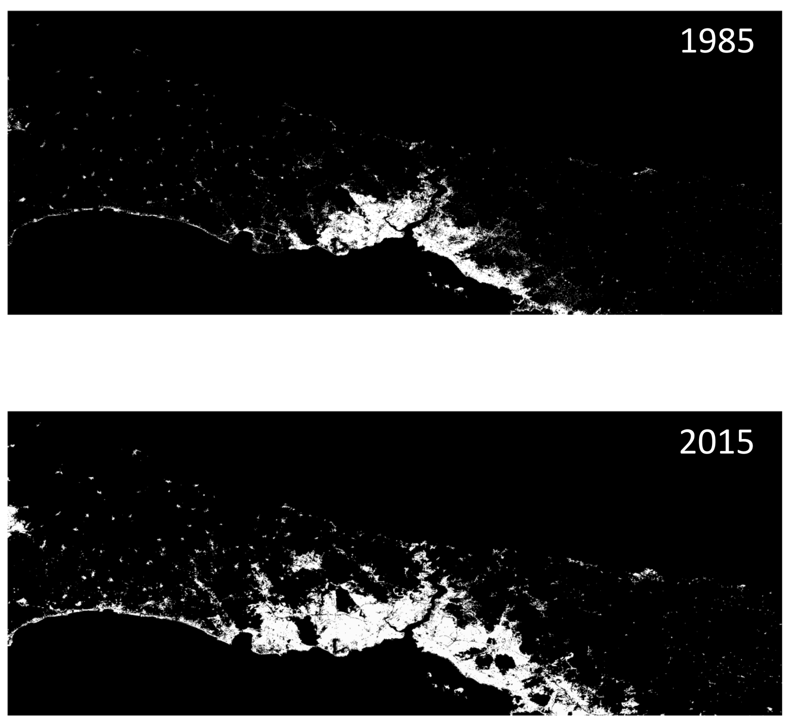


Fig. 4: World Settlement Footprint (WSF) Evolution on a yearly basis from 1985 (top) to 2015 (bottom) and a spatial resolution of 30 m pixels

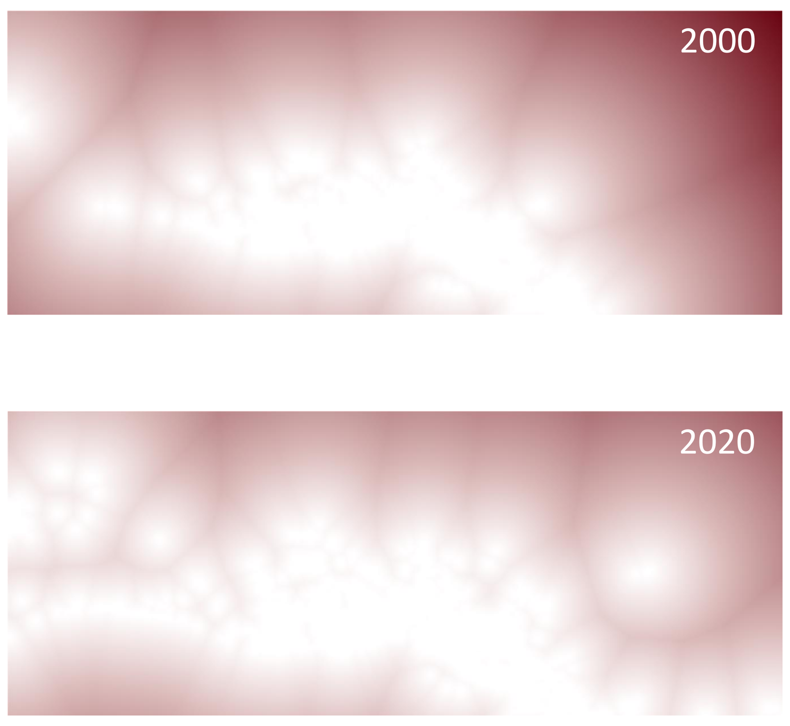


Fig. 5: Distance to urban boundary – derived from WorldPop grid with urban and non-urban values and scaled from 0 to 1

Time-invariant

Fig. 6: EU-DEM Slope with the slope in degrees and a spatial resolution of 25 m pixels

Fig. 7: Distance to roads – derived from OSM and scaled from 0 to 1

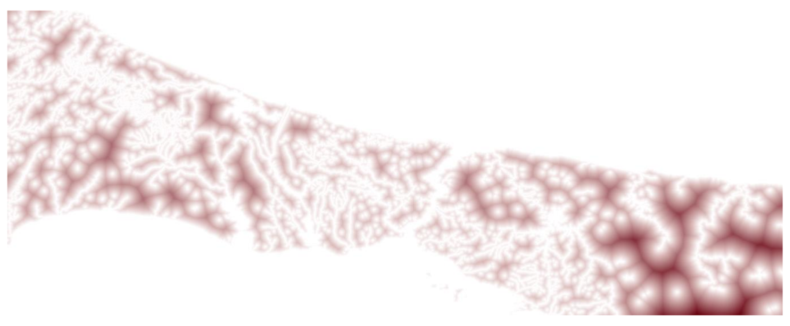


Fig. 8: Distance to water – derived from OSM and DEM water surfaces and scaled from 0 to 1

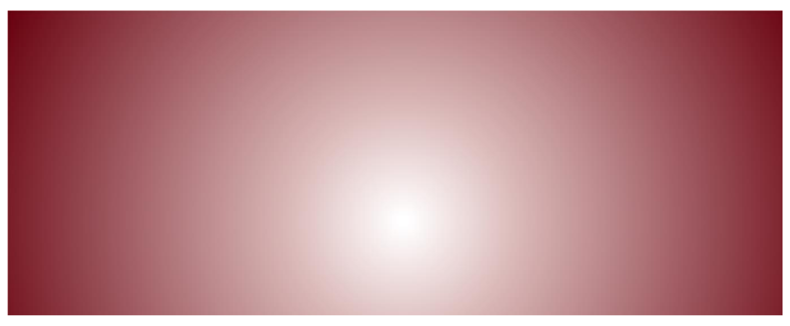


Fig. 9: Distance to city center by using the historical and business city center, scaling it from 0 to 1

Methodology

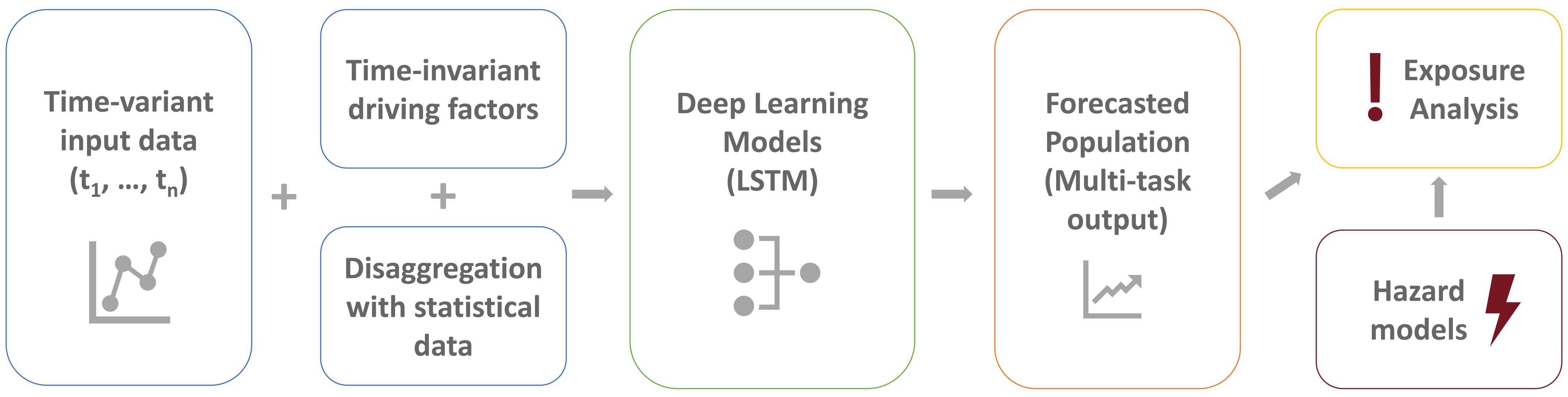


Fig. 10: Methodology overview

Current EO datasets, in particular long time series data with high temporal and thematic resolution, and new techniques from the field of Artificial Intelligence (AI), like Long Short-Term Memory Cells (LSTM), offer innovative possibilities to extrapolate exposure information spatiotemporally [2, 3]. Specifically, within the project EO time series data is compiled that describe changes in global population and land use since around 2000, while providing high spatial, temporal, and thematic resolution (Fig. 2 to 5). The different datasets are preprocessed to the same temporal (years 2000 – 2020) and spatial extent (100 m pixels). In combination with static features (Fig. 6 to 9) the time series then serves as the basis for a novel AI-model, that identifies characteristic change trajectories in the target variables over time and can extrapolate the target variables correspondingly in spatiotemporal terms into the future.

Outlook

By combining multiple target variables, the existing Deep Learning Model can exploit multi-task learning, which allows for improved prediction by encoding the dependencies between the target variables. Additionally, the existing geodata such as population, land cover and land use 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.: Anticipating a risky future: LSTM models for spatiotemporal extrapolation of population data in areas prone to earthquakes and tsunamis in Lima, Peru, EGUsphere [preprint]