OpenStreetMap for Multi-Faceted Climate Risk Assessments

Evelyn Mühlhofer

Institute for Environmental Decisions, ETH Zurich, Zurich, 8092, Switzerland

Chahan M. Kropf

Institute for Environmental Decisions, ETH Zurich, Zurich, 8092, Switzerland
Federal Office of Meteorology and Climatology MeteoSwiss, Zurich-Airport, 8058, Switzerland

David N. Bresch

Institute for Environmental Decisions, ETH Zurich, Zurich, 8092, Switzerland
Federal Office of Meteorology and Climatology MeteoSwiss, Zurich-Airport, 8058, Switzerland

Elco Koks

Institute for Environmental Studies, VU Amsterdam, Amsterdam, the Netherlands

E-mail: `evelyn.muehlhofer@usys.ethz.ch`

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Abstract. Natural hazards pose significant risks to human lives, infrastructure, and ecosystems, necessitating a comprehensive understanding of climate risks for effective adaptation planning and risk management. However, climate risk assessments mostly focus on economic asset values and a few types of physical infrastructure, because publicly available data on more diverse exposures are scarce. The increasing availability of crowd-sourced geospatial data, notably from OpenStreetMap, opens up a novel means for assessing climate risk to diverse exposures. To this end, we present a stand-alone, lightweight, and highly flexible Python-based OpenStreetMap data extraction tool (OSM-flex). We demonstrate the potential and limitations of the OpenStreetMap data universe for risk assessments by coupling OSM-flex to the open-source natural hazard risk assessment platform CLIMADA, and computing the current climate's winter storm risk and event impacts from the severe winter storm Lothar across Switzerland. Specifically, we evaluate the risks and impacts on forests, UNESCO heritage sites, railways, healthcare facilities, and airports, contrasting them with traditional impact metrics such as asset damages and affected population. This study aims to provide researchers, practitioners, and decision-makers with insights into utilizing open-source software tools for conducting multi-faceted and high-resolution climate risk assessments.

1. Introduction

Natural hazards affect humans, human-made structures, and nature. Impacts and consequences of such events may therefore be as diverse as the exposed assets. Understanding these multiple dimensions of disaster risk across economic, social, health, educational, environmental, and cultural heritage is also a main priority within the Sendai Framework for Disaster Risk Reduction (cf. § 24 f) [1]. While capturing many facets of risk incurred by natural hazard events can allow for better and more informed risk management practices, capabilities to do so are often severely constrained by data availability within all stages of the risk assessment chain - not least on the exposure side.

The Sendai Framework, therefore, stresses the importance of access to reliable data, including geographic information systems (GIS), to "strengthen technical and scientific capacity to capitalize on and consolidate existing knowledge and to develop and apply methodologies and models to assess disaster risks, vulnerabilities, and exposure to all hazards" [1]. As the research community and decision-makers are urged to move towards more diverse analyses of natural hazard-induced risks in a changing climate, open-source tools are needed to facilitate these.

The increasing level of detail with which the visible environment is mapped on OpenStreetMap (OSM) offers opportunities for natural hazard risk assessment [2]. As a freely available and open-source resource for georeferenced exposure data, OSM has been used as an input layer in an increasing number of studies in a wider area of natural hazard risks, spanning direct damage assessments [3], service disruptions [4], emergency response [5] and adaptation planning [6]. Many of them focus predominantly on general building stocks [7, 8] and major transportation assets such as roads and railways [3, 9, 10], and to a lesser degree, on other (critical) infrastructure assets such as airports [11], social facilities [2, 4] or power generation and distribution assets [2]. However, as it is not limited to modern human-made structures, the OSM data universe supports the study of other risk areas of the built-up and natural environment, such as forests, agricultural land, UNESCO heritage sites, and ecosystem services [12].

Although a number of well-maintained stand-alone Python tools have been developed for the retrieval of certain high-resolution exposure data from OSM (for instance, pyrosm [13] or OSMnx [14]), there is no versatile linkage to access the entire data universe and efficiently perform natural hazard risk assessments on these data on a large scale.

This study has a three-fold aim: first, to bridge a data access gap by presenting a lightweight, stand-alone, and highly flexible Python module (OSM-flex [15]) that enables users to efficiently and consistently retrieve geospatial exposure data from OSM with all available information; second, to demonstrate seamless integration within an open-source natural hazard risk assessment platform (CLIMADA [16]) to perform end-to-end risk assessments; and third, to show how many more facets of natural hazard-induced risks may be explored when opening up to the potentials of more diverse exposure data. Modules and processes were illustrated using a case study on winter storm impacts across diverse exposure types in Switzerland.

While certainly of importance, it is not the aim to provide an extensive evaluation of OSM suitability for certain research purposes or a discussion of OSM data completeness or data quality, which can be found elsewhere

[17, 18, 19, 20, 21, 22].

2. Methods

2.1. Obtaining geospatial data from OSM with OSM-flex

Features can be extracted from OSM and converted into geographical tabular format for use in Python in two ways: either by reading data directly from the Overpass API or by downloading regional data dumps (Protocolbuffer Binary Format-files, *.osm.pbf) from dedicated online data-repositories such as `geofabrik.de` [23], from which the desired data can then be parsed.

Two well-known Python packages, pyrosm [13] and OSMnx [14]), exist, which excel at opposite ends of this retrieval spectrum. Both packages are well maintained, easily installable using standard package managers, and feature additional integration with the graph-analysis packages networkX [24] and igraph [25]. Because OSMnx relies on API queries for data retrieval, it is limited by restrictions on query sizes and requires a constant Internet connection for this process. Pyrosm circumvents this by parsing downloaded data dumps, yet relies on OSMnx in the background for other functionalities. Both packages allow for data extraction using pre-written data category wrappers and user defined flexible queries; however, they are limited in the spatial range of query flexibility (allowing only rectangular bounding boxes). Both come with a range of non-standard package dependencies, such as the above-mentioned graph packages.

Here, we introduce the lightweight Python-based package OSM-flex [15], which efficiently extracts any user-specified data queries from *.osm.pbf data dumps within arbitrary geographical boundaries, such as city-shapes, multi-country regions, states or bounding boxes. This provides the flexibility required to perform multi-faceted risk analyses. Its availability on common software distribution channels (PyPI and GitHub) and its low dependency requirements make it suitable for integration within larger and more complex software packages such as the CLIMADA risk assessment platform discussed in section 2.2. The package is maintained, tested, and readily installed through a package manager. The general workflow of the OSM-flex package includes four steps, as illustrated in the upper panel of Fig. 1:

(i) **Download** a country, regional or planet data dump (*.osm.pbf file) from an online repository

(ii) **Clip** the data dump to the area of interest (*optional*)

(iii) **Extract** the desired features from OSM [26] into tabular format using the OSM tagging syntax

(iv) **Post-process** the extracted data set (*optional*)

OSM-flex favors the one-time download of *.osm.pbf data dumps over the direct query of individual features from the Overpass API, as feature extraction does not require a constant internet connection nor is constrained by query size limitations. Appendix A.1 provides details on what access points and (regional) versions of data dumps that are readily obtainable within OSM-flex.

The optional step of clipping a larger data dump to specific bounding boxes or (multi-)polygons is useful when dealing with regions or small islands that are not available as dedicated own files on one of the OSM data repositories, or when wanting to clip from, for example, the global level along
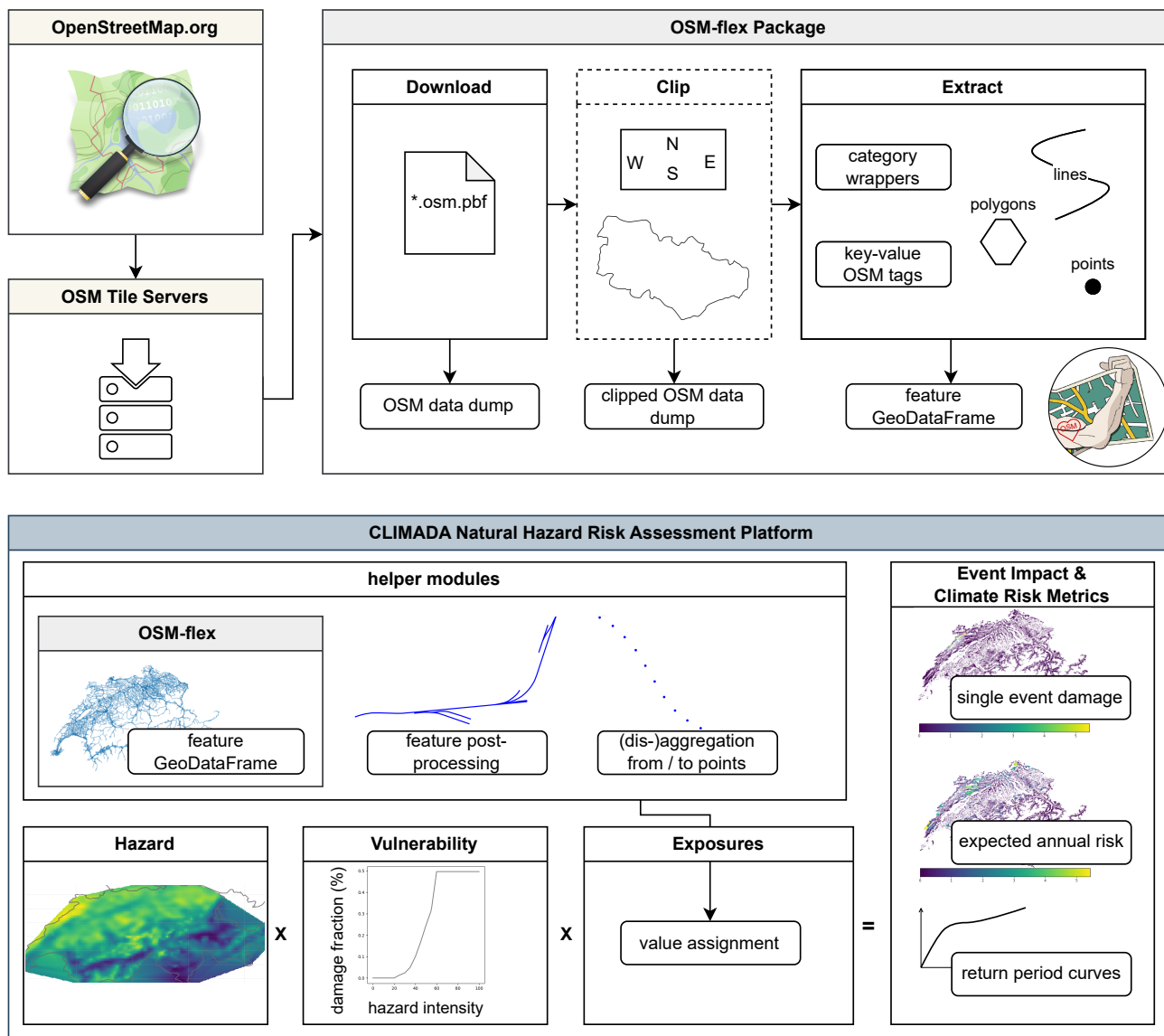
Figure 1. Schematic representation of a climate risk assessment workflow for OSM features using the OSM-flex package and CLIMADA. Top panel: basic steps for OSM feature extraction in the OSM-flex module: an OSM data dump is downloaded in *.osm.pbf format; optionally the area is clipped to an arbitrary polygon shape; the elements of interest are extracted using pre-written or custom queries with OSM tags; the data is converted into a GeoDataFrame. Bottom panel: integration of OSM data into the CLIMADA risk assessment workflow. The helper modules within CLIMADA conveniently allow users to directly derive point-based CLIMADA Exposures by accessing the OSM-flexmodule and disaggregating lines and polygons exposure elements to points. The obtained point exposure can then be combined with the hazard and vulnerability models to compute point impacts (risk). Finally, point-based impact and risk data can be re-aggregated to the original OSM feature geometries.

own predefined borders. It currently requires manual installation of either osmconvert [27] or osmosis [28], small command-line executables which facilitate the clipping commands within OSM-flex. In future iterations of OSM-flex, this step may be further simplified using a dedicated Python package such as PyOsmium [29]. See Appendix A.2 for details on clipping options and these tools.

While OSM-flex is built to be lean and accessible, its use requires some familiarization with the syntax of keys and values in OSM, that is, the attributes that characterize geolocated data and allow it to be queried. For increased user friendliness, common exposure data categories can also be retrieved with pre-written extraction wrappers, such as road and railway assets, healthcare and education facilities, or power infrastructure. Additional details are provided in Appendix A.3. Because geographical features are extracted into Pandas or GeoPandas (Geo)DataFrames [30, 31], the optional prior clipping step may be circumvented through posterior filtering of results using GeoPandas or shapely methods. However, this may be less efficient if the source files and/or queries are particularly large.

After obtaining the desired geospatial information in tabular format with point-, line-, and polygon-based object geometries and attribute columns, further post-processing may be required (step iv), such as filtering out very small, yet numerous polygons belonging to large natural areas, removing duplicates, or simplifying transportation network geometries. See Appendix A.4 for helpful post-processing resources and steps.

More extensive code documentation and detailed tutorials featuring usage examples are available at `osm-flex.readthedocs.io` to guide users. Starting from the possibility of readily extracting a wide range of exposure

data from OSM, the following paragraph outlines how this data can be efficiently integrated into a climate risk assessment workflow.

2.2. Using OSM features in climate risk assessments with CLIMADA

CLIMADA is an open-source Python platform for natural hazard impact computations, climate risk assessments, and adaptation option appraisal [16, 32]. It computes risk according to the IPCC risk definition as the product of exposure, vulnerability, and hazard [33]. Hazard represents events as geographically explicit intensity footprints, where each event can be assigned an occurrence probability to form a probabilistic set. Exposures are a spatially explicit representation of the elements at risk. Vulnerability is the linking element between both and is modelled as an impact function relating the hazard intensity to the damage extent of the exposure value (which can be monetary, a surface area, a number of infrastructure elements, etc.).

Exposure data which represents the spatial distribution of monetary asset values [34] or population counts most commonly forms the basis of climate risk assessments. CLIMADA has the advantage of being flexible with regard to input data, thus allowing arbitrary exposure inputs, vulnerability function definitions, and hazard footprints.

To perform such a risk analysis on OSM features, exposure data must first be extracted into a GeoDataFrame as described in Section 2.1. As CLIMADA's engine is designed only for points data, line and polygon-based data must be interpolated to points before the impact computations, and re-aggregated afterwards, which can be done with a dedicated utility module (see Appendix B for the logic

of this helper module and (dis-)aggregation options). Similarly, dedicated hazard and vulnerability data must be provided and can be obtained via the CLIMADA data API for several hazards [35] or be ingested from users own resources.

3. Application: A Multi-Faceted View on Winter Storm Risk

On December 26 and 27, 1999, winter storms *Lothar* and *Martin* swept across France, Germany, Italy, and Switzerland, leaving a trace of destruction. In Switzerland, the combined event is among the top three most impactful winter storms, with significant tolls on human lives [36], critical infrastructure, building damag, forest loss [37], and wildlife [38].

In the following sections, the methodology presented above is explored by computing the wind impacts of Lothar on OSM-extracted built-up and natural assets across Switzerland. The results are compared with more conventional metrics such as the total value of physical assets damaged and the number of people affected, and validated with event reports. Furthermore, the average annual risk of winter storms to these exposures, obtained from a probabilistic hazard set representing today's climate, is reported.

3.1. Winterstorm Impact Calculations with OpenStreetMap and CLIMADA

3.1.1. OSM Exposure Data Extraction Using OSM-flex, OSM data from Switzerland was downloaded from https://geofabrik.de on March 13, 2023. Points, lines and polygon data were extracted into GeoPandas Geo-DataFrames for 1155 major healthcare facilities (hospitals, clinics, and doctor practices),

20'100 km of railways (individual rails, incl. trams and narrow gauge rails), 15 airports, 12'500 km² of forests, and 11 UNESCO World Heritage sites (see Fig. C2). The exact queries (OSM tags) are noted in 2.1. Geo-spatial data were post-processed to eliminate very small areas ($<100\text{m}^2$) of forest, and duplicates for healthcare facilities and airports.

3.1.2. Wind Impact The wind field of storm Lothar (maximum 3-sec sustained wind speeds at 10 m above ground over 72 h at a resolution of approximately 4.4 km), prepared in [39] based on the Windstorm Information Service (WISC) of the Copernicus Climate Change Service, was obtained via the CLIMADA Data API and stored as a CLIMADA Hazard object (see Fig. C1). OSM data were stored as CLIMADA Exposure objects, together with a general asset value exposure for Switzerland based on the product of nightlight intensity and population count data at 30 arcsec resolution (LitPop, [34]), and a population exposure at the same resolution based on the SEDAC GPW v4.0 dataset [40]; see Fig. C3). Impact functions (vulnerability curves) relating hazard intensity to damage extent were obtained from [39] for wind-induced general asset damages, which were calibrated to the Swiss context. For all other exposures, step functions were employed that mirror warning categories [41, 42] issued by the Swiss Federal Office of Meteorology and Climatology; for population, railways, healthcare facilities and airports, wind intensities above 30.5 m/s (110 km/h, warning category 4) were considered critical based on the warning rationales provided by official sources [41], whereas for forests, wind intensities above 38.9 m/s (140 km/h, warning category 5) were considered more adequate to capture tree snapping in accordance with

findings in the literature [43]. See Fig. C4 for the plots of all impact functions used. Impacts are computed for all exposures within the CLIMADA ImpactCalc module, whereby line and polygon-based data (i.e. railways and forests) are interpolated to a 100 m resolution and re-aggregated (by summation) afterwards into their original shapes. The impact data are shown in Fig. 2.

3.1.3. Wind Risk In addition to the extreme storm Lothar (and Martin), we also considered the general winter storm risk in Switzerland following the IPCC definition of the probability of occurrence of an event multiplied by its severity. To this effect, we used the WISC probabilistic extension hazard set, a probabilistic windstorm hazard event set [44, 39] available through the CLIMADA Data API. This hazard set is based on the same historic ground data as Lothar, but features an additional 29 synthetic hazards per historic hazard occurrence for the year range 1940-2014. It was calibrated on the years 1990 - 2010, which can be seen as representative of climate conditions today. Furthermore, for the physical asset and population exposure layers, we used the reference year 2020 instead of 1999.

3.2. Results

Table 1 summarizes the impacts of storm Lothar computed for different exposures. Although affected by varying absolute and relative degrees, the impacts are considerable across all studied dimensions. At this point, an important distinction must be made with regards to what these impact figures stand for: while for forests and general asset values, physical losses and damages are modelled, for the remaining exposure categories the numbers of items *exposed* to a certain hazard intensity are

Table 1. Impacts from winter storm Lothar (1999) across Switzerland for general asset values, population counts, and five categories of OSM-retrieved exposures.

Exposure type	Event impact	Metric
Asset Values[a]	179.4 mio (0.01)	US$ (%)
Population[a]	4.17 mio (57.2)	people (%)
Healthcare Facilities[b]	649 (56.2)	units (%)
Airports	6 (40.0)	units (%)
UNESCO Sites	3 (27.3)	sites (%)
Railways[c]	6'951 (50.4)	km (%)
Forests	464.6 (3.7)	km^2 (%)

[a] reference year: 2000; [b] hospitals, clinics and doctor's practices; [c] all individual lines counted separately, also for parallel tracks.

modelled without direct implications of (full) loss. This is an imminent consequence of the design of impact functions in this particular application, and it is therefore unsurprising to obtain lower relative impact figures in explicit damage computation cases. Validation with print media accounts, official records and insurance reports confirms the severity of the event across many dimensions of (public) live and strengthens the picture of multi-faceted impacts obtained from the computations presented in this study: reported impact metrics tend to revolve around (insured) building damages (in the case of Lothar, around 600m CHF) and affected population or fatalities (15 people died during, and roughly the same amount afterwards during clean-up and reconstruction efforts). The standard impact computations within CLIMADA capture these metrics as asset damages (though under-estimated with 179 mio USD or 113.3 mio CHF at the time), and affected population (4.17 mio, a number that is inherently difficult to track and verify, as reports tend to focus on the well-reported number of fatalities instead). However, other dimensions of societal importance were equally captured, such as rail transportation - mapped

Table 2. Average annual risk from winter storms across Switzerland for general asset values, population counts and five categories of OSM-retrieved exposures.

Exposure type	Annual risk	Metric
Asset Values[a]	4.8 mio (0.0003)	US$ (%)
Population[a]	91'200 (1.3)	people (%)
Healthcare Facilities[b]	14.4 (1.3)	units (%)
Airports	0.5 (1.3)	units (%)
UNESCO Sites	0.08 (0.7)	sites (%)
Railways[c]	17.3 (1.3)	km (%)
Forests	9.83 (0.08)	km² (%)

[a] reference year: 2020; [b] hospitals, clinics and doctor's practices; [c] all individual lines counted separately, also for parallel tracks

here as affected to roughly 50 % - was indeed interrupted on many lines across the German-speaking part of Switzerland (covering approximately 65 % of Swiss territory); estimated forest losses (amounting to 750 mio CHF in economic worth, and 4.3% of the Swiss forest area), is close to the modelled 3.7% of the area. It was not possible to retrieve explicit reports on the impacts to airports (apart from flight cancellations), healthcare facilities or (UNESCO) heritage sites. Not modelled within the scope of this illustrative case-study, but frequently mentioned in reports were impacts on the power grid and road transportation. While structural impacts on the latter may be easily computed with the presented approach, modelling systemic impacts on the energy sector is not only restrained by power line mapping quality on OSM, but would also require consideration of the cascades of failing infrastructures as shown in [4]. The results highlight how, when using multiple exposure layers, important aspects of a natural hazard event, apart from conventionally reported metrics such as (undifferentiated) asset damages, can be captured relatively effortlessly and guide holistic risk management efforts.

As introduced in Section 3.1.3, it may be insightful to consider probabilistic risk metrics apart from single-hazard event impacts, to gauge the potential risk landscape and to adequately place the occurrence of historic events therein. Various metrics may be relevant, such as the risk associated with a one-in-a-hundred-year event or the average annual risk. Table 2 presents the latter, modelled from the probabilistic winter storm set. Evidently, since most winter storms are less extreme than Lothar (cf. Table 1), the average annual risk values are much lower (less than 1.5% of the total count or value for all exposure categories). The extremes of Lothar's impacts are even more strikingly illustrated when locating these impact figures on return period curves generated from the probabilistic hazard set (Fig. C5). With return periods between roughly 80 and 150 years depending on the choice of exposure category, this highlights the potential for disastrous consequences of tail risk events as compared to the average, in particular for non-monetary elements.

Furthermore, under a rapidly changing climate, studies have demonstrated that winter storm risk (measured in losses to general asset values) may increase by up to 50% between 2020 and 2050, both for average events and for more extreme events [45]. This increase might bring significant economic challenges, yet does not provide a full picture of the potential for disruption of the railway system, or the losses to vital forest ecosystems and irreplaceable cultural sites, which may hence be explored using the demonstrated workflow.

4. Discussion

We showed how OSM-flex, a flexible OSM feature extraction package, can be seamlessly integrated into the CLIMADA risk modelling
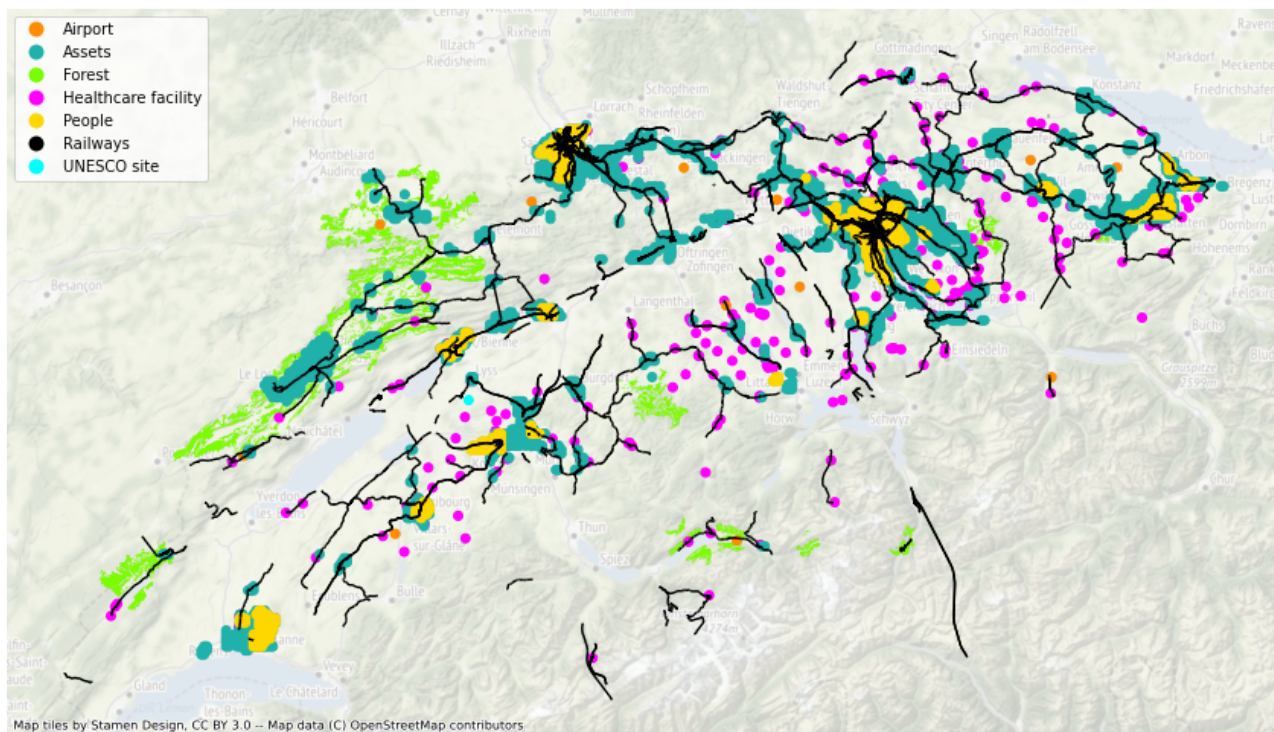
Figure 2. Geographical representation of all impacted elements by storm Lothar (c.f. Table 1). For visual clarity, only asset value grid cells and population grid cells with impacts above $10'000\$$ and $1'000$ persons, respectively, are shown. Note that in certain areas (e.g. around the city or Zürich in the top right) many impacts overlap.

framework, and how this can provide a basis for multi-faceted natural hazard impact and climate risk assessments on a variety of exposure types. More examples of seamless integration of OSM data for natural hazard risk calculations can be found in [3] and [2]. In [3], the authors combined state-of-the-art global hazard mapping of cyclones, floodsm and earthquakes with approximately 50 mio kilometer of transport network data included in OSM to study multi-hazard infrastructure risk and the viability of protection measures [3]; in [2], the world's main critical infrastructure systems are extracted, categorized, and rasterized into a global database, from which the Critical Infrastructure Spatial Index (CISI) is developed, expressing the global spatial intensity of CIs, used in several natural hazard risk studies (e.g. [46] for landslides). Both studies draw on the

extraction and processing source code for OSM data presented in section 2.1, which is now packaged into the OSM-flex module, and available to an even wider research audience.

More generally, this may open up complementary possibilities for areas of study that traditionally rely on other types of data sources such as satellite imagery [47]). In recent years, there has been a trend towards more holistic, quantitative views of the consequences of extreme weather events as opposed to focusing on monetary asset losses alone, as shown in a number of exemplary studies that look at displaced people [48], basic service disruptions [4], or affected ecosystems. Wider quantitative perspectives will allow decision makers to not inherently prioritize monetary elements because of the absence of other quantifiable criteria. Thus, the diverse indicators of natural

hazard risk, towards which the here-presented approach contributes, can form the basis of multi-criteria adaptation decision frameworks [49, 50, 51, 52], leveling the playground with economic interests and allowing us to tackle questions such as the role of social inequalities, urban-land divides, and environmental justice in a (semi-)quantitative way.

However, it should be noted, that the risk modelling approach based on OSM exposure data has several limitations. The extracted features are by no means complete. For instance, only 11 of the 13 UNESCO World Heritage Sites in Switzerland were listed, and of the 58 prehistoric pile dwellings around the Alps, only five were included. There is a large disparity in OSM coverage between countries and world regions, and between different types of assets [18, 17] and attributes further describing these assets [53]. Furthermore, being a crowd-sourced project, not all entries are checked for their accuracy [19, 22]. Hence, the quality of the risk analysis based on OSM exposure data can vary significantly. Nevertheless, it is often the only freely available resource, and its catalog is continuously growing and improving. No future projection of OSM exists, and currently, neither is a reliable past one. Thus, an assessment of future risks based on climate projection can be made with respect to current exposure. Additional modelling is required for future exposure projections. On the technical side, the disaggregation step from OSM polygons and lines to CLIMADA point exposures, as well as the reaggregation of the impact values to these original polygon and line shapes, introduces imprecision owing to the finite resolution of the interpolation algorithm. The uncertainty related to the resolution can be assessed using Monte Carlo approaches [54]. Extracting features from OSM beyond the pre-written exposure category wrappers in the OSM-flex module can be cumbersome, as the required keys and values need to be identified and often requires some back-and-forth iterative consultation of the OpenStreetMap wiki [26] or OSM taginfo databases [55]. The extracted features may further need to be post-processed for best results. This may limit their wide use to non-expert practitioners in the field of climate risk modelling.

5. Conclusion

Despite the limitations inherent to crowd-sourced open data, OSM is an extremely potent tool for informing multi-faceted climate risk analysis and supporting adaptation decision-making, which goes beyond the common focus on (coarse-resolution) monetary asset values and population counts. In addition to the showcased exposures in this manuscript (healthcare facilities, railways, UNESCO World Heritage Sites, forests, airports), OSM can be used to retrieve a larger variety of types: a non-exhaustive listing includes urban assets at single building scale; different land uses such as agriculture, forestry, or pastures; assets for different economic sectors such as mining, industrial manufacturing, commerce, energy or tourism; culturally relevant sites and regions; road networks; critical infrastructures for education, water management, communication, energy supply, etc.; and ecological regions important for ecosystem service provision, biodiversity preservation, and leisure. Furthermore, the free and world-wide availability of OSM data is an advantage that cannot be understated. Finally, the seamless integration of a light-weight Python-based OSM feature extraction tool (such as the presented OSM-flex) into an established open-

source risk modelling framework, CLIMADA, promises a large diffusion and applicability of the methodology, in academia, among public institutions, in the private sector, and in the humanitarian sector.

Acknowledgement

Data Availability

All the data and source code are publicly available as mentioned in the manuscript. Scripts to reproduce results and result figures can be found at `https://github.com/Evelyn-M/osm-climate-risks`.

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Appendix A. OSM-flex module

The main steps in the OSM feature extraction process using the OSM-flex package, introduced in section 2.1, are explained in more detail in the following paragraphs. The OSM-flex package is available on GitHub [56] and as PyPI package [15]. The modules available within the OSM-flex package are structured according to the previously introduced fours steps.

Appendix A.1. Download

OSM data is downloaded in Protocolbuffer Binary Format (*.osm.pbf; see `https://wiki.openstreetmap.org/wiki/PBF_Format` for further description). Automated download options are currently available for the entire planet file (retrieved from `https://planet.openstreetmap.org/pbf/planet-latest.osm.pbf`), for world regions (Africa, Antarctica, Asia, Australia and Oceania, Central America, Europe, North America, South America) and for all countries available on, for example, `download.geofabrik.de`. If the desired region or country is not available via the download-API, it is recommended to clip the desired area from a larger source file (see next step).

Appendix A.2. Clip

This optional step of clipping (cutting) larger source files to any user-defined area requires a one time installation of either osmconvert (`https://wiki.openstreetmap.org/wiki/Osmconvert`) or osmosis (`https://wiki.openstreetmap.org/wiki/Osmosis`. More command line executables for handling *.osm.pbf files exist, some of which are available via pip and conda distribution channels, such as pyOsmium (`https://osmcode.org/pyosmium/`). However, not all of those currently support all operating systems, which is why the OSM-flex package gives preference to osmconvert and osmosis.

There are three ways to specify the area to which to clip: by passing a bounding box (the corners of a geographical rectangle), passing a shapely (multi-)polygon, or passing a Polygon filter file (*.poly; see `https://wiki.openstreetmap.org/wiki/Osmosis/Polygon_Filter_File_Format` for further description) containing the (multi-)polygon outline information.

Convenience functions are available to obtain country and admin-1 shapes within the OSM-flex package, and there are several ways to obtain .poly files externally (for example, `https://github.com/jameschevalier/cities` for a good description of how to find and obtain them via `http://polygons.openstreetmap.fr/`, and for a .poly file collection of many cities of the world). It should be noted that clipping to (multi-)polygons requires the creation of a temporary .poly file under the hood, and that OSM-flex provides a simplification method for complex shapes owing to file size restrictions. Clipping may take a while, and this process is faster if the source file is smaller (e.g. when taking a region file instead of the entire planet file to clip a contained sub-region).

Appendix A.3. Extract

There are two broad ways to extract OSM features into tabular (Geo)Pandas [31] format: via predefined wrappers for some frequently-used exposure categories, or via defining user-specific queries. Extraction wrappers are currently available for assets of many critical infrastructure sectors such as road, rail and air transportation, power, telecommunication, gas, healthcare and education. For user-defined queries, keys, key-value pairs or logic concatenations of these are allowed, together with a specification of which additional attribute keys should be parsed as columns the output table, and which geometry types should be considered. Finding suitable OSM keys or key-value pairs can be challenging at first, yet useful information may be obtained via the OSM wiki map feature documentation (`https://wiki.openstreetmap.org/wiki/Map_features`) or the OSM tag-info webpage (`https://taginfo.openstreetmap.org/`). There are some particularities when extracting uncommon features with may not yet be "registered" in the osmconf.ini file, which comes with the distribution. In such cases, the unknown keys must be manually added in the corresponding sections of the file.

Appendix A.4. Post-process

The following is a non-exhaustive list of common post-processing tasks which may be needed, but are not part of this package:

- simplifying networked geo-data (e.g. roads, rails, power lines): see for instance the "trails" package [57]
- removing duplicates (same amenities with slightly different names) and near-duplicates (e.g., amenities may be marked as points, but building-shapes of the same amenities are also collected as multi-polygons): for example GeoPandas sjoin with a certain buffer tolerance (e.g. 100m, ..)
- removing small multi-polygon shapes in large multi-polygon based results (e.g. forest outlines) by filtering polygon area (a built-in shapely geometry attribute)

Appendix B. Lines and Polygons utility module

This utility module disaggregates line and polygon geometries into points, which, for instance, is necessary to spatially overlay (or, essentially, point-match) hazard footprints and exposures in CLIMADA impact calculations.

The desired disaggregation resolution can be specified in units of either the original coordinate reference system (crs) or in metres. In the latter case, geometries are automatically re-projected to a metre-based cylindrical projection centered around the object's central coordinate, to minimize distortions from the re-projection. For polygons, a regular raster of the chosen resolution is created and all points of the raster inside of a polygon are assigned to it. For polygons smaller than the raster resolution, at least one single point inside the polygon is assigned (even if this point is not part of the raster). Note that one does thus not have a common raster for all polygons, but one raster per object (since each object uses its own centered

projection). Users that want to use a common raster can define one for the disaggregation (the re-projection must then be performed by the user). Lines are divided into segments equal in length in such a way that the total length of all lines is preserved. This is achieved by first computing the number of points N per line by dividing the line length by the resolution and rounding the result. The minimum number of points is one. Second, the line is divided into corresponding $N + 1$ equal-length segments, and the points are placed in the middle of the segments.

More precisely, the number of points a line is divided in is

$$N = \max\left[\text{round}[(l/r) - 1)], 1\right] \tag{B.1}$$

with l the total length of the line and r the resolution. The effective resolution of the line is then

$$r_e = \frac{L}{N}. \tag{B.2}$$

These N points are then distributed on the line at fractions of the line lengths starting from $r_e/2$

$$f_1 = r_e/2 \; ; \; f_2 = r_e \; ; \; f_3 = 3r_e/2 \; , \; \ldots . \tag{B.3}$$

Several examples are listed in Table B1.

Length	Resolution	Number Points	Effective resolution	Fractions
l=1	r=2	N=1	$r_e = 1$	$f_1 = 0.5$
l=1	r=0.8	N=1	$r_e = 1$	$f_1 = 0.5$
l=1	r=0.6	N=2	$r_2 = 0.5$	$f_1 = 0.25, f_2 = 0.75$
l=1	r=0.4	N=2	$r_e = 0.25$	$f_1 = 0.25, f_2 = 0.75$
l=1	r=0.2	N=5	$r_e = 0.2$	$f_1=0.1, \quad f_2=0.3, \quad f_3=0.5,$ $f_4=0.7, f_5=0.9$

Table B1. Disaggregation examples for lines of varying lengths and target resolutions.

The exposure value associated with each original line or polygon geometry can then either be divided equally among all points or be assigned wholly to each point. The former is typically used to disaggregate quantitative values such as the number of people, or to compute relative affected areas by disaggregating the value 1 over each geometry. The latter can be used to assign the area of the corresponding raster cell to each raster point, or the length of the corresponding line element to each line point, or to propagate qualitative values such as an ecosystem type. Note that the disaggregation leads to a certain distortion of the values, in particular, due to boundary effects, and the user should carefully choose the resolution of the raster to fit the purpose of the study. One way to check the approximation resulting from the disaggregation step is to re-aggregate the values by geometry and compare.

Appendix C. Application: Input data and method details

Appendix C.1. OpenStreetMap queries

The exposures used for the impact computation reported in Table 1 and 2 were based on the GeoDataFrames retrieved with the OSM-flexmodule using the OSM tags (keys and values) as described in Table C1. Note that for the critical infrastructures 'Healthcare facilities' and 'Airports', a single-line helper function is implemented within the CLIMADA OpenStreetMap module, which facilitates common queries.

Exposure Type	OSM Keys	OSM Values	Geometry Type
Healthcare facilities	'amenity' 'building' 'healthcare'	'hospital' or 'doctors' 'hospital' or 'clinic' 'hospital' or 'clinic' or 'doctors'	points, multipolygons
Railways	'railway'	'rail' or 'tram' or 'light_rail' or 'narrow_gauge'	lines
Airports	'aeroway'	'aerodrome'	multipolygons
UNESCO sites	'heritage_operator'	'whc'	points, multipolygons
Forests	'landuse'	'forest'	multipolygons

Table C1. OSM tags (keys and values) and geometry types, which were extracted from the osm.pbf data dump for the respective exposure types, using the OSM-flexpackage

Appendix C.2. Hazard, Exposure, and Vulnerability Data

Fig. C1 displays the winter storm hazard footprints retrieved from the CLIMADA data API [35]. Fig. C2 displays exposures for Switzerland, retrieved using the OSM-flex module, and fig. C3 asset value distributions from LitPop [34] and gridded population density [40]. Fig C4 displays impact functions (vulnerability curves) wind storm intensity to expected exposure impacts.
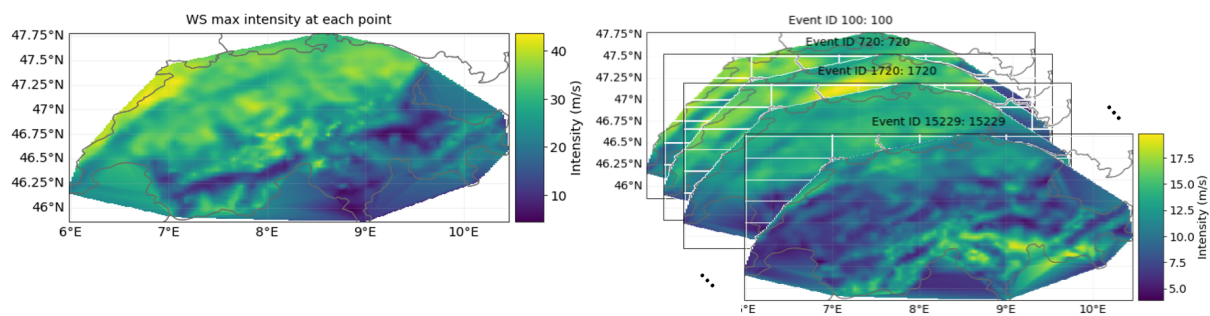
Figure C1. Winter storm hazard footprints (maximum 1-minutes sustained wind speed over 3-days) of Lothar (left) and of the WISC probabilistic extension hazard set for current climate (right) from [44, 39].
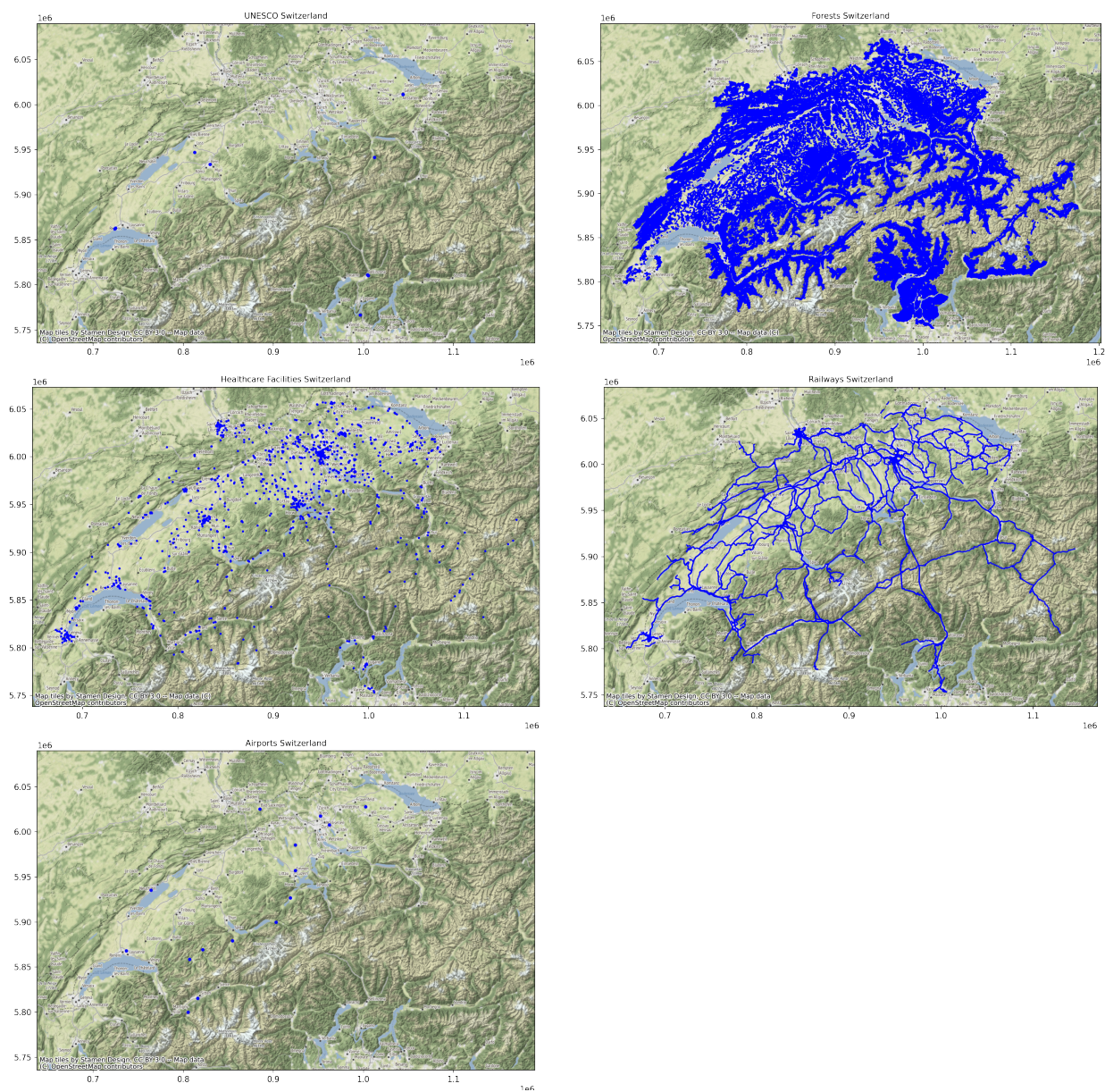
Figure C2. Exposure data extracted with the OSM-flexmodule (UNESCO heritage sites, forests, healthcare facilities, railways, airports) after post-processing (removal of duplicates, removal of polygons with area below 0.01.
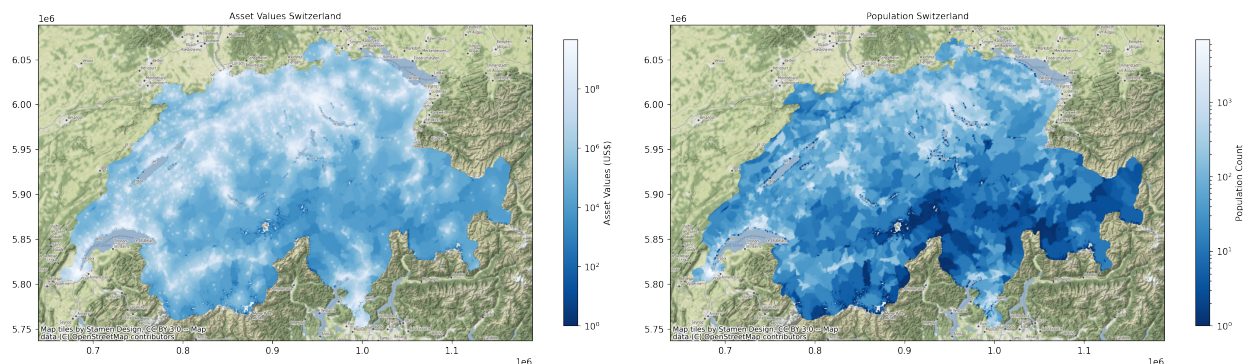
Figure C3. Exposure data often used for climate risk assessment: asset value distributions from LitPop [34], and gridded population density [40].
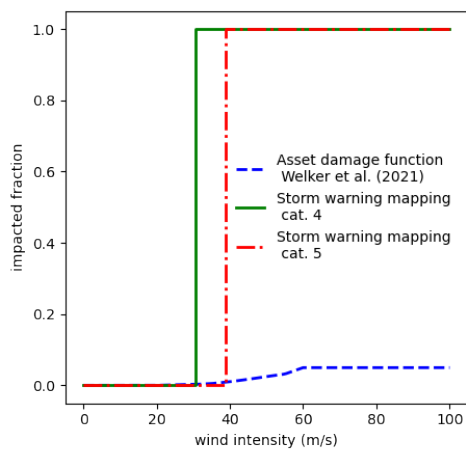

Figure C4. Impact functions employed for event impact and risk computations from winter storms for asset damages (blue, based on [39]), for affected healthcare facilities, UNESCO heritage sites, population and railways (green, based on the Federal Office for Meteorology and Climatology's warning category 4 wind-speed threshold (110 km/h or 30.5 m/s), and for forest loss (red, based on the warning category 5 wind-speed threshold (140 km/h or 38.9 m/s)).
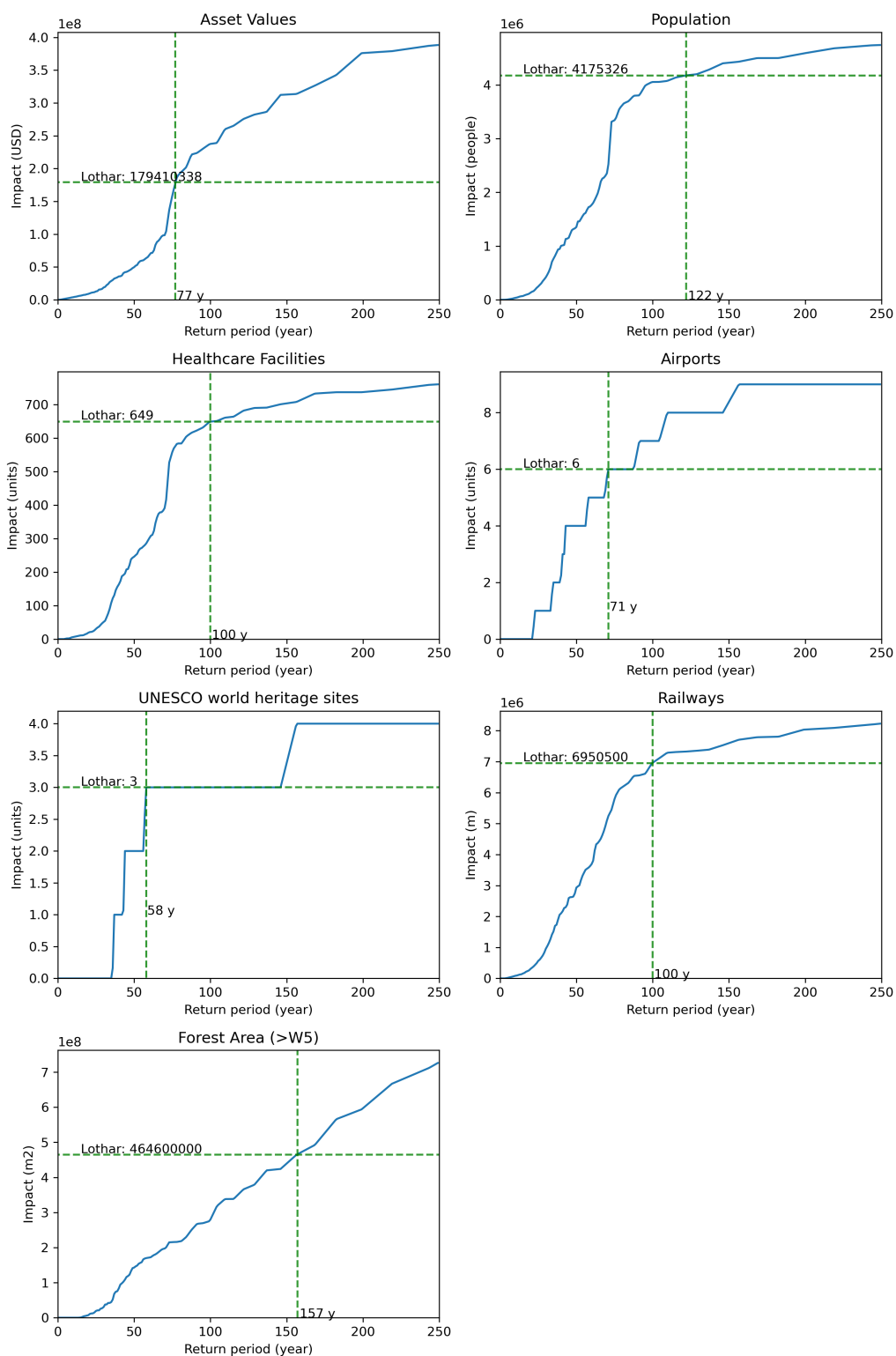
Figure C5. Return period curves of winter storm impacts for all exposure data categories used in this work's climate risk assessment, computed from the WISC probabilistic extension hazard set for current climate from [44, 39]. Historic impacts from winter storm Lothar are indicated on the vertical axis, the corresponding computed return period values of these impacts are indicated on the horizontal axis.