

Author's Accepted Manuscript

Spatio-temporal population modelling as improved exposure information for risk assessments tested in the Autonomous Province of Bolzano

Kathrin Renner, Stefan Schneiderbauer, Fabio Pruß, Christian Kofler, David Martin, Samantha Cockings



PII: S2212-4209(17)30334-5
DOI: <https://doi.org/10.1016/j.ijdr.2017.11.011>
Reference: IJDRR717

To appear in: *International Journal of Disaster Risk Reduction*

Received date: 23 May 2017
Revised date: 15 November 2017
Accepted date: 18 November 2017

Cite this article as: Kathrin Renner, Stefan Schneiderbauer, Fabio Pruß, Christian Kofler, David Martin and Samantha Cockings, Spatio-temporal population modelling as improved exposure information for risk assessments tested in the Autonomous Province of Bolzano, *International Journal of Disaster Risk Reduction*, <https://doi.org/10.1016/j.ijdr.2017.11.011>

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting galley proof before it is published in its final citable form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Spatio-temporal population modelling as improved exposure information for risk assessments tested in the Autonomous Province of Bolzano

Kathrin Renner^a, Stefan Schneiderbauer^a, Fabio Pruß^a, Christian Kofler^a, David Martin^b, Samantha Cockings^b

^aInstitute for Earth Observation, Eurac Research, Viale Druso 1, 39100 Bolzano, Italy

^bGeography and Environment, University of Southampton, Southampton, SO17 1BJ, UK

ABSTRACT

Population data is commonly available for administrative units referring to the year of the last census. That level of aggregation and the static character of the information pose particular difficulties for spatial analysis in applications such as disaster management or spatial planning, for which much more time-sensitive population distributions are required. In this study, a flexible model to create dynamic gridded population data with a spatial resolution of 100 m is implemented for the mountainous, hazard-prone and highly touristic region of the Autonomous Province of Bolzano, based on the integration of multiple data sources within an explicit spatio-temporal modelling framework. It is argued that dynamic gridded population information provides an improvement to the existing regional datasets. Our study shows that integrating daily and seasonal changes to the distribution of population improves exposure information for risk assessments especially in highly touristic areas.

Keywords: population exposure, spatio-temporal modelling, population dynamics, population grid, BolzanoBolzano

1. Introduction

Spatio-temporal information about population is crucial for many fields of application such as spatial planning, traffic management, climate change mitigation and adaptation, environmental protection, migration and mobility as well as risk assessment and management [1]; [2]; [3]; [4]; [5]. User requirements for such population data regarding spatial and temporal resolution as well as spatial accuracy vary considerably according to purpose and spatial scale of the application. In the case of hazardous events such as technical accidents, criminal acts or natural hazards, the availability of information on population distribution at the highest possible spatial and temporal resolution is crucial for an effective emergency response [6]; [7]; [8].

A majority of applications demand population data that is independent from enumeration and administrative areas [2]. Consequently, during the last decades a variety of methods have been developed to spatially decompose census data into grids of regular cell size leading to an increase in spatial accuracy and facilitation of a broad range of spatial analyses [2]; [3]; [4]; [5]; [9]; [10]; [11]; [12]

[13] [14] [15]; [16]. Usually these datasets are based partly on census data with a dasymetric mapping methodology applied. Still these datasets in most cases merely represent the night-time population distribution. People, however, are mobile, and therefore their potential presence in a hazard zone is a function of *space* and *time* [5]; [17];[18]. When integrating population data as an exposure layer into risk assessments for sudden hazard events it is necessary to account for this mobility. Recently, several activities have aimed to integrate the temporal dynamics into population distribution mapping and monitoring including work described by [19]; [3]; [5]; [18]; [2]; [13].

The objective of this study was to improve risk assessments of sudden hazard events by creating high-resolution population data for different points in time for a whole region comprising rural and urban areas and the particularities of a touristic region. The test case is the Autonomous Province of Bolzano, Italy. Martin et al. [18] have previously devised a general framework for modelling population distribution in space and time for a UK setting based on integration of available information from census and administrative sources [18]. This study demonstrates a first implementation of Martin et al's modelling approach in an entirely new national data setting from that in which it was developed.

This paper begins by providing an insight into population information as an important component of integrative risk assessments, giving an overview of the available datasets and the applied methodology. It then demonstrates results of the applied spatio-temporal population distribution model as well as the impacts on a flood risk assessment in a high-alpine touristic area. To conclude, the paper discusses the uncertainties of the model and provides an outlook to future work required.

1.1. *Population information as an important component of integrative risk assessments*

Crichton [20] defined risk from natural hazards as: “the probability of loss, which depends on three elements, hazard, vulnerability, and exposure”. These three components can be regarded as equally important in their contribution as described by Crichton as the ‘risk triangle’ [20]. “‘Exposure’ means the population, the infrastructure and the built environment” [20]. Exposure, in particular the population, is highly dynamic varying across spatial and temporal scales. Depending on the scale of the risk assessment, population is in general considered at the level of individual buildings or administrative units. Quantifying population in terms of numbers of persons is challenging because of its independent and dynamic character [21]. Commonly, officially available population data is collected by means of a census, resulting in the temporal and spatial characteristics of the information being static, between infrequent updates. Population registers offer more detailed data with more frequent updates than censuses but the information represented is still inherently static. When officially available population information is not adequate for the envisaged risk assessment, several approaches may be applied. One such method is exposure modelling where census data is enhanced with auxiliary datasets [22]. Another common example is to use Earth observation to produce up-to-date proxies of population distribution. In the latter approach, satellite images of different spatial resolutions are analysed to derive land cover land use maps or individual buildings. The results are then used to improve the available population data per administrative units [23], [24]. Ehrlich and Tenerelli [25] describe a method to quantify spatial and temporal changes of buildings as a proxy for human presence by using remote sensing change detection techniques.

Despite the well-developed conceptual understanding of disaster exposure and its dynamic variability, there exist few published examples that describe approaches and methods to generate spatio-temporal population datasets [3]; [5]; [13]; [18]; [19]; [26]. Most of the European countries have developed exposure databases, which are often hazard specific and static and difficult to integrate into risk analysis [21].

1.2. Status of population information at European and global levels

Exposure information commonly used in risk assessments, including the population estimates generated from the approaches listed above is static, referring to a single point in time. However, there is a demand for accurate, high-resolution and up-to-date population information for disaster risk management and civil protection entities. A number of initiatives are working on providing this kind of information at a global, European and country level. Global gridded population datasets include GPW [27], GRUMP [28] and LandScan [29]. The Worldpop dataset is available for large parts of the developing world, has a high spatial resolution of 100m and is produced following the approach of improving official population count data with land cover land use information and population distribution modelling methods [30] or following a Random Forest-based mapping approach [16]. The Global Human Settlement Layer (GHSL) is a settlement dataset with a resolution of 38m used to produce the GHS population grid with a resolution of 250m, based on the same census data underlying GPW [31]. More recently, gridded population maps at a scale of 30m are being made available for selected countries by Facebook's connectivity lab and the Center for International Earth Science Information Network - CIESIN [32].

Examples of day/night population maps include works in Europe [13] and in the USA [5]. In [5], population counts of the LandScan population grid were re-allocated depending on a range of different data sets such as land use classes, population census data, transport networks, statistics, elevation, education and employment information as well as aerial imagery. Similarly in [13] multiple datasets were combined to model population distribution for application in a risk assessment. A number of publications discuss developing a population database for estimating people at risk [3], [13], [29] and [33].

Aubrecht et al.[2] presented an approach of a night-time/daytime population distribution model extended to include work-home transition periods in the mornings and evenings. Martin et al. [12] developed a flexible framework for spatio-temporal population modelling, by which spatial population distributions were produced for multiple reference times.

1.3 Status of population information in the Autonomous Province of Bolzano

The case study area for this research, the Autonomous Province of Bolzano, is located in the Alps in northeast Italy (Figure 1 inset map). Population distribution data publically available for the Autonomous Province of Bolzano, provided by the regional authorities are census data consisting of the total number of registered inhabitants per municipality, which is collected in a ten-year cycle by the National Institute for Statistics (ISTAT). The regional statistical office provides updated yearly figures based on registered residences at the end of each year. In risk assessments and emergency management the Regional Department for Civil Protection uses resident locations from the population register, workplace locations of workers with an employee contract registered with the regional authorities, the locations and capacities of schools, universities, hospitals and touristic accommodations. This information is nonetheless static and not available as a continuous dataset, as an overview table or map in any form. This data is in a point format and updated monthly. It is available just for governmental use.

2. Materials and methodology

2.1. Study areas: population distribution modelling and risk assessment

The Autonomous Province of Bolzano is a mountainous region with an elevation that ranges from 194 m to 3,893 m a.m.s.l. Of its total area of 7399,15 km² only 5.5 % (407,84 km²) are classified as potential permanent settlement area [35] (Figure 1). Because of the steep terrain, the region is prone to natural hazards such as landslides, rockfalls, avalanches and floods. The mostly rural population is dispersed across the entire region and highly mobile in their daily commutes and weekend leisure activities. Due to the mountainous topography, there is limited space for settlements, which requires spatial planning to find a balance between the use of space and the risk of infrastructures to be exposed to natural hazards. Most settlements and thus human activities are concentrated in the valleys with limited space for roads, which makes the planning of traffic flows important, in particular in tourist areas. Total population of the Province for 2015 was 520,891 [36]. Municipalities are covering a large area of up to 300 km² (municipality Sarntal/Sarentino) with population figures ranging from 203 (municipality Waidbruck/Ponte Gardena in 2015) to 106,384 (municipality Bozen/Bolzano in 2014). One fifth of the total population lives in the regional capital Bozen/Bolzano. While the method developed in this paper was applied for the entire region, results presented here focus on two test areas: 1) the city of Bolzano for a detailed analysis of the dynamically modelled population distribution and 2) the small settlement Suldén/Solda located in a remote valley for the integration of the modelled population distribution into a risk assessment (Figure 1).

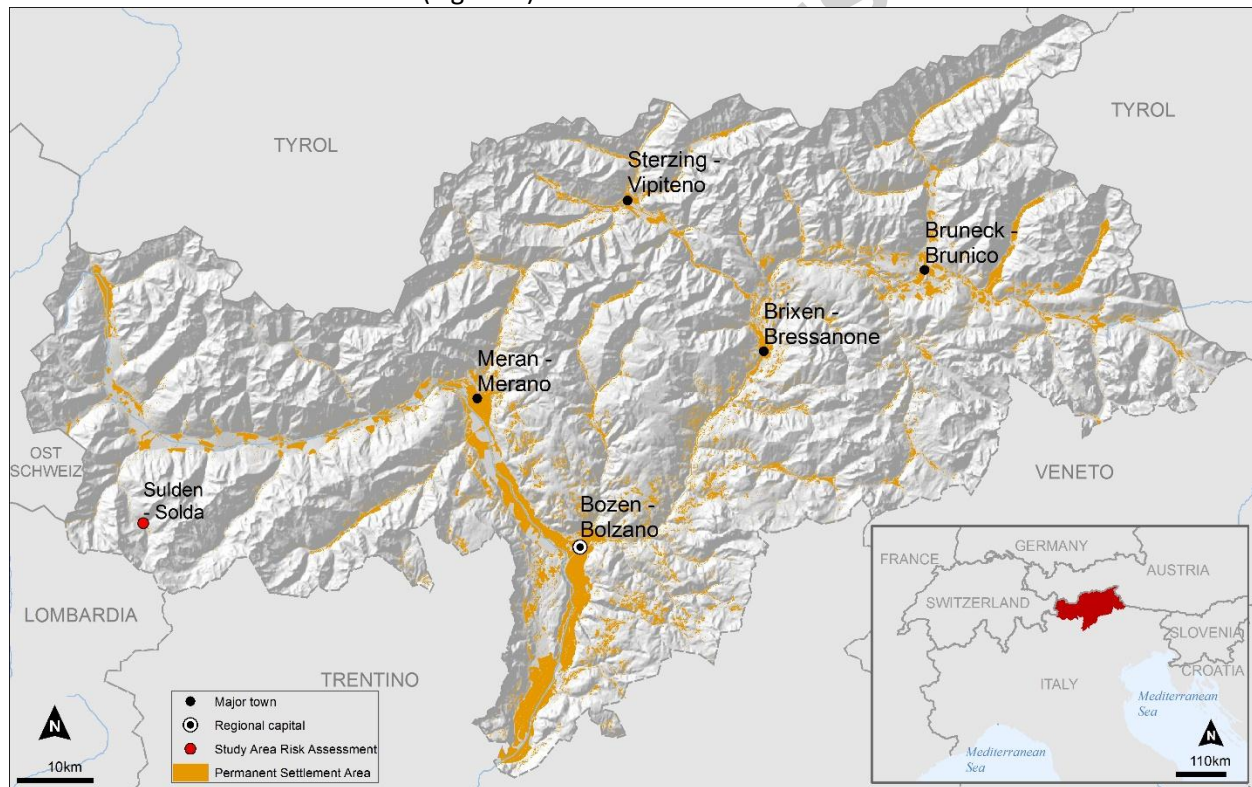


Figure 1: The study area, the Autonomous Province of Bolzano with the permanent settlement area by ASTAT, 2012.

The first test site, the city of Bolzano, with a resident population of 106,441 in 2015 and an area of 52.34 km² represents the administrative, economic and cultural centre of the Province [36]. The city of Bolzano is where most people commute to for work and education. The city's layout shows a rather clear distinction between residential and commercial / industrial areas (Figure 2).

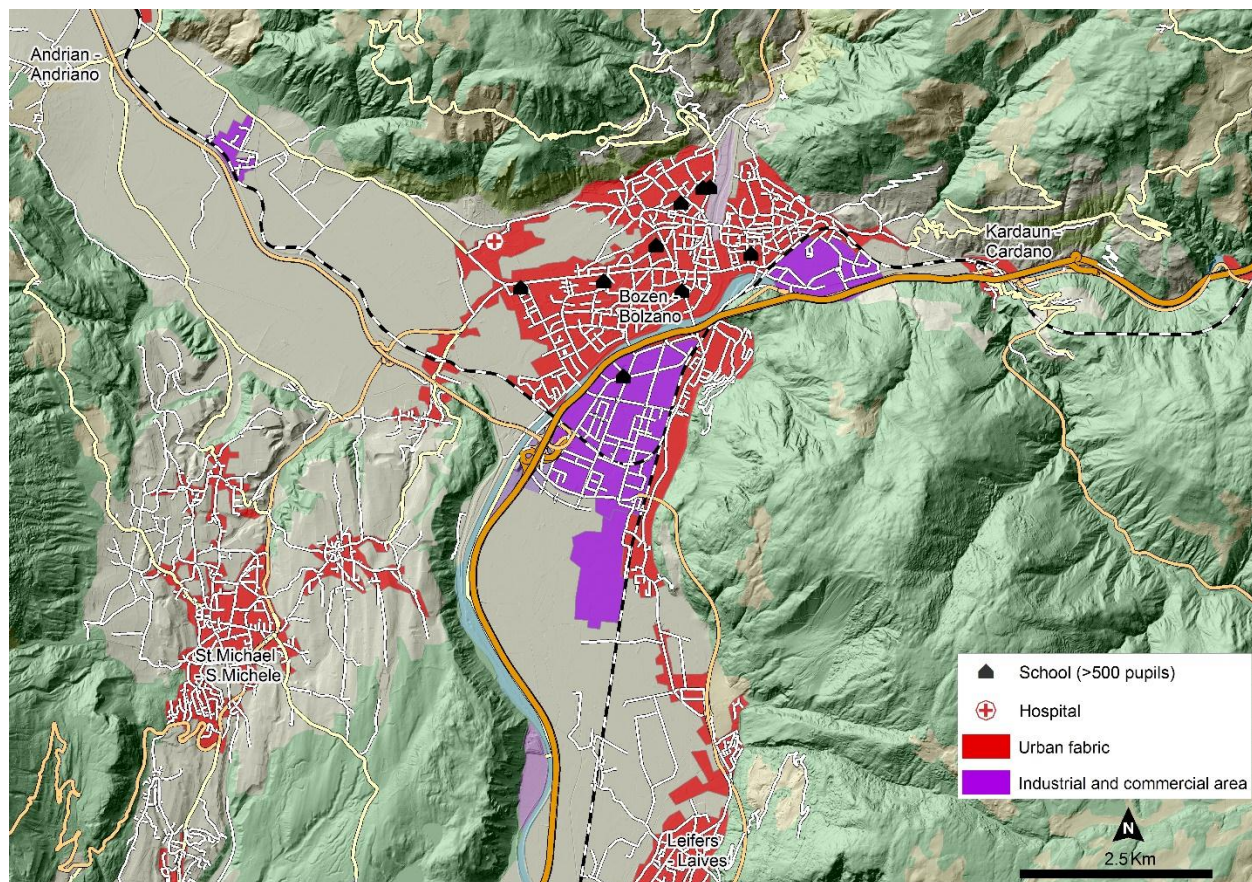


Figure 2: Bolzano and surroundings (industrial area in purple, south of the town, river and motorway)

The test site for the application of the risk assessment is the small settlement of Suldén/Solda located in the west of the Province in the municipality of Stilfs/Stelvio (Figure 1). Approximately 400 people live in this settlement [37]. The most important economic sector is tourism with major seasons during the winter and summer months. August represents a considerable peak in tourist numbers with 15,931 arrivals registered in the municipality in 2015, whereas the least number of tourists stayed in May with 762 people [38]. Due to its location at 1,906 m a.m.s.l. and its position below the glacier of Mount Ortles (3,905 m a.m.s.l.) local tourist operators are able to offer a particularly long skiing season. Steep terrain and the nearby glacier make the area prone to several natural hazards of gravitational and fluvial character. The hazard map covering Suldén/Solda shows debris flows and debris floods as the main hazard types potentially affecting the settlement area (Figure 6).

2.2. Modelling approach

For the spatio-temporal population mapping described in this paper, the approach developed by Martin et al. [12] was implemented, using the SurfaceBuilder247 software tool [12]. This has previously been applied to model the population distribution for England and Wales in the UK [39], [40], including a demonstration of use cases in integrated disaster risk management [6], [41]. SurfaceBuilder247 was chosen for this study as it offers a comprehensive volume-preserving spatiotemporal model, suitable for our needs. This has necessitated restructuring of locally available data sources to match the conceptual design and data structures employed by SurfaceBuilder247. Innovative methods were applied to analyse

the available datasets in order to derive the input datasets required for the modelling as follows. Firstly, due to the lack of homogeneous census output areas we created population weighted concentration points as 100 m raster cells based on resident and workplace employees locations. Secondly, since no dense network of traffic counting stations providing the required statistics of vehicle types and their numbers at different times of the day was available, we calculated this information using the data available from the 75 counting stations and a density function. Moreover, tourists present at touristic accommodations were calculated based on actual occupancy rates per relevant month (section 2.4).

As described in Martin et al. [18] the model follows a dasymetric and volume preserving approach, in that the total population is re-distributed across space according to various weights and constraints. The general framework includes three types of information: spatial containers, temporal characteristics and corresponding attributes. The spatial objects relate to containers of human activity, for example administrative areas or individual sites and buildings [18]. In general, it is assumed that people are either at their place of residence (origins), at work or another location (destinations), or they are in transit between locations of these two types. These three components with examples and simplified time profiles are depicted in Figure 3. The attribute information for each spatial container identifies the population that may be present (capacity), which may be broken down by population sub group (for example age groups). The population present at origin locations defines the total population present in the model. For destination locations, additional information describes the proportions of population who travel from different distance bands. Temporal information is recorded in the form of time profiles, assembled to reflect the pattern of expected presence of population. Background mapping layers are prepared for different times, weighted according to expected travel densities in the transport network and demarcating any areas (e.g. lakes) in which no population is allowed to be estimated. Data preparation involves the pre-processing of relevant datasets into standard origin and destination records, for example residential census data for origin locations and information on school and workplace locations as destinations, including numbers of students or employees, working hours and distances travelled. It is straightforward to derive estimated numbers of people travelling to or from a destination at any time, based on distance and time profiles. The SurfaceBuilder247 data structures are described more fully in [42]. According to the information available, distance and time profile information may be specified for each individual site, or standard values used for sites of different types (for example a standard time profile and catchment area for a type of school). Spatial containers of human activity are referenced by point coordinates, but source datasets may relate to a variety of spatial objects and output time-specific population distributions are estimated on a regular grid. The translation of point information into a raster representation happens during the spatial redistribution of population based on the provided assumptions on time constraints, capacities and wide area dispersion parameters, as described in the next paragraph.

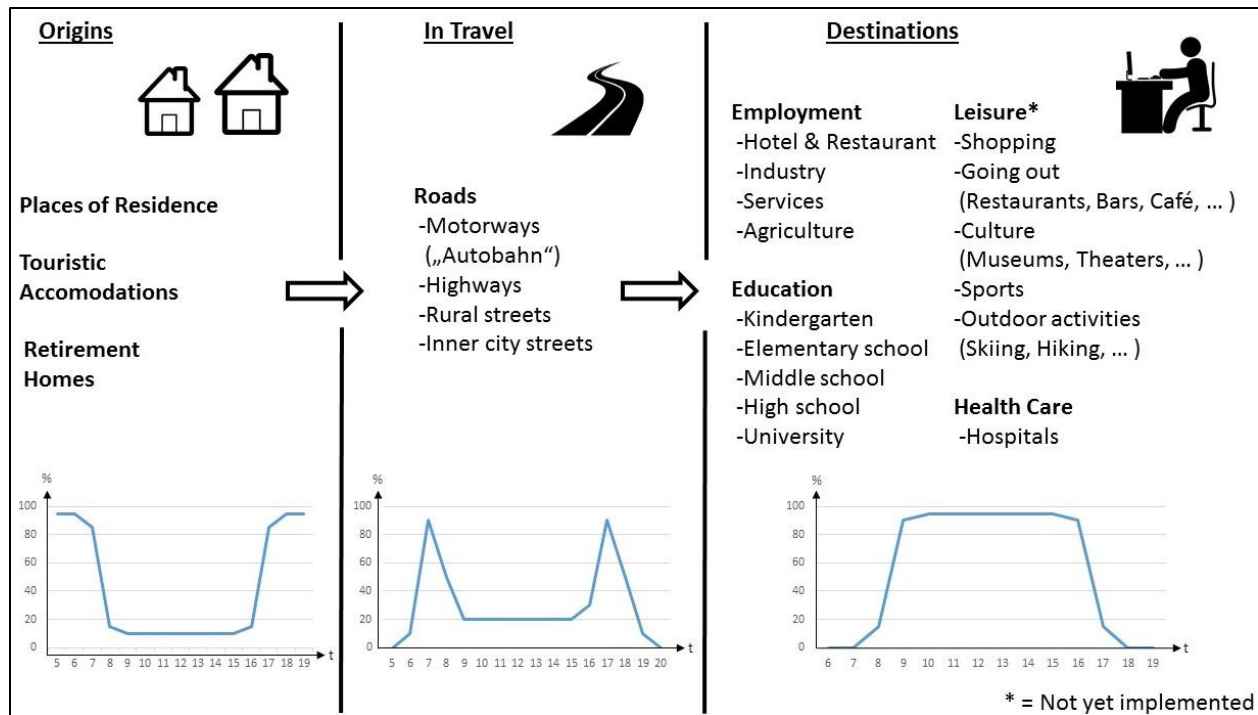


Figure 3: Overview of three components of population re-distribution (in the upper part) and simplified time profiles depicted as graphs (in the lower part)

Modelling proceeds by the selection of a target time for the population model. The entire library of origins, destinations and background layers is then processed in relation to that time, allocating the required numbers of people to destination activities such as schools and workplaces. The population required at each destination at the target time is reallocated by random sampling from the origin population data, stratified to match the proportions known to travel from each distance band to that destination. Thus the distribution of population travelling different distances to each destination is correctly reproduced. Each population sub group is processed separately, allowing the population reallocated to each destination to reflect its known demographic profile. The population deemed to be in transit at any point in time is spread across the weighted background map layer within the distance bands associated with each destination. The unallocated population will remain at the origin locations and the total population within the model is preserved. This approach, based on a structured library of spatio-temporal reference data, permits any number of time-specific population distributions to be derived, reflecting specific scenarios or research questions. The basic population distribution concepts are very generic and internationally applicable, but the present study is the first of which we are aware that uses SurfaceBuilder247 for a non-UK application.

2.3. Data sets

Table 1 provides an overview of the data sets used in this work. They comprise resident locations, workplaces, education facilities, kindergarten, nurseries, hospitals, touristic accommodations, restaurants, the road network, traffic count stations, touristic overnight stays and the official hazard zone map for the municipality of Stilfs/Stelvio. The datasets were provided especially for this research and under certain use restrictions by the Public Administration of the Autonomous Province of Bolzano.

Table 1: Summary of the data used

Data set name	Further description	Source	Updating interval	Reference year
Residents and Employee locations	Location information of workplace and place of residence	Regional Department of Labour Market Information (Amt für Arbeitsmarktbeobachtung)	Monthly	2015
Destination locations and capacities	Locations and capacities of schools, hospitals, touristic accommodations	Regional Department for Civil Protection		2015
Traffic density	Traffic flow (cars per hour) per traffic counting station	ASTAT (Statistical office)	Daily	2015
Student residency/school municipality	Municipality of schools and municipality of residence per student	Regional Department of School Administration (Schulamt Südtirol)	Yearly	2015
Touristic overnight stays	Number of tourists staying in the region per municipality and per capacity of a touristic accommodation	ASTAT	Monthly	2015
Natural hazard zones	Official hazard zone map for the municipality of Stils/Stelvio	Regional Department for Civil Protection		2015

2.4. Population modelling input data preparation & assumptions

Spatial information

Spatial containers of population in SurfaceBuilder247 are georeferenced by point coordinates [18]. For the Autonomous Province of Bolzano population weighted concentration points, i.e. centroids, were created for resident-, workplace- and touristic accommodation locations. This was done by first creating a net of 100 x 100 m cells covering the Province of Bolzano. Population centroids were created for each of those cells by calculating a population weighted mean location for each 100 x 100 m cell and then assigning it the sum of the number of people within that cell. Since each data point represents one person the population weighted mean could be calculated by taking the average X and Y coordinate within the corresponding 100 m cell.

Population present (capacities)

The population available for re-distribution from origin centroids was calculated as the sum of all residents in residence locations and tourists in touristic accommodation. Capacities of destination are numbers of students per school or numbers of employees per centroid workplace location. The number of people at the hospital were estimated based on data on services provided by the hospital management.

To estimate the amount of people that are 'in travel', i.e. people that are in transit between destinations and origins, traffic flow data from traffic counting stations was analysed. There are 75 traffic-counting stations distributed in the region. Data available from each station includes number of cars and average speed for every hour of every day of the year. Four types of roads were differentiated: motorways,

primary roads, secondary roads and inner city roads. In order to calculate the number of people that are on average on a 100 x 100 m road grid cell we first calculated the car density for each of the four types of road. The number of cars per hour were divided by the average velocity of cars expressed in km / h divided by ten. The equation can be written as:

$$\text{Density (cars per 100 m)} = 0.1 \frac{\text{Amount of cars } \frac{\text{cars}}{\text{hour}}}{\text{Avg. velocity } \frac{\text{kilometres}}{\text{hour}}}$$

We found that on primary roads, for example, over the course of 24 hours, cars per 100 m range from an average of 0.2 at night to 1.8 in the morning. Based on similarities we grouped car densities for the following times during working days and weekends: 00-06am, 06-09am, 09am-1600, 1600-1900 and 1900-00. Subsequently the car density was multiplied with a factor to estimate the number of persons per car. [33] adopted this approach to estimation of population in road traffic, which is consistent with the method used by [44], based on data from the National Travel Survey of Great Britain. For the test case of the Autonomous Province of Bolzano the same assumption as [33], i.e. occupancy rates of 1.5 persons per car on a weekday and 1.9 persons per car on weekends, was made.

Attribute information

Population origins based on residents were allocated age proportions per municipality classified as follows: under 19 years old, 20 to 65 years old and over 65 years old. For population origins based on tourists, no age information was available. Tourist origins were assigned the attribute 'immobile' due to the lack of data on possible destinations. In other words, tourists at all times of the day are assumed to remain at touristic accommodation.

Wide Area Dispersion (WAD)

Wide Area Dispersion refers to the distances over which population is expected to travel to a particular destination. For workplaces, these are based on calculations of average distances residents travel to work. The resulting distances were divided into classes. The estimates of average home to work distances revealed for example that 40 % of all workers employed in the hotel & restaurant sector travel less than one km to work. Accordingly, the WAD was set so that 40 % of employees in this sector are pulled from within a radius of one km of hotel & restaurant destinations. 15% of workers in this sector travel between one and three km to work and so on. Similarly, students' average distances to school (primary-, middle-, high- and vocational schools) were calculated based on home and school municipalities and type of school. For example, results revealed that 60 % of all middle school students travel on average less than three km to school. Consequently, the WAD was set so that 60 % of all middle school students are travelling less than three km to middle school destinations.

Temporal component: time profiles

Apart from school opening times, time profiles of destinations are based to a large degree on the public authorities and the authors' local knowledge and experience. Time profiles were developed for four categories of workplaces, which share similar working hours: industry, agriculture, service and hotel & restaurant. An example time profile for the industry sector is shown in Figure 4. The blue graph indicates the proportion of employees in the industrial sectors who are 'on site' at a given time. For example, between 09:00 and 16:00 90 % of employees are assumed to be at their workplaces. In other words, the maximum capacity of a workplace in the industrial sector in a given 100 x 100 m cell between 09:00 and 16:00 on a weekday is 90 % occupied. The yellow graph, on the other hand, indicates the

proportion of employees that are 'in travel'. For example, between 06:30 and 07:00, 25 % of all employees in the industrial sector are traveling to industrial workplaces. Additionally, a latent proportion of 10 % was added between the first and last 'in travel' occurrence (in this example's case between 06:30 and 18:30). This percentage reflects the proportion of workers who are not at their work place. This is to account for people who generally are not working in the office or are travelling for work. Different time profiles were created for weekdays and weekends. However, here we only show results for weekdays. The time profiles for the different school types (of primary-, middle-, high- and vocational schools), were created based on opening- and teaching hours of various schools.

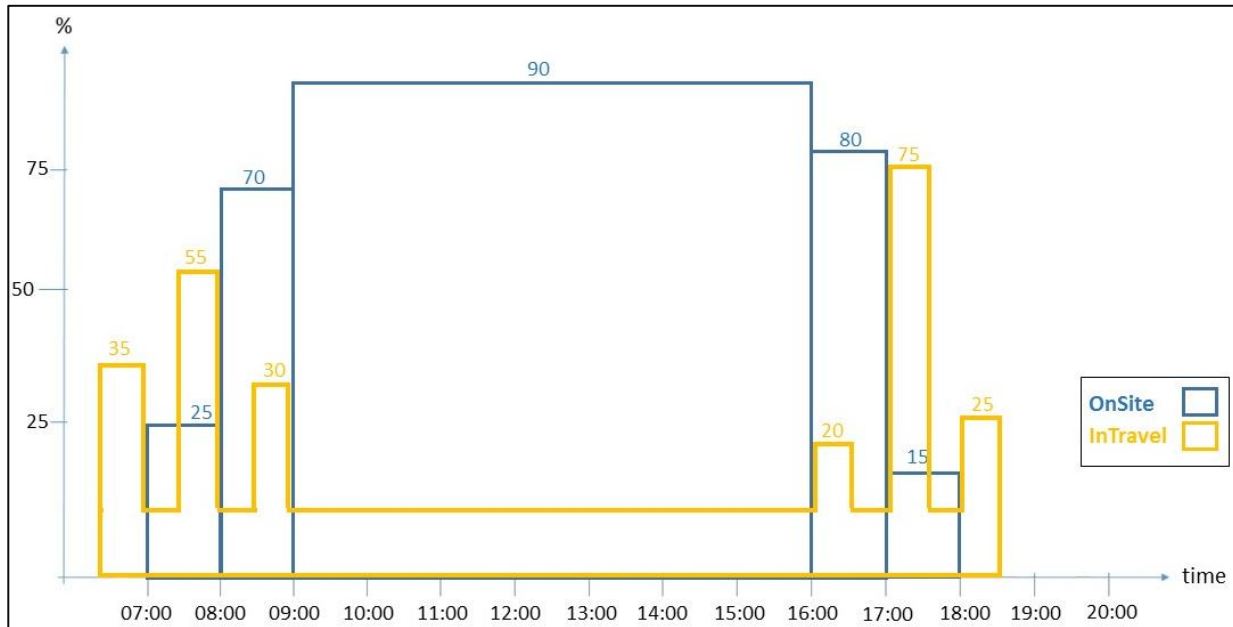


Figure 4: Time profile for industrial sectors on weekdays

The data and assumptions described in this section are not free from error. The most relevant uncertainties are discussed in section 4.

2.5. Dynamic population exposure to flood hazards at Suldén/Solda

As discussed in section 2.1, with respect to population numbers, the town of Solda is characterised by considerable tourist numbers during the summer and winter months. Therefore, time-dependent population distribution is expected to have a seasonal fluctuation rather than a daily one. Considering the various types of natural hazards threatening the settlement, this would mean that during the tourist seasons more people are at risk than outside the main season. To test this hypothesis, we firstly identified precisely the period of the year representing the main tourist season for Solda. August was identified as the month with the highest number of overnight stays and May the month with the lowest. The output resolution of the modelled population data was 100 m, which was found suitable to represent the population distribution for the entire Province and the regional capital of Bolzano. However, in order to analyse this data together with the very detailed hazard information some up-scaling was applied. The 100 m population grid cells were resampled to 1 m by means of equal distribution. To account for the induced risk, the official hazard zone map was used to extract all those grid cells which are exposed to a hazard. Hereby, a distinction between the three types of hazard zones (medium, high, very high danger) was made. Finally, the grid cells located within the various hazard

zones were summed up for the high-peak and low-peak tourist seasons. The same procedure was applied using the day and night population data sets.

3. Results

3.1. *Spatio-temporal population distribution during a working day and night*

In order to display the results in detail we focus on the area around the regional capital Bolzano. To aid orientation and interpretation of the results we show this subset area with residential and industrial zones as well as the transport network in Figure 2. We are comparing the following times: 02:00, 7:35, 10:00 and 14:00 on a weekday during term-time as shown in Figure 5.

In Figure 5, population density is shown in ten classes with green representing less and red depicting more people per 100 x 100 m. Although the general distribution pattern is the same in each of the four maps, it is apparent that at 02:00 the residential areas in Bolzano, located mostly north of the river as well as the nearby villages, show higher population numbers and a higher population density. Bolzano hospital is clearly visible as a population hotspot in all four maps. In the morning, at 7:35, the influence of the transportation network is clearly visible, even if the majority of the road network is classified in the lowest population density class. We also notice several red cell in the city of Bolzano that do not appear in the picture of the night-time distribution. These red cells represent the locations of schools and kindergarten. Also noticeable is that the industrial zone at 7:35 shows higher population numbers due to some sectors having working hours starting at 7:30. The inset map at the bottom left shows the population distribution at 10 o'clock in the morning. For the first time we see a substantial concentration of population where workplaces are located, i.e. in the northeast of the old town as well as the industrial zone, which now is much more densely populated than earlier in the day. The high population numbers where education facilities are located, remain. By 14:00 the concentration of people at and around workplaces remain the same as at 10:00, however the school locations do not stand out anymore as school generally finishes at 13:30.

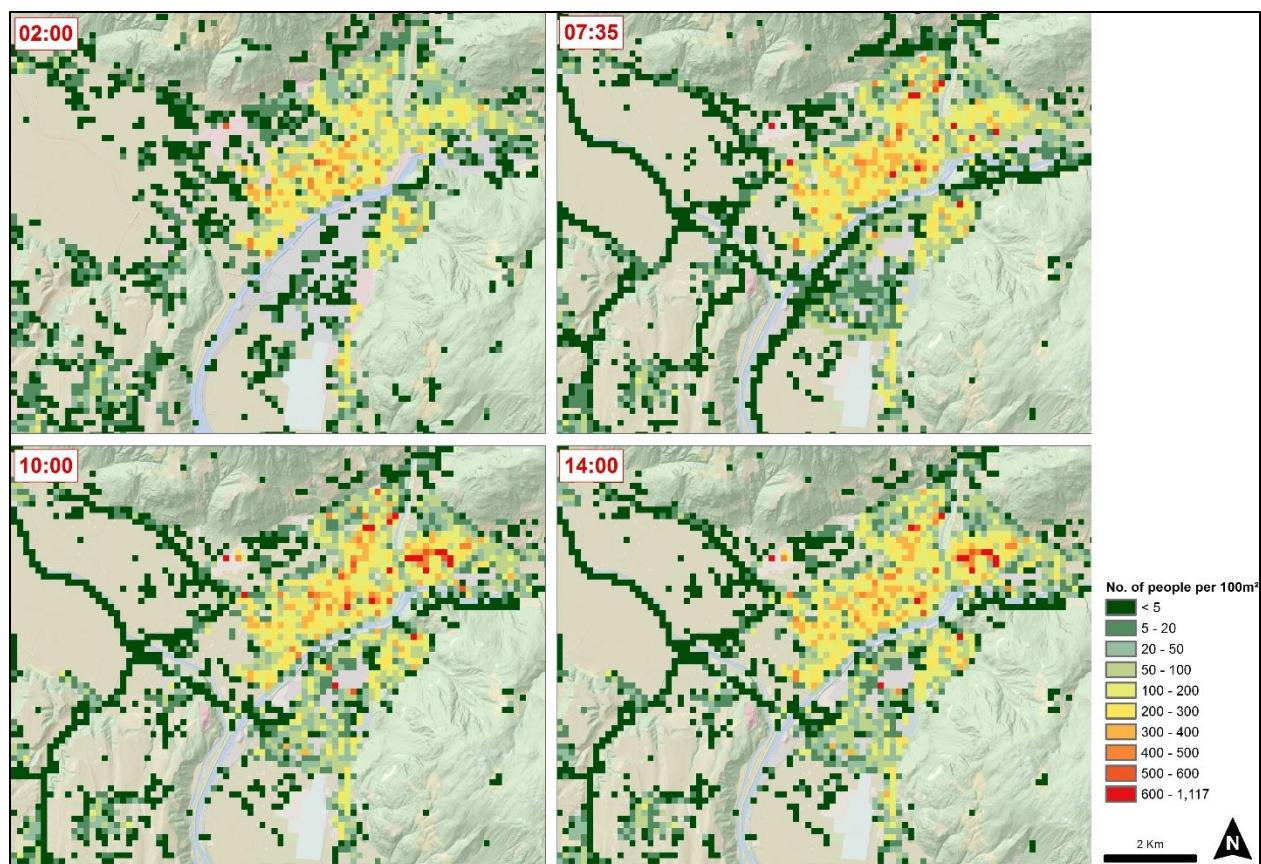


Figure 5: Population distribution in Bolzano and surroundings over the course of the day

Scrutinising the results by visual interpretation reveals that - in general - the dynamics of population distribution in Bolzano and surroundings are well represented. A gridded population dataset provides an interesting picture of the distribution of population at different times. However, there are several difficulties in validating the result. Uncertainties in the result obtained and assumptions made are discussed in section 4.

3.2. Dynamic spatial population exposure to flood hazards

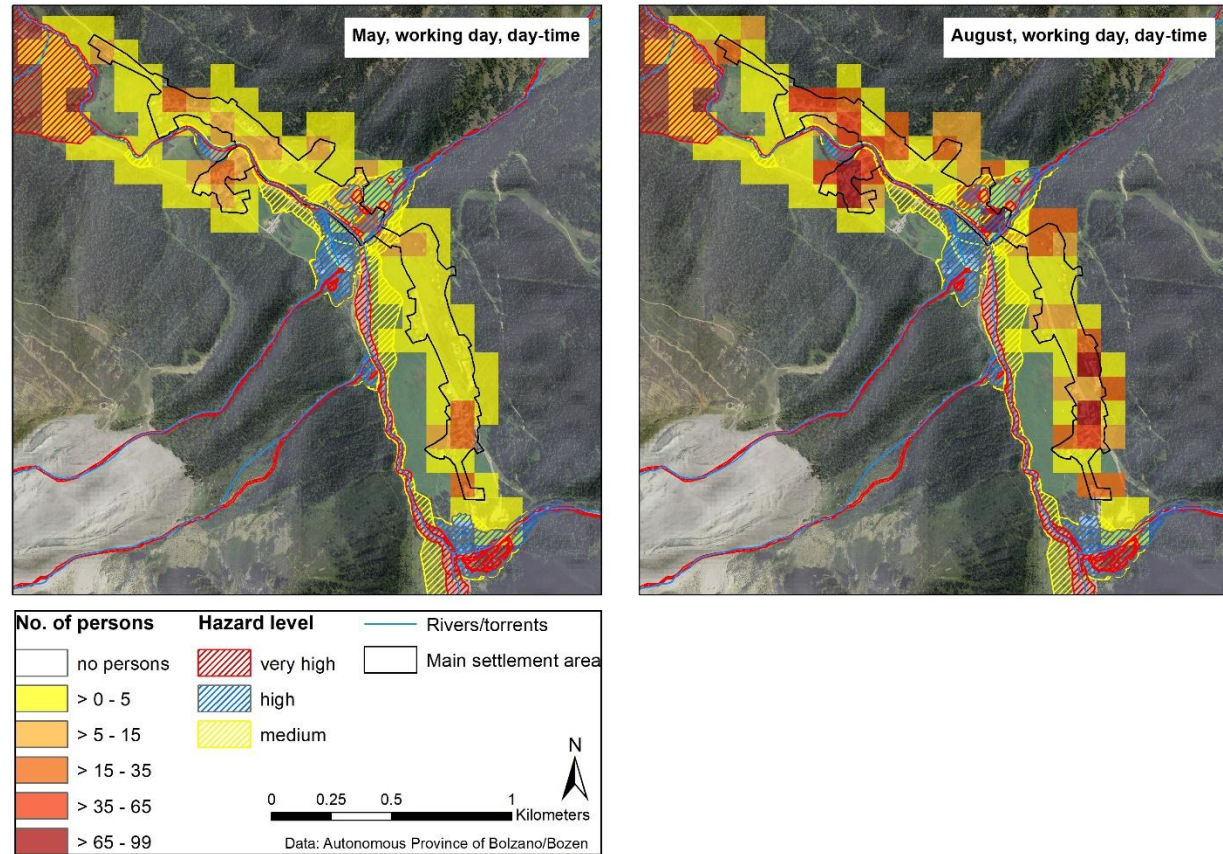


Figure 6: Hazard zones of Suldén/Solda and spatial population distribution at different seasons

The 100 x 100 m grid cells representing population distribution at different time slices and the hazard zones for the town of Solda are visualised in Figure 6. The delineation of the hazard zones is obtained by combining the magnitude and the return interval of the respective hazard type under consideration. The level of danger is shown in yellow (medium), blue (high) and red (very high) [43]. It can be seen that in general the number of people located at Solda is higher in August than in May. The figure reveals also that in both May and August a substantial number of people are located within the hazard zones, especially in the central part of the settlement nearby the outlets of lateral valleys. A comparison of daily and seasonal variation of population located within hazard zones is shown in Table 2. The results confirm what can be seen on the maps: More people are exposed to natural hazards in August than in May. Furthermore, the results show that the fluctuation from day- to night-time is minimal in both months. This is partly due to the assumption that tourists are immobile, but it also shows a compensating effect of inflow and outflow of workers during the day.

Table 2: Comparison of daily and seasonal variation of population located within hazard zones

	May		August	
	Day-time	Night-time	Day-time	Night-time
Medium	12	12	48	48
High	18	17	83	75
Very high	3	3	19	18
Sum	33	32	150	142

4. Discussion

This paper presents an implementation of a model to generate spatio-temporal population distribution maps for a region where hazard assessment demands much more than static night-time population mapping. High-resolution dynamic gridded population data has long been recognised as necessary for a variety of applications. The analysis has shown that creating gridded population datasets for different times during the day and over the year is feasible, with some effort, and the results represent an enhancement to existing population data sets (such as the official data set provided by the statistical office). Understanding and communicating population exposure in a single continuous raster layer is a notable improvement, compared to common population mapping based on administrative units. Implementing the existing SurfaceBuilder247 modelling environment allowed us to test the algorithm in an area characterised by high mountains and a prevailing tourism industry. The model application to a study site in a small side valley has shown that for touristic destinations the variation of population exposure to natural hazards is higher between high and low season than between day and night. This is to some extent due to the assumption made that tourists are immobile, which is not realistic but was necessary due to a lack of data on potential touristic locations. This limitation of the implementation could be addressed differently in a follow-up study. If supplementary data were available or collected purposively. In terms of risk management the paper implements a method which can be used to produce information which can be used to support emergency response and evacuation planning actions.

The paper shows that while the data situation was different to the original development environment and application area of the model in the UK, the basic population concepts are readily transferrable. The analysis found the local reality well represented. We found the results could be further improved by using more directly measured datasets for some of the model assumptions such as working hours and journey times to work or education facilities. Most of the inaccuracies in the results are related to the following factors: (1) inaccuracies and incompleteness of the underlying datasets (2) the exclusion of activities from the applied model, (3) inaccuracies in the assumptions made with regard to the time profiles 4) simplicity of the model and 5) simplifying, in particular the assumption that tourists are immobile.

Underlying datasets & model limitations

The simple distance-based redistribution algorithm applied by the standard model pays no regard to topography. This is reflected in the concentric WADs implemented in the algorithm. In the mountainous study area, topography has an influence on catchment areas and distances travelled.

Leisure activity and public transport not included

In this study, leisure activities such as sports, shopping, going to restaurants, bars, clubs, museums or events were not modelled, although it is recognised that those activities capture the movements of a considerable proportion of the population in particular in the evening hours and at weekends. Many tourists spend most of the daytime in places like ski areas, national parks or other touristic attractions. Such leisure activities are difficult to conceptualise and quantify, and no datasets on which to base modelling assumptions existed for the study area. Similarly, because for the study area, no studies on leisure activities on which to base model assumptions exist, no assumptions were made regarding the population using public transportation.

Simplification in assumptions

Time profiles are generalised and uncertain since they are in most cases not based on directly surveyed data. Abrupt changes between 'in travel' and 'on site' (for example at 08:00 in Figure 4) do not occur in reality. Thus 10 % of the working population was assumed to be 'in travel' at all times. The calculations of car densities are also rough estimates based on traffic counting stations and values are averages per

100 m for different types of roads. Irregular traffic flows or congested areas are not taken into consideration.

Validation of results

Primarily model results were checked visually and found to reflect the reality well. Visual checks involved looking at the population distribution results at different time overlayed onto baseline data such as residential areas, commercial areas, schools, hospitals and roads. Visual checks were also based on local knowledge. For a basic quantitative validation night-time model results were compared against the model input data. As this is a volume-preserving approach this validation was done by checking whether for example the day-time population in the model output matched the sum of the input data, i.e. residents not working, all workers (including those coming into the province to work from outside the province) and number of tourists based on occupancy rates per month and per municipalities for that year. We found an error of less than 1 %. We attribute the error to the number of tourists in the province on a specific day, which is an approximation based on average monthly occupancy rates and accommodation capacities. Day-night differences from the model were compared with commuting statistics from the 2011 census. The census data is available on a municipality level. We calculated an average error across all municipalities of 0.1 %.

Conclusion

Modelling spatio-temporal gridded population distribution using SurfaceBuilder247 offers a pragmatic approach that is flexible in the assumptions that have to be made as well as in the required input data sets. We found the model results for the case of the Autonomous Province of Bolzano provide a realistic picture of the distribution of people at different times. For a risk assessment of a touristic hotspot located in the mountains we found the exposure information in a gridded format for different months in the year added very useful information that would not be available without this kind of modelling. Vulnerability assessments, even though it is not the main focus of this paper, will gain from this type of approach.

A major consideration in the generation of the spatio-temporal models using this approach is the effort involved in preparing the diverse input datasets required. This is time-consuming and is unlikely to be

cost effective for a one-off risk assessment, but has great potential where there is likely to be ongoing demand for time-specific modelling or development of several different scenarios and a detailed up-to-date base data to work with is available, for example for multi-agency emergency planning or response purposes. The output models could be improved with the inclusion of more destination types (for example leisure activities, as noted above) and more sophisticated time profiles and travel data, particularly relating to the delineation of more realistic data for travel to work and school. However, the approach appears to be readily extensible and has worked effectively in an entirely different national data context from that in which it was first developed.

In future, these data demands may more easily be met by direct use of new Big Data sources such as social media and mobile phone data to enhance the mapping of population dynamics, addressing both the timely import of data and the identification of appropriate distance and time profile information. Ahas et al. [45] and Deville et al. [11] provide early examples of population mapping based on these types of data. However, these new sources only provide partial proxies for the presence of population and there will still be a need for calibration with administrative registers, auxiliary information and background mapping in ways very similar to those used here. Our approach could readily be extended to include these types of novel data source. Whichever specific input data are used, it is clear that a full understanding of population exposure to hazard requires spatio-temporal modelling which moves beyond current static sources and representations.

References

- [1] C.T. Lloyd, A. Sorichetta, A.J. Tatem, High resolution global gridded data for use in population studies, *Sci. Data*. 4 (2017) 170001. doi:10.1038/sdata.2017.1.
- [2] C. Aubrecht, K. Steinnocher, H. Huber, DynaPop - Population distribution dynamics as basis for social impact evaluation in crisis management, *ISCRAM 2014 Conf. Proc. - 11th Int. Conf. Inf. Syst. Cris. Response Manag.* (2014) 314–318. <http://www.scopus.com/inward/record.url?eid=2-s2.0-84905869676&partnerID=40&md5=c7c2013d66c885aedc410427b89c95da>.
- [3] T. Ahola, K. Virrantaus, J.M. Krisp, G.J. Hunter, A spatio-temporal population model to support risk assessment and damage analysis for decision-making, *Int. J. Geogr. Inf. Sci.* 21 (2007) 935–953. doi:10.1080/13658810701349078.
- [4] S. Schneiderbauer, Risk and Vulnerability to Natural Disasters—from Broad View to Focused Perspective, FU Berlin, Digit. Diss. Available At< (2007) 121. http://edocs.fu-berlin.de/diss/servlets/MCRFileNodeServlet/FUDISS_derivate_000000003126/00_Schneiderbauer.pdf?hosts=.
- [5] B. Bhaduri, E. Bright, P. Coleman, M.L. Urban, LandScan USA: A high-resolution geospatial and temporal modeling approach for population distribution and dynamics, *GeoJournal*. 69 (2007) 103–117. doi:10.1007/s10708-007-9105-9.
- [6] A. Smith, D. Martin, S. Cockings, Spatio-Temporal Population Modelling for Enhanced Assessment

- of Urban Exposure to Flood Risk, *Appl. Spat. Anal. Policy*. 9 (2016) 145–163. doi:10.1007/s12061-014-9110-6.
- [7] S. Freire, C. Aubrecht, Assessing Spatio-Temporal Population Exposure to Tsunami Hazard in the Lisbon Metropolitan Area, *Proc. 8th Int. ISCRAM Conf.* (2011) 1–5.
- [8] S. Freire, C. Aubrecht, Integrating population dynamics into mapping human exposure to seismic hazard, *Nat. Hazards Earth Syst. Sci.* 12 (2012) 3533–3543. doi:10.5194/nhess-12-3533-2012.
- [9] C. Aubrecht, J. Ungar, S. Freire, Exploring the potential of volunteered geographic information for modeling spatio-temporal characteristics of urban population A case study for Lisbon Metro using foursquare check-in data, *Int. Conf. Virtual City Territ.* 2011. Lisboa. (2011) 11–13.
- [10] K. Steinnocher, C. Aubrecht, H. Humer, H. Huber, Modellierung raum-zeitlicher Bevölkerungsverteilungsmuster im Katastrophenmanagementkontext Klaus Steinnocher, Christoph Aubrecht, Heinrich Humer, Hermann Huber, 8 (2014) 909–913.
- [11] P. Deville, C. Linard, S. Martin, M. Gilbert, F.R. Stevens, A.E. Gaughan, V.D. Blondel, A.J. Tatem, Dynamic population mapping using mobile phone data, *Proc. Natl. Acad. Sci.* 111 (2014) 15888–15893. doi:10.1073/pnas.1408439111.
- [12] I. Bracken, D. Martin, The generation of spatial population distributions from census centroid data, *Environ. Plan. A*. 21 (1989) 537–543. doi:10.1068/a210537.
- [13] S. Freire, A. Florczyk, S. Ferri, Modeling Day-and Nighttime Population Exposure at High Resolution: Application to Volcanic Risk Assessment in Campi Flegrei, *Proc. ISCRAM 2015 Conf.* (2015). <http://iscram2015.uia.no/wp-content/uploads/2015/05/5-2.pdf>.
- [14] C. Linard, V.A. Alegana, A.M. Noor, R.W. Snow, A.J. Tatem, A high resolution spatial population database of Somalia for disease risk mapping, *Int. J. Health Geogr.* 9 (2010) 45. doi:10.1186/1476-072X-9-45.
- [15] M. Langford, Rapid facilitation of dasymetric-based population interpolation by means of raster pixel maps, *Comput. Environ. Urban Syst.* 31 (2007) 19–32. doi:10.1016/j.compenvurbsys.2005.07.005.
- [16] F.R. Stevens, A.E. Gaughan, C. Linard, A.J. Tatem, Disaggregating census data for population mapping using Random forests with remotely-sensed and ancillary data, *PLoS One*. 10 (2015). doi:10.1371/journal.pone.0107042.
- [17] E. Steiger, R. Westerholt, B. Resch, A. Zipf, Twitter as an indicator for whereabouts of people? Correlating Twitter with UK census data, *Comput. Environ. Urban Syst.* 54 (2015) 255–265. doi:10.1016/j.compenvurbsys.2015.09.007.
- [18] D. Martin, S. Cockings, S. Leung, Developing a Flexible Framework for Spatiotemporal Population Modeling, *Ann. Assoc. Am. Geogr.* 105 (2015) 754–772. doi:10.1080/00045608.2015.1022089.
- [19] T.N. McPherson, M.J. Brown, Estimating daytime and nighttime population distributions in U.S. cities for emergency response activities, *Bull. Am. Meteorol. Soc.* (2004) 557–566. doi:10.1215/9780822384625-001.
- [20] D. Crichton, The risk triangle, *Nat. Disaster Manag.* (1999) 102–103.
- [21] D.C. Simmons, Understanding disaster risk: risk assessment methodologies and examples, in:

- (Eds.) Poljanšek, K., Marin Ferrer, M., De Groeve, T., Clark, I. (Ed.), *Sci. Disaster Risk Manag.* 2017 Knowing Better Losing Less, Publications Office of the European Union, 2017: p. 553. doi:10.2788/688605.
- [22] B. De Bono, Andrea ; Chatenoux, A global exposure model for GAR 2015, 2015. http://www.grid.unep.ch/products/3_Reports/GAR2015_exposure_model.pdf.
 - [23] U. Deichmann, D. Ehrlich, C. Small, G. Zeug, Using High Resolution Satellite Data for the Identification of Urban Natural Disaster Risk, *Eur. Union World Bank.* (2011) 1–80. <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Using+high+resolution+satellite+data+for+the+identification+of+urban+natural+disaster+risk#1%5Cnhttp://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Using+High+Resolution+Satellite+Dat>.
 - [24] F. Dell’Acqua, P. Gamba, K. Jaiswal, Spatial aspects of building and population exposure data and their implications for global earthquake exposure modeling, *Nat. Hazards.* 68 (2013) 1291–1309. doi:10.1007/s11069-012-0241-2.
 - [25] D. Ehrlich, P. Tenerelli, Optical satellite imagery for quantifying spatio-temporal dimension of physical exposure in disaster risk assessments, *Nat. Hazards.* 68 (2013) 1271–1289. doi:10.1007/s11069-012-0372-5.
 - [26] Z. Zhang, R. Sunila, K. Virrantaus, A spatio-temporal population model for alarming, situational picture and warning system, *Remote Sens. Spat. Inf. Sci.* 38 (2010) 69–74.
 - [27] E. Doxsey-Whitfield, K. MacManus, S.B. Adamo, L. Pistoiesi, J. Squires, O. Borkovska, S.R. Baptista, Taking Advantage of the Improved Availability of Census Data: A First Look at the Gridded Population of the World, Version 4, *Pap. Appl. Geogr.* 1 (2015) 226–234. doi:10.1080/23754931.2015.1014272.
 - [28] D.L. Balk, F. Pozzi, G. Yetman, U. Deichmann, A. Nelson, The distribution of people and the dimension of place methodologies to improve the global estimation, *Urban Remote Sens. Conf.* (2005) 1–6. http://sedac.ciesin.columbia.edu/gpw/docs/UR_paper_webdraft1.pdf.
 - [29] J.E. Dobson, E.A. Bright, P.R. Coleman, R.C. Durfee, B.A. Worley, LandScan: A global population database for estimating populations at risk, *Photogramm. Eng. Remote Sensing.* 66 (2000) 849–857. doi:10.1016/j.scitotenv.2008.02.010.
 - [30] A.E. Gaughan, F.R. Stevens, C. Linard, P. Jia, A.J. Tatem, High Resolution Population Distribution Maps for Southeast Asia in 2010 and 2015, *PLoS One.* 8 (2013) e55882. doi:10.1371/journal.pone.0055882.
 - [31] S. Freire, K. MacManus, M. Pesaresi, E. Doxsey-Whitfield, J. Mills, Development of new open and free multi-temporal global population grids at 250 m resolution, *Proc. 19th Agil. Conf. Geogr. Inf. Sci.* Helsinki, Finland, June 14–17, 2016. (2016).
 - [32] Facebook Connectivity Lab and Center for International Earth Science Information Network - CIESIN - Columbia University, High resolution settlement layer (HRSL) © 2016 DigitalGlobe, (2016). <https://ciesin.columbia.edu/data/hrsl/> (accessed May 23, 2017).
 - [33] A. Smith, Spatiotemporal population modelling to assess exposure to flood risk, University of Southampton, 2015. <https://eprints.soton.ac.uk/377152/>.
 - [34] D. Martin, *SurfaceBuilder247 : user guide*, (2009).

- [35] Provincia Autonoma Di Bolzano, Dauersiedlungsgebiet in Südtirol. Territorio insediativo in provincia di Bolzano, (2012).
- [36] Provincia Autonoma di Bolzano, South Tyrol in figures, 2016.
http://astat.provinz.bz.it/downloads/Siz_2016-eng.pdf.
- [37] Provincia Autonoma Di Bolzano, 14. Allgemeine Volkszählung - Band 4 - Bewohnte Ortschaften, 2001. http://astat.provinz.bz.it/downloads/VZ2001_ortschaften-pdf-neu.pdf.
- [38] Provincia Autonoma Di Bolzano, Datenbanken und Gemeindedatenblatt, (n.d.).
<http://astat.provinz.bz.it/de/datenbanken-gemeindedatenblatt.asp> (accessed May 23, 2017).
- [39] D. Martin, Mapping population data from zone centroid locations, *Trans. Inst. Br. Geogr.* 14 (1989) 90–97. doi:10.2307/622344.
- [40] D. Martin, An assessment of surface and zonal models of population, *Int. J. Geogr. Inf. Syst.* 10 (1996) 973–989. doi:10.1080/026937996137684.
- [41] A. Smith, A. Newing, N. Quinn, D. Martin, S. Cockings, J. Neal, Assessing the Impact of Seasonal Population Fluctuation on Regional Flood Risk Management, *ISPRS Int. J. Geo-Information*. 4 (2015) 1118–1141. doi:10.3390/ijgi4031118.
- [42] D. Martin, Surface Builder: User guide, (2011) 1–10.
<http://www.researchcatalogue.esrc.ac.uk/grants/RES-062-23-1811/outputs/read/ece508b5-6438-4e96-99eb-8fd68f1d3b99>.
- [43] Südtirol-Autonome-Provinz_Bozen, Beschluss der Landesregierung Deliberazione della Giunta Provinciale Nr. 712, Beiblatt Nr. 1 Zum Amtsblatt Nr. 21/I-II Vom 22/05/2012. (2013) 1–82.
- [44] G. Smith, J. Fairburn, Research Report RR678: Updating and improving the National Population Database to National Population Database 2, (2008).
- [45] R. Ahas, A. Aasa, Y. Yuan, M. Raubal, Z. Smoreda, Y. Liu, C. Ziemlicki, M. Tiru, M. Zook, Everyday space–time geographies: using mobile phone-based sensor data to monitor urban activity in Harbin, Paris, and Tallinn, *Int. J. Geogr. Inf. Sci.* (2015). doi:10.1080/13658816.2015.1063151.